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Inequality in social capital in Chile: Assessing the importance of network size and contacts' occupational prestige on status attainment

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ABSTRACT

Long-standing literature argues that social capital is closely implicated in labour market outcomes. However, this hypothesis has yet to be tested in Latin America, the most unequal region in the world. We focus on Chile, one of the most stratified countries in Latin America. This study examines the relationship between social capital and four measures of status attainment, including job prestige and employment income. We use data from the first wave of the Longitudinal Social Study of Chile (ELSOC), a representative survey of the Chilean urban population aged 18–75 years. We analyse a subsample of 1,351 individuals who are currently employed. A Bayesian model of over-dispersion with relational data is used to estimate the size of the network, a novel measure of social capital. We analyse the data set using linear and logistic regression models and a complementary path analysis, first estimating models for the entire sample, and then splitting the sample into three groups to evaluate differences within individuals' socioeconomic background. Results indicate that contacts' occupational prestige has a positive association with job prestige and employment income, while the size of the network increases individuals' salaries and labour participation. We also observe that social capital flows through stratified networks which tend to favour individuals from high socioeconomic backgrounds. We discuss the need to conduct more in-depth evaluations of how better creation of social capital and its effects on status attainment could be closely linked to positions of privilege and advantage accumulation processes in highly unequal contexts.

Introduction

Understanding the formation of social networks is a relevant scientific challenge because personal connections play an important role in shaping people's opportunities in life (Marin and Wellman, 2011). Assessing the relationship between social capital and status attainment has been one of the most important topics in the literature (see Lin, 2001). Research on this issue has widely demonstrated that social capital is strongly associated with several outcome variables, namely labour market entry (e.g. Verhaeghe et al., 2015), job satisfaction (e.g. Flap and Volker, 2001), searching for or changing jobs (e.g. Granovetter, 1975; Tian and Lin, 2016), job prestige (e.g. Campbell et al., 1986; Chen and Volker, 2016; Lin et al., 1981; Lin and Dumin, 1986; Son and Lin, 2012; Volker and Flap, 1999), and employment income (e.g. Bian et al., 2015; Boxman et al., 1991; Bridges and Villemez, 1986; De Graaf et al., 1988).

In this research agenda, the Social Resources Theory (SRT) and later formulations developed by Nan Lin have become influential (Lin, 2001, 1999, 1982; Lin et al., 1981; Lin and Dumin, 1986). He defines social capital as the socioeconomic resources embedded in individuals' social networks. This is an instrumental approach on the study of social capital focused on the returns that can be obtained through individuals' contacts (see also Bourdieu, 1986; Flap and Volker, 2004; Lin and Erickson, 2008), and differs from a more collective view that regards social capital as a set of functions of social life (e.g. Putnam, 2000).

Following this instrumental approach, the main goal of this paper is to test the relationship between social capital and labour market outcomes in Chile. Specifically, we analyse a logical sequence of status attainment that principally includes job prestige and employment income. We contribute to the literature on social capital and status attainment in three ways.

First, we examine a novel context that could be useful for expanding the discussion of social capital towards emerging countries. To date, the relationship between social capital and status attainment has mostly

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been studied in developed Western countries like the US, Great Britain, or the Netherlands, especially in market economies (liberal and coordinated) and societies with a marked meritocratic system (see Chua, 2011). However, the examination of the theory in developing countries with contexts characterised by high levels of inequality from a comparative perspective has been limited. Chile is an interesting case study for remedying this deficit because, as will be shown later, it displays one of the most unequal income distributions in the world.

Second, we contribute by conceptualising and testing the differential influence of ascribed and achieved positions on status attainment. The importance of socioeconomic background (e.g. parents' education level) has been scarcely discussed in the work of Lin and colleagues (c.f. Lai et al., 1998; Lin and Dumin, 1986), and there is limited clarity regarding its broader implications for attained statuses (c.f. Rözer and Brashears, 2018). We suggest that socioeconomic background could be particularly important in Latin American countries like Chile because economic inequality has often been explained by limited intergenerational mobility and inequality of opportunity (Torche, 2014).

Third, we contribute beyond the specificities of our context of study. In order to estimate subjects' available resources or access to social capital, we incorporate a measurement of network size, which is novel in the literature. This measure is estimated on the basis of a Bayesian model of over-dispersion with relational data (see DiPrete et al., 2011; McCormick et al., 2010; Zheng et al., 2006). We argue that network size allows for progress to be made on two important matters. This measure not only represents the size of the network, but also captures the overall variety of contacts in different social domains (e.g. political, ethnic, and religious). Therefore, it explicitly involves greater heterogeneity and novelty of social resources; that is, it represents the essence of "weak ties" (Granovetter, 1975, 1973). Moreover, network size helps to specify the differential role of contact status and variety, two dimensions that have typically been summarised as a composite indicator of social capital (see Hällsten et al., 2015).

Initially, our study is based on linear models and logistic regressions. The second part, carried out with a path analysis, provides evidence of relative associations, both direct and indirect, between the variables included in the model. Our data come from the first wave of the Longitudinal Social Study of Chile (ELSOC), a representative survey of the Chilean urban population aged 18–75 years (with a sample size of 2,984), which were collected during the latter half of 2016. We analyse a subsample of 1,351 individuals who are currently employed.

The Chilean context

Chile is a mid-high income country located in Latin America, a region that displays the world's highest income inequality indexes. Although Chile has made great strides over the last three decades, achieving one of Latin America's highest per capita GDPs — approximately USD 16,143 for 2018 (IMF, 2018) — it has also stood out due to its high economic inequalities and disparities in terms of opportunities; i.e., based on ascribed factors such as parents' education level and inherited wealth (Torche, 2014). More precisely, Chile currently has one of the highest Gini indexes in the region — 0.477 points (World Bank, 2017) — and the share of the income received by the richest 10% is extremely high (37.1%) compared to the OECD average of 24.7% (OECD, 2018). Furthermore, the income share of the richest 1% is 15%, which is the fifth highest in the literature on top incomes. Less conservative estimates have even suggested that, when distributed profits are adjusted for tax evasion, the top 1% share reaches about 22–26% (Fairfield and Jorratt, 2015).

Inequality of opportunity is a further relevant problem in Chile. In contrast with many developed countries where secondary education is guaranteed more or less equally for all people, in Chile the quality of education is strongly conditioned by families' wealth since the most part of the schooling system is completely private or subsidized (Gayardon and Bernasconi, 2017; Otero et al., 2017). Additionally, the higher education system has similar characteristics, and reinforces inequality by offering paths for advantaged families to invest in their children's education and reach better outcomes. Therefore, status attainment is largely based on socioeconomic background rather than on differences in individual effort or luck (Contreras et al., 2014; Contreras and Puentes, 2017; Núñez and Tartakowsky, 2011).

Chile is also a good example of an inverse relationship between cross-sectional income inequality and intergenerational mobility. The most robust evidence obtained in Chile delineates a rather rigid occupational class structure, with an increasingly clear tendency towards polarisation (Espinoza and Núñez, 2014). Another outstanding characteristic is the fragility of the middle classes, visible in vulnerability to poverty and the high restrictions on upward mobility compared to other countries, specifically due to the lack of a social protection system and the high level of closure among the upper classes (Torche, 2005; Torche and Lopez-Calva, 2013). Some variations in this pattern include short-term mobility and some degree of heterogeneity within the middle classes. However, this fluidity remains limited (Espinoza et al., 2013).

In the case of Chile, we presume that social capital might have a strong association with outcomes in the labour market, given the notable expansion of the market economy over the past 45 years. It is a well-known fact that market economies are characterized by the establishment of notorious asymmetries of information through "weak ties" (Tian and Lin, 2016), which end up producing significant advantages for some groups of people, particularly as a function of socioeconomic status. If we consider the fact that resourceful networks are important and unevenly distributed (due to differences in gender, ethnic hierarchies, and employment sector) even in societies where social classes are based on a meritocratic system (e.g. Chua, 2012; Chua et al., 2016), it would be logical to expect the returns on social capital in terms of status attainment, in a highly stratified society like the Chilean one, to play a distinctive role in the accumulation of advantage.

Literature review

Social capital and the latent utility of social contacts

According to Lin, research on the association between social resources and attained statuses should be examined by considering two sub-processes (Lin, 2001, 1999). It is necessary to determine how social capital is produced and explain how social resources are associated with better outcomes in the labour market; that is, the accessed social capital model. Moreover, it is key to examine how certain social ties can be explicitly activated by the ego in the job search process, i.e. the mobilised social capital model. These models have been tested separately, as either the accessed (e.g. Lin, 2001, chapter 7; Rözer and Brashears, 2018; Verhaeghe et al., 2015) or the mobilised social capital model (e.g. Chen and Volker, 2016; Son and Lin, 2012), and also jointly (e.g. Lai et al., 1998; Lin and Ao, 2008).

Although the distinction between capacity and activation of social capital initially seems relatively clear, some strengths and weaknesses of these two models should be considered. Regarding the first strand, focused on the role of the overall variety and prestige of resources embedded in an individual's ego-centric networks (accessed contacts), the main advantage is being able to examine the whole opportunity structure afforded by a social network, which makes it possible to evaluate which network compositions are more valuable for status attainment. Thus, it is implicitly or explicitly assumed that social capital can generate benefits beyond its conscious manipulation or activation (Chua, 2012). However, the main weakness of this strand is that it is not possible to establish whether subjects requested or received help from their contacts, nor are the details of such potential help clear. In consequence, the active mechanisms of status attainment remain latent (Hällsten et al., 2015).

Regarding the effects of "mobilized social capital", often indicated by the resources of a certain contact who has explicitly offered important support to achieve better outcomes in the labour market, the main advantage is the ability to know this contact's characteristics and therefore find out which types of contacts are more useful. However, measuring the mobilisation of social resources as ex post realisations, i.e. directly asking someone about the use of contacts in a job search or transition, involves dealing with a series of empirical difficulties (Lin and Dumin, 1986). For instance, one key problem is that retrospective examinations do not make it possible to capture how people fail in the status attainment process with or without mobilising social capital (Hällsten et al., 2015). Another substantive matter is that, in general, only a small percentage of the individuals interviewed report having used or received help in their job search, which is surprising and seems unlikely. This could occur because people are not always willing to admit and acknowledge having received valuable information or advantages in the job search process, for many reasons, e.g. this practice is not appropriate in democratic societies in which meritocratic imaginary prevails. Another explanation is simply that people are not always aware that connections silently work in their favour (Lin and Ao, 2008). These issues have led some scholars to claim that the advantage that having a certain amount of social capital provides is undoubtedly more subtle and complex than what can be determined by simply asking whether a person used personal contacts during the status attainment process (Smith, 2008); therefore, previous research has only partially represented how social networks or social capital affect individual job outcomes in the labour market (Chua, 2012; Lin and Ao, 2008).

In this study, we assume that if a given amount of social capital is accessible, then subjects will be likely to use this stock of social resources in many ways to find a better job. In other words, we consider that social capital is always operating to help subjects get benefits, regardless of whether this is done consciously or unconsciously. In this regard, our study is closer to the first strand: focusing on personal contacts that are routinely available to the ego and the configuration of resourceful networks instead of identifying one single contact that successfully leads to better status attainment and his or her characteristics (see Lai et al., 1998). We suppose that this strand warrants attention, particularly when one has measures that capture both the status and the volume of social capital, i.e. the number of contacts that may be available.

The position of origin and social capital

We first address the relationship between subjects' position of origin and social capital. The conceptualisation and later analysis of this link are necessary to correctly understand how social capital is associated with better status attainment.

According to Lin's theory, a person's social capital is largely determined by his/her position of origin, which is the combination of achieved positions (e.g. years of schooling) and ascribed positions, like the position inherited from parents (Lin, 2001). Only a few studies have supported this proposition, simultaneously considering occupied and inherited positions (e.g. Rözer and Brashears, 2018). A better position of origin offers opportunities to establish social interactions with people who have better socioeconomic resources because parents from a higher socioeconomic background can transfer their valuable social networks. The well-known tendency to interact with similar people, the homophily principle, also plays an important role (see McPherson et al., 2001). Homophily in terms of status essentially results from the fact that people with similar socioeconomic characteristics tend to be socialised with similar sociocultural codes, and thus develop more mutual understanding, trust and identification. Ultimately, interaction with others is less attractive and requires more effort (Bourdieu, 1998; Portes and Sensenbrenner, 1993). In addition, the social settings where people socialise (e.g. schools, neighbourhoods) tend to be strongly segregated by socioeconomic level, thus reinforcing within group interactions and limiting meeting opportunities between individuals from different groups (Behtoui, 2007; Kossinets and Watts, 2009; Lin, 2000). The above arguments lead us to state the following hypotheses.

Hypothesis 1 (H1). We expect a positive relationship between education and social capital.

Hypothesis 2 (H2). Access to social capital is greater among people from a high socio-economic background.

Network diversity and the richness of embedded resources

In this section, we argue that when people are connected to a larger number of contacts with heterogeneous characteristics as well as higher status positions, they are likely to receive more advantageous information about the labour market and thus be favoured in the status attainment process.

First, we conceptualise the well-known usefulness of having contacts with higher occupational prestige to attain better results in the labour market (Hällsten et al., 2015). In general, besides education and previous positions, it has been suggested that higher-status contacts could exert a significant effect on the status of the job obtained (Lin, 1999). The importance of contact status in achieving better outcomes rests on the premise that social capital is aligned with the type of benefits that one wants to obtain (Flap and Volker, 2001). Indeed, contacts who have a better position in the occupational structure are useful because they have better access to more specific information about the labour market, especially for higher prestige jobs. Moreover, when an individual is actively looking for a job, high status contacts can share information about job opportunities and have the ability to use their reputation to influence decision-making (Chen and Volker, 2016; Lin, 2001). Following these arguments, we state our third hypothesis:

Hypothesis 3 (H3). Social capital in terms of contacts' occupational prestige is positively related to better status attainment.

Second, we highlight the value of network variety in the labour market. In general, network variety is expected to be a complementary indicator in predicting better status attainment (e.g. Erickson et al., 2001; Son and Lin, 2012). We agree that networks with higher numbers of distinctive occupational positions generate more social capital than less varied networks (Erickson, 2003). More precisely, network variety could offer a relative advantage in the job market because it makes it possible to represent the level at which an individual can access qualitatively remote additional resources. This assumption is based on the influential work of Granovetter (1973) regarding "weak ties." He proposes that acquaintances are decisive for instrumental action, such as getting a better job (Granovetter, 1975), in that they provide access to different social circles or other parts of the social structure. The later contribution of Burt (1992) on the "structural holes" deepens this argument, suggesting that weaker and heterogeneous ties in wide-ranging locations throughout the stratification system make it possible to establish bridges connecting people to different groups, facilitating flows, dispositions, and social relationships whereby actors could extend their access to valuable information.

Although network variety could be useful for the status attainment process, we think that its definition and measurement have been somewhat lacking. Specifically, research on the heterogeneity of individual resourceful networks has been largely limited to the number of occupational positions in which the ego has one contact (network extensity), which also has been described in terms of network size (e.g. Fu, 2008), and the difference between the highest and lowest job status accessed (network diversity) (Lin and Dumin, 1986). However, we argue that measurements of this type do not represent the entire range of available opportunities (or "weak ties") in different social domains (cf. Campbell et al., 1986). For instance, political contacts, which often do not hold the highest positions in the occupational structure, could be equally or even more useful for status attainment than contacts with more prestigious positions (e.g. Lin, 2001; Chapter 7).

Furthermore, the mainstream measurements of social capital, i.e. network extensity, diversity, and contact status, are usually highly correlated, even though they represent analytically distinct dimensions. To overcome this issue, researchers have used compound indicators to represent social capital (e.g. Hällsten et al., 2015; Lin and Ao, 2008). Although these compound measurements have solved problems of multicollinearity, they also hide the distinctive helpfulness of network variety and contacts' status in the status attainment process. In view of this, we argue that size might be an important characteristic to better represent the type of structure of opportunities that a social network offers, opening the black boxes generated by certain weaknesses of the conventional measurement of social capital.

Specifically, we argue that if an individual's contacts carry valuable socioeconomic resources (basic theoretical assumption), a larger network should generate more social capital than a smaller one, simply because the former contains more social connections. At the same time, larger networks logically tend to be more heterogeneous because the size of the social groups is restricted. As such, network size should not only increase the variety of available resources, but also the opportunity to access those that can only be found in distinctive places within the social structure. If a person needs to use contacts for an instrumental action, a larger and more heterogeneous network in terms of resources should, by definition, offer a greater likelihood to find and use a resource that is appropriate for the ends sought. In summary, we suggest that an "ideal" measurement of social capital, in terms of heterogeneity, should consider a variety of resources beyond the contacts' occupational category (e.g. political, religious, ethnic) as well as the number of available contacts. Ultimately, the combination of variety and size should more precisely capture the "weak ties" and allows for the identification of an ad-hoc contact who enables a subject to attain a better status. These arguments are stated in the fourth hypothesis below:

Hypothesis 4 (H4). Social capital in terms of network size is positively associated with better status attainment.

The position of origin, social capital and status attainment

Based on the strength of position proposition formulated by Lin early in his career (Lin, 1982), positions of origin are not only important for explaining access to social capital; also, they "are expected to affect attained statuses such as occupational status, authority positions, sectors, or earnings" (Lin, 2001: 82). However, in terms of both theory and empirical analyses of social capital, the distinctive influence of parental positions on the status attainment process has instead been studied as a secondary factor, particularly based on its importance for producing network resources (Lin et al., 1981; Lin and Dumin, 1986).

In this study, we assume that socioeconomic background has a direct relationship with attained statuses. The basis for this assumption can be found in the seminal work of Blau and Duncan (1967) on the determinants of status attainment. We realise that few studies have formulated and tested models that establish a direct relationship between parents' socioeconomic status and individuals' occupational prestige or income. Some researchers report significant effects (e.g. Lai et al., 1998; Rözer and Brashears, 2018), but others do not (e.g. Volker and Flap, 1999).

In general, because socioeconomic background is a proxy for inequality of opportunity, one would expect it to be linked with status attainment for several reasons. For example, parents from a higher socioeconomic background can use their position of prestige in the occupational structure to help their children in the job market, even hiring them to work in their own companies. The transmission of cultural capital by parents in more privileged positions may be even more important in terms of familiarising or socialising their children with the attitudes necessary to achieve better academic performance, e.g. parental involvement, greater expectations, and attitudes focused on influencing the choice of lucrative fields of study that maximise their chances to reach socioeconomic success (Bourdieu and Passeron, 1977; Lareau, 2011; Tilly, 2006; Torche, 2016). Based on this argument, we state the next two hypotheses.

Hypothesis 5 (H5). Years of schooling are positively associated with better status attainment.

Hypothesis 6 (H6). Socioeconomic background is positively associated with better status attainment.

Furthermore, one could argue that individuals from better socioeconomic backgrounds are likely to not only benefit more in the status attainment process, but also to gain more in the labour market thanks to social capital due to the strong group effects among the highest socioeconomic groups. Indeed, a high-status contact may be more willing to help someone with similar socioeconomic characteristics instead of someone with fewer resources (Lai et al., 1998). The concept of "habitus" proposed by Bourdieu (1984), defined as an acquired system of cognitive schemes forming our common sense and lifestyle, helps us to understand this assumption. He states that the habitus is historically configured through primary socialisation processes and thus builds stable preferences and practices, which are frequently independent of individuals' awareness and will (Bourdieu and Wacquant, 1992). The intergenerational transmission of habitus unites members of the upper class and produces network closure, restricting others' access to the group and its resources because they have little in common (Bourdieu, 1998).

Using the theory of habitus to propose that social capital positively affects status attainment mostly among individuals from high socioeconomic background entails acknowledging a process of advantage accumulation over the generations (DiPrete and Eirich, 2006). In the case of the functioning of social capital, this means that those who have not bred valuable networks are excluded, facing a disadvantage in the exchange of resources and during the status attainment process. Tilly (1998) defines this mechanism as "opportunity hoarding," referring to the control of socioeconomic resources by one privileged group that allows it to exclude the rest from access to the benefits and to strengthen social relationships among the individuals who recreate the social networks in which these assets flows.

We assume, however, that the differential association between social capital and status attainment by socioeconomic background might apply more clearly to social capital in terms of contacts' occupational prestige. In the case of social capital in terms of network size, one could expect a compensatory "movement" given a pre-existing unequal distribution of social resources among social groups in the labour market (Son and Lin, 2012). As previously argued, larger networks should be more varied and extend beyond the limits of homogeneous social groups, eventually decreasing the degree of opportunity hoarding. Therefore, individuals from lower and medium socioeconomic backgrounds could benefit from this form of social capital in the status attainment process.

Based on the above arguments, we state our last hypotheses — the socioeconomic background differential association hypotheses:

Hypothesis 7 (H7). The expected positive association between social capital - in terms of contacts' occupational prestige - and status attainment is stronger in individuals from a higher socioeconomic background.

Hypothesis 8 (H8). The expected positive relationship between social capital - in terms of network size - and status attainment is stronger among individuals from middle and low socioeconomic backgrounds.

Recognising the importance of socioeconomic background for understanding differentiated returns on social capital in the labour market implies testing an important assumption formulated by Lin and colleagues called the "ceiling effect" (Lin et al., 1981). They hypothesise

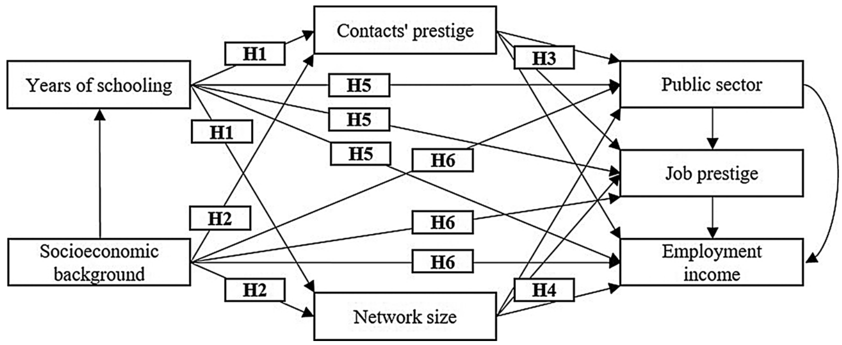

Fig. 1. The conceptual model.

that the use of "weak ties" does not benefit the status attainment process in the higher strata of the social structure, because those connections are likely to lead to lower positions and thus fewer resources. We wonder to what extent this proposition could become plausible in a highly unequal society like that of Chile, where the most affluent groups have increased their advantage over the rest.

A systematic representation of the eight hypotheses formulated can be found in Fig. 1. As can be seen, we propose not only direct links between the variables included in the model's specifications, but also indirect ones, both of which are consistent with the stated hypotheses.

Data and methods

Data

We used survey data from the first wave of the Longitudinal Social Study of Chile (ELSOC), carried out by the Centre for Social Conflict and Cohesion Studies (COES). For the first wave of ELSOC collected in 2016, a random sample of 1067 street blocks was drawn from 94 cities or districts. Next, within those street blocks, three to five addresses were randomly selected. Finally, within those households, one individual aged 18–75 years was randomly selected, who completed the face-to-face interview. The final sample is representative of 93% of the urban population and 77% of the country's population. Out of the 2,984 respondents who participated in the first wave, we primarily analyse a sample of 1,351 individuals who have a job.

Measurements

Labour market outcomes

Following Lin (2001, Chapter 7), we examined a logical sequence of status attainment stages: (1) labour market participation, (2) work sector, (3) job prestige, and (4) employment income. We worked on the assumption that an individual first enters a labour sector, obtains a given position, and then earns an economic return. We describe each of these variables below:

(1) **Labour market participation:** Binary variable that takes a value of 1 for people who work full or part time and 0 for those not in employment, regardless of motive (retirement, unemployment, full-time student).
(2) **Work sector:** Binary variable that summarises the sector in which the respondents who work are employed. It takes a value of 1 for those who work in the public sector and 0 for those who work in the private sector or are self-employed (which means that they are also part of the private sector).
(3) **Job prestige:** Based on other studies in the area (e.g. Son and Lin, 2012), we assigned scores taken from the International Socio-economic Index of Occupational Status (ISEI) to the respondents' professions or occupations, following the International Standard Classification of Occupation (ISCO) 1988 generated by the International Labour Office (Ganzeboom and Treiman, 1996).
(4) **Employment Income:** We calculated the respondents' average monthly earnings from paid jobs in the year surveyed, as has been the case in other studies (Bian et al., 2015). A log-transformation of monthly employment income is used in the statistical models.

Measuring social capital

In order to measure social capital, a unique survey instrument is required, specifically "positional generators" (Marsden, 2005), or a more recent version defined as "relational aggregate data" (McCormick et al., 2013). More precisely, the information is obtained through questions such as "how many people do you know who are X?" in which X can refer to a broad set of social groups. Researchers who study the effects of social capital on social attainment have mainly used the Position Generator, including a variety of occupations (e.g. Lin and Dumin, 1986; Lin and Erickson, 2008; Son and Lin, 2012; Verhaeghe et al., 2015). This instrument has been reported to be an adequate indicator to measure the resources embedded in individuals' social networks (e.g. Hällsten et al., 2015; Van Der Gaag, 2008). Respondents were asked the following question (our translation):

Now I will ask you about some of your acquaintances. It doesn't matter if they are close to you (family members or friends) or not. An acquaintance is someone you know at least by first name and with whom you might talk to if you came across each other on the street or in a shopping mall. Think only of people who live in Chile, can you tell me based on the following card – and even if only approximately –, how many people you know who are …?

In our case, the respondents were shown a list of 13 occupations and asked how many of their acquaintances have those positions, specifically: manager of a large firm; street vendor; secretary; car mechanic; shop assistant; attorney; office cleaner; doctor; preschool teacher; taxi driver; waiter; accountant; and university professor. Seven alternatives were offered as answers: 0, 1, 2–4, 5–7, 8–10, 11–15, and 16 or more.

An innovative aspect of this study is that we also asked about acquaintances in eight socio-political groups or minorities: Catholic priests; Mapuche (majority indigenous group in Chile); member of the UDI (far-right political party); Peruvian immigrant (largest immigrant group); member of the Communist Party; member of the Christian Democratic Party (centre party); gay or lesbian;[1] and unemployed individuals. Moreover, respondents were asked how many of their acquaintances have common male and female names.[2] Table A1 (in Appendix, Section I) summarises the groups included in the ELSOC survey.

To address social capital, we used contacts' occupational prestige, a

[1] Note that the Civil Union Agreement, passed in Chile on 13 April 2015, allows and regulates cohabitation by individuals who are not married regardless of sexual orientation.

[2] The following names were used: Hernán, Ignacio, Ximena, and Viviana. These questions were very important for calculating the size of the individuals' networks (DiPrete et al., 2011). Detailed information on the estimate is presented below.

measure that is regularly included in the literature (see Hällsten et al., 2015), and the size of the individual social network, an innovative measure. Details about how these measures were calculated are presented below.

a) *Contacts' occupational prestige*

The value of contacts in terms of their prestige or status has generally been measured through the highest-status occupation that a person has access to (upper reachability) (Lin, 2001). However, some academics have criticised this measure because it may be sensitive to the occupations selected by researchers (e,g. Van Tubergen and Volker, 2015). In response to these views, complementary measurements have been proposed, such as the average prestige of the occupations accessed (Van Der Gaag, 2008). Like the latter measure, we calculate the average network prestige, which is the sum of the ISEI points divided by the size of the network. We used the ISEI scores associated with the 1988 ISCO occupational categories (Ganzeboom and Treiman, 1996). Table A1 (Appendix, Section I) shows the occupations included in the first wave of the ELSOC survey.

We argue that this measure is appropriate for more precisely identifying the occupational status of an individual's network since, compared to indicators that focus on counting the contacts in the upper part of the occupational structure, it includes more extensive information about social networks. This measure makes it possible to distinguish between networks with more or less prestige and identify certain levels of social capital, even when people have networks composed mainly of contacts with lower-status occupations. In addition, we think that our measure is also more suitable for representing the composition of a network than a measure of network volume, i.e. the addition of the ISEI points of all the contacts in a person's network. Network volume has the weakness of yielding the same score to represent wholly different networks in terms of composition. For instance, a network composed of 1 doctor (ISEI = 88) would be nearly equivalent to one composed of 2 shop assistants; likewise, a network composed of 1 manager (ISEI = 70) would be nearly the same as another composed of 2 waiters. However, it should be noted that our measure has the weakness of equalling a network composed of 1 doctor with another made up of 10 doctors.

- *Network size*

In order to estimate the size of individuals' social networks, the over-dispersion model developed by Zheng et al. (2006) was used.[3] Certainly, one could instead estimate the size of an individual's social network using the scale-up method described in McCormick et al. (2010). However, the problem with this approach is that it assumes that everyone has an equal propensity to know someone from each group. Alternatively, it is also possible to use either the Erdös–Renyi model (Erdös and Renyi, 1959) or the null model (Zheng et al., 2006), which are particular cases of the over-dispersion model that we used. Nevertheless, Zheng et al. (2006) show that the over-dispersion model generates more accurate predictions than the two aforementioned models, even in categories with high over-dispersion.

Specifically, Zheng et al. (2006) propose a multilevel (or hierarchical) model and use Bayesian inference for determining the size of individuals' social networks. We present the details of the distributional assumptions in the Appendix (Section II). Based on this modelling, the posterior distribution of the variables of interest was built and realizations of these variables were simulated using a Markov chain Monte Carlo (MCMC) algorithm.

It is worth mentioning that although the statistical properties of the estimators depend on whether the specification of the model is correct, Zheng et al. (2006) show that the over-dispersion model proposed generates predictions that are very close to the real data, even in categories with high over-dispersion.

As previously discussed, network size as calculated here is an interesting indicator of social capital for two reasons. First, it helps to understand the variety of social resources to which people have access. This was considered to a certain extent by Lin (2001, chapter 7), to explain how social capital is related to status attainment. He distinguishes between the general social capital represented by access to contacts with different types of occupations and political social capital that includes political connections. In our case, network size does not only include contacts with individuals with a variety of occupational statuses and political affiliations, but also with other socio-cultural groups (e.g. gay and lesbian, religious, ethnic). Rather than representing the size of the egocentric network, it essentially expresses the size of the network of "weak ties" that offer access to potentially non-redundant resources (Granovetter, 1975, 1973). Second, our measurement of network size helps to differentiate between contacts' occupational prestige and network diversity, which has been difficult to achieve in the literature. The problem is that these indicators of individual social capital tend to be closely correlated, which has led researchers to use compound measurements (e.g. Hällsten et al., 2015). In our case, the correlation between these two dimensions of social capital is low ($r = 0.177$).

The position of origin

We have distinguished between achieved and inherited positions (see Lin, 2001: 65). A person's achieved position is measured through years of schooling. To quantify a subject's inherited position, we use the highest educational level achieved by the respondent's parents, as has been done in previous studies (e.g. Lai et al., 1998; Rözer and Brashears, 2018). Specifically, we build three categories which create the basis for differentiated linear or logistic regressions: higher (technical tertiary or university education), middle (high school diploma), and lower (did not graduate from high school). In practice, this distinction makes it possible to evaluate whether social capital only favours individuals from a high educational background.

Control variables

Finally, we consider control variables employed in the literature (e.g. Chua, 2011; Lin, 1999; Pena-López and Sánchez-Santos, 2017; Son and Lin, 2012; Tian and Lin, 2016; Verhaeghe et al., 2015). These variables are sex, age, married or cohabitating, subjective health status, participation in religious and political associations, tenure at current job (years), union participation, and political orientation (measured by a left–right self-placement scale). Socio-political identification and participation in voluntary associations have been underscored in the literature because they capture institutional capital (see Lin, 2001). In our case, we include categorical variables related to the respondents' city of residence, given the high urban labour concentration in Santiago and other larger cities such as Valparaíso and Concepción. Table 1 shows the descriptive statistics of the variables used in this study differentiated by socioeconomic background.

Statistical procedures

Before presenting the models that we estimate to assess the proposed hypotheses, some notation must be introduced. For the i-th individual in the sample, let P_i be the labour market participation indicator that takes the value one if unit i is employed and zero otherwise; let PS_i be the public sector indicator taking the value one if individual i works in the public sector and zero if individual i works in the private sector; let $\log(W_i)$ be the logarithm of employment income; let JP_i denote the job prestige; let X_i be a vector of covariates including characteristics such as sex, age and educational level; let NS_i be the network

[3] The details of this methodology also can be seen in DiPrete et al. (2011).

Table 1
Descriptive statistics by socioeconomic background (n = 1351).

	Total				Higher	Middle	Lower
	Mean	SD	Min	Max	Mean	Mean	Mean
Status attainment							
Work sector = public	11.90%				16.00%	12.60%	8.70%
Job prestige	39.5	14.6	16	85	51.1	39.5	33.8
Employment income (x1000)	$514.9	$632.8	$10.0	$13,400.0	$780.8	$504.9	$403.4
Social capital							
Contacts' occupational prestige	47	10.3	16	88	54.2	46.6	44.3
Network size	341.8	222.7	78.4	1649.5	389.9	353	299.6
Years of schooling	12.5	3.5	0	19	15.2	13	10.4
Control Variables							
Gender = female	46.90%				46.60%	46.90%	47.10%
Age	42.2	12.7	18	75	38.6	39.8	47.9
Married or cohabiting (1 = yes)	50.50%				46.30%	49.20%	54.70%
Subjective health status	2.8	0.9	1	5	3.1	2.9	2.7
Religious participation (1 = yes)	27.80%				15.50%	28.30%	32.80%
Political participation (1 = yes)	5.00%				7.80%	4.30%	4.70%
Tenure at current job (years)	8.1	10	0	56	6.5	7.3	10.1
Participation in unions (1 = yes)	14.80%				15.50%	14.60%	14.80%
Political orientation							
Left-wing	15.70%				17.00%	15.10%	15.90%
Centre	31.00%				37.40%	31.40%	27.40%
Right-wing	11.70%				14.60%	12.20%	9.40%
Independent	6.20%				6.30%	6.00%	6.60%
Non-response	35.40%				24.80%	35.30%	40.70%
City of residence							
Santiago	22.80%				32.50%	21.90%	19.40%
Valparaíso	13.70%				20.90%	13.30%	10.80%
Concepción	11.60%				9.20%	12.40%	11.50%
Large cities	17.00%				16.50%	17.90%	15.70%
Medium-sized cities	18.90%				13.10%	20.60%	19.00%
Small cities	16.00%				7.80%	13.90%	23.70%
Percentage					**15.23%**	**53.22%**	**31.56%**
Source: ELSOC 2016.							

size; and let NQ_i denote the status of contacts.

Initially, we estimate six models separately. First, for the network size and the status of contacts, we fit standard linear models using X_i as control variables. Second, for the probability of labour market participation, we fit a logistic regression by Maximum Likelihood (ML). Specifically, we assume that independently

$$P_i \sim \text{Bernoulli}([1 + e^{X_i'\alpha + \beta \log(NS_i) + \gamma NQ_i}]^{-1}) \tag{1}$$

Third, for the propensity of working in the public sector, we also estimate a logistic regression by ML, that is, we assume that independently

$$PS_i \sim \text{Bernoulli}([1 + e^{X_i'\delta + \theta \log(NS_i) + \vartheta NQ_i}]^{-1}) \tag{2}$$

Moreover, to analyse the relationship between social capital and labour income, the following Mincer equation is estimated by OLS (Mincer, 1974):

$$\log(W_i) = X_i'\pi + \rho \log(NS_i) + \sigma NQ_i + \varepsilon_i, \tag{3}$$

where ε_i is white noise. Finally, in order to explain the influence of social capital on job prestige, the next linear model is estimated by OLS:

$$JP_i = X_i'\tau + \varphi NS_i + \eta NQ_i + \varepsilon_i, \tag{4}$$

where ε_i is white noise.

Our second empirical strategy relies on path analysis, a simple case of a Structural Equation Model (SEM) (see Kline, 2011). This empirical strategy not only allows us to conduct a robustness check on our findings, but also examines all paths in our model simultaneously (see Fig. 1). The advantage of using a SEM is that it provides estimates for three types of associations between the variables included in our model: direct, indirect, and total associations. This benefit comes at a cost, however, because now we must assume that all our equations came from linear models.

More precisely, we estimate the following system of equations.

$$E_i = X_i'\pi_E + \varepsilon_{Ei}, \tag{5}$$

$$\log(NS_i) = X_i'\pi_{NS} + \beta_E^{NS} E_i + \varepsilon_{NSi}, \tag{6}$$

$$NQ_i = X_i'\pi_{NQ} + \beta_E^{NQ} E_i + \varepsilon_{NQi}, \tag{7}$$

$$PS_i = X_i'\pi_{PS} + \beta_E^{PS} E_i + \beta_{NS}^{PS} \log(NS_i) + \beta_{NQ}^{PS} NQ_i + \varepsilon_{PSi}, \tag{8}$$

$$JP_i = X_i'\pi_{JP} + \beta_E^{JP} E_i + \beta_{NS}^{JP} \log(NS_i) + \beta_{NQ}^{JP} NQ_i + \beta_{PS}^{JP} PS_i + \varepsilon_{JPi}, \tag{9}$$

$$\log(W_i) = X_i'\pi_w + \beta_E^{w} E_i + \beta_{NS}^{w} \log(NS_i) + \beta_{NQ}^{w} NQ_i + \beta_{PS}^{w} PS_i + \beta_{JP}^{w} JP_i + \varepsilon_{wi}, \tag{10}$$

where E_i denotes the years of schooling of individual $i; X_i$ is a vector of covariates including characteristics such as sex, age, and parents' educational level (excluding years of schooling); and the rest of the variables defined as before.

A direct association is the relationship of one variable with another net of the indirect connection assumed in the model specification. In contrast, an indirect association is the relationship of one variable with another mediated by other variables in the model, while the sum of the direct and indirect associations is the total association. For instance, in our model, there exists a direct association between years of schooling and working in the public sector that is given by the parameter β_E^{PS}; however, there are also two indirect associations between them mediated by network size and contacts' occupational prestige, i.e. years of schooling is related to network size (and contacts' occupational prestige), while network size (and contacts' occupational prestige) is associated with working in the public sector. Following this example, the indirect associations mediated by network size and contacts' occupational prestige would be $\beta_E^{NS} \times \beta_{NS}^{PS}$ and $\beta_E^{NQ} \times \beta_{NQ}^{PS}$, respectively. In the

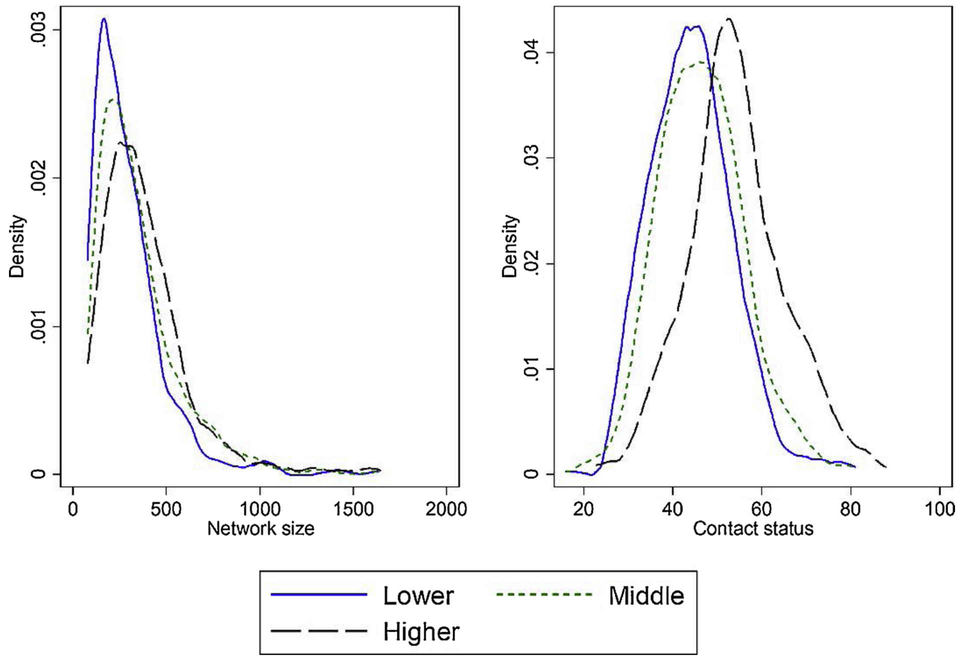

Fig. 2. The distribution of social capital by socioeconomic background.

same manner, years of schooling is directly associated with job income, and indirectly related to it through network size, contacts' occupational prestige, working in the public sector, and job prestige. As mentioned, Fig. 1 presents all the direct and indirect associations considered in our model specification. Note that, in comparison with the models presented in Sections 5.3 and 5.4, here we have added an equation for years of schooling, that allows us to separate the direct relationship between socioeconomic background (parents' education) and network size (or other outcome variable) from the indirect association between them, which is mediated by years of schooling. Finally, if we assume that the expected values of the disturbance terms (the $\varepsilon's$ in equations (5)–(10)) are zero, that each disturbance term has a constant variance (not necessarily equal among them), and that there is no autocorrelation between the disturbance terms, the estimation of the parameters of interest is straightforward.

Results

Descriptive analysis

We first describe the variables used in this study. As Table 1 shows, the average monthly income in the sample is 514,900 Chilean pesos, or about USD 800. The average job prestige is 40 ISEI score points. The average number of completed years of schooling is about 12.5. As expected, the values increase notably with socioeconomic background for the latter two variables.

Regarding social capital measures, the contacts' occupational prestige reaches an average of around 47 ISEI score points and ranges from 44 points to 54 points among the various socioeconomic backgrounds. The ISEI scores are, on average, lower for the survey respondents than for their contacts. Individuals have an average network size of 342 contacts, which increases considerably with socioeconomic background, from 300 contacts for the lowest group to 353 contacts for the middle group to 390 contacts for the highest group. We verify that the differences in network size and contacts' occupational prestige among individuals from different socioeconomic backgrounds are statistically significant by implementing tests of comparison of means. Results suggest that the differences are plausible at a significance level of 1%.

Fig. 2 associates network size and contacts' occupational prestige (the x-axis) to the density function of having a certain network size and contacts with a certain level of occupational prestige (the y-axis), which allows to expand the previous analysis. The density functions of network size are similar among individuals from different socioeconomic backgrounds. However, the mass is less concentrated towards the left when the individuals are from a higher socioeconomic background. Finally, Fig. 2 suggests that contacts' occupational prestige seems greater when socioeconomic background is greater, although the density functions for those individuals from lower and middle socioeconomic backgrounds are similar.[4]

Table 2 presents additional information about the differences in network size and contacts' occupational prestige across different socioeconomic background groups. As can be seen, the sample means of both network size and contacts' occupational prestige are greater for people from a higher socioeconomic background. The 25th and 75th percentiles of network size and contacts' occupational prestige again show how heterogeneous the socioeconomic background groups are.

Who is more likely to gain better social capital?

The analysis begins with access to social capital. We specifically refer to linear models fitted by OLS, where the network size and the contacts' occupational prestige are used as dependent variables separately (see Table 3). Although the main goal of this study is not to address access to social capital in depth, testing variables that serve as predictors of social capital should also be related to the expected labour market returns.[5]

Under H1 and H2, the position of origin would have a positive relationship with social capital. We define a person's position of origin in

[4] We also conducted Kolmogorov–Smirnov tests to check if the distributions are statistically different. The tests show that, at a significance level of 0.01, the distributions of the network size and contacts' occupational prestige are not equal among socioeconomic background groups.

[5] To expand on access to social capital, one could address the importance of types of connections (e.g. Lin, 2001: chapter 7); the role of voluntary organisations (e.g. Benton, 2016); partner selection (e.g. Rözer and Brashears, 2018); schools (e.g. Lai et al., 2015); general trust and well-being (e.g. Pena-López and Sánchez-Santos, 2017); and other factors such as personality (e.g. Tulin et al., 2018), cognitive abilities and neighbourhood wealth (e.g. Van Tubergen and Volker, 2015).

Table 2
Statistics of social capital by socioeconomic background.

	Contacts' occupational prestige				Network size			
	Total	Higher	Middle	Lower	Total	Higher	Middle	Lower
Mean	47.0	54.2	46.6	44.3	341.8	389.9	353.0	299.6
SD	10.3	10.8	9.8	9.4	222.7	240.3	224.6	203.3
25th percentile	39.4	47.6	39.5	37.5	184.9	233.4	194.9	162.7
Median	46.5	53.5	46.2	43.9	288.0	334.8	296.0	250.2
75th percentile	53.3	60.6	53.0	50.2	423.4	480.5	432.9	380.1

Table 3
OLS regression models on the occupational prestige of contacts and network size.

	Network size **(log)**	Contacts' occupational prestige
Control variables		
Female	0.032	1.995***
	(0.031)	(0.517)
Age	0.014*	−0.041
	(0.008)	(0.129)
Squared age	−0.000	0.002
	(0.000)	(0.001)
Married or cohabitating	−0.018	0.367
	(0.031)	(0.512)
Subjective health status	−0.025	0.293
	(0.018)	(0.300)
Religious participation	0.131***	0.156
	(0.034)	(0.566)
Political participation	0.094	0.606
	(0.070)	(1.163)
Years of schooling	0.050***	1.204***
	(0.005)	(0.084)
Socioeconomic background (ref = higher)		
Middle	−0.006	−5.059***
	(0.045)	(0.747)
Lower	−0.067	−5.031***
	(0.054)	(0.890)
Constant	4.760***	34.074***
	(0.192)	(3.171)
Observations	1,351	1,351
Adjusted R squared	0.14	0.24

Notes: Controls for political orientation, city of residence, and being a student are included in all models.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

terms of differences produced by education (achieved position) and inherited advantages such as good socioeconomic background. As suggested by H1, individuals' years of schooling are significantly associated with social capital, both in terms of network size and contacts' occupational prestige. However, socioeconomic background is significantly related to social capital in terms of contacts' occupational prestige, but not to network size. As a result, H2 is partially confirmed.

Determinants of status attainment

In this section, we analyse the relationship between social capital and the process of status attainment. Four attainment variables are used: labour market participation, work sector, job prestige, and employment income.[6] In Table 4, we report the results of four general

[6] We also tested an additional model with dependent variable related to formality of employment: permanent vs. non-permanent contract. In these models, the social capital variables did not show a statistically significant coefficient after controlling for employment income and working in the public sector. Without these control variables, network size is not significantly related to formality of employment, but contacts' occupational prestige has a positive and significant association with the likelihood of having a formal job. Results are available upon request.

Table 4
Models of status attainment.

	Participation	Public sector	Job prestige	Employment income
Control variables				
Female	−0.212***	0.044*	1.887*	−0.408***
	(0.024)	(0.023)	(0.985)	(0.049)
Age	0.037***	0.008	0.136	0.056***
	(0.005)	(0.006)	(0.229)	(0.009)
Squared age	−0.000***	−0.000	−0.002	−0.001***
	(0.000)	(0.000)	(0.003)	(0.000)
Married or cohabiting	0.008	0.020	0.058	0.116**
	(0.026)	(0.023)	(0.925)	(0.049)
Subjective health status	0.013	0.013	1.188**	0.066**
	(0.018)	(0.012)	(0.570)	(0.027)
Religious participation	−0.065**	−0.006	−2.711***	−0.178***
	(0.030)	(0.025)	(0.997)	(0.061)
Political participation	−0.067	0.114***	1.197	0.143*
	(0.049)	(0.040)	(2.383)	(0.077)
Tenure at current job (years)	–	0.006***	0.142***	0.002
	–	(0.001)	(0.051)	(0.004)
Union participation	–	–	−0.701	0.062
	–	–	(1.159)	(0.047)
Years of schooling	0.011***	0.017***	1.627***	0.047***
	(0.004)	(0.005)	(0.185)	(0.009)
Socioeconomic background (ref = higher)				
Middle	0.032	0.026	−7.096***	−0.114**
	(0.037)	(0.032)	(1.504)	(0.058)
Lower	0.057	0.020	−7.397***	−0.147**
	(0.043)	(0.041)	(1.677)	(0.073)
Social capital				
Contacts' occupational prestige	−0.000	0.002	0.303***	0.009***
	(0.001)	(0.001)	(0.049)	(0.002)
Network size (log)	0.107***	−0.029	−0.048	0.110***
	(0.024)	(0.019)	(0.848)	(0.038)
Public sector	–	–	2.250	0.191***
	–	–	(1.749)	(0.066)
Job prestige	–	–	–	0.007***
	–	–	–	(0.002)
Constant	–	–	4.759	9.952***
	–	–	(6.564)	(0.313)
Observations	2,507	1,351	1,351	1,351
Adjusted R squared	–	–	0.43	0.40

Notes: Controls for political orientation, city of residence, and being a student are included in all models.
It should be noted that by including not only workers but also people not in employment, the sample size in the labour market participation model increases.
The participation and public sector models are estimated with logistic regressions, and we report the marginal effects of the variables. The job prestige and employment income models are estimated with linear regression; thus, we report the coefficient of the variables.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Logit regression models of labour participation and work in the public sector by socioeconomic background.

	Participation			Public sector		
	Higher	Middle	Lower	Higher	Middle	Lower
Control variables						
Female	−0.074	−0.240***	−0.279***	−0.105*	0.101***	0.058*
	(0.054)	(0.032)	(0.038)	(0.055)	(0.029)	(0.034)
Age	0.038***	0.040***	0.031***	0.019	0.010	0.010
	(0.009)	(0.007)	(0.010)	(0.015)	(0.010)	(0.008)
Squared age	−0.000***	−0.000***	−0.000***	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married or cohabitating	−0.009	0.021	0.009	−0.075	0.081**	0.016
	(0.050)	(0.036)	(0.044)	(0.050)	(0.032)	(0.028)
Subjective health status	−0.004	−0.024	0.073***	0.019	0.001	0.013
	(0.030)	(0.027)	(0.025)	(0.030)	(0.019)	(0.014)
Religious participation	0.030	−0.124***	0.009	−0.104	−0.046	0.050
	(0.082)	(0.040)	(0.045)	(0.117)	(0.032)	(0.032)
Political participation	0.023	−0.058	−0.122	0.102	0.127**	0.079**
	(0.071)	(0.060)	(0.103)	(0.087)	(0.050)	(0.038)
Tenure at current job (years)				−0.002	0.008***	0.004***
				(0.003)	(0.002)	(0.001)
Years of schooling	0.024*	0.012*	0.005	−0.003	0.032***	0.005
	(0.013)	(0.006)	(0.005)	(0.015)	(0.006)	(0.005)
Social capital						
Contacts' occupational prestige	0.001	−0.001	−0.001	0.001	0.000	0.004***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Network size (log)	0.095**	0.077**	0.164***	−0.114***	−0.019	−0.004
	(0.042)	(0.034)	(0.040)	(0.038)	(0.020)	(0.031)
Observations	381	1,273	853	205	720	426

Notes: Controls for political orientation, city of residence, and being a student are included in all models. Marginal effects are reported. It should be noted that by including not only workers but also people not in employment, the sample size in the labour market participation model increases.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

models. We include as control variables tenure at current job (years) and union participation. As can be seen in the participation model, women participate in the labour market 21% less than men on average. The participation rate decreases with age, increases with education, and is lower for people who participate in religious institutions. Socioeconomic background is not associated with differences in levels of participation. Regarding social capital, contacts' occupational prestige is not related to participation, but network size has a positive and significant association with the likelihood of being employed.

As can be noted in the model of working in the public sector, women are more likely to work in the public sector than in the private sector (although at 90% of confidence). Moreover, education has a positive association with the propensity of working in the public sector, as do years of labour work experience and political participation. Socioeconomic background is not associated with differences in participation in the public sector. The same is true for the variables that represent social capital.

The results of the job prestige model reveal that, on average, women tend to have more prestigious occupations than men. As expected, education is a strong predictor of occupational status. Each additional year of education is associated with a 1.63-point increment in job prestige, while each year of experience in one's current position is related to a 0.14-point increment in job prestige. Variables such as age, marital status, and employment sector do not have a statistically significant association with job prestige. Moreover, there is a negative and significant difference in job prestige between the lower and higher socioeconomic background groups (7.4 prestige points). When comparing individuals from middle and upper socioeconomic backgrounds, the latter group again has greater job prestige (7.1 prestige points). Regarding measurements of social capital, although network size does not have a significant association, the occupational prestige of a respondent's contacts has a positive and significant relationship with his/her job prestige. Specifically, a one-point increase in contacts' occupational prestige is related to an additional 0.3 job prestige points on average.

Finally, as can be seen in the employment income model, women's salaries are 41% lower than those of men on average, which is consistent with the evidence of gender salary gaps in the Chilean labour market. The return on education is, on average, 5% per year of schooling, while salary grows at decreasing rates as age rises. Moreover, individuals who are married or live with a partner earn 12% more than single people; public sector employees receive salaries that are nearly 19% higher than those of private sector workers; and job prestige has a positive and significant association with employment income. Regarding socioeconomic background, higher-SES individuals receive significantly more employment income than those from middle or lower socioeconomic backgrounds. Both network size and occupational prestige of contacts have a positive association with employment income. The latter is noteworthy given that this occurs even after controlling for job prestige.

Broadly speaking, the results presented in Table 4 support our H3, H4, and H5. That is, the results reveal that social capital (both in terms of contacts' occupational prestige and network size) and the respondents' socioeconomic background are positively related to better status attainment. More precisely, the evidence supports the assumption that social capital in terms of contacts' occupational prestige is positively and significantly associated with job prestige and employment income (H3). Our innovative contribution is the finding that social capital in terms of network size is positively and significantly related to labour participation and employment income (H4). Moreover, as formulated in H5, years of schooling are associated with better status attainment, whereas supporting evidence is also found for H6, since individuals from a higher socioeconomic background are associated with better outcomes in the labour market, specifically with job prestige and employment income.

Testing the socioeconomic background differential association hypotheses

Tables 5 and 6 present the results for the models differentiated by socioeconomic backgrounds.[7] The models of participation in the labour

[7] Models differentiated by gender also are analysed, but no substantive differences are found.

Table 6
OLS regression models of job prestige and employment income by socioeconomic background.

	Job prestige			Employment income		
	Higher	Middle	Lower	Higher	Middle	Lower
Female	1.358	2.116	1.063	−0.563***	−0.291***	−0.574***
	(2.406)	(1.312)	(1.365)	(0.091)	(0.070)	(0.102)
Age	−0.599	0.305	−0.057	0.130***	0.041***	0.051***
	(0.545)	(0.288)	(0.329)	(0.022)	(0.012)	(0.016)
Squared age	0.003	−0.003	−0.000	−0.001***	−0.000***	−0.001***
	(0.007)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)
Married or cohabiting	1.780	−0.483	0.840	−0.056	0.133*	0.148*
	(2.263)	(1.199)	(1.376)	(0.095)	(0.074)	(0.084)
Subjective health status	3.675***	0.614	0.043	0.039	0.083**	0.066
	(1.397)	(0.794)	(0.696)	(0.058)	(0.040)	(0.043)
Religious participation	−3.007	−1.835	−1.982	−0.316*	−0.177**	−0.103
	(2.445)	(1.371)	(1.275)	(0.162)	(0.087)	(0.086)
Political participation	−7.612*	3.676	7.053**	0.009	0.240**	−0.124
	(4.035)	(2.955)	(3.247)	(0.172)	(0.117)	(0.103)
Tenure at current job (years)	0.500***	0.070	0.097	0.018***	0.001	−0.000
	(0.167)	(0.076)	(0.059)	(0.006)	(0.007)	(0.004)
Union participation	1.475	0.145	−2.221	0.044	0.006	0.172**
	(2.760)	(1.523)	(1.716)	(0.097)	(0.080)	(0.075)
Years of schooling	1.847***	2.238***	0.907***	0.073***	0.057***	0.035***
	(0.636)	(0.295)	(0.178)	(0.022)	(0.016)	(0.012)
Social capital						
Contacts' occupational prestige	0.637***	0.203***	0.227**	0.017***	0.004	0.009**
	(0.130)	(0.063)	(0.090)	(0.006)	(0.004)	(0.004)
Network size (log)	5.376***	−1.100	−0.454	0.193**	0.125**	0.085
	(1.998)	(1.162)	(1.123)	(0.089)	(0.055)	(0.066)
Public sector	1.946	4.321**	−0.482	0.037	0.195*	0.310***
	(3.453)	(2.031)	(2.833)	(0.127)	(0.102)	(0.113)
Job prestige				−0.001	0.007**	0.007*
				(0.003)	(0.003)	(0.004)
Constant	−35.173**	−7.830	24.485**	7.958***	10.048***	10.163***
	(15.694)	(8.123)	(9.973)	(0.623)	(0.447)	(0.519)
Observations	205	720	426	205	720	426
Adjusted R squared	0.44	0.33	0.27	0.53	0.29	0.39

Notes: Controls for political orientation, city of residence, and being a student are included in all models.
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

market, presented in Table 5, reveal that the likelihood of being employed is lower only for women from middle or lower socioeconomic backgrounds, while gender does not have a statistically significant association with being employed in respondents from a higher socioeconomic background. The positive association between age and participation is similar among the groups.

Education has a positive relationship with labour participation for individuals from upper and middle socioeconomic backgrounds, with an estimated association for the higher group being twice that of the middle group, while the association for the lower socioeconomic background group is not significant. Network size has a positive and significant association with participation in the labour market for all groups. The estimated association is greater for the lower socioeconomic background group, but the differences among the coefficients across the groups are not statistically significant. The relationship between occupational prestige of the participants' contacts and labour participation is not statistically significant for any of the groups.

As can be seen in the results of the employment sector models, women from lower and middle socioeconomic backgrounds are more likely to work in the public sector, whereas men in the higher socioeconomic group are more prone to be public sector workers. Age does not seem to be relevant for any group, while schooling has a positive association only for the middle group. Job experience is positively related to the likelihood of working in the public sector only for the lower and middle groups. Network size has a negative and significant association only for the higher group, while the occupational prestige of contacts has a positive and significant relationship only for the lower group. In these models, social capital coefficients are statistically different among the groups, except when comparing the network size coefficients for the higher and middle groups and the contact prestige coefficients for the middle and lower groups.

Table 6 presents the results of the models for job prestige and employment income as dependent variables by socioeconomic background. Education is a strong predictor of job prestige, with a positive and significant association in the three groups. The strongest relationship is observed in the middle group and the weakest in the lower group. Labour experience is important for individuals from a higher socioeconomic background, while working in the public sector has a positive relationship for those ones from a middle socioeconomic background.

Moreover, contacts' occupational prestige again has a positive and significant association with individuals' job prestige, but the association is stronger among individuals from a higher socioeconomic background. In fact, the coefficient for this group is almost three times that of the rest of the population and they are statistically different from each other. In this case, returns on social capital are not statistically different between individuals from middle and lower socioeconomic backgrounds. In addition to this, the relationship between network size and job prestige is only positive for those from the higher group.

The models of employment income differentiated by socioeconomic backgrounds reveal a gender-related salary gap in all groups, though smaller in the middle group. The return on education is positive and statistically significant for all three groups, also increasing based on socioeconomic background. Labour experience is important only for those from a higher socioeconomic background and is also the only element that does not have a positive association for this group regarding working in the public sector. Individuals' job prestige has a positive and significant association only for those from lower and middle socioeconomic backgrounds. Moreover, contacts' occupational prestige has a positive and significant association with labour income for higher and lower socioeconomic groups, with the estimated coefficient for the higher group being twice that of the lower group. Network size is solely important for middle and higher socioeconomic groups and has a greater estimated coefficient for the latter. Note that all the social capital coefficients are statistically different among the socioeconomic background groups.

To sum up, our analysis reveals that the returns associated with social capital differ based on individuals' socioeconomic background. The link between social capital, in terms of contacts' occupational prestige, and better labour market outcomes is significantly stronger in individuals from a higher socioeconomic background (H7). Remarkably, this happens in outcomes such as job prestige and employment income. Finally, the evidence does not support the assumption that the positive association between social capital, in terms of network size, and status attainment is stronger in individuals from lower and middle socioeconomic backgrounds, as a sort of compensation (H8). On the contrary, our findings indicate that this association is stronger for individuals from higher socioeconomic background.

Structural equation modelling: Direct, indirect, and total associations

We tested the robustness of our results using alternative models. We performed a path analysis, a simple case of a SEM (see Section 4.3). This analytical strategy provides more evidence to support the hypotheses derived from our conceptual model (see Fig. 1), distinguishing between direct, indirect, and total associations. The tables showing the results of these estimations only include the variables of interest. We used the same controls as in the models reported in previous sections.

Table 7 presents the results for the full sample. As can be seen, they confirm the direct, positive and significant association between years of schooling and social capital, suggested in H1 (with estimated parameters of 1.258 and 0.055 for contacts' occupational prestige and the log of network size, respectively). More interestingly, the variable representing higher socioeconomic background (relative to middle and lower background) displays a positive and significant overall association not only with social capital in terms of contacts' occupational prestige, but also with social capital in terms of network size. Therefore, this constitutes more evidence supporting H2; that is, that individuals from a higher socioeconomic background have significantly greater access to social capital than their mid- and low-SES counterparts. This conclusion derives from the fact that socioeconomic background displays a strong and significant indirect association with our two variables of social capital, mediated by years of schooling. Such associations were impossible to detect with our initial models, which only employed linear regressions. All this enables us to assert that the relationship between socioeconomic background and social capital is stronger than previously reported (see Table 3).

As Table 7 shows, individuals with higher levels of social capital, both in terms of contacts' occupational prestige and network size, are positively and significantly associated with better status attainment, especially with a higher employment income value. These results are consistent with H3 and H4, but add evidence suggesting that the positive association between social capital and status attainment is mostly direct. For this reason, there are only small differences between the size of the overall associations estimated with SEM and the coefficients estimated using regression models (see Table 4).

Years of schooling (or achieved position) also continue to be positive and significant predictors of status attainment, in line with H5. More precisely, as Table 7 shows, the expected positive relationship between education and status attainment is mainly direct, even though a positive and significant indirect association is also present mostly via social capital. As a result, the presence of significant indirect associations between years of schooling and status attainment variables such as job prestige and employment income, cause education to display stronger final associations with said outcomes compared to previous models (see Table 4).

Regarding ascribed positions, individuals from middle and lower socioeconomic backgrounds display significantly lower levels of job prestige and employment income than high-SES ones. As a result, H6 appears to be plausible again. Interestingly, this happens through direct and indirect associations, that is, there are significant and positive paths from ascribed positions (parents' education) to status attainment, both direct and indirect (via education and social capital). Indeed, indirect associations are rather strong, substantially increasing the overall association of socioeconomic background with job prestige and employment income compared to early estimations (see Table 4).

Below, we analyse SEM differentiated by socioeconomic background. Tables A2, A3, and A4 (in Appendix, Section III) show specific findings.

Results for individuals from a higher socioeconomic background are shown in Table A2. The evidence is consistent with our prior estimations. Years of schooling are positively and significantly associated with social capital (in its two forms). In addition to this, education is positively associated with job prestige and employment income, which occurs through direct and indirect associations. In consequence, years of schooling display stronger overall associations with these outcomes than those reported in Table 6 using linear regressions. As for social capital, our two measures are positively and significantly associated with higher levels of job prestige and employment income, in line with the initial models.

Table A3 presents the results for the mid-SES individuals. Years of schooling are also positively associated with better access to social capital in this group. In addition to this, education is positively associated with better results in all the labour outcomes considered, mainly through direct associations. Regarding social capital, significant associations, mostly direct ones, are observed between contacts' occupational prestige and job prestige (with a point estimate of 0.204) as well as between network size and employment income (with a point estimate of 0.112). All these findings are consistent with the estimates analysed in section 5.4.

Table A4 presents the results for individuals from a lower socioeconomic background. Like in previous groups, education is positively associated with greater access to social capital. Education also displays a positive and significant association with better job prestige and employment income, which occurs mostly through direct associations. As for the relationship between social capital and status attainment, only contacts' occupational prestige is significant, most clearly in association with employment income (with a point estimate of 0.012). This happens mostly through direct associations (with a point estimate of 0.009).

Finally, Table 8 summarises the overall associations estimates differentiated by socioeconomic background. It focuses on job prestige and employment income. Under H7, the positive association between social capital, in terms of contacts' occupational prestige and status attainment is stronger in individuals from a higher socioeconomic background. Again, results are consistent with this conjecture. Individuals from high socioeconomic background display the strongest overall association between contacts' occupational prestige and status attainment, in terms of both job prestige (with a point estimate 0.645) and employment income (with a point estimate of 0.017).

As before (see Table 6), the evidence derived from the SEM leads to the rejection of H8. According to this hypothesis, the association between social capital in terms of network size and status attainment is stronger in individuals from lower and middle socioeconomic backgrounds. However, the evidence suggests that instead of compensating for pre-existing socioeconomic gaps, the structure of opportunities represented by network size favours individuals from a higher socioeconomic background, benefiting unequal networks through greater availability of social resources and better returns in the status attainment process.

Table 7
Structural equation modelling (total sample).

	Years of schooling	Social capital		Status attainment		
		Contacts' prestige	Network size **(log)**	Public sector	Job prestige	Employment income
Direct associations						
Years of schooling		1.258***	0.055***	0.016***	1.627***	0.048***
		(0.112)	(0.007)	(0.005)	(0.183)	(0.009)
Socioeconomic background (ref = higher)						
Middle	−1.995***	−5.143***	−0.013	0.026	−7.087***	−0.115**
	(0.226)	(1.024)	(0.064)	(0.037)	(1.49)	(0.057)
Lower	−4.000***	−5.649***	−0.09	0.016	−7.423***	−0.145**
	(0.319)	(1.246)	(0.075)	(0.043)	(1.661)	(0.072)
Social capital						
Contacts' occupational prestige				0.002	0.303***	0.009***
				(0.001)	(0.049)	(0.002)
Network size (log)				−0.038*	−0.083	0.114***
				(0.02)	(0.831)	(0.038)
Status attainment						
Public sector					2.185	0.197***
					(1.729)	(0.066)
Job prestige						0.007***
						(0.002)
Indirect associations						
Years of schooling				0.000	0.411***	0.034***
				(0.002)	(0.094)	(0.005)
Socioeconomic background (ref = higher)						
Middle		−2.51***	−0.109***	−0.04***	−5.585***	−0.263***
		(0.34)	(0.018)	(0.011)	(0.692)	(0.036)
Lower		−5.032***	−0.218***	−0.07***	−9.835***	−0.444***
		(0.579)	(0.033)	(0.019)	(1.02)	(0.047)
Social capital						
Contacts' occupational prestige					0.004	0.002***
					(0.004)	(0.001)
Network size (log)					−0.083	−0.009
					(0.081)	(0.007)
Status attainment						
Public sector						0.015
Job prestige						
Total associations						
Years of schooling		1.258***	0.055***	0.016***	2.039***	0.081***
		(0.112)	(0.007)	(0.004)	(0.172)	(0.008)
Socioeconomic background (ref = higher)						
Middle	−1.995***	−7.653***	−0.122*	−0.014	−12.673***	−0.378***
	(0.226)	(1.077)	(0.065)	(0.035)	(1.623)	(0.062)
Lower	−4.000***	−10.681***	−0.309***	−0.053	−17.258***	−0.589***
	(0.319)	(1.249)	(0.072)	(0.038)	(1.698)	(0.068)
Social capital						
Contacts' occupational prestige				0.002	0.307***	0.011***
				(0.001)	(0.049)	(0.002)
Network size (log)				−0.038*	−0.166	0.105***
				(0.02)	(0.831)	(0.039)
Status attainment						
Public sector					2.185	0.211***
					(1.729)	(0.066)
Job prestige						0.007***
						(0.002)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In brief, based on estimations derived from SEM, individuals from a higher socioeconomic background also display strong associations between education and status attainment, especially job prestige. Individuals in this group also display the strongest associations between social capital and status attainment. Therefore, individuals from more privileged backgrounds obtain status benefits through formal and informal channels. As for individuals from a middle socioeconomic background, education is the main path for them to achieve better outcomes in the labour market, although other associations also stand out: between contacts' occupational prestige and job prestige as well as between network size and employment income. It is interesting to observe that individuals from lower socioeconomic background display clear associations between contacts' occupational prestige and the two main status measures. All in all, social capital appears to be a relevant resource throughout the social stratification structure. Differences tend to concern intensity and the types of social resources that generate instrumental returns.

Conclusions

This study examined the relationship between social capital and status attainment, especially job prestige and employment income. Unlike most studies conducted in developed countries with relatively high levels of social mobility, we focused on Chile, an emerging country located in Latin America that displays a high level of economic inequality and a fair amount of rigidity in its stratification structure.

This paper found evidence that social capital generally allows individuals to obtain better outcomes in the labour market, consistent with the general assumptions of SRT, later analyses developed by Lin and colleagues (e.g. Lin, 2001, 1982; Lin et al., 1981; Lin and Dumin,

Table 8
Summary of total associations between social capital, job prestige and employment income by socioeconomic background.

	Job prestige			Employment income		
	Higher	Middle	Lower	Higher	Middle	Lower
Years of schooling	3.351***	2.586***	1.081***	0.114***	0.094***	0.06***
	(0.512)	(0.27)	(0.183)	(0.018)	(0.013)	(0.011)
Social capital						
Contacts' occupational prestige	0.645***	0.204***	0.216**	0.017***	0.006	0.012***
	(0.121)	(0.063)	(0.085)	(0.005)	(0.004)	(0.004)
Network size (log)	5.123***	−1.179	−0.626	0.185**	0.112**	0.09
	(1.835)	(1.143)	(1.029)	(0.076)	(0.055)	(0.064)
Status attainment						
Public sector	2.067	4.328**	−0.896	0.039	0.226**	0.335***
	(3.228)	(1.995)	(2.905)	(0.119)	(0.098)	(0.114)
Job prestige				−0.001	0.007***	0.007*
				(0.003)	(0.003)	(0.004)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

1986), and the results from recent research (e.g. Bian et al., 2015; Rözer and Brashears, 2018). Our analysis revealed that the positive associations between social capital and attained statuses not only result from contacts' occupational prestige: in some cases, they are also due to a network of "weak ties" that is larger and more varied in socioeconomic and political terms. Influential studies (Campbell et al., 1986; Granovetter, 1975, 1973; Son and Lin, 2012) have suggested that increased network heterogeneity (in several social domains) may have positive implications for status attainment; however, these benefits have seldom been tested empirically, mainly because the dimensions of social capital measured with the Position Generator (e.g. average occupational prestige of contacts, network extensity) tend to be strongly correlated (Hällsten et al., 2015).

Our analysis also revealed the relationship between socioeconomic background, social capital, and status attainment through direct and indirect associations. More precisely, we found evidence that parents' education is associated with differences in the relationship between social capital and status attainment, especially in terms of job prestige and employment income. Although education is the most important predictor of better labour market outcomes for the middle and upper socioeconomic background groups, social capital (both in terms of contacts' prestige and network size) is a complementary and highly distinctive resource for the higher-SES group. In other words, the most privileged group in terms of socioeconomic background attains better status not only through education, but also through the two forms of social capital considered. Based on these findings, it is possible to suggest that, for example, the "ceiling effect" that people supposedly encounter when they reach higher positions in the occupational hierarchy relative to the advantages that their "weak ties" may provide (Lin et al., 1981), might be different in societies with longstanding inequality and comparatively rigid social structures, as is the case of Chile. In such contexts, one might expect a clearer accumulation of advantages linked to the availability of opportunities as well as of material and symbolic resources to convert them into benefits (Bourdieu, 1986; Tilly, 1998).

Although the evidence does not allow us to detect any causal effects, it is possible to ask to what degree social capital could be involved in the reinforcement of inequality. We suggest that researchers interested in the Chilean context attempt to use longitudinal data to conduct more in-depth examinations of this issue in the future, contrasting these results with models that include the conscious mobilization of social capital and distinguishing the type of help received (e.g. information, favouritism) (Bian et al., 2015).

Regarding international discussion, future works should continue reflecting on the two points to which this study seeks to contribute: measurements of social capital and the role of socioeconomic background. We argue that it is essential to rethink the traditional indicators of social capital in order to stress the importance of the number of available contacts, extending the notion of "weak ties" beyond the occupational characteristics of a person's contacts. In addition, we think it necessary to further examine how social capital is produced, paying close attention to the degree of homogeneity of individuals' wider social networks (DiPrete et al., 2011). To date, the latter aspect has received little scholarly attention, even in contexts where social capital and its implications have been extensively researched. A more specific measurement of the homogeneity of acquaintanceship networks would make it possible to enrich the debate on the differentiated role of social capital and homophily in status attainment (e.g. Chen and Volker, 2016; Mouw, 2003).

Finally, it is important to discuss not only how social capital is distributed unequally depending on positions of origin (ascribed and achieved), a relationship for which evidence is increasingly abundant in the literature on access to social resources (e.g. Rözer and Brashears, 2018), but also how social capital could bring greater status attainment benefits to people with better inherited positions or who enjoy a better socioeconomic status. Future research should also attempt to incorporate new mechanisms that can shed light on the relationships between people's position of origin, social capital, and status attainment; more precisely, school selectivity, the transmission of preferences for entering lucrative and reputed fields of study, and specific aspects of family socialization. At a time in which the material gap between the most affluent groups and the rest is increasing, these lines of inquiry could become a necessity, even in developed nations.

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Appendix

Section I

See Table A1.

Table A1
Average number of contacts per social group.

	ISEI 88	Socioeconomic background			
		Total	Higher	Middle	Lower
Occupations					
Doctor	88	1.96	2.97	1.98	1.43
Attorney	85	1.54	2.74	1.5	1.01
University professor	77	1.9	3.87	1.83	1.07
Manager or director of a large firm	70	1.6	2.9	1.54	1.06
Accountant	60	1.7	2.15	1.81	1.29
Secretary	53	2.64	3.14	2.79	2.14
Shop assistant	43	3.19	3.34	3.44	2.69
Preschool teacher	43	2.25	2.43	2.36	1.97
Car mechanic	34	2.47	2.32	2.52	2.47
Waiter	34	1.27	1.83	1.36	0.85
Taxi driver	30	2.63	1.97	2.78	2.7
Street vendor	29	2.67	2.19	2.73	2.81
Office cleaner	16	1.94	1.89	2.07	1.75
Political groups and minorities					
Catholic priest		0.76	0.73	0.83	0.67
Mapuche		2.5	2.21	2.52	2.62
Member of the UDI		0.84	1.61	0.83	0.48
Peruvian immigrant		1.37	1.74	1.42	1.11
Member of the Communist Party		1	1.73	1.01	0.65
Member of the Christian Democratic Party		1.1	1.87	1.04	0.85
Gay or lesbian		2.58	3.35	2.76	1.9
Individuals who are unemployed		4.48	3.8	4.76	4.35
Names					
Hernán		1.45	1.38	1.51	1.38
Ignacio		1.86	2.02	1.96	1.59
Ximena		1.62	1.66	1.69	1.48
Viviana		1.44	1.45	1.5	1.34

Note: In Spanish, the occupation “contador” can refer to an accountant or a bookkeeper. In order to calculate the network prestige, the average score of these two occupations was used.

Section II

Zheng et al. (2006) propose a multilevel (or hierarchical) model of Bayesian inference for learning about the size of individuals’ social networks. Specifically, let$N$ denote the size of the population and letp_{ij} denote the likelihood that individual i knows person j. The groups in the population are indexed by k (that is, individuals with the first name Juan, Mapuche population, gays and lesbians, women, men, etc.). For its part, the group k defines a subset of the population that belongs to it. This subset is denoted by S_k.

Following the notation of Zheng et al. (2006), the level of sociability (gregariousness) of individual i is denoted as $a_i = \sum_{j=1}^{N} p_{ij}$; the level of sociability of the population as $B = \sum_{i=1}^{N} a_i$; the level of sociability of individuals who belong to group k as $B_k = \sum_{i \in S_k} a_i$; the proportion of total links that involve group k as $b_k = \frac{B_k}{B}$; the expected number of people from group k known by individual i as $\lambda_{ik} = \sum_{j \in S_k} p_{ij}$; and the relative propensity to know individuals from group k on the part of unit i as $g_{ik} = \frac{\lambda_{ik}}{a_i b_k}$. In our case, we define n as the number of people who answer the survey ($n = 2, 846$) and K as the subgroups included in the survey. Finally, y_{ik} is the number of people who the surveyed individual i says that they know in.

Given the above, Zheng et al. (2006) model y_{ik} as follows:

$$y_{ik} \sim Poisson\ (e^{\alpha_i+\beta_k+\gamma_{ik}}) \tag{A1}$$

where $\alpha_i = \log(a_i)$, $\beta_k = \log(b_k)$, and $\gamma_{ik} = \log(g_{ik})$. The authors assume that g_{ik} follows a Gamma distribution with a mean 1 and a second parameter equal to $\frac{1}{\omega_k - 1}$, where ω_k is the parameter of over-dispersion. As a result, they show that:

$$y_{ik} \sim Binomial - Negative\ (median = e^{\alpha_i+\beta_k},\ over - dispersion = \omega_k) \tag{A2}$$

With regard to the statistical inference of this model, Zheng et al. (2006) propose a multilevel (or hierarchical) model of Bayesian inference. The model is hierarchical because y_{ik} is estimated as a negative binomial that depends on the parameters α_i, β_k and ω_k. Note that in a Bayesian approach, said parameters are not taken as constants, but as random variables following certain distributions —detailed below — which could also depend on certain parameters that also follow certain prior distributions. Based on this modelling, the posterior distribution is built and realizations of the variables of interest are simulated using Markov chain Monte Carlo (MCMC).

Specifically, it is assumed that α_i follows a normal distribution with median μ_α and standard deviation σ_α (as hyper prior for these parameters assume non-informative normal distributions). For β_k a normal distribution is also assumed with the median μ_β and standard deviation σ_β. However, in this case, these two parameters are calibrated to normalize the estimates regarding population size in Chile. This procedure is conducted using real population data from Chile for the members of each group used and the properties of the median and variance of log-normal distribution. Unfortunately, the actual size of the population of all the groups is not available; therefore, we estimate with $K = 18$. Finally, as prior for the inverse of the parameter of over-dispersion, we assume a uniform (0,1).

Although the statistical properties of the estimate depend on whether the specification of the model is correct, in terms of the distributional suppositions, Zheng et al. (2006) show that the over-dispersion model proposed generates predictions that are very close to the real data, even in categories with high over-dispersion. For the Chilean case, it is important to mention that the scaling method yields a very similar estimate of α_i to that of the over-dispersion model. The correlation between the two estimates is over 95%.

Section III

See Tables A2, A3 and A4.

Table A2
Structural equation modelling (Higher socioeconomic background sample).

	Social capital		Status attainment		
	Contacts' prestige	Network size **(log)**	Public sector	Job prestige	Employment income
Direct associations					
Years of schooling	2.077***	0.046**	−0.002	1.779***	0.071***
	(0.306)	(0.021)	(0.018)	(0.596)	(0.021)
Social capital					
Contacts' occupational prestige			0.001	0.643***	0.018***
			(0.003)	(0.123)	(0.006)
Network size (log)			−0.155***	5.443***	0.195**
			(0.051)	(1.869)	(0.084)
Status attainment					
Public sector				2.067	0.041
				(3.228)	(0.120)
Job prestige					−0.001
					(0.003)
Indirect associations					
Years of schooling			−0.005	1.572***	0.043***
			(0.008)	(0.383)	(0.013)
Social capital					
Contacts' occupational prestige				0.002	0.000
				(0.008)	(0.002)
Network size (log)				−0.32	−0.010
				(0.475)	(0.025)
Status attainment					
Public sector					−0.002
					(0.007)
Job prestige					
Total associations					
Years of schooling	2.077***	0.046**	−0.006	3.351***	0.114***
	(0.306)	(0.021)	(0.017)	(0.512)	(0.018)
Social capital					
Contacts' occupational prestige			0.001	0.645***	0.017***
			(0.003)	(0.121)	(0.005)
Network size (log)			−0.155***	5.123***	0.185**
			(0.051)	(1.835)	(0.076)
Status attainment					
Public sector				2.067	0.039
				(3.228)	(0.119)
Job prestige					−0.001
					(0.003)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *.

Table A3
Structural equation modelling (Middle socioeconomic background sample).

	Social capital		Status attainment		
	Contacts' prestige	Network size **(log)**	Public sector	Job prestige	Employment income
Direct associations					
Years of schooling	1.363***	0.055***	0.031***	2.238***	0.057***
	(0.191)	(0.011)	(0.007)	(0.290)	(0.016)
Social capital					
Contacts' occupational prestige			0.000	0.203***	0.004
			(0.002)	(0.063)	(0.004)
Network size (log)			−0.019	−1.096	0.125**
			(0.023)	(1.139)	(0.054)
Status attainment					
Public sector				4.328**	0.195*
				(1.995)	(0.101)
Job prestige					0.007***
					(0.003)
Indirect associations					
Years of schooling			−0.001	0.347**	0.037***
			(0.002)	(0.139)	(0.009)
Social capital					
Contacts' occupational prestige				0.001	0.002**
				(0.007)	(0.001)
Network size (log)				−0.084	−0.012
				(0.109)	(0.010)
Status attainment					
Public sector					0.031
					(0.019)
Job prestige					
Total associations					
Years of schooling	1.363***	0.055***	0.030***	2.586***	0.094***
	(0.191)	(0.011)	(0.006)	(0.270)	(0.013)
Social capital					
Contacts' occupational prestige			0.000	0.204***	0.006
			(0.002)	(0.063)	(0.004)
Network size (log)			−0.019	−1.179	0.112**
			(0.023)	(1.143)	(0.055)
Status attainment					
Public sector				4.328**	0.226**
				(1.995)	(0.098)
Job prestige					0.007***
					(0.003)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *.

Table A4
Structural equation modelling (Lower socioeconomic background sample).

	Social capital		Status attainment		
	Contacts' prestige	Network size **(log)**	Public sector	Job prestige	Employment income
Direct associations					
Years of schooling	0.990***	0.051***	0.004	0.902***	0.036***
	(0.162)	(0.009)	(0.004)	(0.174)	(0.012)
Social capital					
Contacts' occupational prestige			0.004**	0.220**	0.009**
			(0.002)	(0.086)	(0.004)
Network size (log)			−0.014	−0.638	0.099
			(0.027)	(1.032)	(0.064)
Status attainment					
Public sector				−0.896	0.341***
				(2.905)	(0.107)
Job prestige					0.007*
					(0.004)
Indirect associations					
Years of schooling			0.003	0.179*	0.024***
			(0.002)	(0.105)	(0.006)
Social capital					
Contacts' occupational prestige				−0.003	0.003**
				(0.011)	(0.001)
Network size (log)				0.013	−0.009
				(0.045)	(0.011)
Status attainment					
Public sector					−0.006

(*continued on next page*)

Table A4 (*continued*)

	Social capital		Status attainment		
	Contacts' prestige	Network size **(log)**	Public sector	Job prestige	Employment income
					(0.020)
Job prestige					
Total associations					
Years of schooling	0.99***	0.051***	0.007*	1.081***	0.060***
	(0.162)	(0.009)	(0.004)	(0.183)	(0.011)
Social capital					
Contacts' occupational prestige			0.004**	0.216**	0.012***
			(0.002)	(0.085)	(0.004)
Network size (log)			−0.014	−0.626	0.090
			(0.027)	(1.029)	(0.064)
Status attainment					
Public sector				−0.896	0.335***
				(2.905)	(0.114)
Job prestige					0.007*
					(0.004)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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