A New Perspective of the Territorial Impactof Primary Sector Activities

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A New Perspective of the Territorial Impact of Primary Sector Activities

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A mis padres.

Que la distancia durante estos años haya valido la pena.

"Education is the most powerful weapon which you can use to change the world."

— Nelson Mandela

Preface

I left the task of writing this page for the end. Primarily because I consider it an act of farewell, a season finale. And I am writing it on the same table where I began working on the proposal for this thesis in October 2020, when I couldn't even envision this moment. Yet, here we are today. These pages contain the work of all these years, which have cost days, nights, therapy, and uprooting.

This thesis would not have become what it is today without the help of my supervisor, Rosella Nicolini. I am and will always be very grateful for her valuable guidance, which began with her supervision during my master's thesis work. Since then, she has seen me grow as a researcher, and I hope she can feel proud of her work as she sees me at the culmination of this stage.

I am grateful to life for the valuable company I have had all this time. Nothing I have experienced during these years would have been possible without Enrique by my side. Thank you for always being there. For existing. For making me wish the world were full of people like you so that it would be a much better place.

Thanks to my parents and siblings, who always gave me their words of support from afar. For every time they said they were proud of me. Without a doubt, they have been the light at the bow of my boat, even when we are physically separated. This achievement is for you and to make all this time we've been apart worthwhile.

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sure their comments and suggestions will improve this research.

Finally, I would like to acknowledge the opportunity granted by the University of Antofagasta to pursue my postgraduate studies through the Academic Disciplinary Improvement Program.

Prefacio

He dejado la tarea de escribir esta página para el final. Principalmente, por considerarla un acto de despedida. Un final de temporada. Y la escribo sobre la misma mesa en la que comencé a trabajar en la propuesta de esta tesis, en octubre de 2020. Cuando aún ni siquiera vislumbraba este momento. Sin embargo, hoy estamos aquí. Y en estas páginas se encuentra el trabajo de todos estos años, que ha costado días, noches, terapia y desarraigo.

Esta tesis no habría podido llegar a ser lo que es hoy sin la ayuda de mi supervisora Rosella Nicolini. Estoy y estaré siempre muy agradecido de su valiosa dirección, que comenzó con su supervisión durante mi trabajo de tesis de máster. Desde entonces ha podido verme crecer como investigador y espero que pueda sentirse orgullosa de su trabajo al verme en la culminación de esta etapa.

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Chapter 1

Introduction

Knowledge has a relevant and well recognized role as one of the principal factors driving growth (Lucas, 1988; Romer, 1986, 1990). Education and knowledge lead to innovation and new technologies that optimize the returns of factors of production and constitute the basis of endogenous growth. Recently, the rapid transmission of information on a global scale has progressively enabled developing economies to access to ideas, knowledge, and technology, which contribute to set the foundations for a long-term growth. However, these economies tend to heavily rely on natural resource-based industries. This feature raises the question whether there is compatibility between the foundations of endogenous growth, and the traditional production sectors. How can intangible assets, like knowledge and education, and these traditional production sectors coexist, in order to provide long-run growth and economic development?

The potential impact that productive sectors relying on the endowment of natural resources (primary sector) may generate on the creation and distribution of knowledge are gaining increasing attention in the literature (Aljarallah & Angus, 2020; Alvarado et al., 2023; Gelebo, Plekhanov, & Silve, 2015; Welsch, 2008). One of the main mechanisms through which knowledge and education meet the primary sector is education, but rather in competitive than in complementary terms. Investment in education frequently appears to be in conflict with the interests of the primary sector. This disincentive stems from shortsightedness, rent-seeking attitudes, weak institutions, and risk aversion, due to the link between the principal sources of revenues of this sector and international price fluctuations (Mousavi & Clark, 2021). This discussion becomes even more relevant from a regional perspective. The activity of primary sector industries in regions with high endowment of natural resources guarantees high level of employment and wealth in the short term. However, they suffer from the effects of the Resource Curse associated with lower human capital accumulation, entailed by lower levels of investment in education and the crowding out of high-skilled human capital. These effects, in turn, have a negative impact on the creation of ideas, knowledge, and new technologies, which are deemed the drivers of endogenous growth. Another negative side of the low level of human capital refers to the important social consequences it can bring: people have difficulties in establishing networks that can provide access to valuable intangible social resources. These resources can include information about available job positions or support for entrepreneurship, as well as access to new ideas. Reduced accessibility to such resources indirectly leads to a lower diffusion of knowledge.

The aim of this thesis is to examine the relationship between the concentration of primary sector activities and the drivers of endogenous economic growth from a regional perspective. The research focuses on the case of Chile: a high-income developing economy but highly dependent on natural resources. In particular, the mining industry plays a significant role in the country's economy. The high geographical concentration of mining deposits provides an interesting context for studying this relationship at a sub-national level, justifying the regional approach adopted in this thesis. The specific objective of this thesis is, firstly, to assess the impact of the concentration of primary sector activities on the human and social capital levels among sub-national units. Consequently, to provide evidence on the beneficial impacts of a higher concentration of knowledge-intensive activities on the productivity of the mining sector.

The first chapter of the thesis, *Mines, fields, or classrooms: Effects of primary activities agglomeration on local human capital accumulation*, deals with the interplay between education and the primary sector. In this chapter we analyze the impact of spatial concentration of mining and non-mining primary activities on human capital accumulation at the municipal level. We focus on the case of Chile, where the mining industry is characterized by high wages, mainly due to union negotiations during copper price booms. Our main hypothesis is that a higher concentration of mining activities can impact on the degree of accumulation of human capital by increasing the opportunity costs of getting higher education against the option of entering the labor market. In addition, one can also think that this process holds for non-mining primary activities, but on a more regular basis. The rationale for the latter lies on the imperfectly competitive market structure derived from the high participation in seasonal product markets, which potentially allows for setting higher prices and creates greater incentive for workers to enter this labor market than acquiring higher education. In order to assess this relationship, we followed two approaches. First, we estimate the impact of the agglomeration of this type of activities on the individual likelihood of having college education. This allows us to approximate to the availability of highly educated labor in the municipality. Subsequently, we explore for spatial spillovers, assessing the impact of the agglomeration of mining and non-mining primary activities on the share of highly educated working-age population. A series of Kelejian-Prucha (SAC) models are estimated using cross-sectional data aggregated at the municipal level. Results suggest that a higher concentration of mining activity leads to lower probabilities of working-age population to have college degree in periods in which the copper price records the highest quotes. Conversely, non-mining activities exert relatively more persistent, negative effects. Results from Kelejian-Prucha model estimations suggest spillovers stemming from the concentration of non-mining primary activities across neighboring municipalities. Nevertheless, no conclusive results for spillovers stemming from mining are found. In light of these results, we identify temporal and spatial differences between mining and non-mining activities in terms of the impact on the level of educational attainment. Under these circumstances, placed-based regional development strategies aimed at reinforcing the regional growing capacity in the long term are recommended. Industrial diversification, the attraction of highly skilled human capital into resource-rich territories, and the creation of industrial clusters are crucial in achieving this target.

In this line, the second chapter of the thesis, *How many doctors do you know? Spatial social capital, occupational prestige, and primary sector activities*, explores the extent the local specialization in primary sector activities, by means of the accumulation of human capital, can shape the creation of social capital, as a factor intended to enhance individual welfare. In this second chapter we aim to contribute to the understanding of the relationship between social capital and the local economic structures, from a spatial perspective. Specifically, we exploit data from Chile to examine the extent to which social capital is influenced by the agglomeration of primary sector firms between 2016 and 2021 at the municipal level. The rationale behind this approach is that social resources embedded in social connections are negatively affected by local (and neighboring) economic settings with a high concentration of (low-skill) primary-sector activities, mostly due to the evidence of 'resource curse effects' on the distribution of highly skilled human capital. We expect that territories with higher concentration of primary sector activities provide a lower support for establishing high-status networks in terms of connections with people in prestigious occupations. In this chapter we propose a novel measure of aggregated (spatial) social capital at the municipal level, based on the position generator survey instrument put forward by Lin and Dumin (1986). In this survey, individuals have access to a predetermined list of occupations, then they have to indicate how many people they know who occupy each of these occupations. Here, our interest is to focus on prestigious occupations, such as medical doctors, lawyers, college professors, managers, and accountants. Our findings detect negative direct effects from primary sector agglomeration on social capital at the municipal level, as well as spillover effects between municipalities. Conversely, the results suggest positive direct and indirect spatial effects stemming from the aggregate level of education in the spatial unit. When analyzing separately the effects of the concentration of mining and non-mining activities, the estimations provide consistent outcomes for the latter. Therefore, the conclusions of this chapter highlight the adverse social consequences of high dependence on primary sector at the local level, as well as the importance of education in fostering high-status social networks.

The other important intangible factors driving growth are technology and innovation. We deal with these dimensions in the third chapter of this thesis, *The Impact of KIBS Agglomeration on Chilean Mining Sector Productivity*. This last chapter aims to propose a novel understanding of knowledge and technology (embedded in the concentration of knowledge-intensive business services industry) on the productivity of the mining sector. Specifically, we estimate the impact of the spatial concentration of firms that supply knowledge-intensive business services (KIBS) on mining labor productivity. The idea behind this study is that these specialized firms operate as facilitators and co-producers of innovation, thus impacting in the productivity of their client firms. 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 and firm performance. We perform the analysis by following two approaches. First, we assess the impact of the industrial specialization in KIBS on individual- and aggregate-level labor productivity of mining workers. Consequently, we conduct a spatial analysis of this interaction aiming at exploring the existence of spatial dependencies and spillover effects. 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. Attracting high-skilled human capital and encouraging the creation of knowledge-intensive service firms might stimulate the creation of productive networks and the generation of innovation.

Overall, the results presented in this thesis provide a clear message: long-term development is possible in a primary sector economy, and knowledge is crucial for this achievement. Instead of shifting the productive structure toward one less dependent on natural resources, regions well endowed with natural wealth can leverage the knowledge acquired through specialization and transform it into a valuable asset for local growth. Disparities between regions in terms of human and social capital can be addressed through specialized education in local production processes and the promotion of entrepreneurship in knowledge- and technology-intensive activities beneficial to the primary sector. Policies aimed at this objective will enhance local human capital levels, facilitate social connections with highly qualified individuals, increase innovation directed toward productivity improvements, and promote the creation of specialized services in natural resources. In this way, the path toward a knowledge-based economy can be paved on the foundation of primary sector activities.

Chapter 2

Mines, fields, or classrooms: Effects of primary activities agglomeration on local human capital accumulation[1]

2.1 Introduction

The resource curse literature concludes that resource-rich countries under-perform in terms of economic growth rates compared to resource-poor countries (Auty, 1994, 2000; Sachs & Warner, 1995). This phenomenon has been a topic for debate and empirical research since the end of the 20th Century and it has been studied in a number of countries (Frankel, 2010). A growing number of studies have focused on the impact of resource wealth on human capital accumulation during the last decades (Mousavi & Clark, 2021). The relevance of this interplay lies on the central role that human capital plays in triggering economic growth by driving innovation, productivity growth, and overall economic performance (Lucas, 1988; Mathur, 1999). However, resource abundance may distort the incentives and allocation of resources, potentially hindering investments in human capital (Birdsall, Pinckney, & Sabot, 2004).

Building upon the literature on 'resource curse effects' on human capital, this paper focuses on the specific case of Chile. This country exhibits a high dependence on natural resources as the world's leading producer of copper. Although this economy has been able to overcome the resource curse effects derived from Dutch disease symptoms (Caputo & Valdés, 2016; Marañon

[1]This research benefited from the financial support of the *Programa de Perfeccionamiento Académico Disciplinar* of Universidad de Antofagasta. I am grateful to participants to the XI Doctoral Workshop of the PhD Program in Applied Economics (Barcelona, 2023), Applied Lunch Seminar at the UAB (Barcelona, 2023), VI Seminar for New Academic Researchers (Barcelona, 2023), XII PhD-Student Workshop on Industrial and Public Economics (Reus, 2024), and the 2024 RSAI World Congress (Kecskemét, 2024) for their valuable comments and suggestions. This paper received the RSAI Young Researchers Prize 2024 at the RSAI World Congress held in April 2024, in Kecskemét, Hungary.

& Kumral, 2021), the evidence of effects on human capital accumulation at sub-national levels calls into question the long-run development of natural resource-abundant territories (Alvarez & Vergara, 2022). Additionally, there is a vivid debate about the existence of differences between the detrimental effects exerted by point-based and diffuse natural resources (Papyrakis & Raveh, 2014; van der Ploeg, 2011). Point-source resources refer to those geographically concentrated commodities, such as minerals and fuels. Diffuse resources encompass other less-concentrated, primary sector activities in which resources are usually able to regenerate, such as agriculture, forestry, or fishing. Particularly for Chile, there is no clear evidence on the specific effect of mining activity on the accumulation of human capital, and whether it differs from the impact of other primary sector activities.

This study aims to fill this gap by exploring the role of mining and non-mining resource activities on the distribution of highly skilled human capital following two approaches. First, we assess the effect of the local concentration of mining and non-mining activities on the probability of college degree possession of the working-age population. This approach allows us to approximate to the availability of highly educated labor in the municipality by employing individual level data and controlling for individual-level schooling determinants. One of the expected channels by which this interaction takes place is the attraction of low-education labor into resource-rich territories as a response to the high demand for this type of labor. In turn, the lower availability of labor positions for highly educated workers encourages them to move towards larger urban areas to access to better professional opportunities. In addition to these channels, the mining sector is characterized by a high level of wages, mainly due to union negotiations during copper price booms (de Solminihac, Gonzales, & Cerda, 2018; Paredes & Fleming-Muñoz, 2021). Therefore, it is plausible to assume that a higher concentration of mining activities can impact on the degree of accumulation of human capital by increasing the opportunity costs of getting higher education, with respect to the option of entering the labor market, above all in periods in which the market prices of metals increase. However, one can also think that this process holds for non-mining primary activities with the result to produce again a negative impact on human capital accumulation, but on a more regular basis.

Given the relevance of the spatial dimension in the distribution of productive activities, we are also interested in identifying spatial spillover effects between municipalities concerning the concentration of primary sector activities. The concentration of productive activities can be a factor for attracting working-age population both in a municipality and in the neighboring ones. However, the formation of clusters based on low-skill activities might shape labor markets by both attracting less educated workforce and shrinking the set of labor opportunities for highly educated human capital in surrounding locations. For instance, this is the case of the increasing demand for low-specialization, non-tradable services from the Chilean mining sector (Atienza, Lufin, & Soto, 2021), or the formation of successful wine clusters in the central zone of Chile (Coelho & Montaigne, 2019), that increases the opportunity cost of getting higher education in natural resource-rich municipalities and their neighbors. While businesses in these sectors take advantage of the agglomeration economies, the lower availability of highly skilled human capital in these areas casts doubts about the potential strategies for long-term regional development. We also argue that international prices of primary sector products are determinants of the opportunity cost of obtaining higher education. On one hand, the Chilean mining sector is dominated by copper exports. This makes the sector highly subjected to the fluctuations of international prices. The booms in copper prices might create incentives toward entering the labor market, against to getting higher education. On the other hand, although commodities from non-mining primary industries have a low participation in the total exports of this sector, Chile has a relevant position in international markets of seasonal products. According to data from the Observatory of Economic Complexity (Simoes & Hidalgo, 2011), around 90% of these products were exported to countries in the northern hemisphere between 2006 and 2013. This market structure allows for higher prices than perfectly competitive markets and, consequently, greater incentives for workers to enter this market rather than acquire higher education. The issue is to identify the possible spillover effects across municipalities associated with the presence of those sectors, their returns in terms of wages and their impact on the human capital distribution. In order to assess this, we employ cross-sectional data aggregated at the municipal level to estimate the direct and indirect impacts of the concentration of primary activities on the share of highly educated workforce through a series of Kelejian-Prucha (SAC) models.

Results suggest that the concentration of the mining activity at the municipal level is negatively associated with the probability of a working-age person to hold college degree when the price of copper is at its peak. In this sense, mining activities produce a detrimental effect on the accumulation of highly educated human capital. In the case of the concentration of the rest of primary activities, the effects are negative in several moments, contrasting to the one-off effect from mining. These patterns also hold when focusing on a sub-sample of under-30-year-old workers. We repeat the estimations using a sub-sample of migrant population to capture the effects of those people who recently arrived in the municipality. Results suggest that the effects from mining concentration are stronger when considering international migrants only. On the other hand, the probability of college degree possession of national (inter-municipality) migrants is not significantly affected by the concentration of primary activities. Furthermore, the results do not bring conclusive evidence on the role of tertiary education supply in attenuating these effects. These results provide evidence about the different detrimental effects of the abundance of natural resources on the drivers of endogenous growth. Furthermore, results suggest the presence of negative spillover effects stemming from the concentration of diffuse resource-based activities on the concentration of highly educated working-age population. Conversely, no conclusive results are found regarding the concentration of mining activities.

This study contributes to the literature by further exploring the dynamics underlying the resource curse in Chile. We engage in the discussion regarding the existence of diverging 'resource curse effects' at the sub-national level, depending on whether the sources are point-based or diffuse resources. The impact of concentrated mining activities on local educational attainment highlights the potential for policy interventions aimed at mitigating detrimental effects on human capital accumulation during price booms. In line with this, policymakers should prioritize strategies aimed at diversifying investments in productive activities beyond natural resource extraction. In addition, investing in more knowledge-intensive activities related to local industries may attract highly educated labor to resource-intensive municipalities.

The structure of the article is as follows: In the next section we present the literature and conceptual framework underpinning the hypothesis stated. In Section 3, we explain the methodology followed in this study. Section 4 describes the data and variables employed in the estimations. Section 5 provides the descriptive statistics. In Section 5 we present the results. Section 6 concludes. Additional statistics and results are included in the Appendix.

2.2 Literature review

This study aims to explore and compare the effects of mining activity concentration and the concentration of other primary sector activities on the accumulation of human capital at the municipal level in Chile. The rationale behind this approach lies on the role of the spatial specialization in mining on the shape of local labor markets (Badia-Miró, 2015), above all human capital, and, hence, put forward evidence of the potential effects on the sources of endogenous growth under these circumstances (Lucas, 1988; Romer, 1990). Similarly to other primary sector activities, mining is characterized by a relatively high demand for low-education labor. In addition, the relatively lower demand for more qualified labor might lead to a 'brain drain' phenomenon. Highly-educated, working-age population is attracted by larger urban areas, such as Santiago, to leverage better job opportunities, research environment, and amenities (Atienza & Aroca, 2012), in contrast to smaller, natural resource-intensive territories. Moreover, the existing evidence suggests that primary sector activities might influence economic growth in different manners depending on whether they are based on 'point' or 'diffuse' resources (Auty, 2000; Mousavi & Clark, 2021; Papyrakis & Raveh, 2014; van der Ploeg, 2011). Specifically regarding education-related outcomes, the literature has arrived at mixed conclusions. On one hand, some authors posit an association between point resources and weak institutions, corruption, and the consequent disincentive to invest in education (Bhattacharyya & Hodler, 2010; Boschini, Pettersson, & Roine, 2007; Isham, Woolcock, Pritchett, & Busby, 2005). On the other hand, agricultural sector exports are also associated with lower levels of education, while non-agricultural natural resource exports are linked to improved education indicators (Kim & Lin, 2017). However, our research strategy relies on the existence of intra-national territorial specialization and, thus, on the potential disparities of the distribution of natural resources to propose a comparison between the potential impacts of mining and non-mining primary sector activities on educational attainment.

2.2.1 Natural resource abundance and human capital

A large body of literature on growth and development addressed the relationship between the abundance of natural resources and the countries' economic growth. Most of it has brought evidence of the so-called 'resource curse' (Auty, 1994; Gylfason, 2001; Sachs & Warner, 1995, 1999), although its presence in natural resource-based economies is not axiomatic (Allcott & Keniston, 2018; Marañon & Kumral, 2021). Frankel (2010) provided an in-depth review of this literature. One of the most relevant channels for the association between natural resources and economic growth is the presence of 'Dutch disease' (Corden, 1984). This phenomenon implies that price booms in natural resources sectors negatively affects the rest of tradable activities, specially manufacturing. However, a growing number of studies have focused on the effect of natural resource wealth on the accumulation of human capital (Birdsall et al., 2004; Gylfason, 2001). This approach encompassed different mechanisms underpinning the negative association between natural resources and growth converging in the key role of human capital stock in stimulating national and regional economic growth (Barro, 1992; Gennaioli, La Porta, Lopez-de Silanes, & Shleifer, 2013; Lucas, 1988). Recent within-country studies (Al Rawashdeh, Campbell, & Titi, 2016; Cascio & Narayan, 2022; Zuo, Schieffer, & Buck, 2019) validated the predominant, negative interaction between regional resources endowment and human capital measures. However, contrasting conclusions arise when considering aspects such as the country's tax structure (Agüero, Balcázar, Maldonado, & Ñopo, 2021), or the uneven distribution of regional development (Sun, Sun, Geng, Yang, & Edziah, 2019).

Mousavi and Clark (2021) proposed an extensive review of the literature concerning the interaction between natural resource abundance (or dependence) and the accumulation of human capital. The authors identified the theoretical mechanisms by which this interplay takes place, focusing on non-renewable resources. Some of these mechanisms are the increase in the demand for extraction labor that erodes the wage premium of skilled jobs during resource booms, making demand for higher education to shrink, and the shortsightedness in investment decisions induced by resource booms. Zhan, Duan, and Zeng (2015) concluded that myopia of local residents in Chinese mining areas discourages public local investments in education. Also, natural resource dependency has been historically associated with lower institutional quality. This effect increases income inequality and the likelihood of civil war and, hence, jeopardizes both the demand and provision of education. Another mechanism relates to the high volatility of world prices of natural resources, that increases risks of investment in demand and supply of education. Finally, the weakening of institutional quality and premia to additional education motivates highly skilled workers to migrate to places where the returns of education are higher, leading to a 'brain drain' process. Beine, Docquier, and Oden-Defoort (2011) argued that migration prospects encourages people to pursue higher education, which translates into a 'brain gain' effect. However, if such effect does not compensate emigration levels, resource-dependent territories are led to a loss of human capital.

Concerning the differences in terms of 'resource curse' effects between point-based and diffuse resources, the literature so far has led to mixed conclusions. In general, point-based resources are seen as more likely to produce negative impacts than diffuse resources (Boschini et al., 2007). In the presence of weak democratic institutions, the abundance of natural resources is linked to higher corruption and rent-seeking activities. Corruption lowers the private returns of productive activities, which discourages hard work and investments in human capital (Bhattacharyya & Hodler, 2010; Isham et al., 2005). Cockx and Francken (2016) concluded that point-based resources generate a worse effect on public education expenditure than diffuse resources, but high-quality political institutions can mitigate this effect. On the other hand, Kim and Lin (2017) found that agricultural exports lower education and health indicators while non-agricultural primary exports promote both. However, the authors stated that this beneficial effect is in turn affected by the country's development stage, legal quality, and levels of democratization and corruption. Mousavi and Clark (2021) concluded that there is a weak evidence of point-based resources having more adverse effects on education than the diffuse ones after comparing results in the literature.

2.2.2 Mining and resource curse in Chile

The mining sector has a capital-intensive nature and is spatially concentrated. In Chile, the employment share of this sector does not exceed 3% (Paredes & Fleming-Muñoz, 2021). However, this figure increases to average values between 8% and 18% in the main mining regions.[2] The labor demand in mining is mostly composed by low-educated employees. In the case of Chile's medium-size mining, workers without tertiary education are more than 65 percent (Comisión Chilena del Cobre, 2018). Regarding large mining companies, roughly 60 percent of the workforce are operators and maintainers. As for the educational level among workers in these occupational categories, 81 and 56 percent have a high-school degree only, respectively (Fundación Chile, 2021). In addition, the concentration of mining firms also leads to an increase in the demand for non-tradable, low-specialization services, such as cleaning or hostelry (Atienza et al., 2021). This scenario attracts low-educated workers into mining intensive zones to satisfy this labor demand. On the other hand, workers with a higher level of education represent 78 and 61 percent of the workers in professional and staff occupational groups in large-size mining, respectively (Fundación Chile, 2021). Moreover, professional occupations, i.e, those specialized employees performing duties in engineering, mineral processing, etc., represent less than 14 percent of the total labor in these firms. Regarding staff employees, these are managers and senior administrative positions in headquarters, mainly located in Santiago, far from mining intensive zones. Nevertheless, wages in the mining sector are significantly higher compared to the rest of the economic activities. For 2019, a miner's median monthly salary was around

[2] Values calculated based on data from the National Employment Survey for the period from 2013 to 2023. It considers the regions of Tarapacá, Antofagasta, Atacama, and Coquimbo.

twice as high as the national median wage (Paredes & Fleming-Muñoz, 2021). These higher wages are usually the result of union negotiations during copper price booms (de Solminihac et al., 2018).

The discussion about the 'resource-curse' in Chile has led to mixed conclusions. Badia-Miró and Ducoing (2014) found evidence on low dynamism in the industrial development of Chile associated to mining cycles from the end of the 19th Century up to 1950. From the Dutch disease approach, Larraín, Sachs, and Warner (2000) suggest that Chile has suffered five episodes potentially associated with this phenomenon between 1964 and 1980. From a regional approach, Rehner, Baeza, and Barton (2014) concluded that growth has been prioritized over stability in export-based regions. Stability is considered essential for regional economic development and the lack of it is consistent with the Dutch disease thesis at a regional scale. Furthermore, aspects such as the weak linkages between mining sector and local productive networks, or the enclave setting in mining zones point to a negative effect of this activity on the long-run regional development (Arias, Atienza, & Cademartori, 2014; Atienza et al., 2021). Conversely, recent studies concluded that both tradable and non-tradable sectors have been benefited from mining sector expansion during the period 1990-2018, against the Dutch disease hypothesis (Marañon & Kumral, 2021). A relatively less addressed aspect in the literature has been the impact of mining activity on human capital accumulation. Alvarez and Vergara (2022) studied the association between natural resource abundance and educational attainment at the municipality level. Referring to socio-demographic aggregated data at the municipality level, the authors found that higher natural resource exports discourage young people from enrolling in tertiary education degrees. These individuals are assumed to prefer entering the labor market due to the higher wages derived from commodity price booms, rather than continuing their education. These results are consistent with the thesis that natural resource abundance has negative impacts on long-term human capital accumulation.

However, the literature so far has not brought evidence on the specific effect of mining on human capital accumulation and how this might differ from the effects stemming from the rest of primary sectors. In this study, we propose three possible channels to understand this phenomenon by focusing on the interplay between the concentration level of primary activities and human capital accumulation. First, a higher concentration of mining activity impacts on the opportunity cost of getting college degree in mining intensive municipalities. High-wage jobs offered in the mining sector could skew the willingness of the working-age population away from obtaining higher education. This effect is expected to be stronger in copper price-booming periods, when the demand for low-education labor is higher. Second, the higher concentration of natural resource-based activities might impact on the opportunity cost of people with college degree to live in resource-rich municipalities. The lower demand for higher education labor in resource-rich municipalities compared to that stemming from large metropolitan areas is expected to lead to an 'intra-national brain drain' phenomenon. Highly educated workers can move to urban areas, specially Santiago, to leverage better opportunities in terms of professional experience, research, and amenities (Atienza & Aroca, 2012). Finally, the high demand for low-education workers attracts low-skilled (and low-educated) migrants to locate in resource-rich zones, thus contributing to the concentration of low-skill human capital in these territories.

2.3 Empirical strategy

In this study we explore the effect of spatial concentration of primary activities at the municipal level on human capital accumulation. The focus is set on exploring potential heterogeneity among these effects, based on whether these primary activities are based on mining or non-mining resources. The evidence about the effects of natural resources abundance on education indicators underpins the hypothesis that municipalities with industrial specialization intensive in this type of sectors are less likely to host highly educated workforce. At the same time, it is plausible to think that these effects are non-spatially constrained and, hence, spill over neighboring locations.[3] Also, highly skilled human capital might prefer to migrate from these locations, as the local industrial tissue might be predominantly related to these resource-based industries in near municipalities.

In the case of Chile, the copper industry plays a key role both in mining sector and national exports. In this sense, international prices of copper might influence the impact of mining concentration on education outcomes, whereas other primary sectors, such as agriculture or fishing, might exert a more stable effect. Moreover, mining activities are naturally more capital intensive activities than other activities in the primary sector. This result in the labor demand of the mining sector being relatively lower, which might attenuate spillover effects in surrounding locations. These characteristics nurtured the rationale behind assessing the difference between the effects of mining and non-mining primary sector activities on education outcomes.

2.3.1 Individual-level estimation

Our first approach aims to assess the impact of primary activities on human capital by estimating the effect of the concentration of mining and non-mining primary activities at the municipal level on the probability of a person having a college degree. Following the results presented in the literature, we expect highly educated workforce to be discouraged to locate in municipalities with high demand for operators and technicians.[4] We approximate the concentration of mining activity by employing the share of mining sector employment over the working-age population. This population is composed by people aged 15 or older, following the definitions

[3] Working-age population may potentially see a high opportunity cost of getting high education when close to neighboring municipalities intensive in primary activities.

[4] The term *operators* refers to mining truck drivers, heavy machinery operators, among other technical tasks.

from the Chilean statistics office (*INE*). As for the non-mining primary sector, we consider the agriculture, forestry, fishing, and livestock sectors. We compute the spatial concentration of these activities as we did for mining. The estimation is carried out by exploiting five waves of cross-sectional, individual level data obtained from Chilean National Socioeconomic Characterization (CASEN) surveys. Our model of reference is a logit model as presented in Equation 2.1.

$$P(college_i = 1 \mid \mu_{ct-n}, \delta_{ct-n}, \boldsymbol{X_i}, \boldsymbol{M_{ct-n}}) = \frac{\exp\left(\alpha + \beta^{\mu}\mu_{ct-n} + \beta^{\delta}\delta_{ct-n} + \boldsymbol{X_i}\boldsymbol{\beta^X} + \boldsymbol{M_{ct-n}}\boldsymbol{\beta^M}\right)}{1 + \exp\left(\alpha + \beta^{\mu}\mu_{ct-n} + \beta^{\delta}\delta_{ct-n} + \boldsymbol{X_i}\boldsymbol{\beta^X} + \boldsymbol{M_{ct-n}}\boldsymbol{\beta^M}\right)} \tag{2.1}$$

In Equation 2.1, $P(college_i = 1)$ is the probability of a person in the working-age population to hold college degree; μ_{ct-n} is our measure of spatial concentration of mining activity represented by the share of mining employment over the municipality-level working-age population, whereas δ_{ct-n} is the correspondent measure for non-mining primary sector activities. These concentration proxies are included into the model separately in different specifications, allowing us to assess the marginal effects separately. The vector $\boldsymbol{X_i}$ contains a set of individual characteristics, such as age, gender, and indicator variables for the absence of parents during childhood ($absentpar_i$), physical or mental permanent conditions ($permcond_i$), and location in rural area ($rural_i$). Following Rowe (2013), we include a vector $\boldsymbol{M_{ct-n}}$ for municipality-level characteristics that contribute to determine human capital geographical distribution. The economic conditions of each municipality are expected to generate a positive influence on the accumulation of human capital. In this vector, we include the municipality employment rate in order to control for the local economic conditions, represented by M^{ER}_{ct-n}. In addition, local amenities attract highly educated workers by offering entertainment, redefining lifestyle, and thus driving location decisions (Clark, 2003). Hence, we incorporate into the vector a proxy for amenities, represented by the share of employment in tourism- and entertainment-related activities in the municipality (M^{Am}_{ct-n}). All the continuous variables are log-transformed.[5] The measures of spatial concentration of primary sector activities and the municipality level covariates are lagged (by two or three years, according to data availability). The latter is given by the periodicity of CASEN surveys, further explained in the following section.

In order to explore the impact of natural resource-based activities on educational attainment for different groups of the population, we also estimate the model for a few sub-samples. First, we focus on the young population, i.e., those under 30 years old. This age group is expected to have made the decision to pursue college education during the peak period of copper prices.

[5]The log-transformation of continuous independent variables originally expressed in values between 0 and 1 was calculated as $ln(1 + X)$, where X is the independent variable in levels.

This decision is assumed to have been made with knowledge of the labor conditions at their place of residence. Second, we focus on national and international migrants to explore differences in educational attainment between these two groups. International migrants are defined as people who were living abroad five years before the survey. As for national migrants, we refer to those who lived in other municipalities within the country.[6] These sub-groups are assumed to choose their location based on the availability of labor opportunities and local economic conditions. In particular, international migrants are expected to migrate in search of jobs rather than for educational purposes.[7] In this line, migrants with lower educational levels might be attracted to regions with higher demand for low-skill labor. This would be reflected in a low likelihood of these people to have a college degree in the presence of a concentration of low-skill demanding positions in the primary sector.

Finally, we assess whether the concentration of tertiary education centers smooths the tendency for drafting educational attainment in places where primary activities concentrate. If so, one should detect a less stringent association between low-skill labor demand and educational attainment. In this respect, the density of knowledge-generating institutions stimulates innovation (McCann & van Oort, 2019) and spurs growth. A high concentration of human capital is associated with better regional economic conditions (Rowe, 2013) and, hence, the effects of the concentration of natural resources on educational attainment of the local workforce are expected to be different. To evaluate this, we extend the baseline model by including an interaction term between each measure of concentration of mining and non-mining sectors and the number of higher education institutions in the region at period $t - n$. We perform this extension both employing the full sample of working-age population and the young population sample, i.e. under 30 years old.

2.3.2 Spatial analysis

Our second objective is to determine whether the municipal concentration of primary activities generates spillover effects on the share of highly skilled human capital on surrounding municipalities. The rationale behind this strategy is the idea that the working-age population in a given municipality can also be attracted by labor opportunities in primary sectors from nearby municipalities. This effect might potentially increase the opportunity cost of holding higher education degree in these areas as well. Arias et al. (2014) accounted for the existence of an enclave setting involving mining companies and mining service providers in the Antofagasta

[6]This classification is based on the definitions of the data source (CASEN surveys). It does not differentiate between Chileans or foreigners. Both Chileans and foreigners can be considered international or inter-municipality migrants depending on their place of residence five years before the survey.

[7]Evidence from the Spanish case related to the construction sector points out the importance of the productive structure and the situation of the labor market of the region for the immigrants' location decisions (Alamá-Sabater, Alguacil, & Bernat-Martí, 2014).

region, where non-mining companies are less likely to establish themselves there.[8] In order to address this issue, we estimate a Kelejian-Prucha model, namely SAC model (Kelejian & Prucha, 1998; LeSage & Pace, 2009). This specification allows us to estimate the effects of mining and non-mining activities concentration while adjusting for endogenous interaction effects and interaction effects among the error terms. Equations 2.2 and 2.3 show the models estimated for mining and non-mining activity concentration, respectively. Estimations are performed on a cross sectional basis, considering five waves of aggregated data obtained from CASEN surveys. Only municipalities with available data for all five waves are considered, and, hence, our sample turns to be composed by 297 geographical units.

$$HE_{ct} = \rho \boldsymbol{W} HE_{dt} + \alpha + \beta^{\mu} \mu_{ct-n} + \boldsymbol{X}\boldsymbol{\beta^{X}} + \boldsymbol{M_{ct-n}}\boldsymbol{\beta^{M}} + u_c \tag{2.2}$$

$$HE_{ct} = \rho \boldsymbol{W} HE_{dt} + \alpha + \beta^{\delta} \delta_{ct-n} + \boldsymbol{X}\boldsymbol{\beta^{X}} + \boldsymbol{M_{ct-n}}\boldsymbol{\beta^{M}} + u_c \tag{2.3}$$

where

$$u_c = \lambda \boldsymbol{W} u_d + \epsilon_c$$
$$c = \{1, ..., 297\}, c \neq d$$

In the equations above, HE_{ct} represents the share of working-age population having a college degree, as a proxy for the stock of highly skilled human capital in municipality c. Jointly with the concentration of mining (μ_{ct-n}) and non-mining (δ_{ct-n}) activities, the concentration of human capital is assumed to be endogenously affected by the outcomes in neighboring municipalities d, demographic characteristics aggregated at municipal level included in vector $\boldsymbol{X}$, and the municipality-level variables treated as representative values of the determinants for the likelihood to attract educated workers in the individual estimation (vector $\boldsymbol{M_{ct-n}}$). At the same time, the error term includes a component reflecting interaction among error terms in the estimation of the dependent variables in neighboring municipalities, represented by λ. The weight matrix $\boldsymbol{W}$ is defined as a 5-nearest-neighbor matrix.[9]

2.4 Data and variables

In order to conduct this analysis, we rely on cross-sectional data gathered from Chilean Socioeconomic surveys (CASEN). This survey presents data at individual level, with a sampling

[8] The formation of industry clusters around agriculture activities are often related to manufacture and food processing activities (Stimson, Stough, & Roberts, 2006)

[9] This definition stems from the median and mean number of neighboring municipalities in contiguity. Also, the geographic reference used to locate the corresponding centroids are the capital urban or populated area from each municipality, which are often different from the centroids of polygons depicting geographical areas.

based on the census methodology. Therefore, it includes expansion factors used to project estimations to the municipal scale. This survey has been run biennially and triennially since it was created in 1990 by the *Ministerio de Desarrollo y Planificación* (nowadays *Ministerio de Desarrollo Social y Familia*).[10] Data are gathered for five waves, corresponding to years 2003, 2006, 2009, 2011, and 2013. This survey does not supply longitudinal data and, therefore, the total coverage of municipalities also varies over time. Table 2.1 presents the coverage of municipalities and individuals in the working-age population for each wave. As depicted in Figure 2.1, our period of analysis encompasses the copper price boom started in 2003. This is relevant given the importance of this commodity to Chile's mining industry and, consequently, the size of the country's largest export.[11]

Table 2.1: CASEN survey coverage, 2003-2013.

Wave	Number of observations	Weighted number of obs.	Number of municipalities
2003	189,475	11,460,189	313
2006	205,753	12,385,857	335
2009	193,775	13,247,437	334
2011	229,802	13,301,686	324
2013	172,352	13,612,122	324

Source: CASEN surveys, *Ministerio de Desarrollo Social y Familia.*

The dependent variable of the individual level specification corresponds to a binary indicator that takes value 1 whether the individual from the working-age population holds college degree or higher, and zero otherwise. Similarly, the dependent variable of the spatial models is represented by the share of working-age population holding at least a college degree at the municipal level. This variable is a proxy for the stock of highly educated or skilled human capital in each municipality. It is computed aggregating individual level data from CASEN surveys, using expansion factors as weights.[12] Figure 2.2 depicts the distribution of the highly educated human capital throughout the territory in 2011. As expected, Santiago and municipalities located in the Metropolitan Region exhibit the highest shares of highly educated population. Instead, those areas located in the central-north and central-south zones exhibit lower shares of highly educated population.

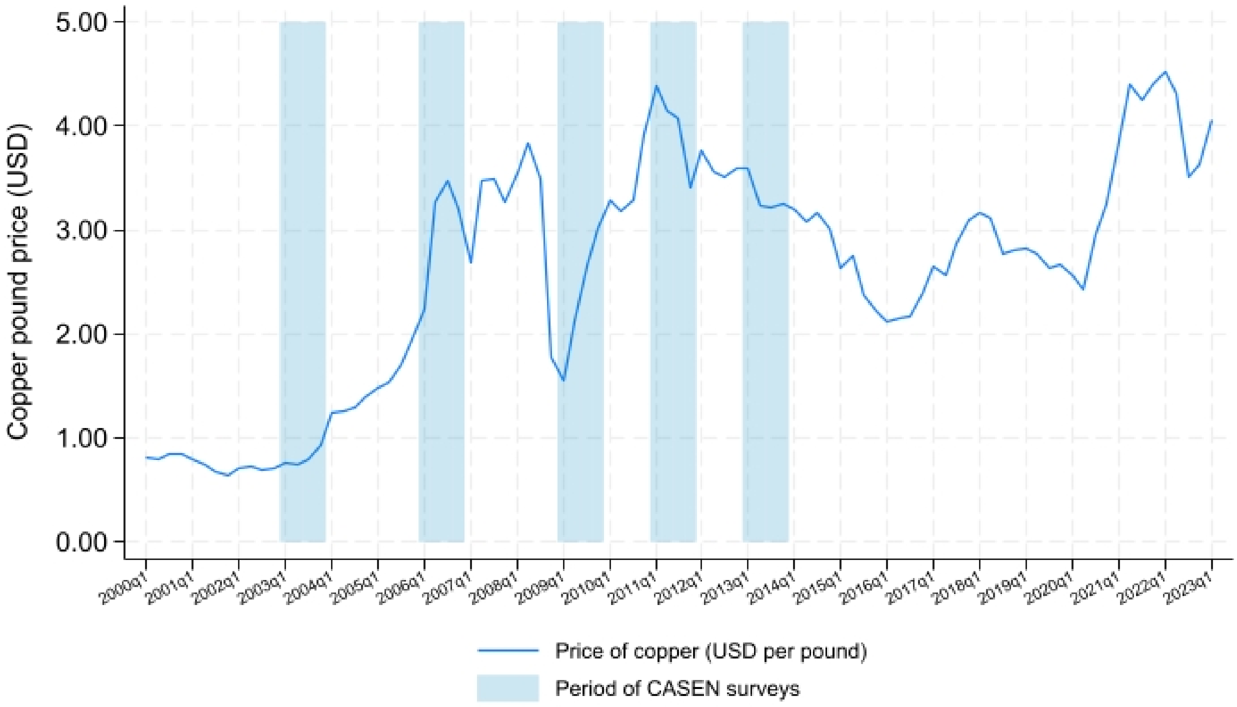
Our key regressor is the concentration of natural resource-based activities, distinguishing between mining and non-mining sectors. These are represented by the share of employment in

[10] From 2000 to 2009, CASEN surveys were conducted each three years. From 2009 onward surveys are biennial.

[11] The price of one pound of copper is not the only relevant aspect for Chilean mining industry. The international valuation of the dollar plays also a key role in the Chilean economy. A higher valuation of this currency implies an increase in the price for copper importing economies, with an effect on the exported quantity and, thus, having an impact on the Chilean business cycle.

[12] Municipalities are the smallest administrative division of Chilean territory. In total, up to date, there are 346 municipalities distributed heterogeneously among sixteen regions (the greatest administrative division). In this study we employ the last territorial distribution aiming to homogenize the identification of each territory for all the waves.

Figure 2.1: Evolution of copper price in USD per pound, 2000-2023.



Source: Own elaboration, based on data from Banco Central de Chile.

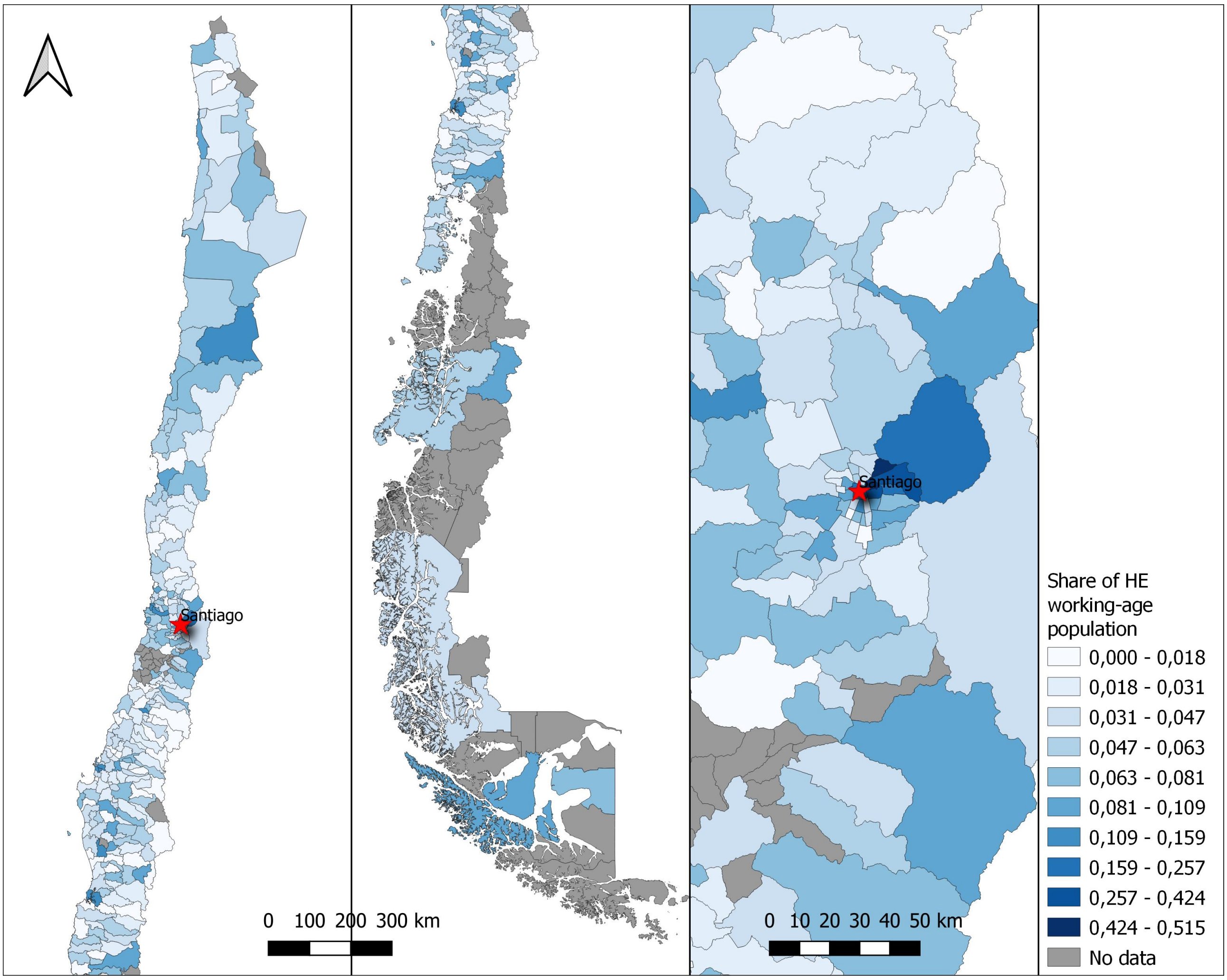
each sector, over the total working-age population.[13] Figures 2.3 and 2.4 depict the territorial distribution of our proxy variable for concentration of mining and non-mining activities in 2009, respectively. In Chile, mining activity is mostly concentrated around the Atacama Desert, and less prominently along the Andes range in the Central zone. In addition, a cluster of coal and oil extraction sites locates in the southernmost zone (the Magallanes region). Instead, non-mining primary sector activities are relatively more scattered throughout the territory, although mostly located in the central and southern regions, especially agriculture and forestry.

Concerning the municipality level covariates, we select the employment rate (share of employed working-age population) as a proxy for economic conditions in each municipality. In order to adjust for the level of amenities of each municipality, we introduce the share of employment in tourism- and entertainment-related activities.[14] A summary of the variables included in this study is presented in Table 2.2.

[13]We refer by non-mining primary sector activities to agriculture, fishery, and forestry.

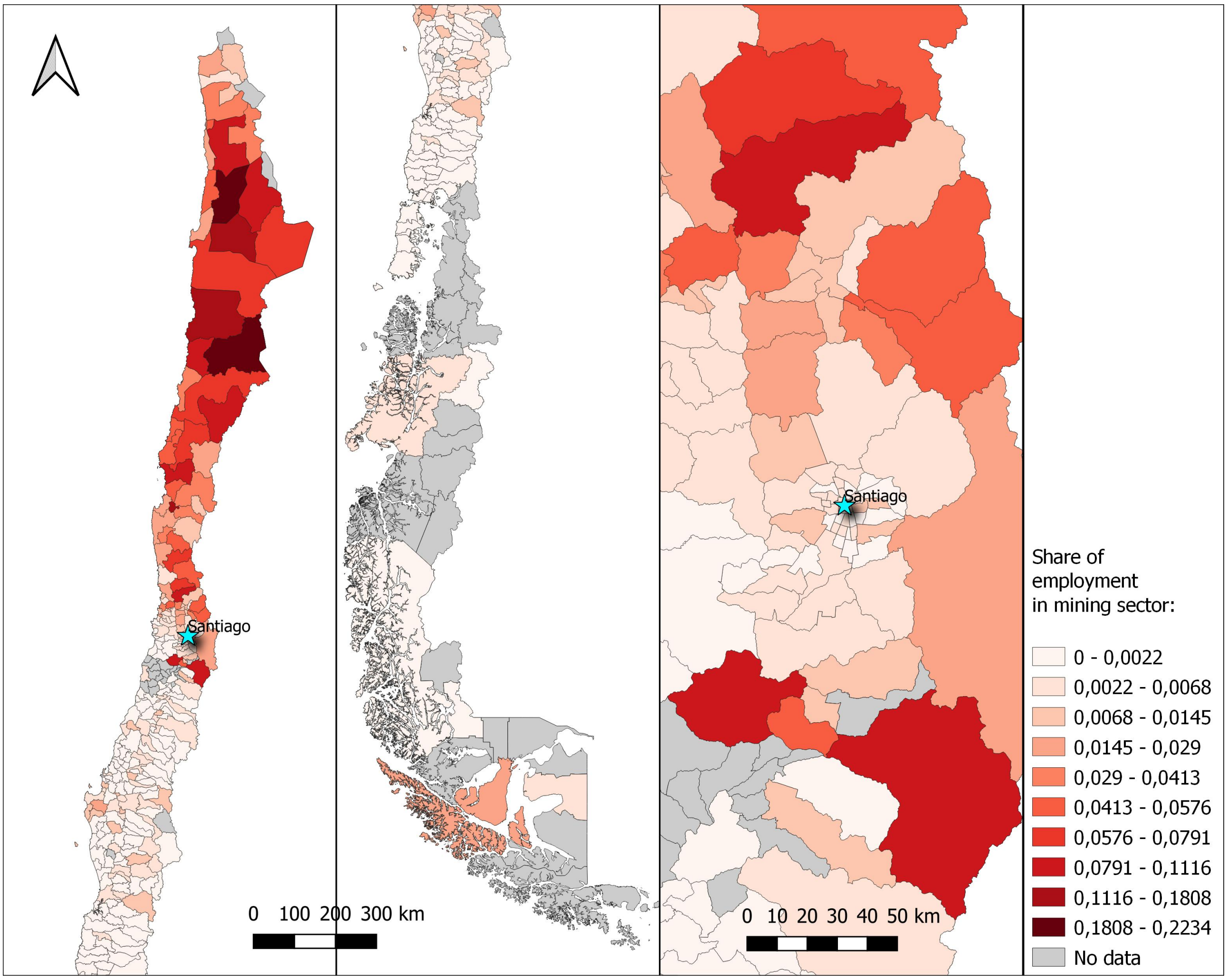
[14]For the sake of homogeneity between periods, ISIC rev. 2 codes considered in tourism- and entertainment-related activities are 6310, 6320, 9414, 9415, 9490, and 9420 for CASEN data before 2011. For data from CASEN 2011, ISIC rev. 3 codes used are 5510, 5520, 9214, 9219, 9241, 9231, 9232, and 9233.

Figure 2.2: Territorial distribution of highly educated working-age population, 2011.



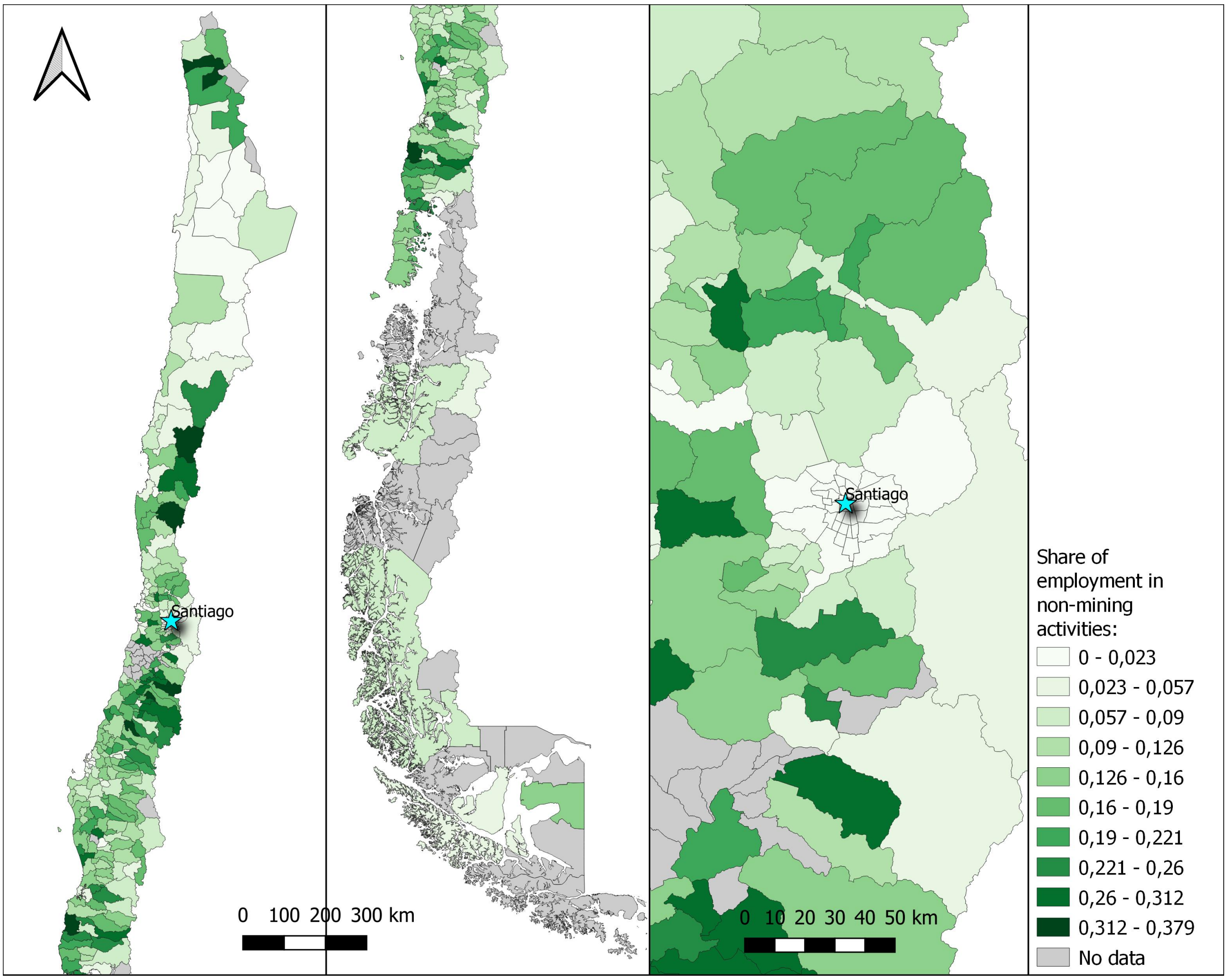
Source: Own elaboration.

Figure 2.3: Territorial distribution of employment in mining sector, 2009.



Source: Own elaboration.

Figure 2.4: Territorial distribution of employment in non-mining primary sectors, 2009.



Source: Own elaboration.

Table 2.2: Summary of variables Chapter 2.

Variable	**Definition**
Municipality level variables	
Concentration of mining activity (μ_{ct-n})	Share of employment in mining sector over working-age population in municipality c, lagged by n years.
Concentration of diffuse natural resource-based activities (δ_{ct-n})	Share of employment in agriculture, fishing, and forestry sectors over working-age population in municipality c, lagged by n years.
Employment rate (M^{ER}_{ct-n})	Share of employed working-age population in municipality c, lagged by n years.
Amenities intensity proxy (M^{Am}_{ct-n})	Share of employment in tourism- and entertainment-related activities in municipality c, lagged by n years.
Individual characteristics	
$college_i$	Indicator for college degree attainment.
age_i	Age (in years) at the time of the survey.
$female_i$	Indicator for gender reported as female.
$permcond_i$	Indicator for permanent physical, mental, or psychological conditions.
$absentpar_i$	Indicator for absent parents during childhood.
$rural_i$	Indicator for housing in rural area.

Source: Own elaboration.

2.5 Descriptive statistics

Table 2.3 presents the individual level covariates included in the model specification for the period from 2006 to 2013.[15] These figures give us insights about the distinguishing facts of the the population with at least a college degree. From 2006 onward, the share of highly educated population increased from 6% to 9.5% in 2013. However, whereas the maximum share of highly educated population at the municipality level increased, the minimum (zero) kept unchanged. This evidence emphasizes an increasingly uneven distribution of highly educated working-age population between municipalities.

Table 2.3: Descriptive statistics. Demographic characteristics, 2003-2013.

		Mean	SD	Min	Max	N
2006						
	age_c	40.72480	1.74906	34.67435	51.56174	205742
	HE_c	0.06494	0.07392	0.00000	0.45152	205742
	$female_c$	0.52157	0.01557	0.42361	0.58498	205742
	$permcond_c$	0.08279	0.02919	0.00694	0.26209	205742
	$absentp_c$	0.17499	0.02937	0.06250	0.33514	205742
	$rural_c$	0.12862	0.20059	0.00000	1.00000	205742
2009						
	age_c	41.92183	1.90711	36.96011	54.40206	193763
	HE_c	0.07187	0.08629	0.00000	0.51051	193763
	$female_c$	0.52766	0.01963	0.43077	0.58333	193763
	$permcond_c$	0.09144	0.03020	0.00769	0.28429	193763
	$absentp_c$	0.18854	0.03168	0.09654	0.35052	193763
	$rural_c$	0.12988	0.20014	0.00000	1.00000	193763
2011						
	age_c	42.15609	2.25418	35.64230	53.05268	229780
	HE_c	0.08484	0.08441	0.00000	0.51536	229780
	$female_c$	0.53359	0.02174	0.40187	0.66033	229780
	$permcond_c$	0.07786	0.02863	0.00265	0.25006	229780
	$absentp_c$	0.18365	0.03529	0.06975	0.37150	229780
	$rural_c$	0.12460	0.19599	0.00000	1.00000	229780
2013						
	age_c	42.90821	2.19817	36.48557	55.71473	172330
	HE_c	0.09533	0.09676	0.00000	0.65569	172330
	$female_c$	0.53428	0.02464	0.43694	0.65243	172330
	$permcond_c$	0.07696	0.02969	0.01328	0.24665	172330
	$absentp_c$	0.17624	0.03694	0.03466	0.37191	172330
	$rural_c$	0.13318	0.20193	0.00000	1.00000	172330

Source: Own elaboration using data from CASEN 2006, 2009, 2011, and 2013. Age values averaged at the municipality level. N represents the number of observations in each wave.

Table 2.4 proposes the descriptive statistics for municipality-level variables for the period from 2003 to 2013. On average, the concentration of mining activities (μ_c) is steadily increasing, and reflects the growth of the mining sector during the first decade of the 21st Century. Conversely, the average concentration of the rest of primary sector activities shows a slightly downward trend since 2006. The average employment rate and employment share in amenity-related activities are stable during the overall period. However, the high variance of the employment rate is noticeable, and thus suggests a persistent heterogeneity in labor market conditions.

[15] In order to obtain population-adjusted metrics, these are based on the weighted average values for each municipality.

Table 2.4: Descriptive statistics. Municipality level variables, 2003-2013.

		Mean	SD	Min	Max	N
2003						
	μ_c	0.00976	0.02763	0.00000	0.26292	302
	δ_c	0.15162	0.10779	0.00041	0.50552	302
	M_c^{ER}	0.48595	0.06759	0.31598	0.67712	302
	M_c^{Am}	0.01771	0.01322	0.00000	0.13516	302
2006						
	μ_c	0.01168	0.02834	0.00000	0.21155	335
	δ_c	0.15297	0.11097	0.00000	0.80657	335
	M_c^{ER}	0.49693	0.07045	0.27057	0.86504	335
	M_c^{Am}	0.02147	0.01566	0.00000	0.13497	335
2009						
	μ_c	0.01258	0.02906	0.00000	0.22340	334
	δ_c	0.12879	0.09004	0.00000	0.37908	334
	M_c^{ER}	0.46943	0.06866	0.29521	0.76154	334
	M_c^{Am}	0.01913	0.01755	0.00000	0.14388	334
2011						
	μ_c	0.01633	0.03614	0.00000	0.24978	324
	δ_c	0.11501	0.09003	0.00000	0.59205	324
	M_c^{ER}	0.49036	0.06973	0.29408	0.71538	324
	M_c^{Am}	0.02005	0.01690	0.00000	0.17363	324
2013						
	μ_c	0.01759	0.03491	0.00000	0.28608	324
	δ_c	0.11858	0.09002	0.00000	0.39713	324
	M_c^{ER}	0.49369	0.07393	0.28038	0.80150	324
	M_c^{Am}	0.02199	0.02163	0.00000	0.23023	324
Total						
	μ_c	0.01362	0.03153	0.00000	0.28608	1619
	δ_c	0.13325	0.09932	0.00000	0.80657	1619
	M_c^{ER}	0.48725	0.07073	0.27057	0.86504	1619
	M_c^{Am}	0.02009	0.01733	0.00000	0.23023	1619

Source: Own elaboration using data from CASEN 2003, 2006, 2009, 2011, and 2013.

2.6 Results

2.6.1 Individual-level model estimation results

Results from the estimation of the baseline model and the marginal effects are presented in Tables 2.5 and 2.6. The variables for individual characteristics are included in all the estimations. Proxies for municipality amenities and economic conditions are gradually incorporated. Post-estimation VIF measurements allows us to rule out multicollinearity. Standard errors are clustered by region, assuming the existence of spatial similarities among municipalities within greater geographic divisions. Results in Table 2.5 suggest that the concentration of mining activity is negatively associated with the probability of holding college degree in the local working-age population. The coefficients show negative signs for all the estimations of the baseline model. However, these statistics are significant only in 2011. This tendency holds when including the proxies for amenities in the municipality and labor market conditions represented by the employment rate.

Table 2.5: Estimation results: μ_{ct-n} on college degree probability (Working-age population).

		μ_{ct-n}		$\boldsymbol{X_i}$	M_{ct-n}^{ER}	M_{ct-n}^{Am}	Marg. Eff. μ_{ct-n}		Obs	Pseudo R^2
2006	(1)	-1.589	(2.220)	Yes	No	No	-0.0863	(0.113)	12,117,580	0.1414
	(2)	-0.571	(3.651)	Yes	Yes	No	-0.0309	(0.194)	12,117,580	0.1472
	(3)	-1.559	(2.139)	Yes	No	Yes	-0.0847	(0.109)	12,117,580	0.1414
	(4)	-0.832	(3.563)	Yes	Yes	Yes	-0.0450	(0.188)	12,117,580	0.1482
2009	(5)	-2.938*	(1.732)	Yes	No	No	-0.175*	(0.106)	13,247,437	0.1236
	(6)	-1.839	(2.913)	Yes	Yes	No	-0.108	(0.164)	13,247,437	0.1345
	(7)	-2.579	(2.636)	Yes	No	Yes	-0.151	(0.153)	13,247,437	0.1369
	(8)	-2.009	(2.974)	Yes	Yes	Yes	-0.118	(0.169)	13,247,437	0.1392
2011	(9)	-3.470**	(1.481)	Yes	No	No	-0.240*	(0.127)	13,301,686	0.1176
	(10)	-3.744***	(1.221)	Yes	Yes	No	-0.255***	(0.0775)	13,301,686	0.1334
	(11)	-3.078***	(1.010)	Yes	No	Yes	-0.211**	(0.0868)	13,301,686	0.1282
	(12)	-3.391***	(1.147)	Yes	Yes	Yes	-0.230***	(0.0727)	13,301,686	0.1364
2013	(13)	-1.030	(0.966)	Yes	No	No	-0.0782	(0.0707)	13,612,122	0.1223
	(14)	-1.325	(1.646)	Yes	Yes	No	-0.1000	(0.118)	13,612,122	0.1289
	(15)	-1.081	(1.068)	Yes	No	Yes	-0.0819	(0.0772)	13,612,122	0.1236
	(16)	-1.322	(1.632)	Yes	Yes	Yes	-0.0997	(0.117)	13,612,122	0.1289

Clustered standard errors at the regional level from logit models in parentheses.
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1.

Conversely, as shown in Table 2.6, the concentration of non-mining primary activities has a negative impact on college degree probability in most of the waves, even when controlling for the municipality employment rate and concentration of amenities. The results of the marginal effects in 2009 are no conclusive when adjusting for the concentration of amenities. Overall, these results are consistent with those obtained by Alvarez and Vergara (2022) at the aggregate level, where the higher concentration of natural resources-based activity exerts a negative impact on educational outcomes in municipalities.

Table 2.6: Estimation results: δ_{ct-n} on college degree probability (Working-age population).

		δ_{ct-n}		$\boldsymbol{X_i}$	M_{ct-n}^{ER}	M_{c-tn}^{Am}	Marg. Eff. δ_{ct-n}		Obs	Pseudo R^2
2006	(1)	-4.912***	(0.740)	Yes	No	No	-0.266***	(0.0677)	12,117,580	0.1479
	(2)	-3.763***	(0.461)	Yes	Yes	No	-0.203***	(0.0355)	12,117,580	0.1508
	(3)	-5.497***	(1.056)	Yes	No	Yes	-0.297***	(0.0904)	12,117,580	0.1486
	(4)	-4.519***	(0.545)	Yes	Yes	Yes	-0.243***	(0.0510)	12,117,580	0.1531
2009	(5)	-4.441***	(0.557)	Yes	No	No	-0.263***	(0.0575)	13,247,437	0.1295
	(6)	-2.526***	(0.914)	Yes	Yes	No	-0.149***	(0.0393)	13,247,437	0.1362
	(7)	-1.775	(1.155)	Yes	No	Yes	-0.104*	(0.0575)	13,247,437	0.1374
	(8)	-1.272	(1.452)	Yes	Yes	Yes	-0.0746	(0.0770)	13,247,437	0.1394
2011	(9)	-4.200***	(0.587)	Yes	No	No	-0.289***	(0.0675)	13,301,686	0.1221
	(10)	-2.094**	(0.939)	Yes	Yes	No	-0.143***	(0.0547)	13,301,686	0.1340
	(11)	-2.582***	(0.452)	Yes	No	Yes	-0.177***	(0.0392)	13,301,686	0.1295
	(12)	-1.477*	(0.835)	Yes	Yes	Yes	-0.100**	(0.0503)	13,301,686	0.1365
2013	(13)	-4.262***	(0.722)	Yes	No	No	-0.323***	(0.0382)	13,612,122	0.1260
	(14)	-2.967**	(1.452)	Yes	Yes	No	-0.224**	(0.0930)	13,612,122	0.1305
	(15)	-3.874***	(0.707)	Yes	No	Yes	-0.293***	(0.0382)	13,612,122	0.1263
	(16)	-3.162**	(1.244)	Yes	Yes	Yes	-0.238***	(0.0770)	13,612,122	0.1306

Clustered standard errors at the regional level from logit models in parentheses.
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1

The estimated coefficients for μ_{ct-n} in 2011 are consistent with the peak in the copper price for this period (see Figure 2.1). In this sense, the results from the baseline model provide insights about the difference between the impact of point-based and diffuse natural resources on educational attainment in Chile. On one hand, a higher concentration of non-mining primary activities at the municipality level is associated with lower probabilities of holding college degree in the working-age population in several periods. On the other hand, mining activities appear to generate a significantly negative impact on this outcome during price booming periods only. In this sense, municipalities with a productive structure intensive in agriculture, fishery, and forestry, are permanently attracting less educated workers. Instead, in municipalities concentrating mining activities this effect is limited to specific moments in time.

2.6.2 Extensions

We perform the estimation of the baseline model in different sub-samples to explore for differences among the impacts concerning age group and migration status. First, we perform the estimations covering only people between the ages of 15 and 30. Second, we explore for differences in the estimation outcomes for international and national migrants. Marginal effects are included in Tables 2.7, 2.8, and 2.9. Coefficients from logit models are presented in the Appendix.

a) Subsample of young population

When focusing on the population between 15 and 30 years old, results emphasize the existence of different patterns between for younger workers. Estimation results suggest negative marginal effects of the concentration of mining activity in 2011. This holds when including the proxies for economic conditions and amenities, consistent with the baseline estimations. This outcome suggests that the educational attainment of young workers is negatively affected by mining activity concentration during price booming periods. Conversely, a higher concentration of diffuse resource-based activities is associated with lower availability of highly educated workforce in local labor markets in two out of four studied periods, suggesting a more persistent effect. The lack of consistency in 2011, with respect to the baseline estimation, can be assumed as exogenous shocks impacting on the location decisions of highly educated young population. A possible explanation for this is the occurrence of the 2010 Earthquake, which mainly affected territories intensive in non-mining primary activities. This event could have caused a disruption in the distribution patterns of human capital reflected by the younger population. However, this phenomenon deserves further study.

Table 2.7: Marginal effects. μ_{ct-n} and δ_{ct-n} on college degree probability (Young population).

		Marg. Eff. μ_{ct-n}		Marg. Eff. δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Obs
2006	(1)	-0.0292	(0.0554)	-0.178***	(0.0431)	Yes	No	No	3,988,730
	(2)	0.0138	(0.110)	-0.128***	(0.0193)	Yes	Yes	No	3,988,730
	(3)	-0.0261	(0.0532)	-0.192***	(0.0566)	Yes	No	Yes	3,988,730
	(4)	0.00511	(0.107)	-0.151***	(0.0287)	Yes	Yes	Yes	3,988,730
2009	(5)	-0.133	(0.101)	-0.189***	(0.0484)	Yes	No	No	4,242,287
	(6)	-0.0876	(0.135)	-0.102***	(0.0357)	Yes	Yes	No	4,242,287
	(7)	-0.120	(0.116)	-0.0783*	(0.0440)	Yes	No	Yes	4,242,287
	(8)	-0.0950	(0.130)	-0.0557	(0.0617)	Yes	Yes	Yes	4,242,287
2011	(9)	-0.203**	(0.0906)	-0.163***	(0.0465)	Yes	No	No	4,294,883
	(10)	-0.213***	(0.0697)	-0.0772**	(0.0321)	Yes	Yes	No	4,294,883
	(11)	-0.177***	(0.0647)	-0.0791***	(0.0276)	Yes	No	Yes	4,294,883
	(12)	-0.189***	(0.0645)	-0.0429	(0.0284)	Yes	Yes	Yes	4,294,883
2013	(13)	-0.136*	(0.0811)	-0.181***	(0.0268)	Yes	No	No	4,213,697
	(14)	-0.148	(0.110)	-0.120**	(0.0543)	Yes	Yes	No	4,213,697
	(15)	-0.136	(0.0849)	-0.145***	(0.0256)	Yes	No	Yes	4,213,697
	(16)	-0.147	(0.108)	-0.117**	(0.0522)	Yes	Yes	Yes	4,213,697

Standard errors in parentheses (VCE specified as clustered at the regional level).
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1

b) Subsample of migrant population

Results from estimations centering on the migrant population sub-sample suggest that, on one hand, international migrants arriving to municipalities with higher concentration of mining activity had lower probabilities of having college degree during in 2009 and 2011. Results in Table 2.8 suggest that mostly low-educated workers from other countries were attracted to mining-intensive territories during the period in which the price of copper rose to reach the maximum recorded at the time. We infer that higher prices of cooper increased the demand for low-skilled labor not only in the mining industry, but also in the overall regional economy due to a local multiplier effect (Moretti, 2010). This results is an attractive economic environment for low-educated migrants seeking new job opportunities. On the other hand, results for national migrants are not conclusive when taking into account the proxies for economic conditions or amenities. Therefore, workers arriving from other countries to mining-intensive municipalities have lower probabilities of holding college degree. Conversely, there are no conclusive results about a lower probability of higher education attainment within the national migrant population in municipalities with higher mining activity concentration.

Referring to the effects of the concentration of other primary sector activities on the probability of holding college degree within the sub-sample of international migrants, results point out just a slightly significant, negative effect in 2009 when considering covariates at the municipal level. Estimations of the marginal effects for other periods are inconclusive. Thus, different from the mining sector, this would imply that this type of migrants do not significantly contribute to lower the concentration of highly educated workers in municipalities intensive in agriculture, fishery, or forestry. Results for the sub-sample of national migrants, in turn, are not conclusive for years before 2013. This might suggest the existence of uncontrolled shocks that led low-educated workers to move toward municipalities intensive in non-mining primary activities.

Table 2.8: Marginal effects. μ_{ct-n} and δ_{ct-n} on college degree probability (International migrants).

		Marg. Eff. μ_{ct-n}		Marg. Eff. δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Obs
2006	(1)	-2.547	(2.095)	-0.837	(0.769)	Yes	No	No	58,102
	(2)	-2.193	(2.040)	-0.0693	(0.585)	Yes	Yes	No	58,102
	(3)	-2.821	(2.114)	-1.415	(0.927)	Yes	No	Yes	58,102
	(4)	-2.558	(1.993)	-0.599	(0.630)	Yes	Yes	Yes	58,102
2009	(5)	-2.783***	(0.978)	-1.016***	(0.311)	Yes	No	No	74,955
	(6)	-2.538**	(1.043)	-0.806**	(0.381)	Yes	Yes	No	74,955
	(7)	-2.829***	(0.913)	-0.620*	(0.324)	Yes	No	Yes	74,955
	(8)	-2.918***	(1.057)	-0.632*	(0.355)	Yes	Yes	Yes	74,955
2011	(9)	-3.047**	(1.184)	-0.217	(0.343)	Yes	No	No	66,453
	(10)	-2.475*	(1.356)	0.426	(0.381)	Yes	Yes	No	66,453
	(11)	-2.652**	(1.198)	0.338	(0.317)	Yes	No	Yes	66,453
	(12)	-2.412*	(1.239)	0.536	(0.354)	Yes	Yes	Yes	66,453
2013	(13)	-0.931	(0.835)	-0.0230	(0.366)	Yes	No	No	109,308
	(14)	-0.788	(0.830)	0.111	(0.376)	Yes	Yes	No	109,308
	(15)	-0.915	(0.839)	0.0264	(0.362)	Yes	No	Yes	109,308
	(16)	-0.866	(0.806)	-0.0254	(0.413)	Yes	Yes	Yes	109,308

Standard errors in parentheses (VCE specified as clustered at the regional level).
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1

Table 2.9: Marginal effects. μ_{ct-n} and δ_{ct-n} on college degree probability (National migrants).

		Marg. Eff. μ_{ct-n}		Marg. Eff. δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Obs
2006	(1)	0.292	(0.384)	-0.247**	(0.116)	Yes	No	No	988,280
	(2)	0.390	(0.468)	-0.122	(0.0801)	Yes	Yes	No	988,280
	(3)	0.314	(0.423)	-0.188*	(0.107)	Yes	No	Yes	988,280
	(4)	0.390	(0.471)	-0.114	(0.0747)	Yes	Yes	Yes	988,280
2009	(5)	-0.605**	(0.307)	-0.431***	(0.148)	Yes	No	No	957,326
	(6)	-0.422	(0.380)	-0.183***	(0.0644)	Yes	Yes	No	957,326
	(7)	-0.610*	(0.354)	-0.125*	(0.0705)	Yes	No	Yes	957,326
	(8)	-0.509	(0.349)	-0.0631	(0.0965)	Yes	Yes	Yes	957,326
2011	(9)	-0.410	(0.463)	-0.434*	(0.258)	Yes	No	No	1,126,705
	(10)	-0.363	(0.286)	-0.0916	(0.0955)	Yes	Yes	No	1,126,705
	(11)	-0.292	(0.372)	-0.140	(0.180)	Yes	No	Yes	1,126,705
	(12)	-0.293	(0.292)	-0.00904	(0.104)	Yes	Yes	Yes	1,126,705
2013	(13)	0.375*	(0.210)	-0.574***	(0.118)	Yes	No	No	1,095,116
	(14)	0.401	(0.299)	-0.338*	(0.180)	Yes	Yes	No	1,095,116
	(15)	0.398*	(0.223)	-0.478***	(0.131)	Yes	No	Yes	1,095,116
	(16)	0.401	(0.291)	-0.360**	(0.163)	Yes	Yes	Yes	1,095,116

Standard errors in parentheses (VCE specified as clustered at the regional level).
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1

c) Availability of education centers

Results of the estimations of the models including the interaction with the tertiary education supply are presented in Table 2.10. Excluding 2013, the association between the concentration

Table 2.10: Extension: Interaction with number of tertiary education institutions in the region.

Full sample.	μ_{ct-n}		μ_{ct-n} × TE Instit		Marg. Eff. μ_{ct-n}		Obs	Pseudo R^2
2006	-65.87	(45.05)	22.72	(15.28)	1.391	(1.607)	12,117,580	0.1526
2009	-26.38	(22.10)	8.859	(7.822)	0.544	(0.861)	13,247,437	0.1400
2011	-9.319	(8.832)	1.491	(2.348)	-0.224	(0.143)	13,301,686	0.1367
2013	-45.82*	(24.51)	14.54*	(8.012)	0.932	(1.047)	13,612,122	0.1314

Young sample.	μ_{ct-n}		μ_{ct-n} × TE Instit		Marg. Eff. μ_{ct-n}		Obs	Pseudo R^2
2006	-59.17	(52.74)	21.48	(18.11)	0.890	(1.076)	3,988,730	0.2820
2009	-37.80	(24.70)	12.98	(8.408)	0.562	(0.653)	4,242,287	0.2515
2011	2.829	(18.32)	-2.979	(5.519)	-0.394**	(0.153)	4,294,883	0.2796
2013	-60.01**	(28.58)	18.63**	(9.162)	0.755	(0.844)	4,213,697	0.2332

Full sample.	δ_{ct-n}		δ_{ct-n} × TE Instit		Marg. Eff. δ_{ct-n}		Obs	Pseudo R^2
2006	-4.581**	(2.274)	0.00343	(0.515)	-0.246***	(0.0631)	12,117,580	0.1531
2009	-3.556*	(2.080)	0.630	(0.591)	-0.0597	(0.0810)	13,247,437	0.1395
2011	-1.267	(2.384)	-0.147	(0.592)	-0.126***	(0.0335)	13,301,686	0.1367
2013	-9.849***	(3.026)	1.841**	(0.782)	-0.186**	(0.0926)	13,612,122	0.1310

Young sample.	δ_{ct-n}		δ_{ct-n} × TE Instit		Marg. Eff. δ_{ct-n}		Obs	Pseudo R^2
2006	-6.000*	(3.348)	0.439	(0.768)	-0.135***	(0.0292)	3,988,730	0.2821
2009	-2.386	(2.529)	0.285	(0.734)	-0.0469	(0.0619)	4,242,287	0.2502
2011	1.401	(2.427)	-0.750	(0.670)	-0.0699**	(0.0272)	4,294,883	0.2788
2013	-4.661	(3.508)	0.750	(0.802)	-0.0853*	(0.0440)	4,213,697	0.2299

Clustered standard errors at the regional level from logit models in parentheses.
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$. *** p<0.01, ** p<0.05, * p<0.1

of natural resource-based activities and the individual probability of having a college degree is not significantly influenced by the number of tertiary education institutions in the region. This suggests that the availability of these institutions does not appear to be able to mitigate the detrimental impacts of resource-based activities on educational attainment. The total marginal effect of mining concentration on the probability of holding college degree in 2011 within the young population is negative and significant. This effect is stronger than that from the baseline model, which may reflect complementarities derived from the fact that resource-rich municipalities are also those with lower availability of tertiary education institutions. Concerning the concentration of the other primary sector activities, the marginal effects are negative and significant after controlling for the availability of education institutions in 2006, 2011, and 2013 waves, consistent with the initial estimations. The change in the magnitude of these effects is divergent between sub-samples and periods, which might identify the presence of not well identified shocks in the evolution of specific factors. Based on these findings, one could conclude that higher educational supply before 2013 was not sufficient to control for effects of labor demand in primary activities on the educational attainment level. This outcome could be due to the high costs for higher education and the preference for technical or vocational studies in regions with important natural resource endowments.

2.6.3 Spatial model estimation results

In order to detect potential spillover effects, we perform a spatial analysis and compare with OLS baseline equations. Results from the estimation of the spatial models are presented in Tables 2.11 and 2.12. Results from the tests assessing for the existence of spatial dependence amid justifying the implementation of spatial models are included in the Appendix. The best specification that fits our data is achieved by following a bottom-up empirical approach (Floch & Le Saout, 2018; Florax, Folmer, & Rey, 2003), starting by the estimation of SAR and SEM models. These estimations indicate that both the estimator for endogenous interaction effect ($\boldsymbol{\rho}$) and the estimator for interaction effects among the errors ($\boldsymbol{\lambda}$) are statistically significant and, hence, we estimate the higher order Kelejian-Prucha (SAC) model. The corresponding covariates approximating municipality-level economic conditions and amenities, as well as demographic characteristics, are included in all the specifications.

The estimation of the coefficients for both $\boldsymbol{\rho}$ and $\boldsymbol{\lambda}$ confirms the existence of spatial interactions between municipalities. This suggests that the local concentration of highly educated human capital is spatially correlated to the outcomes in nearby municipalities. In addition, there are omitted spatially structured variables influencing the share of highly skilled human capital, which is reflected by $\boldsymbol{\lambda}$. This pattern is present across years, both when evaluating the impact of mining and non-mining activities. According to the Akaike Information Criterion (AIC), the model specification that better fits our data is the Kelejian-Prucha (SAC) model. In order to correctly interpret the effects derived from the concentration of primary sector activities, the direct and indirect impacts are estimated by means of Monte Carlo simulations. The results are summarized in Figures 2.5 and 2.6. The detailed values of empirical means and confidence intervals are presented in the Appendix.

Results from the estimation of direct and indirect effects from mining activities on human capital availability do not provide conclusive evidence, as shown in Figure 2.5. In this sense, the concentration of mining activities is not significantly associated with changes in the share of highly educated workforce, both in a given municipality or the neighboring locations. However, the results suggest the existence of spillover effects from covariates included in the specification. Specifically, both the share of the population with absent parents during childhood and the share of population in rural locations are negatively associated with the share of highly skilled human capital across all years. Additionally, the employment ratio is positively associated with the availability of high-education workforce, at least at the 90% confidence level. We infer that these features shape the economic environment within and across municipalities, attracting or displacing human capital away from the local labor markets.

Conversely, results summarized in Figure 2.6 suggest the existence of both direct and indirect impacts of the concentration of non-mining primary activities on the share of highly educated workforce. These outcomes indicate that a higher concentration of activities related to agriculture, fishing, or forestry, might be associated with a lower level of human capital in surrounding municipalities. These spillover effects are negative and significant in most of the waves, something that is consistent with the persistent effects of non-mining activities detected when estimating models with individual-level data. However, for 2011, the estimation does not provide conclusive evidence of spillover effects stemming from the concentration of this type of activities. We infer that the mechanisms through which these effects spill over surrounding municipalities were disrupted by the earthquake occurred the year before, in line with the observed results from the estimation using the young population sub-sample.

These findings support our hypothesis that low-educated workers are attracted by local labor markets that are intensive in natural resource activities. In this sense, the opportunity cost of getting higher education against entering the labor market would increase both in each municipality and in their neighbors when there is a high concentration of activities linked to agriculture, fishing, or forestry. Furthermore, these results support the idea that inter-municipality clusters of low-skill workers in presence non-mining primary activities can be consolidated. Different from the mining sector, the rest of primary activities do associate with lower availability of highly skilled human capital, something at odds with the foundations of sustainable regional growth in the long run.

Table 2.11: Spatial analysis: Estimation of OLS and spatial models, μ_{ct-n}, 2006-2013.

			μ_{ct-n}	$\boldsymbol{\rho}$	$\boldsymbol{\lambda}$	Obs	Adj R-squared	LR test (χ^2)	LM Resid Auto Test	Hausman test	AIC
2006	(1)	OLS	0.0465			297	0.4008				-1183.057
			(0.0797)								
	(2)	SAR	0.0512	0.6247***		297		114.87***	5.178**		-1295.927
			(0.0623)	(0.0412)							
	(3)	SEM	0.0036		0.7063***	297				41.408***	-1291.32
			(0.0712)		(0.043)						
	(4)	SAC	0.0127	0.4411***	0.3617***	297		120.99***			-1300.049
			(0.0685)	(0.099)	(0.1326)						
2009	(5)	OLS	-0.0477			297	0.3762				-1098.094
			(0.0877)								
	(6)	SAR	-0.0113	0.6798***		297		138.04***	5.8946**		-1234.136
			(0.0658)	(0.0390)							
	(7)	SEM	-0.0727		0.7503***	297				29.993***	-1227.392
			(0.0815)		(0.0377)						
	(8)	SAC	-0.0671	0.4880***	0.3770***	297		144.39***			-1238.487
			(0.0758)	(0.1058)	(0.1417)						
2011	(9)	OLS	-0.0909			297	0.3545				-1051.282
			(0.0893)								
	(10)	SAR	-0.0276	0.5596***		297		78.369***	2.3219		-1127.651
			(0.0749)	(0.0492)							
	(11)	SEM	-0.0112		0.6269***	297				13.432	-1125.798
			(0.0982)		(0.0517)						
	(12)	SAC	-0.0357	0.3683***	0.3186**	297		81.499***			-1128.781
			(0.0876)	(0.1265)	(0.1544)						
2013	(13)	OLS	-0.0947			297	0.3244				-928.9396
			(0.0904)								
	(14)	SAR	-0.0496	0.5691***		297		82.843***	3.8939**		-1009.783
			(0.0754)	(0.0493)							
	(15)	SEM	-0.0657		0.6368***	297				25.048***	-1007.651
			(0.0953)		(0.0506)						
	(16)	SAC	-0.0729	0.3816***	0.3294**	297		86.896***			-1011.836
			(0.087)	(0.1332)	(0.1606)						

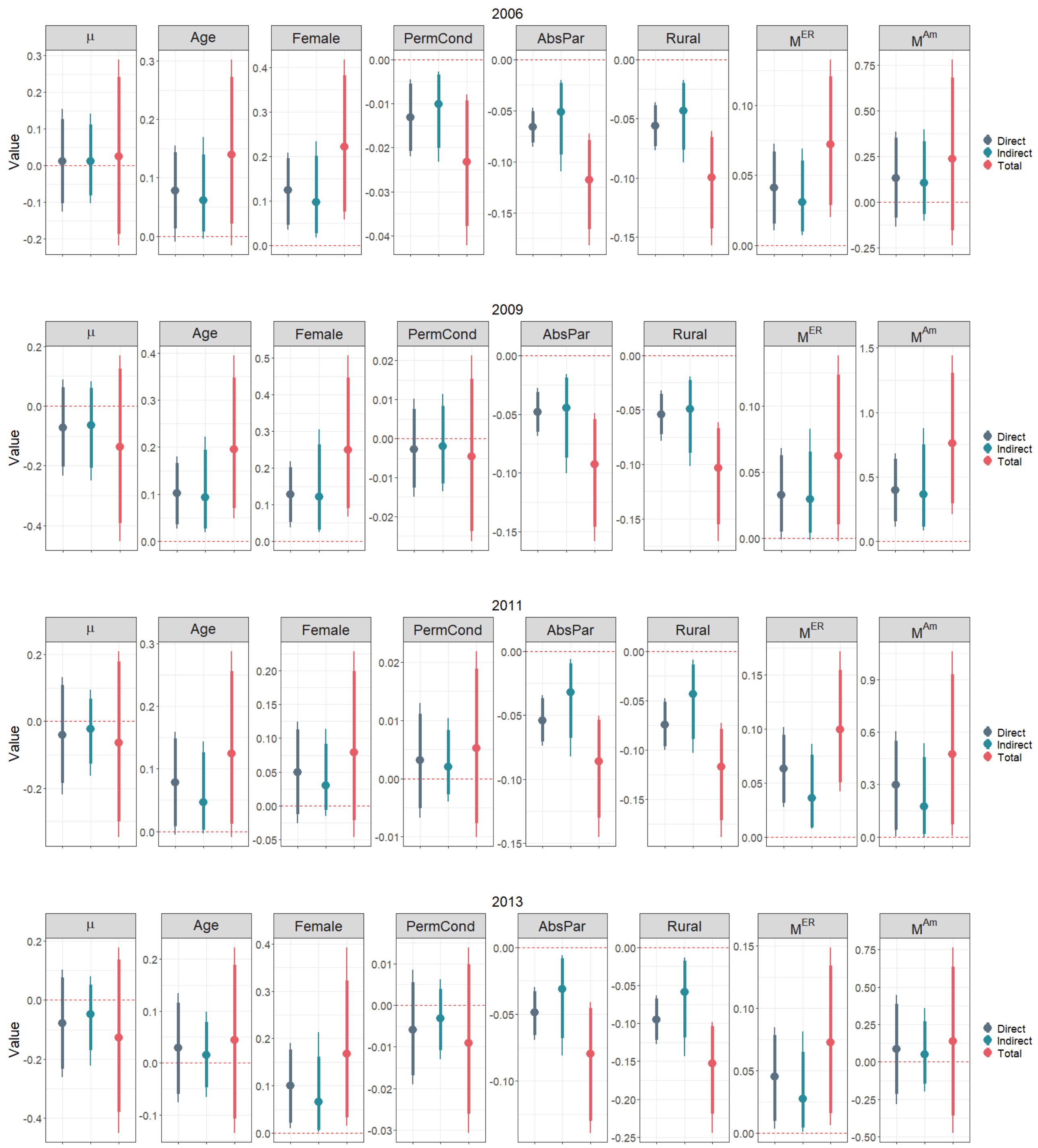
Standard errors in parentheses. M^{ER}_{ct-n}, M^{Am}_{ct-n}, $\boldsymbol{X_c}$: Yes. $\boldsymbol{X_c}$: age_c, $permcond_c$, $absentpar_c$, $rural_c$.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.12: Spatial analysis: Estimation of OLS and spatial models, δ_{ct-n}, 2006-2013.

			δ_{ct-n}	$\boldsymbol{\rho}$	$\boldsymbol{\lambda}$	Obs	Adj R-squared	LR test (χ^2)	LM Resid Auto Test	Hausman test	AIC
2006	(1)	OLS	-0.189*** (0.0415)			297	0.4403				-1203.335
	(2)	SAR	-0.1143*** (0.0336)	0.5994*** (0.0417)		297		105.42***	9.032***		-1306.753
	(3)	SEM	-0.133*** (0.035)		0.6388*** (0.044)	297				30.883***	-1305.406
	(4)	SAC	-0.1329*** (0.0353)	0.3969*** (0.099)	0.4001*** (0.1221)	297		114.74***			-1314.072
2009	(5)	OLS	-0.1394*** (0.0521)			297	0.3907				-1105.085
	(6)	SAR	-0.0868*** (0.0396)	0.6732*** (0.0388)		297		135.97***	11.654***		-1239.051
	(7)	SEM	-0.1577*** (0.0401)		0.7556*** (0.0371)	297				33.759***	-1241.688
	(8)	SAC	-0.15*** (0.0412)	0.4002*** (0.1558)	0.4931*** (0.1216)	297		148.95***			-1250.037
2011	(9)	OLS	-0.1569*** (0.0526)			297	0.3716				-1059.254
	(10)	SAR	-0.1162*** (0.0451)	0.5513*** (0.0495)		297		77.088***	7.4458***		-1134.342
	(11)	SEM	-0.1915*** (0.0461)		0.6441*** (0.0499)	297				14.706*	-1142.452
	(12)	SAC	-0.1853*** (0.0468)	0.3683*** (0.1265)	0.3186** (0.1544)	297		87.696***			-1142.95
2013	(13)	OLS	-0.2059*** (0.0691)			297	0.3421				-936.8308
	(14)	SAR	-0.1367** (0.058)	0.5589*** (0.0501)		297		80.045***	4.6894**		-1014.876
	(15)	SEM	-0.1669*** (0.0599)		0.6381*** (0.0505)	297				28.151***	-1014.843
	(16)	SAC	-0.1606*** (0.0607)	0.3395** (0.1392)	0.3768** (0.1533)	297		85.239***			-1018.069

Standard errors in parentheses. M^{ER}_{ct-n}, M^{Am}_{ct-n}, $\boldsymbol{X_c}$: Yes. $\boldsymbol{X_c}$: age_c, $permcond_c$, $absentpar_c$, $rural_c$.
*** p<0.01, ** p<0.05, * p<0.1

Figure 2.5: Direct, indirect, and total impacts, SAC models with μ_{ct-n}, 2006–2013



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

Figure 2.6: Direct, indirect, and total impacts, SAC models with δ_{ct-n}, 2006–2013

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

2.7 Conclusions

This paper proposes to investigate the potential effects of the spatial concentration of primary sector activities on the accumulation of human capital at municipality level. The aim of the study is to shed some light on the different impacts that mining and non-mining primary activities might exert on the distribution of highly skilled human capital. The focus is set on Chile, whose economy is highly dependent on natural resources, especially mining resources. The concentration of mining activities shape the local labor markets by attracting low-education labor and generating 'brain drain' processes. However, mineral price booms and high wages in the mining sector also increase the opportunity cost of pursuing higher education in mining intensive municipalities. By exploring four waves of cross-sectional, individual-level data from 2006 to 2013, we explored the role of spatial specialization in mining and non-mining activities in shaping local labor markets and the drivers of endogenous growth. Moreover, we searched for the existence of spatial spillover effects between municipalities referring to the concentration of primary sector activities on the availability of high-skilled human capital. Labor markets built upon low-specialization tasks might be appealing for low-education workers in neighboring locations as well. This would also imply a higher opportunity cost of getting higher education against entering the labor markets both in a given municipality or in the surrounding ones.

Our study brings new evidence to the current policy discussion in the topic in Chile. The discussion entailed by the "resource curse" phenomenon in Chile yielded mixed conclusions over the past decades. We built on the research proposed by Alvarez and Vergara (2022), who explored the association between natural resource abundance and educational attainment at municipal level. Our study expands upon their findings by proposing the existence of differences between the effects of mining concentration on educational outcomes with respect to those derived from agriculture, fishing, and forestry. Our results for individual-level data suggest that the concentration of mining activities has a detrimental effect on the presence of highly educated workers during the peak periods of the prices of copper. Conversely, the concentration of non-mining primary activities is suggested to have a negative influence on the educational attainment of the working-age population in most of the waves. These patterns hold for the cohort of young people. When focusing on migrants, the estimation reveals that the mining activity mostly attracts international migrants with a low educational background. Instead, the concentration of the rest of primary activities is not significantly associated with the likelihood of migrants to have higher education. Finally, there is no evidence of an attenuating effect of the academic supply prior to 2013. A deeper understanding in this regard could be supplied by studying data from the following years.

As for the spatial analysis, the results identify differences in direct and indirect effects between mining and non-mining activities. On one hand, results from the estimation of spatial models suggest the existence of spillover effects stemming from the concentration of non-mining primary activities on the share of highly educated working-age population. These findings support the hypothesis that a higher concentration of diffuse resource based-activities is negatively associated with the availability of high-skilled human capital in surrounding municipalities. On the other hand, we find no conclusive results about a significant effect of the concentration of mining activity on educational outcomes at the municipal level. In this respect, the spatial concentration of clusters intensive in agriculture, fishing, or forestry, would harm the distribution of human capital both in a municipality and its surroundings. A great concentration of companies engaged in these activities could drive away highly qualified human capital and hinder regional development in the long term.

The findings presented in this paper support the idea that the abundance of natural resource plays a role against the accumulation of human capital in the long term. We identify temporal and spatial differences between point-based and diffuse natural resources in terms of impact on the level of educational attainment. Those differences highlight the need to implement placed-based regional development strategies to reinforce the regional growing capacity in the long term. Diversification and investment in sectors beyond primary resource-based activities are crucial for mitigating the long-term negative effects on human capital accumulation. The implementation of clusters providing knowledge-intensive activities to agriculture, fishing, or forestry, might fuel a better distribution of skilled human capital throughout the country. Similarly, the creation of knowledge-intensive activities linked to the mining sector might allow for taking advantages of the mineral price booms for attracting high-skilled workers into the mining zones. The windfalls linked to peak prices in international markets can potentially be used to finance research, technology, and specialized services, such to create demand for human capital. Greater availability of highly skilled human capital specialized in natural resources might allow the promotion of tradable and non-tradable services and paving the transition toward a knowledge-based economy (Marin, Navas-Alemán, & Perez, 2015).

2.8 Appendix

2.8.1 Logistic regression tables

Table 2.13: Estimation results: μ_{ct-n} on college degree probability (Young population)

		μ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	-0.900	(1.758)	Yes	No	No	0.2681	3,988,730
	(2)	0.430	(3.365)	Yes	Yes	No	0.2765	3,988,730
	(3)	-0.804	(1.682)	Yes	No	Yes	0.2682	3,988,730
	(4)	0.159	(3.320)	Yes	Yes	Yes	0.2774	3,988,730
2009	(5)	-3.431	(2.502)	Yes	No	No	0.2328	4,242,287
	(6)	-2.290	(3.661)	Yes	Yes	No	0.2458	4,242,287
	(7)	-3.155	(3.030)	Yes	No	Yes	0.2469	4,242,287
	(8)	-2.495	(3.519)	Yes	Yes	Yes	0.2500	4,242,287
2011	(9)	-4.664***	(1.807)	Yes	No	No	0.2631	4,294,883
	(10)	-4.959***	(1.749)	Yes	Yes	No	0.2750	4,294,883
	(11)	-4.114***	(1.410)	Yes	No	Yes	0.2747	4,294,883
	(12)	-4.438***	(1.629)	Yes	Yes	Yes	0.2792	4,294,883
2013	(13)	-2.626	(1.629)	Yes	No	No	0.2241	4,213,697
	(14)	-2.870	(2.242)	Yes	Yes	No	0.2293	4,213,697
	(15)	-2.614	(1.725)	Yes	No	Yes	0.2258	4,213,697
	(16)	-2.841	(2.219)	Yes	Yes	Yes	0.2294	4,213,697

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

Table 2.14: Estimation results: δ_{ct-n} on college degree probability (Young population)

		δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	-5.522***	(0.704)	Yes	No	No	0.2749	3,988,730
	(2)	-4.004***	(0.504)	Yes	Yes	No	0.2799	3,988,730
	(3)	-5.944***	(1.023)	Yes	No	Yes	0.2753	3,988,730
	(4)	-4.728***	(0.485)	Yes	Yes	Yes	0.2820	3,988,730
2009	(5)	-4.905***	(0.744)	Yes	No	No	0.2392	4,242,287
	(6)	-2.675**	(1.229)	Yes	Yes	No	0.2474	4,242,287
	(7)	-2.052	(1.363)	Yes	No	Yes	0.2475	4,242,287
	(8)	-1.464	(1.791)	Yes	Yes	Yes	0.2502	4,242,287
2011	(9)	-3.759***	(0.774)	Yes	No	No	0.2657	4,294,883
	(10)	-1.797**	(0.840)	Yes	Yes	No	0.2748	4,294,883
	(11)	-1.842***	(0.584)	Yes	No	Yes	0.2748	4,294,883
	(12)	-1.003	(0.712)	Yes	Yes	Yes	0.2787	4,294,883
2013	(13)	-3.486***	(0.454)	Yes	No	No	0.2260	4,213,697
	(14)	-2.318**	(1.180)	Yes	Yes	No	0.2297	4,213,697
	(15)	-2.797***	(0.594)	Yes	No	Yes	0.2267	4,213,697
	(16)	-2.260**	(1.137)	Yes	Yes	Yes	0.2297	4,213,697

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

Table 2.15: Estimation results: μ_{ct-n} on college degree probability (International migrants)

		μ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	-15.73	(13.54)	Yes	No	No	0.2313	58,102
	(2)	-13.92	(13.52)	Yes	Yes	No	0.2515	58,102
	(3)	-17.69	(13.72)	Yes	No	Yes	0.2416	58,102
	(4)	-17.04	(13.72)	Yes	Yes	Yes	0.2836	58,102
2009	(5)	-22.13**	(8.767)	Yes	No	No	0.3127	74,955
	(6)	-20.30**	(9.287)	Yes	Yes	No	0.3160	74,955
	(7)	-22.85***	(8.719)	Yes	No	Yes	0.3220	74,955
	(8)	-23.57**	(9.825)	Yes	Yes	Yes	0.3222	74,955
2011	(9)	-23.06***	(8.539)	Yes	No	No	0.2375	66,453
	(10)	-19.67*	(10.26)	Yes	Yes	No	0.2709	66,453
	(11)	-21.09**	(8.727)	Yes	No	Yes	0.2715	66,453
	(12)	-19.41**	(9.266)	Yes	Yes	Yes	0.2788	66,453
2013	(13)	-7.028	(6.947)	Yes	No	No	0.2079	109,308
	(14)	-6.084	(7.062)	Yes	Yes	No	0.2242	109,308
	(15)	-6.906	(6.948)	Yes	No	Yes	0.2080	109,308
	(16)	-6.714	(6.891)	Yes	Yes	Yes	0.2272	109,308

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

Table 2.16: Estimation results: δ_{ct-n} on college degree probability (International migrants)

		δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	-5.134	(4.956)	Yes	No	No	0.2264	58,102
	(2)	-0.436	(3.692)	Yes	Yes	No	0.2459	58,102
	(3)	-8.843	(5.846)	Yes	No	Yes	0.2396	58,102
	(4)	-3.949	(4.080)	Yes	Yes	Yes	0.2772	58,102
2009	(5)	-8.074***	(2.652)	Yes	No	No	0.3107	74,955
	(6)	-6.425**	(3.251)	Yes	Yes	No	0.3125	74,955
	(7)	-4.973*	(2.876)	Yes	No	Yes	0.3160	74,955
	(8)	-5.067	(3.103)	Yes	Yes	Yes	0.3160	74,955
2011	(9)	-1.612	(2.553)	Yes	No	No	0.2232	66,453
	(10)	3.351	(3.035)	Yes	Yes	No	0.2627	66,453
	(11)	2.659	(2.488)	Yes	No	Yes	0.2610	66,453
	(12)	4.282	(2.883)	Yes	Yes	Yes	0.2718	66,453
2013	(13)	-0.173	(2.757)	Yes	No	No	0.2029	109,308
	(14)	0.850	(2.861)	Yes	Yes	No	0.2206	109,308
	(15)	0.199	(2.719)	Yes	No	Yes	0.2033	109,308
	(16)	-0.196	(3.179)	Yes	Yes	Yes	0.2227	109,308

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

Table 2.17: Estimation results: μ_{ct-n} on college degree probability (National migrants)

		μ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	3.218	(4.049)	Yes	No	No	0.1687	988,280
	(2)	4.331	(4.914)	Yes	Yes	No	0.1755	988,280
	(3)	3.467	(4.467)	Yes	No	Yes	0.1707	988,280
	(4)	4.337	(4.952)	Yes	Yes	Yes	0.1756	988,280
2009	(5)	-6.558*	(3.676)	Yes	No	No	0.1743	957,326
	(6)	-4.634	(4.576)	Yes	Yes	No	0.1873	957,326
	(7)	-6.731	(4.209)	Yes	No	Yes	0.1907	957,326
	(8)	-5.631	(4.229)	Yes	Yes	Yes	0.1928	957,326
2011	(9)	-3.482	(3.722)	Yes	No	No	0.1387	1,126,705
	(10)	-3.174	(2.512)	Yes	Yes	No	0.1642	1,126,705
	(11)	-2.548	(3.154)	Yes	No	Yes	0.1597	1,126,705
	(12)	-2.582	(2.575)	Yes	Yes	Yes	0.1692	1,126,705
2013	(13)	2.955*	(1.570)	Yes	No	No	0.1482	1,095,116
	(14)	3.216	(2.262)	Yes	Yes	No	0.1627	1,095,116
	(15)	3.148*	(1.649)	Yes	No	Yes	0.1510	1,095,116
	(16)	3.217	(2.200)	Yes	Yes	Yes	0.1627	1,095,116

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

Table 2.18: Estimation results: δ_{ct-n} on college degree probability (National migrants)

		δ_{ct-n}		$\boldsymbol{X_i}$	M^{ER}_{ct-n}	M^{Am}_{ct-n}	Pseudo R^2	Obs
2006	(1)	-2.735**	(1.120)	Yes	No	No	0.1704	988,280
	(2)	-1.357	(0.838)	Yes	Yes	No	0.1754	988,280
	(3)	-2.077*	(1.062)	Yes	No	Yes	0.1714	988,280
	(4)	-1.264	(0.773)	Yes	Yes	Yes	0.1754	988,280
2009	(5)	-4.691***	(1.064)	Yes	No	No	0.1787	957,326
	(6)	-2.006**	(0.829)	Yes	Yes	No	0.1876	957,326
	(7)	-1.383	(0.856)	Yes	No	Yes	0.1901	957,326
	(8)	-0.697	(1.131)	Yes	Yes	Yes	0.1923	957,326
2011	(9)	-3.695*	(1.893)	Yes	No	No	0.1422	1,126,705
	(10)	-0.801	(0.800)	Yes	Yes	No	0.1640	1,126,705
	(11)	-1.225	(1.491)	Yes	No	Yes	0.1598	1,126,705
	(12)	-0.0797	(0.911)	Yes	Yes	Yes	0.1689	1,126,705
2013	(13)	-4.536***	(1.092)	Yes	No	No	0.1516	1,095,116
	(14)	-2.707*	(1.551)	Yes	Yes	No	0.1634	1,095,116
	(15)	-3.784***	(1.171)	Yes	No	Yes	0.1528	1,095,116
	(16)	-2.883**	(1.414)	Yes	Yes	Yes	0.1635	1,095,116

Clustered standard errors at the region level from logit models in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
$\boldsymbol{X_i}$: age_i, $permcond_i$, $absentp_i$, $rural_i$.

2.8.2 Spatial interaction tests

Table 2.19: Spatial interaction tests, μ_{ct-n} models

	2006		2009		2011		2013	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Moran I Resid	0.3951	0.0000	0.4269	0.0000	0.3344	0.0000	0.3412	0.0000
LM Error	132.26	0.0000	154.36	0.0000	94.757	0.0000	98.618	0.0000
LM Lag	129.06	0.0000	153.56	0.0000	91.286	0.0000	99.672	0.0000
Robust LM Error	16.874	0.0000	15.882	0.0000	10.861	0.0009	8.4877	0.0036
Robust LM Lag	13.674	0.0002	15.082	0.0001	7.3897	0.0066	9.5422	0.0020

Table 2.20: Spatial interaction tests, δ_{ct-n} models

	2006		2009		2011		2013	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Moran I Resid	0.3831	0.0000	0.4446	0.0000	0.356	0.0000	0.3343	0.0000
LM Error	124.31	0.0000	167.48	0.0000	107.36	0.0000	94.652	0.0000
LM Lag	114.19	0.0000	150.45	0.0000	91.192	0.0000	97.271	0.0000
Robust LM Error	21.411	0.0000	26.319	0.0000	19.529	0.0000	7.5515	0.0059
Robust LM Lag	11.289	0.0007	9.2918	0.0023	3.3622	0.0667	10.171	0.0014

2.8.3 Direct and indirect impacts

Table 2.21: Spatial analysis: Direct and indirect impacts on HE_{ct}, μ_{ct-n}, 2006.

Parameter	Direct	Indirect	Total
μ_{ct-n}	0.0126	0.0120	0.0246
	[-0.1260; 0.1539]	[-0.1024; 0.1418]	[-0.2174; 0.2894]
	(-0.1023; 0.1269)	(-0.0810; 0.1120)	(-0.1860; 0.2410)
age_{ct}	0.0781	0.0616	0.1397
	[-0.0093; 0.1552]	[-0.0048; 0.1692]	[-0.0157; 0.3024]
	(0.0129; 0.1435)	(0.0080; 0.1400)	(0.0216; 0.2720)
$female_{ct}$	0.1250	0.0971	0.2221
	[0.0345; 0.2087]	[0.0181; 0.2334]	[0.0576; 0.4184]
	(0.0463; 0.1959)	(0.0270; 0.2010)	(0.0760; 0.3829)
$permcond_{ct}$	-0.0131	-0.0101	-0.0232
	[-0.0220; -0.0045]	[-0.0232; -0.0027]	[-0.0422; -0.0080]
	(-0.0208; -0.0055)	(-0.0201; -0.0034)	(-0.0378; -0.0093)
$absentpar_{ct}$	-0.0660	-0.0515	-0.1175
	[-0.0856; -0.0473]	[-0.1095; -0.0199]	[-0.1818; -0.0725]
	(-0.0815; -0.0505)	(-0.0929; -0.0229)	(-0.1659; -0.0788)
$rural_{ct}$	-0.0561	-0.0432	-0.0993
	[-0.0766; -0.0360]	[-0.0870; -0.0175]	[-0.1569; -0.0607]
	(-0.0732; -0.0385)	(-0.0763; -0.0201)	(-0.1427; -0.0654)
M^{ER}_{ct-n}	0.0412	0.0309	0.0721
	[0.0105; 0.0725]	[0.0071; 0.0690]	[0.0200; 0.1327]
	(0.0152; 0.0668)	(0.0098; 0.0605)	(0.0286; 0.1205)
M^{Am}_{ct-n}	0.1323	0.1061	0.2384
	[-0.1325; 0.3842]	[-0.0996; 0.3996]	[-0.2352; 0.7803]
	(-0.0832; 0.3540)	(-0.0635; 0.3329)	(-0.1546; 0.6827)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.22: Spatial analysis: Direct and indirect impacts on HE_{ct}, μ_{ct-n}, 2009.

Parameter	Direct	Indirect	Total
μ_{ct-n}	-0.0720	-0.0640	-0.1360
	[-0.2337; 0.0881]	[-0.2495; 0.0831]	[-0.4527; 0.1697]
	(-0.2024; 0.0628)	(-0.2082; 0.0611)	(-0.3924; 0.1243)
age_{ct}	0.1022	0.0929	0.1952
	[0.0266; 0.1796]	[0.0197; 0.2225]	[0.0481; 0.3950]
	(0.0352; 0.1665)	(0.0269; 0.1936)	(0.0703; 0.3473)
$female_{ct}$	0.1282	0.1210	0.2493
	[0.0373; 0.2180]	[0.0238; 0.3046]	[0.0678; 0.5075]
	(0.0525; 0.2012)	(0.0303; 0.2641)	(0.0896; 0.4459)
$permcond_{ct}$	-0.0027	-0.0019	-0.0046
	[-0.0149; 0.0103]	[-0.0136; 0.0115]	[-0.0263; 0.0213]
	(-0.0126; 0.0075)	(-0.0115; 0.0084)	(-0.0237; 0.0153)
$absentpar_{ct}$	-0.0481	-0.0446	-0.0927
	[-0.0685; -0.0278]	[-0.1001; -0.0160]	[-0.1580; -0.0490]
	(-0.0649; -0.0311)	(-0.0868; -0.0189)	(-0.1459; -0.0540)
$rural_{ct}$	-0.0542	-0.0492	-0.1034
	[-0.0787; -0.0321]	[-0.1014; -0.0195]	[-0.1706; -0.0616]
	(-0.0725; -0.0353)	(-0.0896; -0.0228)	(-0.1552; -0.0669)
M^{ER}_{ct-n}	0.0327	0.0295	0.0622
	[-0.0011; 0.0682]	[-0.0012; 0.0829]	[-0.0023; 0.1383]
	(0.0048; 0.0625)	(0.0042; 0.0656)	(0.0105; 0.1238)
M^{Am}_{ct-n}	0.3957	0.3624	0.7581
	[0.1117; 0.6798]	[0.0820; 0.8748]	[0.2098; 1.4423]
	(0.1543; 0.6399)	(0.1104; 0.7507)	(0.2932; 1.3053)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.23: Spatial analysis: Direct and indirect impacts on HE_{ct}, μ_{ct-n}, 2011.

Parameter	Direct	Indirect	Total
μ_{ct-n}	-0.0403	-0.0236	-0.0639
	[-0.2186; 0.1318]	[-0.1629; 0.0945]	[-0.3461; 0.2094]
	(-0.1847; 0.1080)	(-0.1269; 0.0668)	(-0.2986; 0.1784)
age_{ct}	0.0778	0.0468	0.1246
	[-0.0055; 0.1593]	[-0.0029; 0.1433]	[-0.0090; 0.2877]
	(0.0081; 0.1481)	(0.0023; 0.1266)	(0.0119; 0.2559)
$female_{ct}$	0.0494	0.0298	0.0792
	[-0.0260; 0.1242]	[-0.0150; 0.1135]	[-0.0463; 0.2285]
	(-0.0124; 0.1124)	(-0.0067; 0.0916)	(-0.0214; 0.1989)
$permcond_{ct}$	0.0032	0.0021	0.0053
	[-0.0068; 0.0130]	[-0.0040; 0.0104]	[-0.0101; 0.0219]
	(-0.0051; 0.0111)	(-0.0028; 0.0084)	(-0.0077; 0.0189)
$absentpar_{ct}$	-0.0541	-0.0320	-0.0861
	[-0.0738; -0.0342]	[-0.0820; -0.0063]	[-0.1451; -0.0501]
	(-0.0706; -0.0368)	(-0.0678; -0.0095)	(-0.1302; -0.0534)
$rural_{ct}$	-0.0742	-0.0432	-0.1174
	[-0.1000; -0.0473]	[-0.1031; -0.0084]	[-0.1883; -0.0728]
	(-0.0965; -0.0514)	(-0.0891; -0.0137)	(-0.1713; -0.0785)
M^{ER}_{ct-n}	0.0633	0.0362	0.0995
	[0.0277; 0.1020]	[0.0077; 0.0862]	[0.0420; 0.1719]
	(0.0319; 0.0944)	(0.0091; 0.0762)	(0.0507; 0.1545)
M^{Am}_{ct-n}	0.2978	0.1750	0.4728
	[0.0048; 0.6019]	[0.0000; 0.5350]	[0.0068; 1.0603]
	(0.0425; 0.5494)	(0.0164; 0.4572)	(0.0731; 0.9278)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.24: Spatial analysis: Direct and indirect impacts on HE_{ct}, μ_{ct-n}, 2013.

Parameter	Direct	Indirect	Total
μ_{ct-n}	-0.0792	-0.0475	-0.1266
	[-0.2622; 0.1019]	[-0.2233; 0.0801]	[-0.4499; 0.1776]
	(-0.2334; 0.0762)	(-0.1695; 0.0519)	(-0.3798; 0.1371)
age_{ct}	0.0289	0.0150	0.0438
	[-0.0758; 0.1345]	[-0.0651; 0.0985]	[-0.1350; 0.2225]
	(-0.0603; 0.1159)	(-0.0474; 0.0794)	(-0.1078; 0.1887)
$female_{ct}$	0.1006	0.0665	0.1671
	[0.0106; 0.1907]	[0.0025; 0.2131]	[0.0152; 0.3926]
	(0.0211; 0.1766)	(0.0068; 0.1609)	(0.0325; 0.3224)
$permcond_{ct}$	-0.0059	-0.0032	-0.0091
	[-0.0191; 0.0086]	[-0.0130; 0.0062]	[-0.0307; 0.0139]
	(-0.0168; 0.0054)	(-0.0107; 0.0039)	(-0.0260; 0.0098)
$absentpar_{ct}$	-0.0485	-0.0310	-0.0795
	[-0.0694; -0.0296]	[-0.0807; -0.0058]	[-0.1389; -0.0410]
	(-0.0656; -0.0329)	(-0.0680; -0.0080)	(-0.1297; -0.0456)
$rural_{ct}$	-0.0947	-0.0584	-0.1532
	[-0.1272; -0.0632]	[-0.1431; -0.0133]	[-0.2446; -0.0981]
	(-0.1220; -0.0673)	(-0.1185; -0.0173)	(-0.2191; -0.1041)
M^{ER}_{ct-n}	0.0450	0.0274	0.0724
	[0.0035; 0.0846]	[0.0012; 0.0812]	[0.0061; 0.1487]
	(0.0097; 0.0783)	(0.0041; 0.0647)	(0.0159; 0.1340)
M^{Am}_{ct-n}	0.0880	0.0495	0.1375
	[-0.2806; 0.4468]	[-0.1967; 0.3571]	[-0.4743; 0.7633]
	(-0.2143; 0.3864)	(-0.1482; 0.2701)	(-0.3587; 0.6349)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.25: Spatial analysis: Direct and indirect impacts on HE_{ct}, δ_{ct-n}, 2006.

Parameter	Direct	Indirect	Total
δ_{ct-n}	-0.1374	-0.0879	-0.2252
	[-0.2100; -0.0644]	[-0.1839; -0.0265]	[-0.3629; -0.0992]
	(-0.1967; -0.0773)	(-0.1634; -0.0324)	(-0.3369; -0.1220)
age_{ct}	0.0937	0.0600	0.1536
	[0.0172; 0.1690]	[0.0087; 0.1405]	[0.0245; 0.2934]
	(0.0298; 0.1558)	(0.0144; 0.1210)	(0.0477; 0.2655)
$female_{ct}$	0.0935	0.0598	0.1532
	[0.0008; 0.1792]	[-0.0001; 0.1533]	[0.0013; 0.3190]
	(0.0160; 0.1691)	(0.0081; 0.1292)	(0.0265; 0.2916)
$permcond_{ct}$	-0.0132	-0.0085	-0.0217
	[-0.0221; -0.0042]	[-0.0200; -0.0018]	[-0.0405; -0.0068]
	(-0.0204; -0.0058)	(-0.0167; -0.0025)	(-0.0361; -0.0091)
$absentpar_{ct}$	-0.0665	-0.0428	-0.1094
	[-0.0839; -0.0496]	[-0.0885; -0.0156]	[-0.1631; -0.0712]
	(-0.0804; -0.0522)	(-0.0770; -0.0188)	(-0.1513; -0.0770)
$rural_{ct}$	-0.0123	-0.0077	-0.0200
	[-0.0423; 0.0181]	[-0.0322; 0.0128]	[-0.0739; 0.0314]
	(-0.0380; 0.0140)	(-0.0271; 0.0084)	(-0.0629; 0.0224)
M^{ER}_{ct-n}	0.0637	0.0401	0.1037
	[0.0326; 0.0950]	[0.0143; 0.0855]	[0.0535; 0.1651]
	(0.0381; 0.0888)	(0.0170; 0.0741)	(0.0621; 0.1509)
M^{Am}_{ct-n}	-0.0406	-0.0249	-0.0655
	[-0.3178; 0.2264]	[-0.2342; 0.1667]	[-0.5339; 0.3941]
	(-0.2751; 0.1809)	(-0.1828; 0.1330)	(-0.4468; 0.3171)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.26: Spatial analysis: Direct and indirect impacts on HE_{ct}, δ_{ct-n}, 2009.

Parameter	Direct	Indirect	Total
δ_{ct-n}	-0.1568	-0.1032	-0.2601
	[-0.2414; -0.0724]	[-0.2394; -0.0291]	[-0.4585; -0.1171]
	(-0.2270; -0.0839)	(-0.2050; -0.0357)	(-0.4066; -0.1386)
age_{ct}	0.1193	0.0781	0.1974
	[0.0413; 0.1895]	[0.0175; 0.1908]	[0.0733; 0.3507]
	(0.0572; 0.1796)	(0.0215; 0.1571)	(0.0891; 0.3239)
$female_{ct}$	0.0948	0.0635	0.1584
	[0.0050; 0.1802]	[0.0028; 0.1742]	[0.0077; 0.3289]
	(0.0207; 0.1695)	(0.0073; 0.1507)	(0.0307; 0.3089)
$permcond_{ct}$	0.0002	0.0006	0.0008
	[-0.0114; 0.0120]	[-0.0074; 0.0103]	[-0.0187; 0.0216]
	(-0.0097; 0.0102)	(-0.0054; 0.0078)	(-0.0149; 0.0175)
$absentpar_{ct}$	-0.0499	-0.0334	-0.0834
	[-0.0696; -0.0312]	[-0.0763; -0.0086]	[-0.1382; -0.0453]
	(-0.0664; -0.0340)	(-0.0673; -0.0117)	(-0.1266; -0.0507)
$rural_{ct}$	-0.0091	-0.0060	-0.0151
	[-0.0430; 0.0241]	[-0.0351; 0.0178]	[-0.0760; 0.0401]
	(-0.0380; 0.0190)	(-0.0273; 0.0123)	(-0.0617; 0.0320)
M^{ER}_{ct-n}	0.0684	0.0449	0.1134
	[0.0297; 0.1086]	[0.0113; 0.1056]	[0.0498; 0.1974]
	(0.0366; 0.1002)	(0.0155; 0.0902)	(0.0589; 0.1806)
M^{Am}_{ct-n}	0.1118	0.0714	0.1833
	[-0.1931; 0.4102]	[-0.1458; 0.3340]	[-0.3345; 0.7310]
	(-0.1395; 0.3708)	(-0.0951; 0.2741)	(-0.2421; 0.6023)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.27: Spatial analysis: Direct and indirect impacts on HE_{ct}, δ_{ct-n}, 2011.

Parameter	Direct	Indirect	Total
δ_{ct-n}	-0.1871	-0.0551	-0.2422
	[-0.2860; -0.0935]	[-0.1607; 0.0091]	[-0.4096; -0.1192]
	(-0.2708; -0.1062)	(-0.1378; 0.0006)	(-0.3729; -0.1354)
age_{ct}	0.0994	0.0304	0.1298
	[0.0226; 0.1786]	[-0.0038; 0.1013]	[0.0284; 0.2543]
	(0.0361; 0.1643)	(-0.0004; 0.0838)	(0.0428; 0.2256)
$female_{ct}$	0.0390	0.0123	0.0514
	[-0.0305; 0.1095]	[-0.0096; 0.0576]	[-0.0405; 0.1542]
	(-0.0199; 0.0993)	(-0.0053; 0.0459)	(-0.0223; 0.1352)
$permcond_{ct}$	0.0031	0.0010	0.0041
	[-0.0056; 0.0124]	[-0.0022; 0.0058]	[-0.0074; 0.0170]
	(-0.0047; 0.0107)	(-0.0013; 0.0046)	(-0.0058; 0.0149)
$absentpar_{ct}$	-0.0495	-0.0150	-0.0645
	[-0.0674; -0.0320]	[-0.0435; 0.0021]	[-0.1013; -0.0370]
	(-0.0644; -0.0352)	(-0.0378; 0.0001)	(-0.0934; -0.0408)
$rural_{ct}$	-0.0321	-0.0096	-0.0417
	[-0.0639; 0.0019]	[-0.0360; 0.0025]	[-0.0906; 0.0024]
	(-0.0597; -0.0028)	(-0.0280; 0.0008)	(-0.0812; -0.0039)
M^{ER}_{ct-n}	0.0995	0.0291	0.1286
	[0.0581; 0.1409]	[-0.0049; 0.0856]	[0.0734; 0.1986]
	(0.0658; 0.1336)	(-0.0003; 0.0723)	(0.0813; 0.1851)
M^{Am}_{ct-n}	0.0067	-0.0003	0.0063
	[-0.2932; 0.3110]	[-0.1314; 0.1317]	[-0.4195; 0.4271]
	(-0.2490; 0.2607)	(-0.0988; 0.0923)	(-0.3227; 0.3468)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 2.28: Spatial analysis: Direct and indirect impacts on HE_{ct}, δ_{ct-n}, 2013.

Parameter	Direct	Indirect	Total
δ_{ct-n}	-0.1662	-0.0868	-0.2531
	[-0.2847; -0.0480]	[-0.2554; -0.0079]	[-0.4864; -0.0756]
	(-0.2670; -0.0671)	(-0.2047; -0.0132)	(-0.4350; -0.1031)
age_{ct}	0.0526	0.0250	0.0776
	[-0.0484; 0.1545]	[-0.0310; 0.1016]	[-0.0789; 0.2540]
	(-0.0349; 0.1378)	(-0.0180; 0.0849)	(-0.0545; 0.2004)
$female_{ct}$	0.0852	0.0482	0.1334
	[-0.0063; 0.1751]	[-0.0030; 0.1656]	[-0.0090; 0.3289]
	(0.0049; 0.1600)	(-0.0000; 0.1345)	(0.0068; 0.2767)
$permcond_{ct}$	-0.0067	-0.0032	-0.0099
	[-0.0197; 0.0061]	[-0.0132; 0.0044]	[-0.0302; 0.0105]
	(-0.0181; 0.0041)	(-0.0114; 0.0024)	(-0.0273; 0.0067)
$absentpar_{ct}$	-0.0508	-0.0274	-0.0782
	[-0.0701; -0.0327]	[-0.0775; -0.0030]	[-0.1363; -0.0421]
	(-0.0674; -0.0356)	(-0.0649; -0.0058)	(-0.1234; -0.0467)
$rural_{ct}$	-0.0531	-0.0278	-0.0809
	[-0.0973; -0.0093]	[-0.0842; -0.0008]	[-0.1688; -0.0155]
	(-0.0911; -0.0147)	(-0.0716; -0.0035)	(-0.1480; -0.0228)
M^{ER}_{ct-n}	0.0661	0.0335	0.0996
	[0.0195; 0.1090]	[0.0042; 0.0922]	[0.0345; 0.1804]
	(0.0283; 0.1016)	(0.0066; 0.0787)	(0.0451; 0.1663)
M^{Am}_{ct-n}	-0.1050	-0.0588	-0.1638
	[-0.4632; 0.2556]	[-0.3703; 0.1462]	[-0.7630; 0.3808]
	(-0.3894; 0.1884)	(-0.2772; 0.1032)	(-0.6467; 0.3050)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Chapter 3

How many doctors do you know? Spatial social capital, occupational prestige, and primary sector activities[1]

3.1 Introduction

How and with whom people establish social relationships is largely determined by macro-level factors (Blau, 1994). Despite the availability of communication and transportation technologies, people still build and sustain their networks mostly within the same geographic area they live in (Kuo & Fu, 2021). In this sense, the characteristics of the local environment, such as the industrial or occupational structure, become crucial in understanding social capital formation. Social capital can be defined as the resources embedded in social networks to which an individual can have access by means of human interaction (Lin, 2002). These resources can be related with information, wealth, power, among others, and are often assumed to be positively associated with the occupational prestige of the members of the network (van der Gaag, Snijders, & Flap, 2008). This type of capital is often linked to a number of economic outcomes: social capital is perceived to enhance them. This outcomes are mostly related with upward income mobility (Benton, 2016; Chetty et al., 2022), labor market entry and job outcomes (Chen & Volker, 2016; Verhaeghe, Van der Bracht, & Van de Putte, 2015), regional economic growth (Forte, Peiró-Palomino, & Tortosa-Ausina, 2015; Muringani, Fitjar, & Rodríguez-Pose, 2021), and innovation (Capello & Lenzi, 2014; Peiró-Palomino, 2019; Xu, 2011). In this wake, one can deduce that the geographical heterogeneity in social capital formation stemming from the local industrial characteristics can also lead to significant differences in economic outcomes within a country, increasing inequality among sub-national units. However, to the best of our knowledge, this

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last dimension centering on the spatial dependence of social capital among geographical units have remained unexplored.

This paper seeks to contribute to understand the interplay between social capital and the local industrial structure from a spatial perspective. Specifically, we explore the association between the level of social capital at the municipal level and the local agglomeration of primary sector activities. By including the spatial dimension into the study we expect to provide evidence of how social capital generates and is subject to spatial externalities. The hypothesis behind this approach is that social resources embedded in networks at municipal level are negatively affected by local (and surrounding) economic settings intensive in primary sector. Considering the evidence of 'resource curse' effects on the distribution of highly skilled human capital (Mousavi & Clark, 2021), we expect that spatial units with higher concentration of primary sector activities provide a lower support for establishing high-status networks in terms of connections with people in prestigious occupations.[2]

To test this hypothesis, we elaborate an original measure of social capital at macro level based on the position generator instrument (Lin & Dumin, 1986).[3] We focus on the five available occupations with the highest ISEI scores (Ganzeboom & Treiman, 2003) in order to measure the the resources embedded in the individuals' high-status social networks in terms of occupational prestige. Next, we aggregate these values at the municipal level. The selected occupations are medical doctors, lawyers, college professors, managers, and accountants. We rely on three waves of the cross-sectional position generator instrument included in the ELSOC survey from Chile: 2016, 2018, and 2021 (Centre for Social Conflict and Cohesion Studies COES, 2023). Furthermore, we explore spatial heterogeneity of social capital specifically associated with the agglomeration of mining industry, as well as non-mining primary activities. The dominant geographical concentration of Chilean mining industry is expected to generate different patterns of social capital formation. In order to explore for spatial dependencies of those we implement and estimate a spatial autoregressive setting.

Overall, our findings reveal a negative association between the local agglomeration of primary sector firms and the aggregate measure of social capital in each municipality. These results are consistent across all waves studies, both with spatial and non-spatial specifications. Accounting for spatial dependence enhances the degree of goodness-of-fit of the model. Spatial models suggest negative spillover effects for 2016 and 2018. Results on indirect impacts in 2021 are inconclusive, possibly due to the pandemic's disruption of social ties. Moreover, a positive impact of education on social capital is observed for 2016 and 2018, highlighting the role of educated people in fostering high-status connections. These results are in line with the existent

[2]In the literature of social capital, the term 'high-status' is used to refer to occupations or connections involving a high level of prestige. Some of the most prestigious occupations are medical doctor, lawyer, professor, among others (Ganzeboom & Treiman, 2003).

[3]This instrument consists of a survey that asks individuals how many "X" they know, where "X" is an occupation. More details in this subject are provided in the following section.

literature: the presence of highly qualified workers nurtures the availability of social resources. For 2016 and 2018, this effect spills over the closest neighbors, suggesting that a more educated population in the surrounding locations allows a greater access to resources from social connections. However, the pandemic appears to have weakened these effects in 2021. Concerning the separated effects of mining and non-mining industries, while the latter provides consistent coefficients with the baseline estimations, there are no conclusive results in favor of spillover effects stemming from mining firms agglomeration.

The evidence of this interplay highlights the complicated relationship between the concentration of primary sector and the social capital formation. Our findings confirm the positive effects of higher education levels on social capital, as stated in the literature (van Tubergen & Volker, 2015), emphasizing the importance of human capital in fostering high-status social networks. Lastly, our results provide some evidence on how the COVID-19 pandemic disrupted the existence and impact of social networks in the society. Our results suggest the importance to put in place policies to help social capital to support local activities and, hence, foster a more resilient local economy.

The rest of the paper is structured as follows. Section 2 reviews the literature on social capital. Section 3 introduces our definition of social capital and the research strategy. Section 4 details the data and selected variables. Section 5 outlines the empirical results. Lastly, Section 6 provides concluding remarks.

3.2 Literature review

Social capital is perceived as the investment made by people to nurture their social networks with the purpose to get returns from them in the marketplace (Lin, 2002). Individuals can benefit strategically from networks in the way to increase information inflows, their influence on decision-making agents, social credentials, as well as reinforce their own identity and self-esteem. Social networks also play a key role in the matching process of workers to vacancies, the diffusion of information and technology, and learning (Jackson, 2011). Resources embedded in these connections are key for the achievement of goals and obtaining social support (Contreras, Otero, Díaz, & Suárez, 2019; Otero, Volker, & Rozer, 2022).[4]

[4]Bourdieu (1986) also proposed that social capital manifests as resources at the individual level. However, he defines social capital as the process through which individuals in the dominant class maintain and reproduce privilege groups which also hold economic or cultural capital.

3.2.1 Operationalization and determinants of social capital

The literature extensively discusses the effects of social capital on various economic outcomes, such as upward income mobility (Benton, 2016; Chetty et al., 2022), labor market entry and job outcomes (Chen & Volker, 2016; Verhaeghe et al., 2015), regional economic growth (Forte et al., 2015; Muringani et al., 2021), and innovation (Capello & Lenzi, 2014; Peiró-Palomino, 2019). However, the causes behind the heterogeneity in the level of social capital have been much less studied. Economic geography and regional studies addressing this topic at the regional level have primarily focused on the 'communitarian' approach to social capital proposed by Putnam, Leonardi, and Nonetti (1993), based on norms, trust, and (or) civic engagement (as approximations for social networks). This type of capital is seen as a tool to provide community-level returns in the form of effectiveness when pursuing collective objectives (Glaeser, Laibson, Scheinkman, & Soutter, 1999). Nevertheless, this conceptualization of social capital as a 'catch-all' or 'umbrella' idea referring to various social features is criticized as fuzzy (Huber, 2009; Markusen, 2003). Under this approach, a wide range of non-equivalent and social phenomena (i.e. trust, civic engagement, etc.) is covered in a single concept, which makes it lack specificity and substance (Hauser, Tappeiner, & Walde, 2007).

Social capital is also treated as the resources embedded in social ties (known as the *Linean* approach). Under this perspective, they are often operationally defined in terms of the individual's connections with people in various occupational positions and different levels of prestige. This type of information is gathered by means of the so-called 'position generator' survey, proposed by Lin and Dumin (1986). In this survey, individuals are given a predetermined list of occupations, so they indicate how many people they know who occupy each of these occupations. This instrument is intended to measure the "access" to social resources useful for *instrumental* actions (e.g. information on job vacancies) (van der Gaag et al., 2008). The idea behind this strategy is to be able to exploit the information on the occupational prestige as good indicator for measuring the resources an individual can access given the composition of their own social network (Hällsten, Edling, & Rydgren, 2015). In general, individuals in high-prestige occupations possess larger amounts of assets, including income, education, and workplace authority (Lin & Erickson, 2008).[5] In this sense, people with larger networks with individuals in high-status occupations are expected to register a higher level of social capital.[6]

[5]The authors also acknowledged that occupations of all levels of prestige contribute with resources, such as job opportunities based on worker referrals. However, the overall volume of resources may decrease as the level of prestige is lower.

[6]A survey on the operationalization of social capital from the approach of social networks resources was presented by Weiler and Hinz (2019).

3.2.2 Social capital at the local level

Following the Linean approach, the study of the determinants of social capital disparities has been conducted mostly at the micro level of analysis. van Tubergen and Volker (2015) concluded that age and education level are positively associated with social capital. Benton (2016) found that the participation in civic organizations affects the relationship between an individual's social position and the access to social resources. Focused on China, Lu, Ruan, and Lai (2013) found that migrating from rural to urban areas was associated with deficits of social capital and its returns. Otero et al. (2022) showed that social capital distribution in Chile is determined by social class structure. Specifically, social networks in upper-class population are greater, more diverse, and include occupations of higher prestige than the ones of low-class population.

Instead, the spatial or local social capital has received relatively less attention in the literature. In order to assess the determinants of firm success, Schutjens and Völker (2010) associated the concept of local social capital with the level of social capital in neighborhoods. This was approximated both in terms of the number of accessed positions ("local extensity"), and the average prestige of those positions in each locality ("local mean reach"). They found that entrepreneurs in denser locations had smaller local networks. However, an increase in the number of business services firms and highly educated entrepreneurs generate a higher level of local social capital in terms of average prestige. Some studies have provided insights on how macro-level forces (such as local industrial composition) can shape social structures at individual level and thus lead to geographic heterogeneity of social capital. Personal networks are significantly affected by geographical location (Beggs, Haines, & Hurlbert, 1996). For instance, empirical evidence shows that network compositions vary substantially depending on whether the individuals are located in rural or urban places (Enns, Malinick, & Matthews, 2008). Following this approach, Kuo and Fu (2021) studied how the occupational structures at different spatial levels impact on social capital of individuals. These authors concluded that the access to professional-type resources is more likely in counties, metropolis, and states where more residents work in education, training, and library-related occupations. Conversely, resources from farming and production occupations are only perceived at the smallest spatial level. Wang (2023) calculated the county-level social capital as the weighted average of individual level measures obtained by position generator questions as a determinant of ethnic differences in income levels in China. The idea behind this method is that, as for the individual level measure, the aggregated measure reflects the community's access to social resources. In turn, the opportunities for such access are facilitated or constrained by the local occupational structures.

In this paper we contribute to this strand of the literature by exploring the effect of the local industrial structure on the aggregate level of social capital. Specifically, we estimated the impact of the concentration of primary sector companies on the social resources that the community can access. The rationale behind this approach lies in the potential existence of heterogeneous levels of social capital derived from local structures based on low-skilled occupations. In this sense, inhabitants of municipalities that are more intensive in the primary sector would have less access to social resources coming from connections with high-status occupations. This led us to formulate the hypothesis that the concentration of primary sector companies is negatively associated with social capital at the municipal level. In order to conduct this study, we focused on the municipalities of Chile. This economy heavily relies on primary sector activities. By 2023, more than 86 percent of total exports corresponded to primary sector products (Banco Central de Chile, 2024). However, the mining industry of this country has a high predominance within the primary sector, as well as the national economy. Almost 60 percent of total exports corresponded to mining products. Moreover, this industry is highly geographically concentrated in the municipalities of the Northern regions. For this reason, it is relevant to estimate the specific impact of the agglomeration of the mining and non-mining industries. In addition to the geographic heterogeneity of local human capital derived from the primary sector, an additional layer of differentiation between localities could be linked to the predominant type of primary sector industry in each municipality.

Another hypothesis proposed in this study is the existence of spatial dependence between municipalities. The access to social resources is determined by the local level of participation of the primary sector and, therefore, by the availability of natural resources. This implies that the effects on social capital cannot be restricted to the spatial border of each municipality, but they can spill over nearby spatial units. Hence, the spatial approach allows us to take into account that social connections among individuals are not necessarily limited within the same municipality.

3.3 Empirical strategy

In this study we estimate the effect of the agglomeration of primary sector at (municipal level) on an aggregate measure of social capital, that we label 'spatial social capital'. In order to do so, we followed a Linean approach (Lin, 2002; Lin & Dumin, 1986). We calculate the spatial social capital based on a position generator instrument in order to address the individuals' access to resources embedded in their social network. The municipality-level agglomeration of primary sector is approximated by the industrial specialization of this sector (ψ_c), this is, the log-transformed share of primary sector firms over the total number of firms in the municipality c. The employees of a certain sector can live and work in different places, but, instead, we assume that firm location is driven by the availability of resources (natural resources, human capital, etc.). The availability of these resources is largely due to geographic characteristics, such as climate, mineral deposits, accessibility, among others. Therefore, this measure is proposed as a more adequate measure for reflecting the spatial distribution of primary sector activity than the share of employment. To address the potential existence of spatial dependency between municipalities, a spatial analysis is performed. The rationale of this choice is two-fold. First, we posit that social capital might be affected by geographical features that lead to different levels of concentration of primary sector activities. Such features are deemed to exist across several nearby municipalities. Second, we assumed that individuals can access to social resources from close municipalities, as networks are not limited by administrative boundaries. These situations entail potential spatial patterns that might influence the level of social capital in the municipality.

3.3.1 Measurement of social capital

We propose a measure of spatial social capital stemming from the perspectives put forward by Lin (2002), and applied to the context of municipalities. This measure is based on a position generator instrument focused on high-status occupations, that refers to questions like "How many X do you know", where "X" corresponds to a prestigious occupation. The answers are used to calculate the individual ratio of acquaintances in different prestigious (high-status) occupations over the total number of acquaintances in these groups, relative to the share of the population represented by each of these occupations in the corresponding province. This setting allowed us to address the composition of each person's high quality networks and, thus, to approximate to their access to these social resources.[7] We refer to the International Socio-economic Index of occupational status (ISEI), based on ISCO-88, to assign different scores to acquaintances in each occupation (Ganzeboom & Treiman, 2003).

Let a_{ikt} be the number of acquaintances in occupation k of individual i in period t, while the (fixed) ISEI score associated to each occupation is denoted by S_k.

$$\pi_{ikt} = \frac{S_k a_{ikt}}{\sum\limits_{k \in K} S_k a_{ikt}} \tag{3.1}$$

π_{ikt} represents individual i's scored ratio of contacts in each k occupational group. Next, let b_{pkt-n} be the number of people in province p with a high-status occupation k in period $t - n$.

$$\Pi_{pkt-n} = \frac{S_k b_{pkt-n}}{\sum\limits_{k \in K} S_k b_{pkt-n}} \tag{3.2}$$

Π_{pkt-n} is the share of workers belonging to each group of prestigious occupation over the to-

[7]The calculation resembles the location quotient from the literature on economic base analysis (Dinc, 2002; Galambos & Schreiber, 1978), or the revealed comparative advantage "Balassa" index (Balassa & Noland, 1989).

tal number of people in these groups in the province.[8] By employing the number of high-status workers in the province we assume that people can establish connections and have casual encounters within not only the same municipality but also the province. Therefore, the individual level of social capital would be given by:

$$\kappa_{it} = \sum_{k \in K} \frac{\pi_{ikt}}{\Pi_{pkt-n}} \tag{3.3}$$

The aggregated measure of social capital by municipality–the spatial social capital–has the form:

$$\kappa_{ct} = \sum_{i}^{N} \frac{\kappa_{it} \times \omega_i}{N_{ct}} \tag{3.4}$$

In Equation 3.4, κ_{ct} is the measure of spatial social capital for municipality c in period t. It is computed as the weighted average of κ_{it} using an individual weight ω_i, which is based on the inverse probability of each individual to be included in the survey sample. Finally, municipal population level is represented by N_{ct}.

Thus, we compute κ_{it} by the ratio of an individual's high-status contacts in occupation k at time t and the ratio of people employed in occupation k within the high-status sub-population K at time $t-n$. If the proportion of individual i's acquaintances in occupation k (e.g., medical doctors) among his or her total high-status contacts is lower than the proportion of professionals at occupation k in the province-level, high-status sub-population K from a few years ago (i.e., $\pi_{ikt} < \Pi_{pkt-n}$), this indicates that individual i has fewer group-specific acquaintances compared to the potential contacts that could have met during lapse n. Consequently, a value less than one is assigned to that occupational category. This value plus the share of the rest of the K occupations gives the final score for each individual. These individual measures of social capital based on contacts' occupational prestige are then aggregated at the municipal level, κ_{ct}. The aggregation is weighted by parameter ω_i.

3.3.2 Spatial analysis

The exploration of the impact of the agglomeration of primary sector firms on the level of social capital at the municipal level is performed by means of a spatial autoregressive (SAR) model. The results of the Rao's Score (Lagrange multiplier) diagnostic tests for choosing this

[8]In the case of Chile, a province is a mid-level administrative division unit. It ranks between a municipality (lowest level) and a region (highest level division).

specification as the most appropriate are presented in Tables 3.6, 3.7, and 3.8 in the Appendix. The SAR model specification allowes us to adjust for endogenous interaction effects stemming from neighboring municipalities. The Equation 3.5 describes the model to be estimated. The estimation is performed on a cross-sectional basis, introducing (spatial) lagged data of the independent variables.

$$\kappa_{ct} = \alpha + \beta^{\psi}\psi_{ct-n} + \rho \boldsymbol{W}\kappa_{dt} + \boldsymbol{X}\boldsymbol{\beta}^{\boldsymbol{X}} + \epsilon_c \tag{3.5}$$

where

$$c = \{1, ..., 93\}, c \neq d$$

In the specification above, our measure of social capital κ_{ct} is regressed on our key variable proxying the agglomeration of primary sector activities ψ_{ct-n}. The outcomes in neighboring municipalities were represented by κ_{dt} and ρ corresponds to the endogenous interaction term. The weight matrix $\boldsymbol{W}$ is defined as a 3-nearest neighbors matrix. This is based on the average number of continuous neighbors among the municipalities in the sample. The vector of municipal-level covariates $\boldsymbol{X}$ includes variables suggested by the empirical evidence in the literature (Alfred, 2010; Glaeser, Laibson, & Sacerdote, 2002). They are the average age of the total municipal population; the density of the populated areas of each municipality, considering the working-age population; the average years of education among inhabitants over 25 years of age, as well as the share of international migrants, as the share of the local population who was living abroad five years before the data were registered.[9] In line with Glaeser et al. (2002), we expect that the number of acquaintances increases at a decreasing rate with age, consequently, the resources obtained from social ties also increase. One relevant predictor for the quality of social ties is the level of education. The more educated a person is, the more prone to contact with people in prestigious occupations is. As for the relevance of the share of migrants, Alfred (2010) concludes that migrants develop strong ties within their social groups, but weak *bridging* networks outside of them. This would negatively affect the propensity to establish high-status connections. Regarding the density, we assume that social interactions are more abundant in large, dense urban environments, enhancing agglomeration economies and urban productivity. This is due to the proximity of people in big cities, increasing opportunities for social interactions compared to rural areas (Andersen et al., 2016).

We augment the baseline estimation by separately addressing the specific impacts of the agglomeration of mining and non-mining activities on social capital. The particularities of the Chilean mining sector might not provide the support for high-status social ties. Given the

[9] Working-age population consists on people over fifteen years old.

Table 3.1: Summary of variables Chapter 3.

Variable	**Definition**
Agglomeration measures	
Concentration of primary sector industries (ψ_{ct-n})	Share of primary sector firms over total firms in municipality c, in period $t-n$. Industries included are agriculture, livestock, forestry, fishing, and mining.
Concentration of mining industry (μ_{ct-n})	Share of mining industry firms over total firms in municipality c, in period $t-n$.
Concentration of non-mining industries (δ_{ct-n})	Share of firms in agriculture, livestock, fishing, and forestry industries over total firms in municipality c, in period $t-n$.
Demographic variables	
Age_{ct-n}	Average age of municipal population in period $t-n$.
$Density_{ct-n}$	Municipal working-age population over the surface of populated areas in square kilometers in period $t-n$.
$Education_{ct-n}$	Average years of education of the municipal population over 25 years of age in period $t-n$.
$Migration_{ct-n}$	Share of international migrants over total municipal population in period $t-n$.

Source: Own elaboration.

'fly-in, fly-out' (FIFO) work systems and the concentration of headquarters in the national capital, far from the northern mining sites (Aroca & Atienza, 2011; Atienza et al., 2021), the quality of social ties in terms of occupational prestige is likely to be severely eroded. In this line, we conducted the estimation of the models including separately as key variables proxies for the agglomeration of mining, μ_{ct-n}, and non-mining primary activities, δ_{ct-n}. The variables included in the study were summarized in Table 3.1.

3.4 Data and variables

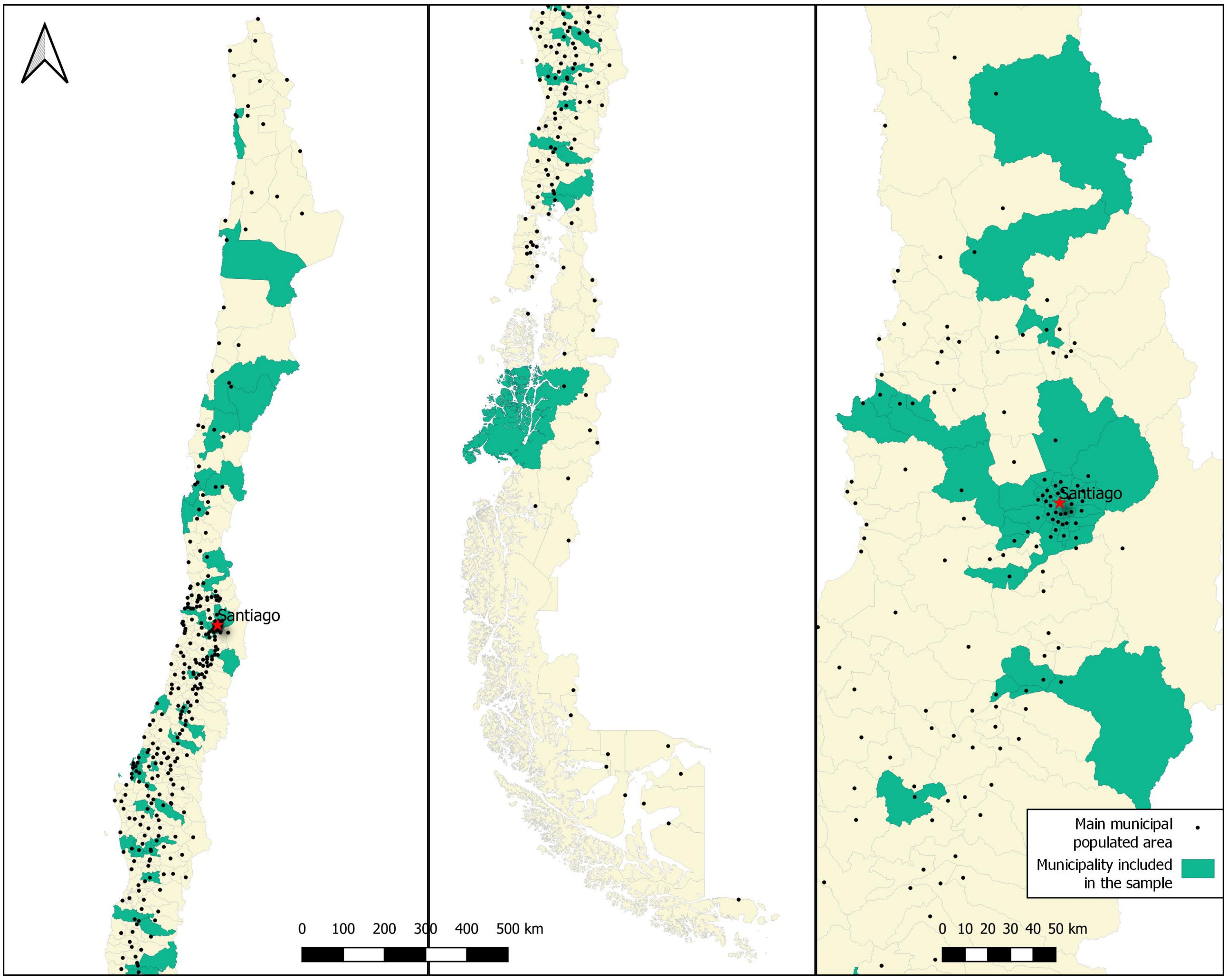
In order to perform our analysis, we need to approximate a measure of social capital, as well as a measure of agglomeration. As for social capital, data on acquaintances by occupation are taken from the Social Longitudinal Study of Chile (ELSOC) survey, which has been conducted since 2016 by the Centre for Social Conflict and Cohesion Studies COES (2023). The original sampling framework of the survey encompassed 94 municipalities, representing 77% of total country population and 93% of urban population.[10] The sample is representative for urban population, in cities with 10,000 or more inhabitants.[11] The geographic localization of municipalities covered in the sample of this study is shown in Figure 3.1.

The ELSOC survey provides information on the social ties of people based on position

[10] Based on the original sampling for the first wave in 2016.

[11] However, we discard one municipality from the sample due to inconsistent and outlier values between the waves, which increased the noise in the estimations. Therefore, our sample was composed by 93 municipalities.

Figure 3.1: Municipalities included in the sample.



Source: Own elaboration.

generator questions formulated as "how many people you know are...?". A person is considered an "acquaintance" if, at least, her name is known and a conversation could start in a casual meeting in the street or shopping mall. Participants are asked about acquaintances for 13 occupations, from which we focus on those with the five highest ISEI scores associated to their ISCO-88 code (Ganzeboom & Treiman, 2003). The selected occupations (and their ISEI scores) are Medical doctor (88), Lawyer (85), College Professor (77), Manager or director in a large firm (70), and Accountant (69). The participants have seven answer options: 0, 1, from 2 to 4, from 5 to 7, from 8 to 10, from 11 to 15, and 16 or more. Options involving a range of answers are then collapsed as the median number of the range to compute π_{ikt} from Equation 3.1. The highest category correspond to the number 16. Information on individual networks is provided every two years. Therefore, we refer to data from waves 2016, 2018, and 2021 to calculate π_{ikt}.

Data of sub-population in high-status occupations by province are estimated from National Socio-economic Characterization (CASEN) survey. This survey provides individual level, cross-sectional data, including expansion factors that allow us to project estimations of the number of people with prestigious jobs. In order to compute Π_{pkt-n} from Equation 3.2, we use waves 2013, 2015, and 2017 from CASEN survey.

To approximate a measure agglomeration of primary sector activities, we focused on the industrial specialization of each municipality. This is based on the share of firms in the primary sector over the total number of firms in each spatial unit. Annual data on companies by municipality are taken from the Chilean internal revenue service (SII) database. This database encompasses all formal companies fulfilling a tax declaration in the corresponding fiscal year. The location of the firms is given by the address of the headquarters. Primary sector industries includes agriculture, livestock, forestry, fishing, and mining.

The rest of covariates (mean age, years of education, and share of migrant population) are estimated using the data from CASEN surveys for each $t-n$ period, this is, 2013, 2015, and 2017. The density of working-age population in populated areas (e.g. cities, towns, villages, etc.) is computed using geographical data available in the Library of the National Congress of Chile (BCN), along with population estimations calculated by the National Statistics Institute (INE).

Table 3.2 shows the descriptive statistics of the variables we deal with, including the proxy variables for the agglomeration of mining (μ_{ct-n}) and non-mining (δ_{ct-n}) primary sector firms. The average social capital measure (κ_{ct}) showes a declining trend from 2016 (7.004) to 2021 (4.795), with the standard deviation also decreasing over this period. This suggests a reduction in both the level and variability of social capital across municipalities. The decline in social capital could be associated with a erosion of the social connections due to the COVID-19 pandemic. Physical distancing, isolation, and changes in the way people work reduced face-to-face interactions, negatively impacting on social capital formation (Pitas & Ehmer, 2020).

Concerning our measure of industrial specialization in primary sector activities (ψ_{ct-n}), the average values show a decreasing trend between 2016 and 2021 as well. This might depict a shift away from the primary sector among municipalities, as well as suggests an increase in the share of secondary and tertiary sector firms in the local industrial settings. This effect is mainly driven by the trend of non-mining firms (δ_{ct-n}), whereas the average level of agglomeration of mining firms (μ_{ct-n}) remains quite stable.

Regarding demographics, both the average density of populated areas (measured as working-age population per square kilometer) and the years of education remain relatively stable, despite a slight increase in the latter. However, the variability of educational attainment has also risen, indicating broader disparities between municipalities in terms of human capital. Conversely, both the average age and the proportion of migrants have increased over the period. The former reflects higher life expectancy and lower birth rates. An aging population may affect

Table 3.2: Descriptive statistics, 2016-2021.

		Mean	SD	Min	Max	Count
2016						
	κ_{ct}	7.004	6.759	0.00	32.69	93
	ψ_{ct-n}	0.112	0.125	0.00	0.46	93
	μ_{ct-n}	0.007	0.014	0.00	0.10	93
	δ_{ct-n}	0.105	0.121	0.00	0.45	93
	Age_{ct-n}	35.865	2.631	28.72	44.18	93
	$Education_{ct-n}$	10.611	1.518	8.33	16.02	93
	$Density_{ct-n}$	4,348.740	1,818.643	871.46	10,713.76	93
	$Migration_{ct-n}$	0.008	0.015	0.00	0.12	93
2018						
	κ_{ct}	6.805	5.504	0.09	29.44	93
	ψ_{ct-n}	0.103	0.116	0.01	0.43	93
	μ_{ct-n}	0.007	0.013	0.00	0.09	93
	δ_{ct-n}	0.096	0.113	0.01	0.43	93
	Age_{ct-n}	36.273	2.367	28.16	42.20	93
	$Education_{ct-n}$	10.566	1.611	7.80	16.06	93
	$Density_{ct-n}$	4,693.620	1,998.270	800.04	12,323.35	93
	$Migration_{ct-n}$	0.011	0.018	0.00	0.12	93
2021						
	κ_{ct}	4.795	3.526	0.00	16.83	93
	ψ_{ct-n}	0.092	0.105	0.00	0.40	93
	μ_{ct-n}	0.006	0.011	0.00	0.08	93
	δ_{ct-n}	0.086	0.102	0.00	0.40	93
	Age_{ct-n}	37.560	2.573	28.95	42.63	93
	$Education_{ct-n}$	10.770	1.687	7.47	16.25	93
	$Density_{ct-n}$	4,482.010	2,030.476	1,044.10	12,933.43	93
	$Migration_{ct-n}$	0.024	0.050	0.00	0.38	93
Total						
	κ_{ct}	6.201	5.501	0.00	32.69	279
	ψ_{ct-n}	0.102	0.115	0.00	0.46	279
	μ_{ct-n}	0.006	0.013	0.00	0.10	279
	δ_{ct-n}	0.096	0.112	0.00	0.45	279
	Age_{ct-n}	36.566	2.619	28.16	44.18	279
	$Education_{ct-n}$	10.649	1.603	7.47	16.25	279
	$Density_{ct-n}$	4,508.123	1,949.522	800.04	12,933.43	279
	$Migration_{ct-n}$	0.014	0.033	0.00	0.38	279

Source: Own elaboration using data from ELSOC and CASEN surveys, and SII data on formal firms.

social capital, as older individuals often exhibit different social interaction patterns compared to younger populations. The trend in the level and variability of the share of migrants among municipalities suggests an increased co-localization of migrants in certain areas. This could have contrasting effects on social capital, depending on the social background. On one hand, it might reduce the average quality of social ties due to fewer high-status contacts among migrants in precarious conditions. On the other hand, the immigration of highly skilled workers could enhance social capital by increasing connections in prestigious occupations, particularly among migrant groups (Alfred, 2010).

3.5 Results

Results from the estimation of the baseline model, both non-spatial (OLS) and spatial autoregressive (SAR) models are presented in Table 3.3. The outcomes from both specifications stress that coefficients for the agglomeration of primary sector firms and the average years of education are relatively consistent over time. The estimations of ρ suggest the existence of endogenous interaction effects, thus, the spatial social capital in each municipality is spatially correlated to the outcomes of its nearest neighbors. The inclusion of spatial dependence significantly improved the fit of the model, as suggested by Wald and LR tests. Moreover, the AIC values for SAR models in all the waves are lower than OLS, suggesting it is a more appropriate specification.

Table 3.3: Baseline estimation results: OLS, SAR models, 2016, 2016, 2021.

	Dependent variable: κ_{ct}					
	OLS			SAR		
	2016	2018	2021	2016	2018	2021
	(1)	(2)	(3)	(4)	(5)	(6)
ψ_{ct-n}	−3.236***	−3.278***	−1.864**	−1.812**	−1.663***	−1.701**
	(0.863)	(0.727)	(0.811)	(0.744)	(0.625)	(0.774)
age_{ct-n}	18.790	−81.474	72.985	34.976	−68.307	55.530
	(65.005)	(57.034)	(57.086)	(52.994)	(45.867)	(53.363)
age^2_{ct-n}	−2.377	11.552	−10.171	−4.674	9.662	−7.764
	(9.032)	(7.936)	(7.846)	(7.365)	(6.383)	(7.335)
$Density_{ct-n}$	0.050	0.354***	0.025	0.062	0.263**	0.006
	(0.170)	(0.134)	(0.130)	(0.138)	(0.108)	(0.122)
$Education_{ct-n}$	1.665**	1.172*	0.557	1.395**	1.219**	0.442
	(0.783)	(0.622)	(0.553)	(0.636)	(0.498)	(0.517)
$Migration_{ct-n}$	0.433	1.313	0.918	−0.239	−1.812	0.686
	(5.505)	(4.145)	(1.651)	(4.469)	(3.337)	(1.549)
ρ				0.503***	0.503***	0.241**
				(0.084)	(0.077)	(0.116)
Constant	−39.232	139.797	−130.692	−68.226	116.500	−99.020
	(116.689)	(102.320)	(103.902)	(95.114)	(82.278)	(97.129)
Observations	93	93	93	93	93	93
R^2	0.376	0.522	0.226			
Adjusted R^2	0.333	0.489	0.172			
Log Likelihood				−78.218	−53.261	−66.850
σ^2				0.295	0.172	0.243
Akaike Inf. Crit.	197.945	150.426	153.775	174.437	124.522	151.699
Residual Std. Error	0.669	0.518	0.528			
F Statistic	8.639***	15.652***	4.175***			
Wald Test				35.910***	42.466***	4.270**
LR Test				25.508***	27.904***	4.076**

Standard errors in parenthesis. All variables are expressed in logarithms.
*p<0.1; **p<0.05; ***p<0.01

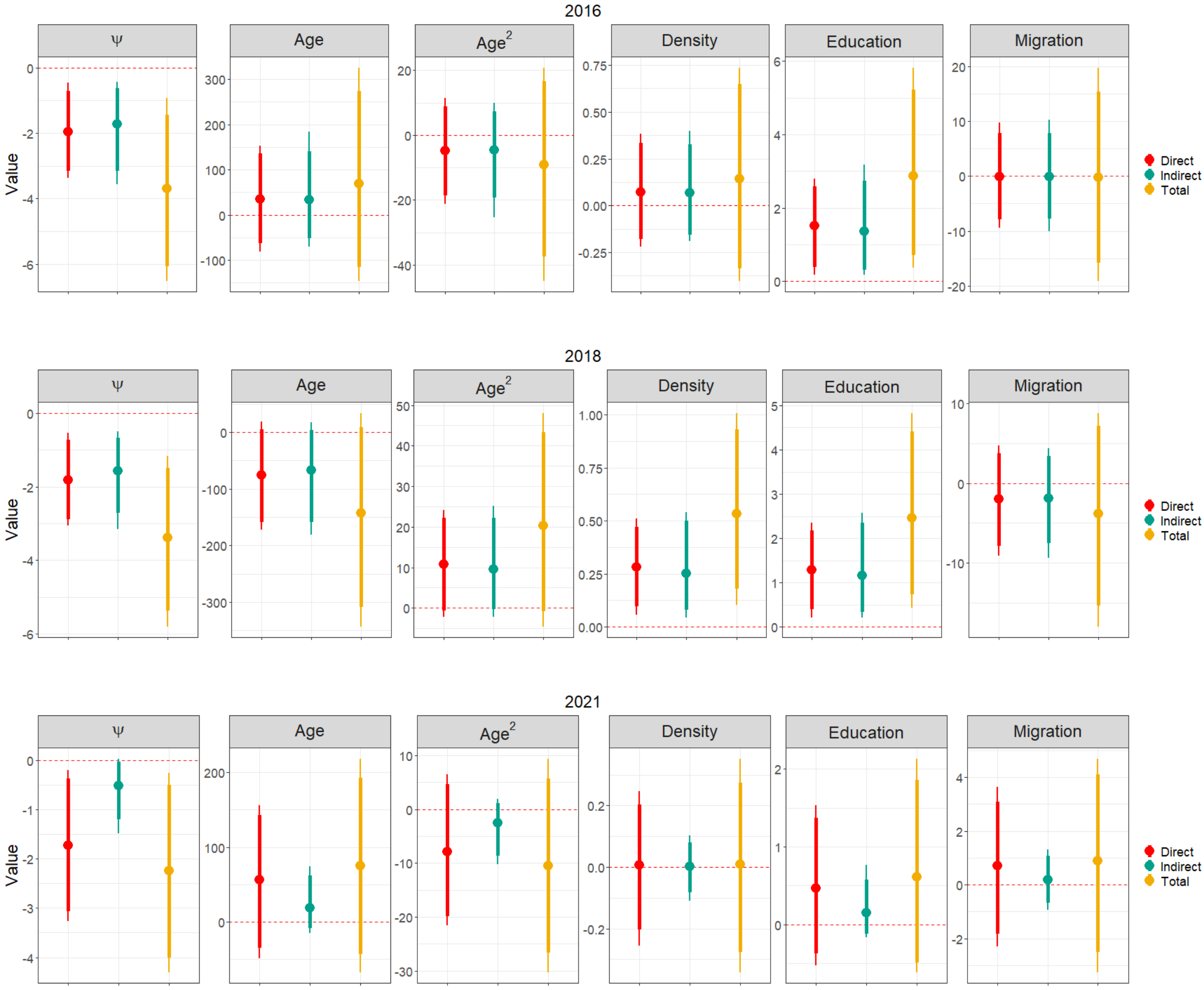
In order to interpret the effect on κ_c, we calculated direct and indirect effects by means of Monte Carlo simulations. Results are summarized and plotted in Figure 3.2. The detailed empirical means and confidence intervals are presented in the Appendix. The outcomes of the estimations suggest the presence of negative direct and indirect impacts of the concentration of primary sector firms on the level of social capital. Specifically, a negative association between each municipality's share of this type of firms and their own level of social capital for the three waves of the survey is observed. On the other hand, the results suggest the presence of spillover effects (indirect impacts) only for 2016 and 2018. The estimation of the impact for 2021 is only slightly significant (at 90% of confidence level). The lack of conclusive results in favor of the existence of spillovers in 2021 can be interpreted as a symptom of the overall erosion of social ties during the pandemic. This disruption could cause the levels of social capital to decrease even in places with a low presence of primary activities around. Thus, our estimation is not able to capture the variability due to ψ_c. This interpretation is consistent with the lower average value and variability of κ_c during this period among the spatial units.

Furthermore, our outcomes reflect positive direct and indirect impacts of the average years of education of the population on the level of spatial social capital in waves 2016 and 2018. This indicates that municipalities benefit from the presence of highly educated population in nearby urban locations by the increased propensity to establish high-status connections. At the same time, this reflects the key role of highly skilled human capital and the localization patterns of educated population for the expansion of high-status social networks to zones that are distant from the capital city. Conversely, the estimations did not provide conclusive results indicating neither direct nor spillover effects of education on the level of social capital. We infer that the pandemic weakened the mechanisms through which the education outcomes translate into social capital gains. Elements such as the prolonged isolation and less face-to-face interaction reduced the social ties with acquaintances in prestigious occupations for a significant share of the population. In addition, the density of working-age population in the municipality is associated with positive direct and indirect impacts on κ_c only in 2018. However, the inconsistency of this outcome with respect to the rest of the waves can be interpreted as an uncontrolled shock that deserves further attention. Regarding the rest of covariates, our results did not provide conclusive insights about their role determining social capital levels.

Consequently, we extend our analysis with the aim to assess the specific direct and indirect impacts from the agglomeration of mining and non-mining firms on spatial social capital. The results from the estimation of OLS and SAR models including the agglomeration measures for mining (μ_c) and non-mining (δ_c) industries firms are presented in Tables 3.4 and 3.5, respectively.

Results from the estimation of models including μ_{ct-n} in Table 3.4 reflect mostly consistent trends with respect to the baseline estimations. Elasticities across all years are negative and significantly greater than those from the baseline estimations, due to smaller values of μ compared with ψ (mean ψ is 0.102, whereas mean μ is 0.006 in the total sample, in Table 3.2). In line with the baseline estimations, results point in favor of accounting for spatial dependencies in the model. The lower AIC values for the SAR models indicate the specifications were improved by including spatial effects. In addition, ρ is statistically significant across all years, which suggests significant spatial endogenous effects.

Figure 3.2: Direct, indirect, and total impacts, baseline SAR models, 2016, 2018, 2021.



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

Direct and indirect impacts are presented in Figure 3.3. The corresponding values are presented in the Appendix. Concerning the proxy for agglomeration of mining activities, μ, estimations did not provide conclusive results in favor of the existence of spillover effects (at 95% of confidence level). Moreover, results suggest a negative average direct impact on social capital levels only for 2021. One possible explanation lies in the complex expected mechanisms behind this interplay. On the one hand, we could expect that cities with high participation of mining activities might be less attractive–as places of residence–for professionals (namely, people with prestigious jobs or occupation). This would be detrimental for the quality of potential links the inhabitants might establish, in terms of contacts' prestige and the returns from these connections. On the other hand, mining zones (specially in Northern regions) are characterized by higher income levels (Paredes, 2013). This might attract suppliers of professional services, such as medical procedures, legal and accounting assistance, among others, hence facilitating to have acquaintances in high-status occupations. Once the pandemic broke out, weak ties dissolved and let the first mechanism emerge.

Table 3.4: Extension results: Models with μ_c, OLS, SAR models, 2016, 2016, 2021.

	Dependent variable: κ_{ct}					
	OLS			SAR		
	2016	2018	2021	2016	2018	2021
	(1)	(2)	(3)	(4)	(5)	(6)
μ_{ct-n}	-15.667^{***}	-9.832^{**}	-14.655^{***}	-7.943^{*}	-2.672	-13.361^{***}
	(5.688)	(4.776)	(5.003)	(4.603)	(3.640)	(4.860)
Age_{ct-n}	28.478	-86.159	81.908	40.897	-69.606	64.942
	(67.225)	(61.921)	(55.943)	(53.423)	(46.825)	(52.495)
Age^2_{ct-n}	-3.927	12.061	-11.523	-5.606	9.781	-9.173
	(9.340)	(8.618)	(7.685)	(7.423)	(6.517)	(7.212)
$Density_{ct-n}$	0.167	0.513^{***}	0.090	0.126	0.321^{***}	0.067
	(0.173)	(0.140)	(0.126)	(0.137)	(0.107)	(0.119)
$Education_{ct-n}$	3.004^{***}	2.785^{***}	1.160^{**}	2.107^{***}	1.946^{***}	1.005^{**}
	(0.683)	(0.546)	(0.448)	(0.554)	(0.433)	(0.421)
$Migration_{ct-n}$	1.257	-1.603	0.411	0.155	-3.427	0.237
	(5.692)	(4.468)	(1.617)	(4.521)	(3.372)	(1.521)
ρ				0.5304^{***}	0.5683^{***}	0.22389^{*}
				(0.0827)	(0.0726)	(0.1171)
Constant	-58.478	144.613	-147.335	-79.897	117.144	-116.516
	(120.636)	(111.108)	(101.800)	(95.859)	(84.001)	(95.523)
Observations	93	93	93	93	93	93
R^2	0.333	0.437	0.253			
Adjusted R^2	0.286	0.397	0.200			
Log Likelihood				-79.738	-56.368	-65.455
σ^2				0.302	0.180	0.237
Akaike Inf. Crit.	204.149	165.691	150.476	177.476	130.736	148.910
Residual Std. Error	0.692	0.563	0.518			
F Statistic	7.157^{***}	11.113^{***}	4.843^{***}			
Wald Test				41.121^{***}	61.344^{***}	3.653^{*}
LR Test				28.673^{***}	36.955^{***}	3.566^{*}

Standard errors in parenthesis. All variables are expressed in logarithms.
*p<0.1; **p<0.05; ***p<0.01

Regarding the rest of the right-hand side variables, our measure for education level exhibit positive direct and indirect effects on the level of social capital for years prior to the pandemic. This is consistent with the baseline estimations and goes in line with the interpretation of the degradation of the weakest (or long-distance) social ties associated with the pandemic. The estimates for the impacts from working-age population density maintain the patterns exhibited when controlling for the whole primary sector.

Lastly, results from the models including the agglomeration proxy of non-mining primary sector firms presented in Table 3.5 are consistent with those from the baseline estimations. As in previous estimations, the inclusion of spatial effects improved the fit of the models for all waves. As suggested by the results, the exclusion of mining firms do not significantly alter the patterns of interaction between the agglomeration measure and the level of social capital. The estimation of direct and indirect effects depicted in Figure 3.4 support the findings of the baseline estimations.

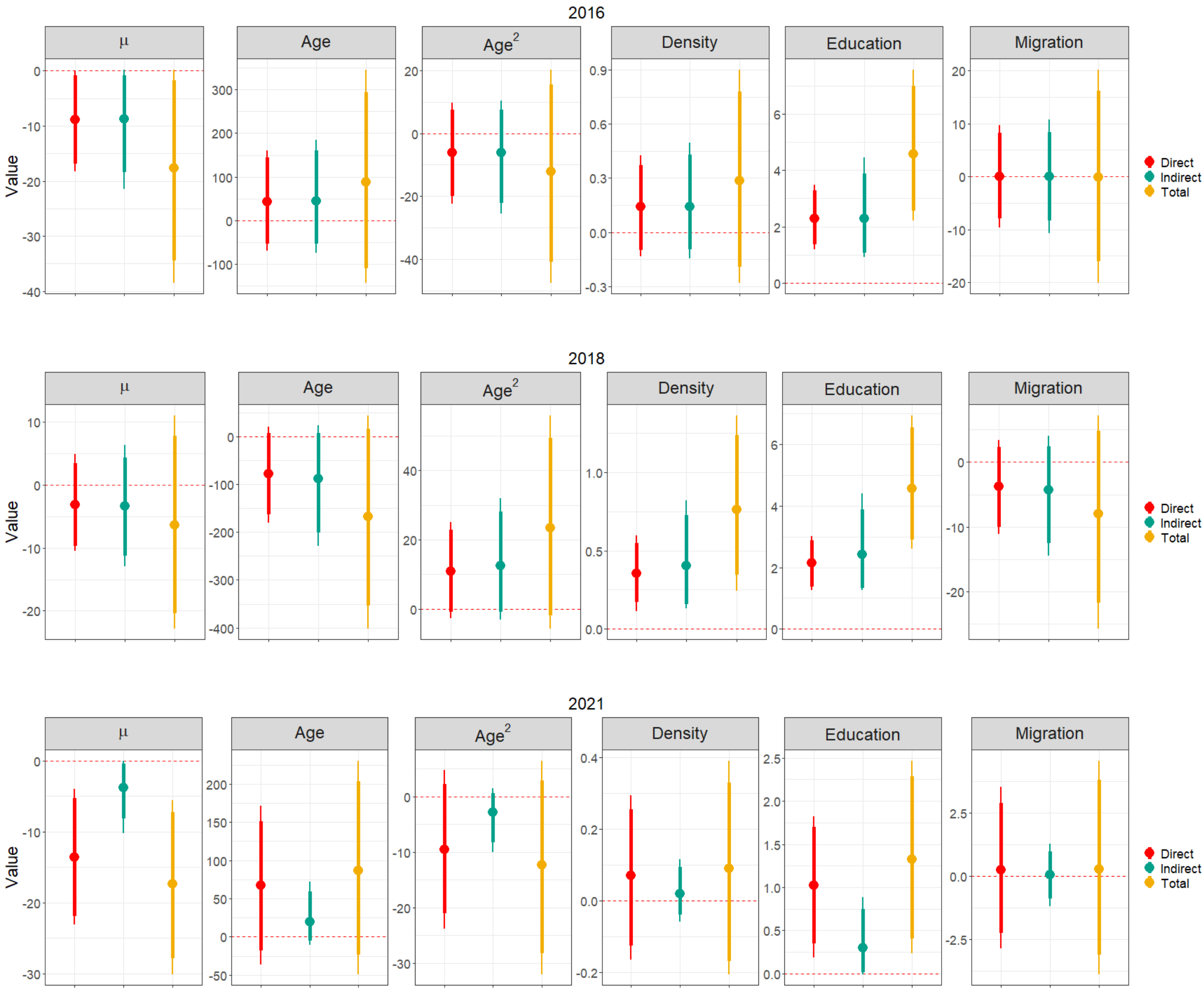
Table 3.5: Extension results: Models with δ_c, OLS, SAR models, 2016, 2016, 2021.

	Dependent variable: κ_{ct}					
	OLS			SAR		
	2016	2018	2021	2016	2018	2021
	(1)	(2)	(3)	(4)	(5)	(6)
δ_{ct-n}	-3.109^{***}	-3.350^{***}	-1.659^{*}	-1.726^{**}	-1.721^{***}	-1.516^{*}
	(0.903)	(0.766)	(0.851)	(0.765)	(0.650)	(0.806)
Age_{ct-n}	18.314	-82.645	73.915	35.007	-68.660	55.855
	(65.734)	(57.346)	(57.571)	(53.177)	(45.860)	(53.737)
Age^2_{ct-n}	-2.302	11.734	-10.311	-4.674	9.721	-7.818
	(9.133)	(7.979)	(7.913)	(7.391)	(6.382)	(7.386)
$Density_{ct-n}$	0.056	0.351^{**}	0.029	0.065	0.258^{**}	0.009
	(0.172)	(0.135)	(0.131)	(0.139)	(0.108)	(0.123)
$Education_{ct-n}$	1.767^{**}	1.137^{*}	0.645	1.441^{**}	1.183^{**}	0.517
	(0.794)	(0.635)	(0.562)	(0.640)	(0.506)	(0.525)
$Migration_{ct-n}$	0.381	1.532	0.904	-0.282	-1.703	0.668
	(5.567)	(4.177)	(1.667)	(4.482)	(3.343)	(1.560)
ρ				0.5127^{***}	0.5079^{***}	0.2474^{**}
				(0.0832)	(0.0766)	(0.1165)
Constant	-38.821	141.755	-132.502	-68.513	117.113	-99.719
	(118.000)	(102.883)	(104.785)	(95.441)	(82.267)	(97.811)
Observations	93	93	93	93	93	93
R^2	0.362	0.517	0.213			
Adjusted R^2	0.318	0.483	0.158			
Log Likelihood				-78.633	-53.279	-67.507
σ^2				0.297	0.172	0.247
Akaike Inf. Crit.	200.006	151.466	155.298	175.265	124.557	153.013
Residual Std. Error	0.677	0.521	0.532			
F Statistic	8.136^{***}	15.318^{***}	3.874^{***}			
Wald Test				37.952^{***}	43.979^{***}	4.508^{**}
LR Test				26.741^{***}	28.909^{***}	4.285^{**}

Standard errors in parenthesis. All variables are expressed in logarithms.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

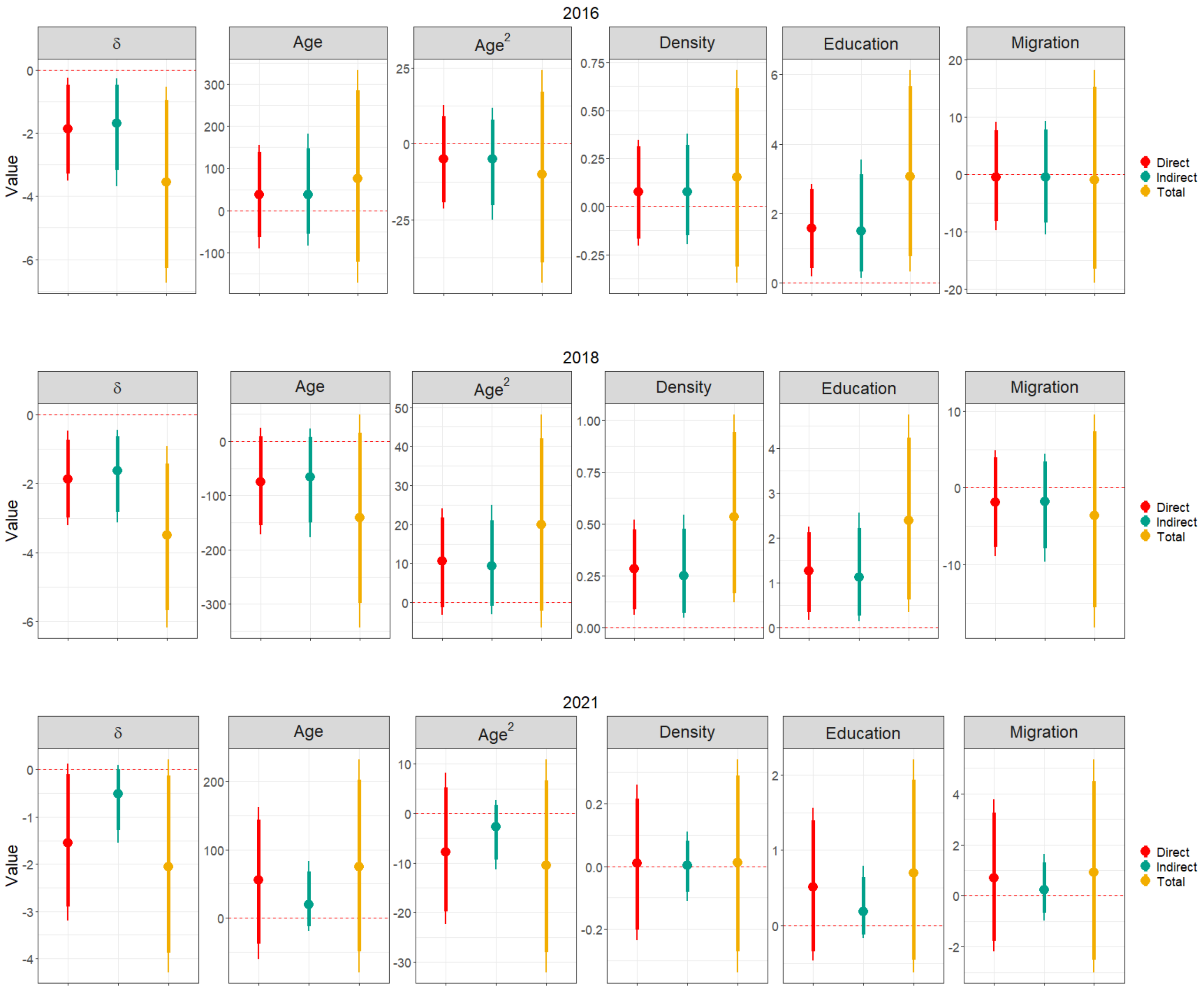
Overall, our findings provide a few insights about the interplay between the concentration of primary sector activities and the level of social capital the communities benefit from. They suggest that municipalities with high concentration of firms related to non-mining primary sector firms are significantly associated with lower levels of social capital that are reflected in the occupational prestige of the inhabitants' contacts. Moreover, these effects spill over the closest urban centers, at least during the years before 2021. A local industrial structure with preponderance of firms from the agriculture, livestock, fishing, or forestry industries might provide a weaker support for the formation of high-quality connections. This entails the existence of territorial lags in terms of labor opportunities, upward social mobility, and innovation.

Figure 3.3: Direct, indirect, and total impacts, SAR models with μ_{ct-n}, 2016, 2018, 2021.



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

Figure 3.4: Direct, indirect, and total impacts, SAR models with δ_{ct-n}, 2016, 2018, 2021.



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

3.6 Concluding remarks

This study explores the association between municipality-level social capital and the local concentration of primary sector activities in Chile. This idea is based on the potential limitations that the relative concentrations of primary activities can exert on the formation of high-status connections in the community. Our findings stress the relevance of the local economic environment on the formation of social networks and occupational prestige within communities. Specifically, our results indicate that a high concentration of primary sector firms negatively affects social capital. Areas with high concentration of primary activities tend to have fewer opportunities for residents to establish connections with individuals in high-status occupations, potentially limiting social mobility and economic progress. However, the estimation of the specific effect of the mining agglomeration did not provide conclusive results. Moreover, in line with the existing literature, our analysis shows that higher levels of education positively influence social capital, suggesting that educated population is more likely to foster high-status connections. However, the COVID-19 pandemic disrupted these dynamics, diminishing the positive effects of education on social capital formation (detected for 2021 data).

In the light of these results, policymakers should prioritize economic diversification in regions heavily dependent on primary sector activities to enhance the possibility to give value to social capital. By promoting the development of industries beyond mining or agriculture, these areas can create a more balanced economic structure. This new environment would help to create diversified employment opportunities, as well as the formation of social networks. Also, the promotion of entrepreneurship and support for SMEs different from primary activities, are crucial in providing diverse employment opportunities and fostering innovation, which can enhance the overall social and economic fabric of communities. Targeted support to SMEs, including access to finance, technical assistance, and market opportunities, can stimulate local economic development and improve social capital.

Lastly, the positive relationship between education and social capital highlights the importance of investing in educational initiatives. Policies aimed at increasing educational attainments and improving the quality of education can have a deep impact on social network formation and economic mobility. Furthermore, policies aiming at attracting highly-skilled human capital into municipalities with industrial structures based on primary activities might endow local citizens with a better access to social resources embedded in high-status connections. In order to do so, the creation of knowledge-intensive business services (KIBS) firms specialized in primary sector businesses might elevate the level of local social ties.

However, the empirical analysis we propose can be furtherly improved. One limitation to be addressed in future steps refers to the position generator instrument. The measure of the access to social capital is sensitive to the number and type of occupations that are included in the survey (Hällsten et al., 2015). Therefore, it could be valuable to have additional evidence to proxy this indicator. In addition, it is necessary to perform new estimates including other occupational groups to study the sensitivity of our measure of social capital to changes in this feature. Another limitation of our study is the number of municipalities covered by the survey used as a data source. Although our data allowed us to focus on the urban population, our results must be interpreted with caution, given that smaller municipalities, located in extreme areas, and/or located in predominantly rural areas, are omitted.

3.7 Appendix

3.7.1 Spatial interaction diagnostics

Table 3.6: Spatial interaction diagnostics, ψ_{ct-n} models.

	2016		2018		2021	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Moran I Resid	0.3829	0.0000	0.3959	0.0000	0.0957	0.0440
RSerr	25.1960	0.0000	26.9320	0.0000	1.5726	0.2098
RSlag	28.1340	0.0000	27.5830	0.0000	4.6781	0.0306
adjRSerr	0.6646	0.4149	2.7888	0.0949	4.9064	0.0268
adjRSlag	3.6018	0.0577	3.4396	0.0637	8.0120	0.0046

Table 3.7: Spatial interaction diagnostics, μ_{ct-n} models.

	2016		2018		2021	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Moran I Resid	0.3983	0.0000	0.4305	0.0000	0.0828	0.0619
RSerr	27.2540	0.0000	31.8520	0.0000	1.1778	0.2778
RSlag	32.2340	0.0000	37.3030	0.0000	4.0831	0.0433
adjRSerr	0.1300	0.7185	1.0506	0.3054	4.4664	0.0346
adjRSlag	5.1105	0.0238	6.5014	0.0108	7.3717	0.0066

Table 3.8: Spatial interaction diagnostics, δ_{ct-n} models.

	2016		2018		2021	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Moran I Resid	0.3871	0.0000	0.4001	0.0000	0.1033	0.0355
RSerr	25.7490	0.0000	27.5110	0.0000	1.8335	0.1757
RSlag	29.7200	0.0000	28.8480	0.0000	4.9245	0.0265
adjRSerr	0.3808	0.5372	2.5460	0.1106	4.8081	0.0283
adjRSlag	4.3524	0.0370	3.8839	0.0488	7.8991	0.0049

3.7.2 Direct, indirect, and total impacts: Baseline model

Table 3.9: Direct, indirect, and total impacts. Baseline model, 2016.

Parameter	Direct	Indirect	Total
psi	-1.9575	-1.7320	-3.6894
	[-3.3688; -0.4578]	[-3.5580; -0.4381]	[-6.5221; -0.9298]
	(-3.1586; -0.7240)	(-3.1644; -0.6197)	(-6.0616; -1.4398)
Age	35.3081	33.3420	68.6502
	[-81.9969; 153.4722]	[-70.1742; 183.4369]	[-146.8095; 325.5595]
	(-62.7253; 135.1401)	(-52.4247; 141.0818)	(-116.0532; 273.0602)
Age^2	-4.7058	-4.4544	-9.1603
	[-21.1336; 11.5125]	[-25.3024; 10.0075]	[-45.0055; 20.8138]
	(-18.6034; 8.9106)	(-19.2889; 7.3104)	(-37.3476; 16.5330)
Density	0.0739	0.0699	0.1438
	[-0.2218; 0.3837]	[-0.1904; 0.3973]	[-0.4044; 0.7367]
	(-0.1806; 0.3327)	(-0.1552; 0.3276)	(-0.3368; 0.6504)
Education	1.5117	1.3593	2.8711
	[0.1793; 2.7973]	[0.1828; 3.1759]	[0.3758; 5.8254]
	(0.3863; 2.5893)	(0.3117; 2.7461)	(0.7055; 5.2180)
Migration	-0.1507	-0.1215	-0.2722
	[-9.3532; 9.7224]	[-10.0271; 10.1981]	[-19.1484; 19.7629]
	(-7.9372; 7.7956)	(-7.7027; 7.8378)	(-15.7763; 15.3887)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.10: Direct, indirect, and total impacts. Baseline model, 2018.

Parameter	Direct	Indirect	Total
psi	-1.8133	-1.5725	-3.3859
	[-3.0617; -0.5355]	[-3.1432; -0.4983]	[-5.8049; -1.1625]
	(-2.8843; -0.7323)	(-2.7076; -0.6742)	(-5.3674; -1.4941)
Age	-75.7588	-67.3138	-143.0726
	[-172.0255; 18.5137]	[-180.5883; 17.5856]	[-343.9829; 34.3025]
	(-159.1925; 5.5046)	(-158.3702; 3.5514)	(-309.5087; 9.2350)
Age^2	10.7118	9.5171	20.2289
	[-2.2773; 24.1981]	[-2.2575; 25.2044]	[-4.6640; 48.0824]
	(-0.5742; 22.2930)	(-0.3893; 22.1234)	(-0.8737; 43.3696)
Density	0.2824	0.2518	0.5342
	[0.0566; 0.5096]	[0.0432; 0.5389]	[0.1049; 1.0089]
	(0.0970; 0.4718)	(0.0797; 0.5017)	(0.1791; 0.9301)
Education	1.2950	1.1636	2.4586
	[0.2138; 2.3477]	[0.2060; 2.5665]	[0.4376; 4.8312]
	(0.3928; 2.1770)	(0.3285; 2.3577)	(0.7299; 4.4050)
Migration	-1.9547	-1.8407	-3.7954
	[-9.1289; 4.7373]	[-9.3668; 4.3474]	[-18.0321; 8.8243]
	(-7.8950; 3.7597)	(-7.5389; 3.3706)	(-15.3847; 7.2403)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.11: Direct, indirect, and total impacts. Baseline model, 2021.

Parameter	Direct	Indirect	Total
psi	-1.7299	-0.5128	-2.2427
	[-3.2711; -0.2024]	[-1.4869; 0.0304]	[-4.3081; -0.2672]
	(-3.0632; -0.3800)	(-1.2036; -0.0382)	(-4.0056; -0.5015)
Age	56.4502	18.4648	74.9150
	[-48.1933; 156.2433]	[-14.6462; 74.0000]	[-67.5921; 218.1741]
	(-34.4566; 142.9512)	(-8.0699; 62.4041)	(-42.7639; 192.1915)
Age^2	-7.8929	-2.5830	-10.4759
	[-21.6160; 6.4953]	[-10.2034; 1.9323]	[-30.3120; 9.3706]
	(-19.8959; 4.6355)	(-8.6417; 1.0906)	(-26.5762; 5.6758)
Density	0.0063	0.0020	0.0083
	[-0.2566; 0.2462]	[-0.1102; 0.1036]	[-0.3427; 0.3527]
	(-0.2032; 0.2043)	(-0.0810; 0.0809)	(-0.2764; 0.2737)
Education	0.4630	0.1530	0.6160
	[-0.5271; 1.5365]	[-0.1661; 0.7636]	[-0.6187; 2.1338]
	(-0.3751; 1.3681)	(-0.1209; 0.5785)	(-0.4902; 1.8568)
Migration	0.6990	0.1858	0.8848
	[-2.2909; 3.6263]	[-0.9325; 1.3128]	[-3.2715; 4.6953]
	(-1.8293; 3.1011)	(-0.6759; 1.0683)	(-2.5194; 4.0983)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

3.7.3 Direct, indirect, and total impacts: Extensions

Table 3.12: Direct, indirect, and total impacts. Model with μ_{ct-n}, 2016.

Parameter	Direct	Indirect	Total
mu	-8.9032	-8.7111	-17.6143
	[-18.3283; 0.0800]	[-21.4861; 0.1309]	[-38.5228; 0.2110]
	(-16.8542; -0.8695)	(-18.4244; -0.8898)	(-34.3674; -1.7775)
Age	43.9109	44.0882	87.9991
	[-69.0585; 161.0161]	[-74.6000; 184.1467]	[-143.8093; 346.2502]
	(-53.0640; 144.2161)	(-52.8837; 160.8456)	(-109.5307; 293.3527)
Age^2	-6.0145	-6.0412	-12.0556
	[-22.3044; 9.7368]	[-25.5068; 10.4716]	[-47.6259; 20.2799]
	(-19.9744; 7.4725)	(-22.2162; 7.4942)	(-40.8028; 15.5623)
Density	0.1437	0.1436	0.2873
	[-0.1341; 0.4260]	[-0.1457; 0.4980]	[-0.2821; 0.9024]
	(-0.0970; 0.3721)	(-0.0939; 0.4286)	(-0.1931; 0.7798)
Education	2.3025	2.2813	4.5838
	[1.1888; 3.4821]	[0.9320; 4.4439]	[2.2288; 7.5702]
	(1.3692; 3.2857)	(1.0634; 3.8781)	(2.5575; 6.9928)
Migration	-0.0339	-0.0526	-0.0865
	[-9.7047; 9.6171]	[-10.6769; 10.7667]	[-20.1414; 20.1949]
	(-7.9318; 8.1874)	(-8.3381; 8.3330)	(-16.0549; 16.1145)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.13: Direct, indirect, and total impacts. Model with μ_{ct-n}, 2018.

Parameter	Direct	Indirect	Total
mu	-3.0671	-3.3045	-6.3715
	[-10.5179; 4.9179]	[-12.9750; 6.3425]	[-22.8751; 11.0859]
	(-9.7499; 3.4949)	(-11.2309; 4.3148)	(-20.3488; 7.8434)
Age	-78.0226	-88.6984	-166.7210
	[-180.1883; 20.2525]	[-228.7932; 23.8325]	[-402.2226; 44.2991]
	(-162.7178; 7.3146)	(-200.5788; 7.1765)	(-354.1287; 15.7815)
Age^2	10.9568	12.4557	23.4125
	[-2.7051; 25.1588]	[-3.1602; 31.8696]	[-5.8157; 55.9930]
	(-0.8562; 22.8700)	(-0.8800; 28.0165)	(-1.8600; 49.4876)
Density	0.3569	0.4056	0.7626
	[0.1118; 0.5952]	[0.1311; 0.8225]	[0.2428; 1.3648]
	(0.1704; 0.5469)	(0.1568; 0.7262)	(0.3453; 1.2367)
Education	2.1527	2.4216	4.5743
	[1.2590; 3.0108]	[1.2525; 4.4068]	[2.6080; 6.9511]
	(1.3707; 2.8807)	(1.3279; 3.8751)	(2.9128; 6.5564)
Migration	-3.7115	-4.2678	-7.9793
	[-11.1346; 3.3586]	[-14.4498; 4.0481]	[-25.7572; 7.2473]
	(-10.9957; 2.2967)	(-12.5093; 2.4375)	(-21.7005; 4.7977)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.14: Direct, indirect, and total impacts. Model with μ_{ct-n}, 2021.

Parameter	Direct	Indirect	Total
mu	-13.6400	-3.7663	-17.4063
	[-23.1411; -4.0315]	[-10.2759; 0.0086]	[-30.1665; -5.5655]
	(-21.8940; -5.2385)	(-8.1805; -0.4703)	(-27.9161; -7.2154)
Age	67.3307	19.6234	86.9541
	[-36.1494; 171.2304]	[-10.4578; 72.1447]	[-49.5364; 230.6065]
	(-18.5199; 150.9425)	(-5.1500; 59.1637)	(-23.7946; 203.2576)
Age^2	-9.5077	-2.7723	-12.2800
	[-23.8353; 4.7467]	[-9.9974; 1.4554]	[-32.0564; 6.4838]
	(-21.0543; 2.2671)	(-8.3069; 0.6633)	(-28.2618; 2.9386)
Density	0.0707	0.0202	0.0909
	[-0.1643; 0.2941]	[-0.0582; 0.1147]	[-0.2061; 0.3904]
	(-0.1255; 0.2552)	(-0.0391; 0.0938)	(-0.1677; 0.3280)
Education	1.0229	0.3001	1.3230
	[0.1900; 1.8182]	[-0.0102; 0.8844]	[0.2390; 2.4678]
	(0.3473; 1.6968)	(0.0194; 0.7440)	(0.4074; 2.2846)
Migration	0.2436	0.0429	0.2866
	[-2.8662; 3.5402]	[-1.1941; 1.2881]	[-3.8964; 4.5697]
	(-2.2521; 2.8952)	(-0.8858; 0.9865)	(-3.1118; 3.7968)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.15: Direct, indirect, and total impacts. Model with δ_{ct-n}, 2016.

Parameter	Direct	Indirect	Total
delta	-1.8601	-1.6841	-3.5441
	[-3.5065; -0.2610]	[-3.6767; -0.2762]	[-6.7435; -0.5302]
	(-3.2766; -0.4793)	(-3.1754; -0.4714)	(-6.2760; -0.9616)
Age	37.9096	38.0560	75.9656
	[-90.4879; 155.2156]	[-82.5023; 182.2133]	[-171.3696; 333.5858]
	(-63.6141; 139.3603)	(-55.8040; 147.3225)	(-121.3828; 285.5256)
Age^2	-5.0661	-5.1044	-10.1705
	[-21.4962; 12.7197]	[-25.1024; 11.8304]	[-45.9197; 24.4435]
	(-19.2658; 9.1067)	(-20.2235; 7.9794)	(-39.2434; 17.1372)
Density	0.0774	0.0752	0.1526
	[-0.2033; 0.3468]	[-0.1969; 0.3802]	[-0.3978; 0.7117]
	(-0.1694; 0.3129)	(-0.1492; 0.3213)	(-0.3134; 0.6140)
Education	1.5771	1.4923	3.0694
	[0.1779; 2.8443]	[0.1376; 3.5381]	[0.3222; 6.1328]
	(0.4308; 2.6940)	(0.3243; 3.1290)	(0.7760; 5.6638)
Migration	-0.4542	-0.4550	-0.9093
	[-9.6930; 9.2226]	[-10.5053; 9.3338]	[-18.9014; 18.2592]
	(-8.1089; 7.6681)	(-8.3300; 7.8781)	(-16.4822; 15.2415)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.16: Direct, indirect, and total impacts. Model with δ_{ct-n}, 2018.

Parameter	Direct	Indirect	Total
delta	-1.8735	-1.6218	-3.4952
	[-3.2098; -0.4674]	[-3.1286; -0.4459]	[-6.1772; -0.9185]
	(-2.9794; -0.7482)	(-2.8286; -0.6334)	(-5.6619; -1.4321)
Age	-74.7741	-66.0265	-140.8006
	[-172.4276; 24.8303]	[-176.7859; 23.2780]	[-343.8098; 49.5141]
	(-155.3550; 8.5935)	(-149.6251; 7.5279)	(-298.3363; 15.3230)
Age^2	10.5884	9.3485	19.9369
	[-3.2506; 24.1542]	[-3.0026; 24.9848]	[-6.4700; 48.1944]
	(-1.1464; 21.7555)	(-0.9506; 21.0030)	(-2.0599; 41.9712)
Density	0.2831	0.2507	0.5339
	[0.0625; 0.5205]	[0.0478; 0.5439]	[0.1212; 1.0299]
	(0.0896; 0.4755)	(0.0703; 0.4776)	(0.1647; 0.9443)
Education	1.2654	1.1288	2.3942
	[0.1740; 2.2555]	[0.1388; 2.5626]	[0.3403; 4.7511]
	(0.3453; 2.1195)	(0.2615; 2.2249)	(0.6221; 4.2336)
Migration	-1.8564	-1.7629	-3.6193
	[-8.9406; 4.8572]	[-9.6212; 4.4163]	[-18.2079; 9.5523]
	(-7.7277; 3.9329)	(-7.9057; 3.4110)	(-15.5900; 7.3217)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Table 3.17: Direct, indirect, and total impacts. Model with δ_{ct-n}, 2021.

Parameter	Direct	Indirect	Total
delta	-1.5441	-0.5106	-2.0547
	[-3.2034; 0.1283]	[-1.5454; 0.0923]	[-4.2983; 0.2208]
	(-2.9075; -0.1014)	(-1.2910; 0.0021)	(-3.8862; -0.1261)
Age	55.2893	19.6455	74.9348
	[-60.3949; 162.4875]	[-20.0021; 82.8293]	[-80.4200; 232.6158]
	(-38.1211; 143.7742)	(-12.5551; 67.3186)	(-49.3714; 202.4713)
Age^2	-7.7396	-2.7519	-10.4915
	[-22.3531; 8.1985]	[-11.3908; 2.6933]	[-32.1553; 10.9595]
	(-19.8350; 5.1915)	(-9.3050; 1.6755)	(-27.9576; 6.6116)
Density	0.0107	0.0029	0.0136
	[-0.2350; 0.2606]	[-0.1111; 0.1105]	[-0.3383; 0.3418]
	(-0.2014; 0.2165)	(-0.0820; 0.0826)	(-0.2700; 0.2885)
Education	0.5166	0.1848	0.7014
	[-0.4638; 1.5600]	[-0.1626; 0.7912]	[-0.6220; 2.2061]
	(-0.3415; 1.3965)	(-0.1182; 0.6390)	(-0.4519; 1.9361)
Migration	0.7021	0.2280	0.9301
	[-2.1761; 3.7648]	[-0.9663; 1.6228]	[-3.0132; 5.3471]
	(-1.7775; 3.2578)	(-0.6764; 1.2927)	(-2.5173; 4.4947)

Empirical means and confidence intervals from 1000 MCMC simulations.
Confidence intervals at 95% (Quantiles at 2.5% and 97.5%) in brackets.
Confidence intervals at 90% (Quantiles at 5% and 95%) in parentheses.

Chapter 4

The Impact of KIBS Agglomeration on Chilean Mining Sector Productivity[1]

4.1 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,

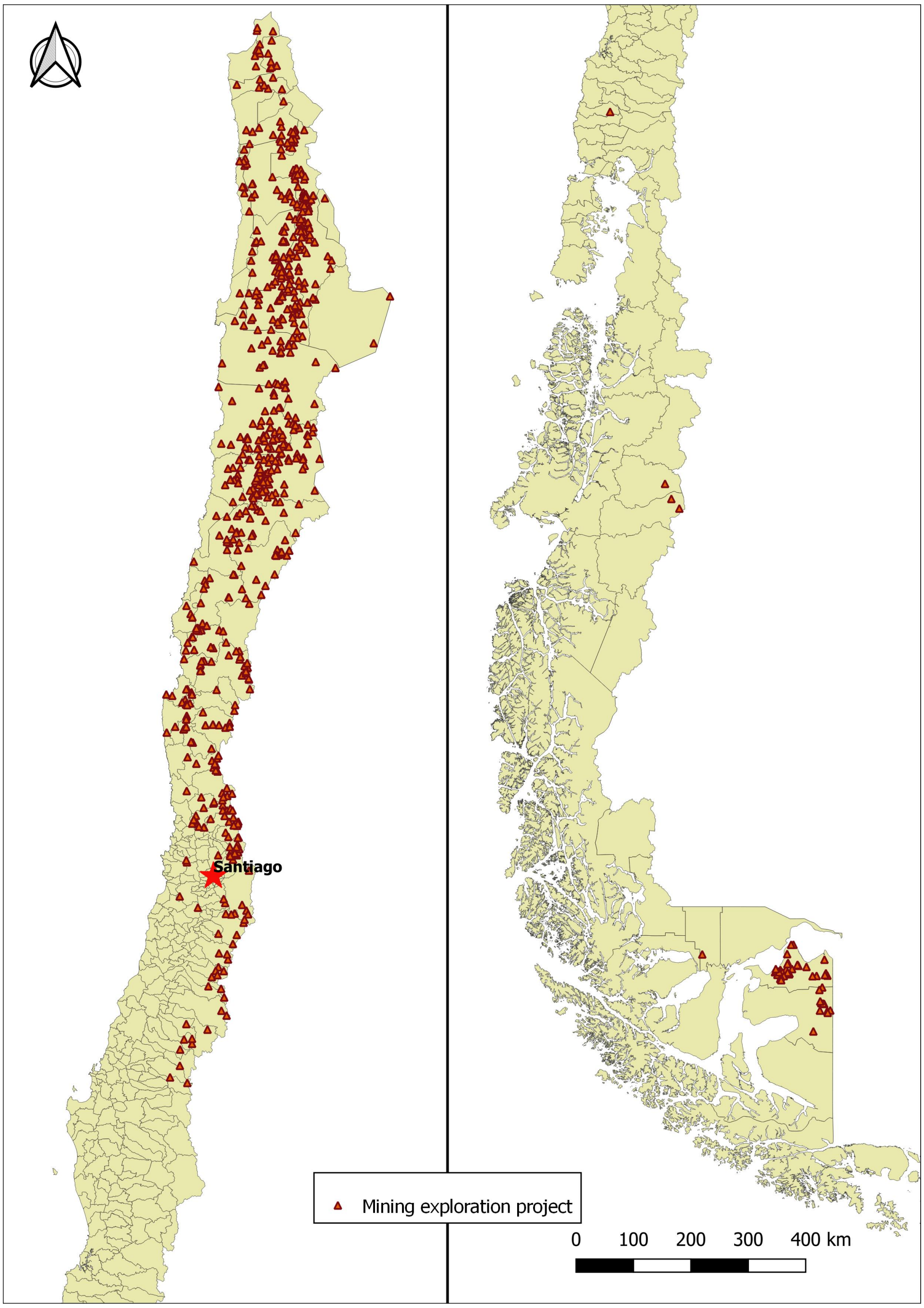
[1]This research benefited from the financial support of the *Programa de Perfeccionamiento Académico Disciplinar* of Universidad de Antofagasta. I am grateful to participants to the X Doctoral Workshop of the PhD Program in Applied Economics (Barcelona, 2022), the XLVII International Conference on Regional Science (Granada, 2022), the XI PhD-Student Workshop on Industrial and Public Economics (Reus, 2023), and the 62nd ERSA Congress (Alicante, 2023) for their valuable comments.

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 et al. (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 et al., 2021; Bravo-Ortega & Muñoz, 2021). This scenario raises questions about the sustainability of economic growth in Chilean mining regions (Arias et al., 2014). Figure 4.1 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

Figure 4.1: Mining exploration projects recorded in period 2018-2021.



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

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. However, 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.

4.2 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.

4.2.1 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 (I. Miles et al., 1995; Muller & Doloreux, 2009).[2] 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

[2] 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.

research; and C-KIBS, covering creative activities such as advertising, architecture, and design (I. D. Miles, Belousova, & Chichkanov, 2018). Shearmur (2010) suggested 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).[3] 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 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

[3] Asheim and Gertler (2006) define regional innovation systems as the institutional infrastructures supporting innovation within the production structure.

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).

4.2.2 KIBS and the Chilean mining sector

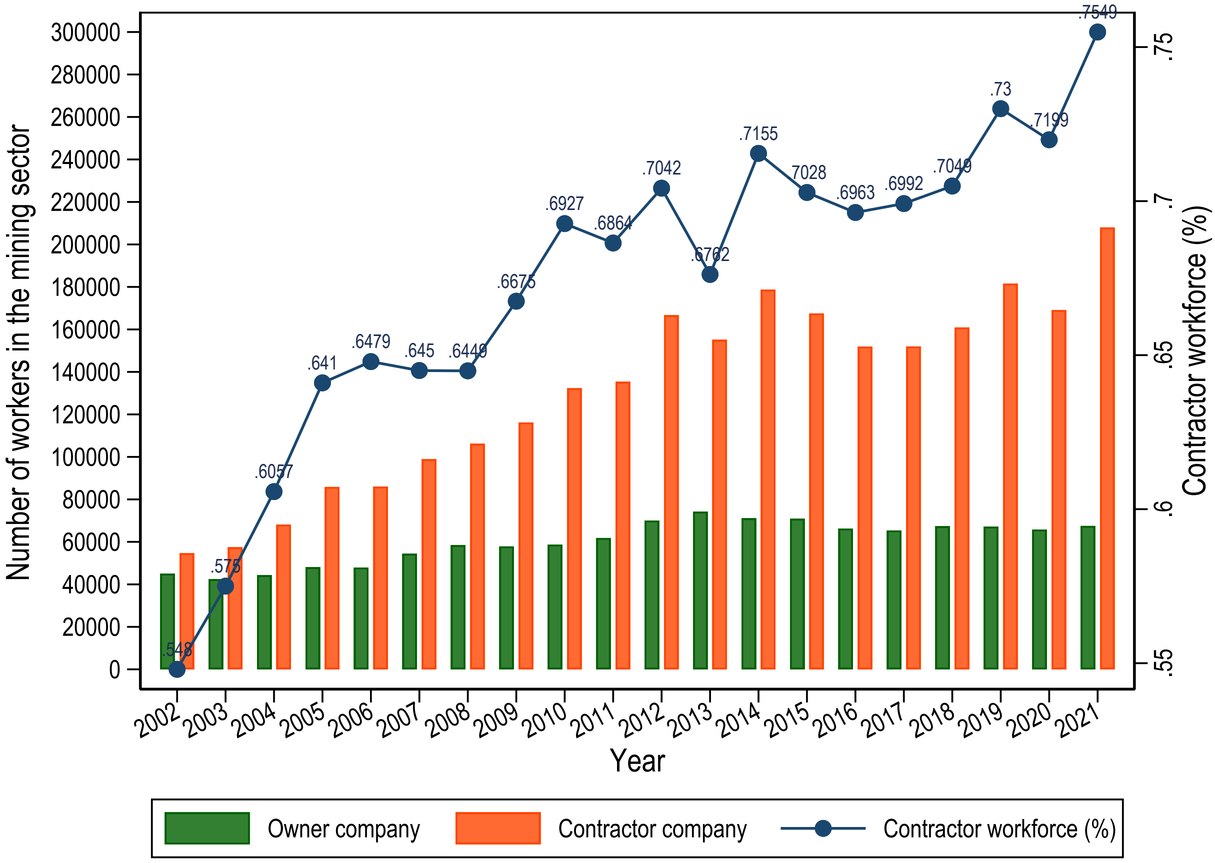
Although often characterized as a latecomer (Morris, Kaplinsky, & Kaplan, 2012), the landscape of mining production has undergone a significant transformation in recent decades, shifting from high integration to notable de-integration and reliance on outsourcing (Marin et al., 2015). This evolution has 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 4.2 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

Figure 4.2: Evolution of workforce in owner and contractor companies in the Chilean mining sector, 2002-2021.



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

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).[4] 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 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,

[4]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.

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.

4.3 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 run 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.

4.3.1 Aggregate level effect estimation

In order to assess the potential average impact of industrial specialization in KIBS in the municipality, a set of models is estimated referring to panel data on mining sector wages.[5] We compute 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 is computed using data lagged by one period. When performing the empirical estimations, we are also concerned about the potential influence of the metropolitan area of Santiago. In order to control for it, we produce estimations with and without the Santiago province. Equation 4.1 presents the baseline estimation.

$$\begin{aligned} lnW_{ct} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \boldsymbol{\beta^{MC}MC}_{ct} + \boldsymbol{\beta^{DC}DC}_{ct} + T_t + \nu_c + \varepsilon_{ct}; \\ c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \end{aligned} \tag{4.1}$$

In Equation 4.1, 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}, is also incorporated. This is 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.[6] T_t is the time-specific effect; ν_c stands for the unobservable municipality-specific effect; and ε_{ct} represents the idiosyncratic error term.

4.3.2 Individual-level effect estimation

The estimation of the impact of KIBS agglomeration on individual productivity is conducted by proxying productivity by the annual income of mining sector workers for each year. As detailed in the next section, the exploited data source reports taxable monthly incomes, which

[5]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.

[6]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.

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 is estimated. The model to be estimated is shown in Equation 4.2. Once more, estimations with and without the Santiago province are performed.

$$\begin{aligned} lnW_{it} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \boldsymbol{\beta^{MC}MC_{ct}} + \boldsymbol{\beta^{IC}IC_{it}} + T_t + \nu_i + \varepsilon_{ict}; \\ i = \{1, ..., 35, 302\},\ c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \end{aligned} \tag{4.2}$$

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

4.3.3 Spatial analysis

For our exploratory spatial analysis, we first assess the existence of relevant spatial structures for the Chilean territory. The underlying hypothesis to test is the centrality of Santiago. We shape 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 are 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.[7] To avoid collinearity, the measures of distance are not included in Model 4.3 simultaneously.

$$\begin{aligned} lnW_{ct} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \beta^{R}Dist^R_c + \beta^{N}Dist^N_c + \boldsymbol{\beta^{MC}MC_{ct}} + \boldsymbol{\beta^{DC}DC_{ct}} + T_t + \nu_c + \varepsilon_{ct}; \\ c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \end{aligned} \tag{4.3}$$

[7] 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.

Furthermore, we are 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 georeference 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 4.3. 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 alternate 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 contiguity within central regions.[8] The empirical approach proposed by Elhorst (2010) is 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.

4.4 Data and variables

4.4.1 Data sources and samples

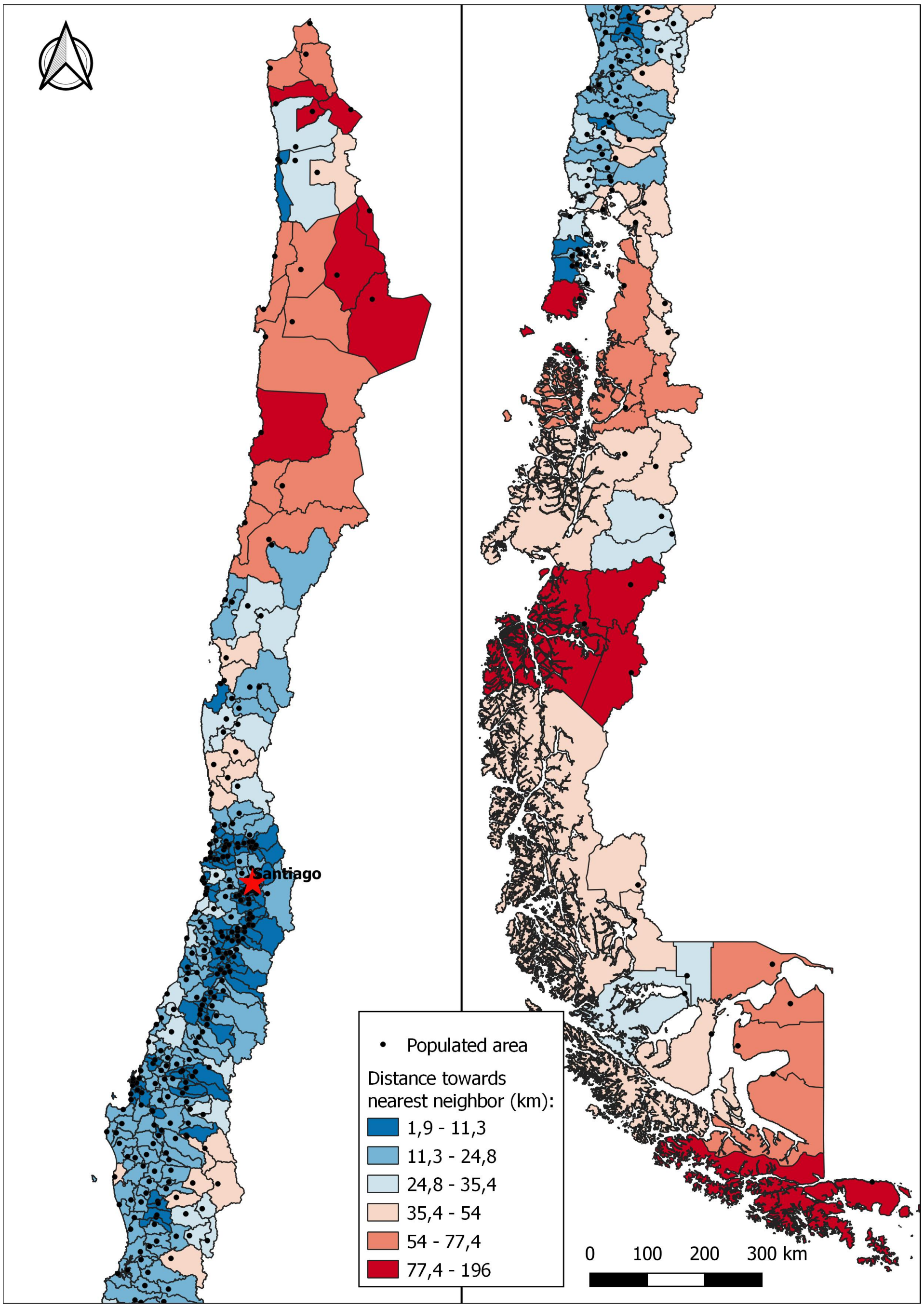
We build an original dataset using information gathered from several public institutions to carry out the empirical analysis. Longitudinal data on income and individual characteristics, i.e. municipality of residence, education level, among others, are taken from the database of workers affiliated with the Public Unemployment Insurance (PUI),[9] released by the *Superintendencia de Pensiones*. Data on companies by economic sector and sub-sector and geographic location are 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 are 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 ob-

[8]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.

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

Figure 4.3: Centroids for urban center and populated areas in Chile.



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

servations, and encompassing 314 out of 345 municipalities that compose the Chilean territory.

4.4.2 Dependent variables

This study exploits 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 is 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.[10] 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 is set up to vary on a monthly basis employing the UF exchange rate at the end of each month.[11] Real monthly wages are obtained by using the top-cap-defining UF value in each month and the UF value for December 28, 2021.

Real monthly wages are used in both aggregate- and individual-level estimations. To estimate the effect of KIBS agglomeration on mining sector productivity at the municipal level, real wages are 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 are 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 is imputed. Wages for a given individual with more than one paying employer for a given month are 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 are adjusted by using the same exchange rate employed when correcting wages, and these are extrapolated to annual values.

4.4.3 Independent variables

Agglomeration measures

Annual data on companies by geographic zone and economic sector provided by the Chilean internal revenue service (SII) database allow us to compute 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 I. D. Miles et al. (2018). We consider NACE rev. 2 divisions classified by

[10] 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%.

[11] *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.

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) are used as reference. Table 4.11 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 mining sector companies to control for potential localization economies. Figures 4.4 and 4.5 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 4.5, 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.

Meso-level controls

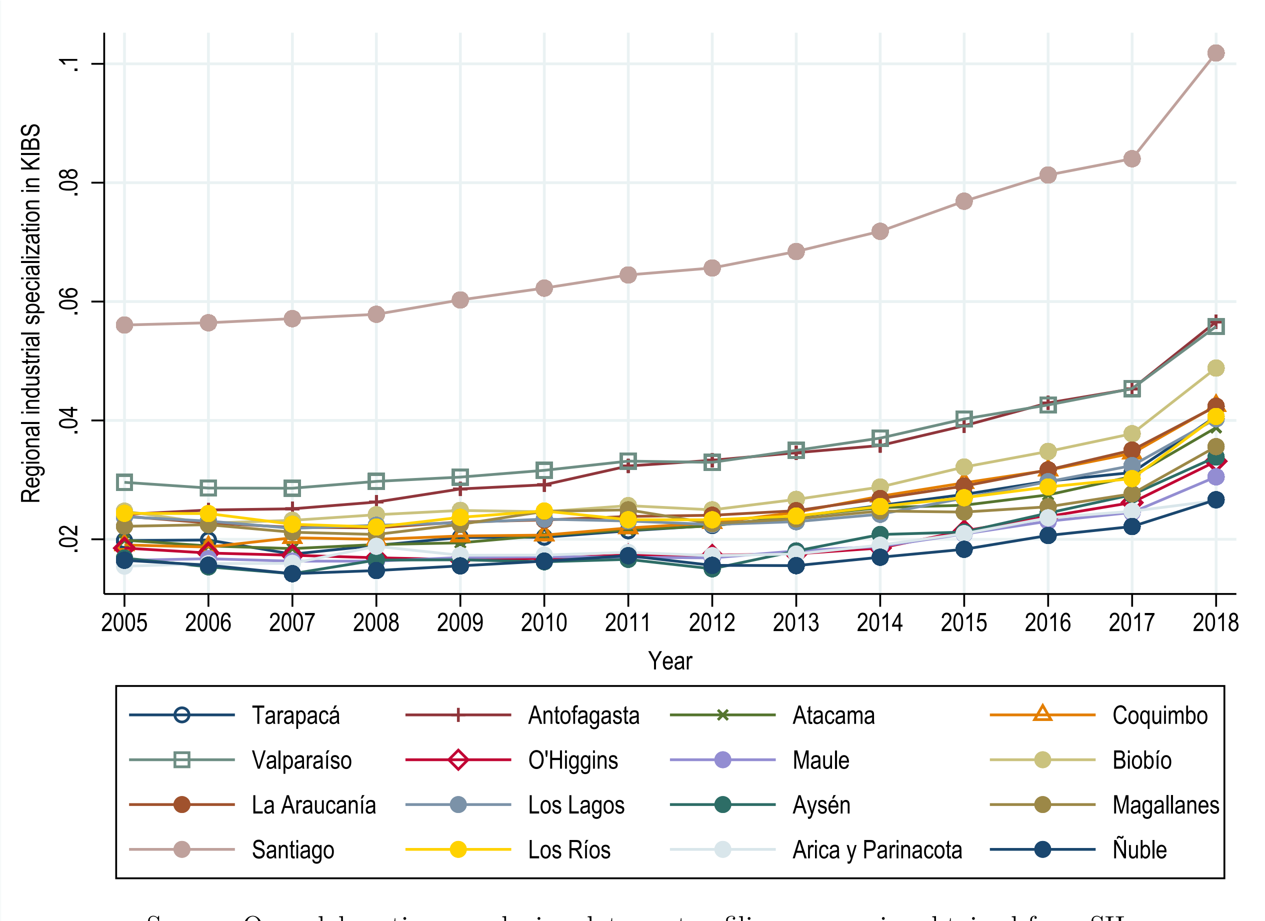
In order to adjust our framework of estimation for local and regional effects, a number of variables at different spatial levels are included in the specification. To adjust for the effect of the regional labor market on income levels, the employment-to-population ratio is used. This ratio corresponds to the share of a region's working-age population with a job.[12]

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 include 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*).

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

Figure 4.4: Industrial specialization in KIBS by region, 2005-2018.



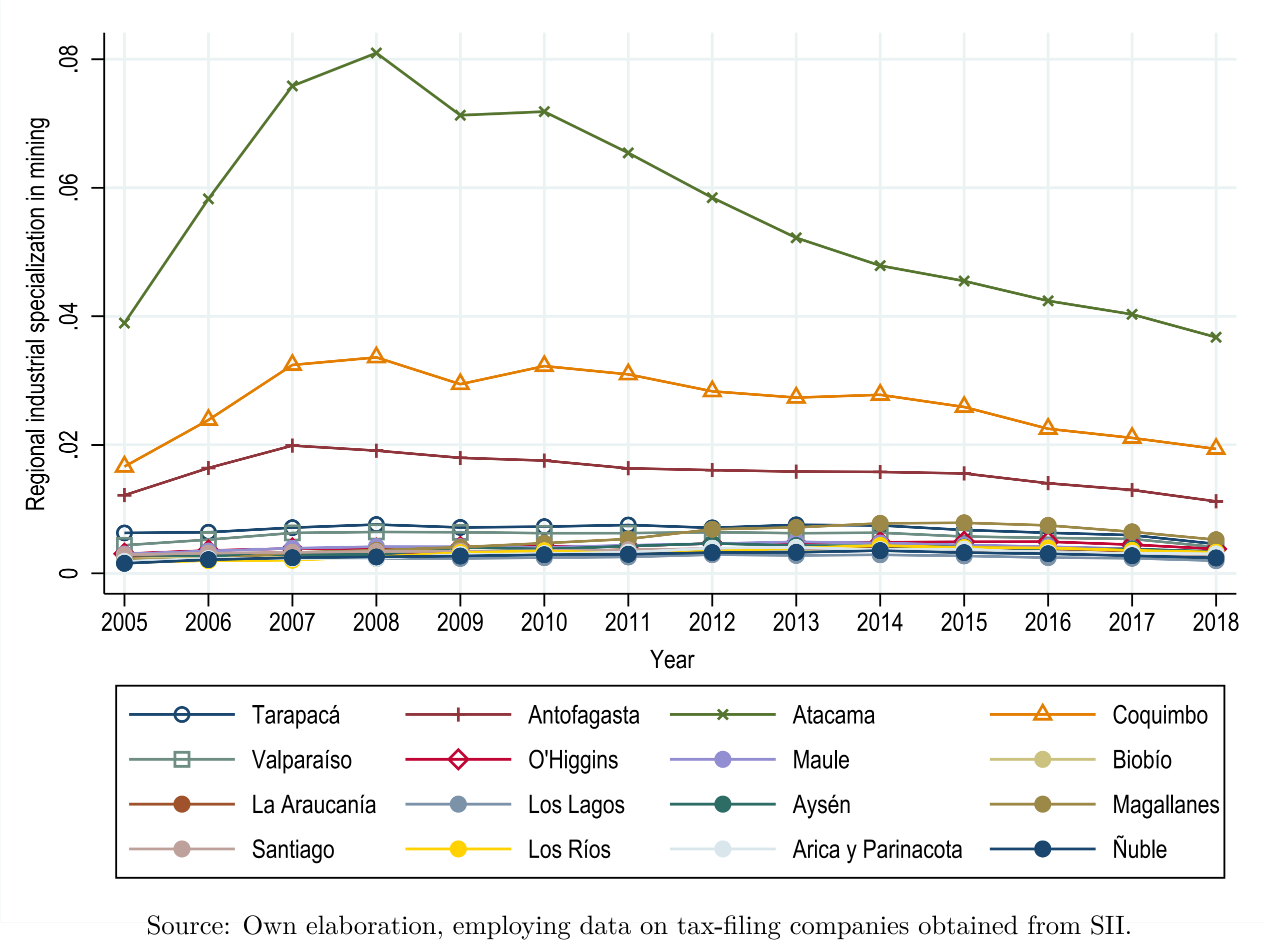
Source: Own elaboration, employing data on tax-filing companies obtained from SII.

4.4.4 Descriptive statistics

Table 4.1 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 4.1, 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 4.2 presents a summary of the descriptive statistics of all the continuous variables mentioned in this section.

From Table 4.2 we can gain some insights of the characteristics of the Chilean mining indus-

Figure 4.5: Industrial specialization in Mining by region, 2005-2018.



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

trial 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).[13] 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 municipal 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.

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

Table 4.1: Summary of variables Chapter 4.

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.

Table 4.2: 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
$Educ^{T}_{ct}$	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.

4.5 Results

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

4.5.1 Aggregate- and individual-level effect estimations

The evaluation of the effect of KIBS agglomeration on mining sector productivity at the aggregate level is conducted by estimating the fixed-effects model in Equation 4.2. After running a Hausman specification test, the results indicated that a fixed-effects specification was appropriate. The errors are clustered at the regional level, assuming the existence of spatial similarities among municipalities within greater geographic divisions.[14] Table 4.3 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.

Table 4.3: 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): $lnEduc^T_{ct}$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

[14] In order to take into account the clustered errors in the model specification test, we estimated the model presented in Equation 4.2 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.

As presented in Table 4.3, 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 apply a random-effects Tobit model, controlling for the top-capped wages reported in the records from the PUI. Results are presented in Table 4.4, 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.

Table 4.4: 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, one can inferred 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.

4.5.2 Extensions

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 includ an interaction term between these two measures. The outputs of these estimations are presented in Tables 4.5 and 4.6 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 4.5). 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 4.6), 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 4.4).

Separated KIBS classifications

We estimate the aggregate- and individual-level effects of agglomeration of the different classifications of KIBS suggested by I. D. Miles et al. (2018) on mining labor productivity. Table 4.7 presents the estimates of the fixed-effects models as in Equation 4.1, but considering the

Table 4.5: 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): $lnEduc^{T}_{ct}$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

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 4.2, we estimate the potential effects of the agglomeration of each class of KIBS firms on individual-level productivity for the mining sector. Table 4.8 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 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.

Table 4.6: 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}

4.5.3 Spatial analysis

Spatial structure exploratory analysis

The estimates of the aggregate-level models including the distance variables are presented in Table 4.9. 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 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 4.7: 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 4.8: 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}

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 follow the approach presented by Elhorst (2010). After estimating a non-spatial linear model, whose results are presented in Column 1 in Table 4.10, Moran's I is estimated, employing the two weight matrices specified in Section 3.3: a

Table 4.9: 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): $lnEduc_{ct}^T$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

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 4.12 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.

Table 4.10: 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)
$lnEduc_{ct}^T$	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)

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

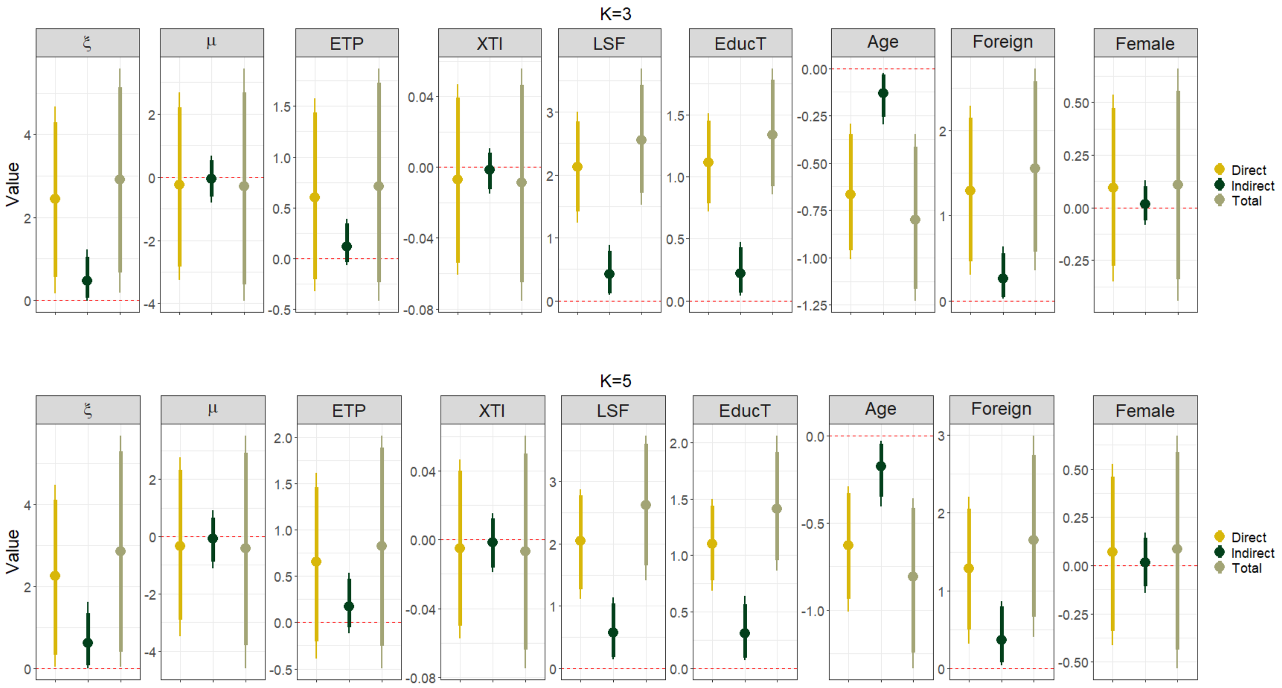
Table 4.10 – continued from previous page

		$W_{k=3}$		$W_{k=5}$	
	(1)	(2)	(3)	(4)	(5)
Variables	OLS	SDM	SAR	SDM	SAR
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	
		(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

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 4.10, 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 4.10. 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 are computed and summarized in Figure 4.6. Following

Figure 4.6: 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.

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 4.13 and 4.14, respectively.

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.

4.6 Concluding remarks

In this study, we provide evidence to the extent 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 I. D. 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.

4.7 Appendix

4.7.1 Correspondence table for KIBS-related activities

Table 4.11: 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: I. D. 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`

4.7.2 Tests for spatial correlation

Table 4.12: 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.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.7.3 Direct, indirect, and total impacts

Table 4.13: 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)
$lnEduc_{ct}^{T}$	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 4.14: 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%).

Chapter 5

Final conclusions

The interplay among knowledge, technology, and primary sector activities as factors of endogenous growth is the core of this thesis. The objective has been to propose a new perspective on the interaction between the spatial concentration of those factors and the economic growth that can stem from them. Our focus on Chile allowed us to study this interaction within the context of a developing economy with a significant regional inequality, derived from the geographical location of key natural resources. In particular, mining activity is highly concentrated in the Northern regions of Chile, where the largest copper deposits are found.

Our findings allow us to conclude that sustainable long-term growth perspectives are possible in regions highly endowed with natural resources. However, our results also reveal differences between the effects arising from the concentration of the mining industry and those associated with other primary sectors. As suggested in Chapter 2 of this thesis, the concentration of mining activities negatively impacts the territorial accumulation of human capital during periods when copper prices reach their highest levels. In contrast, the effects associated with the concentration of other primary activities tend to be more persistent over time. Additionally, the spatial estimations suggest the existence of negative spillover effects on human capital from non-mining activities only. These results reveal temporal and spatial differences in the interaction between primary activities, technology, and knowledge.

Chapter 3 delves into the social consequences of local industrial structures based on natural resources. Specifically, the results of this study suggest that communities in municipalities with a high concentration of primary sector activities have less access to intangible resources stemming from social connections including highly qualified individuals. This leads to disparities among regions in terms of the transmission of information, knowledge, and ideas. However, our results also reveal the role of the population's education level in the formation of social capital at an aggregate level, which exerts positive effects that transmit to nearby spatial units.

Finally, Chapter 4 proposes a new approach to depict the interaction between the determinants of endogenous growth and mining activity. Our study suggests the existence of positive effects between the concentration of knowledge-intensive business activities and labor productivity in the mining sector. Moreover, our results suggest that the positive effects of knowledge-intensive business activities spill over neighboring localities, improving the productivity of miners across territorial boundaries. This outcome emphasizes the role of these firms in facilitating, producing, and transmitting innovation, intended as a main factor driving long-run growth.

Methodological matters

One of the main methodological contributions of this thesis is the application of a spatial approach to study the interaction between primary activities and the determinants of endogenous growth. This methodology allows us to gain insights into the territorial distribution of these factors, as well as the spatial structures that determine the effects stemming from the local concentration of the primary sector. In this study, we exploit data from Chile, which allows us to leverage the territorial and economic characteristics of this country. However, our results can serve as a starting point for conducting similar studies in other territorial contexts. Future extensions of this research could address the limitations to which this thesis is subject. A main limitation is the availability of data at the municipal level, which affects the computation of the variables used in the estimates of each chapter. Specifically, the study addressed in Chapter 2 could be extended to years beyond 2013 using a different data source than the survey exploited in that chapter. The sampling methodology of this instrument changed in 2015 and this makes impossible to perform estimations whose results would be comparable with the period covered in this study. Regarding Chapter 3, the database comprises 94 urban municipalities, so the results should only be interpreted concerning that population sample. Finally, the availability of disaggregated data identifying knowledge-intensive business services companies specifically linked to mining would help to obtain more precise insights about the mechanisms through which KIBS promote innovation in the mining sector. In general, the research presented in this thesis can be improved from a methodological viewpoint when focusing on the spatio-temporal effects of the concentration of primary sector activities on the determinants of long-term growth. The most challenging step would be to track the effect over time by handling panel data.

Policy implications

In the first two chapters of this thesis, the negative effects of the spatial concentration of primary sector activities on the distribution of human capital and the formation of spatial social capital are highlighted. Our results reflect the need to implement policies aimed at improving the local industrial diversification, as well as the promotion and investment in higher education. On the one hand, these measures would increase the stock of human capital in resource-rich territories by enhancing the qualification of the local workforce and attracting professional, specialized workers from other economic sectors. At the same time, this would provide greater support for the creation and consolidation of social connections that facilitate the diffusion of ideas and knowledge. On the other hand, a greater availability of human capital enhances innovation and entrepreneurship in knowledge- and technology-intensive activities. As reflected in the results of Chapter 4, regional promotion of intangible assets, such as knowledge and technology, can lead to productivity improvements in the primary sector. in addition, the innovation activity can set a foundation for the long-term development of regions with high natural resource endowments.

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