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Networks and youth labor market entry

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by

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Abstract

The conditions under which young workers find their first real post-graduation jobs are both very important for the young's future careers and insufficiently known given their public policy implications. To study these conditions, and in particular the role played by networks, we use a Swedish population-wide linked employer-employee data set of graduates from all levels of schooling which includes detailed information on family ties, neighborhoods, schools, and class composition over a period covering high as well as low unemployment years. We find that strong social ties (parents) are an important determinant of where young workers find their first job. This remarkably robust effect is estimated controlling for all confounding factors related to time, location, education, occupation, and the interaction of these. The effect is larger if the graduate's position is "weak" (low education) or during high unemployment years, a pattern which does not emerge when analyzing the role of weak ties (neighbors or friends as measured using classmates and their parents). On the hiring side, by contrast, the effects are larger if the parent's position is "strong" (e.g. by tenure or wage). We find no evidence of substitution in recruitment over time and fields induced by "family ties hires". However, we do find that, just after their child is hired in their plant, parents experience a sharp drop in their wage growth. Overall, our results show that strong (family) ties are more important in the job finding process of young workers in weak positions than those weak ties usually measured in the literature (neighbors, in particular), suggesting that labor market experience and education are essential conditions for weak ties to be strong.

Keywords: Weak ties, social networks, youth employment. JEL-codes: J62, J64, J24

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1 Introduction

Entry on to the labor market is a defining moment for young workers. Multiple decisions must be made (see among many contributions Keane and Wolpin, 1997). Finding and selecting the first “real” job is essential (see among many topics Beaudry and Di Nardo, 1991 and recently Kahn, 2010 on the impact of unemployment on wages of new hires). However, the precise strategies developed by these young job searchers to find this first job are less well-known. Among them, the use of networks should clearly be central. Indeed, there is a large and growing literature documenting the importance of networks in facilitating the process of matching workers and firms on the labor market. We stand at the junction of these two topics and focus on how various networks affect the entry conditions of young graduates.

Nudged by Granovetter (1973, 1983), as well as by a lack of adequate data on strong ties, the network literature has mostly focused on weak ties. And because such weak ties are virtually never registered in data sources, the authors have used indirect measures of ties based on closeness (living in the same block, coming from the same city or the same country, being enrolled in the same regiment...) to examine network effects. The use of matched employer-employee data has offered some improvements by allowing researchers to focus on better-identified networks such as workers employed at the same firm from the same country of origin, or from the same block of housing. Again, however, these strategies do not ensure that the ties indeed exist within the firm or, more importantly, pre-existed workers’ entry at the firm and were used at recruitment. Recent surveys have tried to record information on the (self-declared) friends of the interviewees. Unfortunately, and as above, nothing allows the analyst to know if any of these ties was used at the moment of hiring.

In contrast with the rest of the literature, and (to the best of our knowledge) for the first time, we examine the role played by networks using an empirical strategy which relies on directly observing all three components of the potential match: the firm, the hired worker, and the matchmaker. To accomplish this task, we focus on family links. Such social ties are clearly, using Granovetter’s words, “strong”. As a contrast, we also analyze indicators of ties that are “weak” (at least relative to family links) and also directly observed, such as classmates and their parents or those classmates that are neighbors versus those that are not (a way to approach the set of potential friends).

Because we observe the origin – the family, the class, or the neighborhood – as well as the destination – the agents' employers, together with all other employees in all potential destination firms, we can identify the respective roles of these ties in the process of obtaining the first real job. In particular, we analyze how firm (demand, loosely speaking) and graduate (supply, loosely speaking again) characteristics interact to determine when strong social ties are used, by whom, and how the use of these ties affects subsequent outcomes for the agents involved. Assuming that the agent of the match is the parent in the firm, we will be able to say important things about characteristics of those parents who act as go-between. Furthermore, our different identification strategies will allow us to examine if the parent is indeed the agent of the match (informing their children about job characteristics, job openings, and their employer about their children qualities). When studying weak ties -- classmates, or their parents, be they neighbors or not -- we benefit from similar advantages. Again, classmates should know each other, in particularly if they live in the same neighborhood (something we can identify) and hence be "friends". When analyzing the role of the parents of these classmates, we can again directly classify the two sides of the relationship.

Entry into the labor market is a good moment to examine the role of family networks, and contrast them with other sources of social ties because it is a time when the market has limited information on workers' quality, when the worker has limited information on the labor market and faces maximal uncertainty regarding where suitable matches can be found. Parents' information and connections can help in all these situations. Furthermore, most of the subjects live with their parents, or have just left home. Hence, information is likely to flow freely within the family, in particular about job vacancies; hence such strong ties do not need the type of strategic reinforcement often discussed in the literature on ties' strength. Finally, weak ties through acquaintances met at past jobs and firms should be rarer (not existing, by construction), and the networks should therefore more often build on non-professional acquaintances such as classmates, classmates' parents and neighbors.

Related Literature and our Contribution: The existing literature on the extent and role of social networks in developed economies, is burgeoning both on the theoretical side (see Montgomery, 1991, or more recently Calvó-Armengol, Verdier and Zenou

(2007), Ballester, Calvó-Armengol and Zenou (2006), Calvo-Armengol, 2004, Calvo-Armengol and Jackson, 2004 and 2007, Casella and Hanaki, 2008, among many authors, and Jackson, 2004 for a very thorough survey) as well as on the empirical side (see Munshi, 2003, Bandiera, Barankay and Rasul, 2009, Bayer, Ross and Topa, 2008, Bertrand, Luttmer and Mullainathan, 2000, Fredriksson and Åslund, 2009, Laschever, 2005 again among many authors, and Ioannides and Loury, 2004 for a very detailed survey) after a period of relative calm following the path-breaking articles of Rees (1966), Granovetter (1973), and Boorman (1975).

The “informal” hiring channel is the focus of growing number of empirical contributions. But the phenomenon, as happens virtually always, preceded its extensive study. As early as 1923, De Schweinitz (1932) finds that more than 40% of workers in the hosiery industry in Philadelphia obtained their job through friends and relatives. The importance of this “informal” channel as a resource for getting jobs has been documented by various surveys. It appears to be pervasive irrespective of the occupation or country. Ioannides and Loury (2004) provide a comprehensive overview of many of the literature findings. Bewley (1999, p. 368) gives a slightly older list of studies that were published between the years 1932-1990. The percent of jobs or job offers obtained through the informal channel of friends and relatives goes from 18% to 78% (from 30 to 60% in most cases). In the following paragraphs, we focus on some recent articles that try to get at the *exact channel* of entry into jobs.

Because of their diversity, we focus our discussion on contributions that look at questions also addressed in this paper. We distinguish between four types of issues.

First, we will look at parents (own or classmates’) **as a source of information about jobs**. Indeed, a very active line of study investigates whether the neighborhood constitutes such a source of information and therefore tries to give a more precise content to “friends”. This informational aspect of location networks was used by Topa (2001) to explain the clustering of unemployment within Chicago neighborhoods. He adopted a probabilistic approach for the likelihood of a contact (which allows for “spillover” of information across census tracts). The recent work of Bayer, Ross, and Topa (2008) goes a step further and contributes to a better understanding of the referral aspect of networks again at this neighborhood level. Using micro-level census data for Boston, they find that those who live on the same block are more than 50% more likely to work together, than those living in nearby blocks. Munshi (2003) examines the role of the city of origin for Mexican immigrants but his data does not allow him to investigate the workplace. Laschever (2005) relies on the random assignment of American WWI veterans to military units. Using a small data set (n=1,295), he is able to show that an increase in peers' unemployment decreases a veteran's likelihood of employment. Laschever's focus is identification of various peer effects. To perform his identification of peer effects, he contrasts two reference groups for each veteran: those who served with him at WWI and his closest neighbors (in terms of physical distance) at the 1930 Census. A new set of papers (Cingano and Rosolia, 2008 and Åslund, Hensvik and Skans, 2009, Dustmann, Glitz, and Schönberg, 2010 are three good examples) looks at matched longitudinal employer-employee data to follow workers who have worked in the same firm at some point in time and check if the characteristics (say, the geographic origin) of their network has an impact on job search or other outcomes. Cappellari and Tatsiramos (2011) use a novel source of information on individuals and their friends collected within a British panel (BHPS) to examine how friends' employment affect individuals own employment. Finally, Corak and Piraino (2010) use data somewhat similar to ours but focus on intergenerational earnings mobility for men who have the same main employer as their fathers (but were not necessarily simultaneously employed at the same firm). By contrast with our analysis, their focus is clearly not on referral or networks at the moment of entry on the labor market.

In contrast to most of these papers, we use extremely precise and error-free measures of family and class links between the informed (the child) and the informant (the father or the mother or the parents of the classmates). For all of them, we have virtually all information that one classically has in surveys, even though the data we use are administrative. Hence, these fathers and mothers are our equivalent to the neighborhood in Bayer et al.'s approach. Furthermore, again in contrast with most previous studies, we use an exhaustive sample of individuals. Our data allow us to follow all graduates who leave Swedish schools between 1988 and 1995 during a seven years period (i.e. until 2002 for the latest cohort). In addition, we can use data on any worker employed in the Swedish economy, even though we focus on those employed at plants in which the parents or the children also work. Thus, we can also look at differences in behavior between different parents working in the same firm or plant. In the spirit of Laschever, we define reference groups for each person for whom we examine entry in a first job – most often, students who graduate from the same classroom, i.e. in the same year, at the same school, in the same field of education – but our use of this reference group is different from his. A child and her parents in our strategy constitute the equivalent of Laschever's or Bayer et al.'s reference groups (those with whom a person potentially works and gets job information from). Hence, every child in a classroom faces different information sets because of the privileged access each one has to his or her parents for the strong ties or to his or her classmates' parents living or not in his/her neighborhood for the weak ties . Hence, we can use three types of variations to identify the effects of interest: on the child side (grades, sex, field of education); on the parent's side (in particular, the parent's plant characteristics and identifier, the parent's sex, field of education, wage or tenure,…); on the classmate side (living in the same neighborhood or not, the employer identifier of the classmates' parents). We believe that we are the first to look simultaneously at these different ties in any context (and not only at entry on the labor market).

Second, we try to look at parents **as a source of information on the quality of the applicants**, inspired by a second line of study, mostly theoretical up to now, that insists on the role of networks in solving the **adverse selection** problem that firms face when selecting among job applications. For instance, Montgomery (1991) shows that referrals and networks help the firms to select workers when their type is not widely observable by the market. Other papers insist on this unobserved ability component of the referred individual. Empirically, very few articles have attacked this issue directly, at least to our knowledge. Again, in contrast with all previous studies, we directly measure some aspects of quality of the applicants. First, our data sources include national grades, for all compulsory school and high-school graduates (but not university graduates). Because we include all students in the same class, we are able to compute a relative measure of quality. Second, because we are able to track the exact plant at which young workers are employed, we measure outcomes (such as wages) relative to other new entrants or workers within the employing entity (using plant fixed effects). More precisely, we compare outcomes at the level of the plant where parents and children are working together, by looking at co-workers and new hires that entered this particular plant by channels other than “family hiring”.

Third, and most unusually, because we identify the agent of the match (the parent or the classmates’ parents), we are able to describe the agent’s personal characteristics (wage, education) before entry of the child as well as potential changes in some elements after entry.

Fourth, and finally, we examine how jobs obtained through family links unfold within the employing firm. In particular, we look at **mid-term outcomes** for the children, as well as for the parents. Interestingly, the within-plant relation may allow the firm to solve **moral hazard problems** (if the child does not provide enough effort, breaches the contract, or if the parent lied about the quality of the child) using potential punishments. In general, because we follow workers, parents as well as children, over time we are in a position to examine the mid-term outcomes for those who were hired by referral as well as for those who acted as referral and contrast them with those hired from the same class without a parent in the plant. We believe that we are the first analysts to look at this precise question in the job search context. There is another context, though, where this type of problems emerges: credit market failures in developing economies. Ghatak and Guinanne (1999), Ghatak (2000), and Conning (2005) look at microfinance when peers can monitor members of their social network. This reciprocal monitoring can facilitate credit access. Millo and Pasini (2007) presents a theoretical framework that helps understand how repeated interactions together with social networks help alleviate moral hazard in non-market insurance situations. All these papers may help us understand **how the joint presence of a child and a parent in a plant may be useful for their employing firm**.

Our *findings* can be summarized as follows:

- First, strong social ties in the form of family networks play an important role when young workers find their first jobs.[1] Specifically, for the average (across all education levels) graduate the probability of entering a specific plant is estimated to increase by 8 percentage points if the father works there and by 6 percentage points if the mother works there. Considering that we estimate the counterfactual probability of entering the same plants to be about half a percent,

[1] Our analysis excludes self-employed parents.

the estimates suggest a substantial role for strong social ties in the process of sorting youths over starting jobs. Conversely, a plant is more likely to hire one of his employees' children than someone else from the same class, and the plant hires more graduates in the years when children of the employees enter the market.

- Second, the effects of strong social ties are more pronounced for children with poor labor market prospects, in particular those with low schooling and poor grades as well as in years of high unemployment. This holds also after accounting for characteristics of the parent, region and plant (of the parent).
- Third, the importance of *weak* ties is roughly independent of the level of schooling. The importance of ties strength therefore appears inversely related to the labor market prospects of the entering agent.
- Fourth, strong social ties matter more if the agent of the match (the parent) is well attached to the plant (the demand side). Specifically, networks matter more if the agent is a high-wage worker with relatively long tenure at the plant, even controlling for plant fixed effects. The effect is substantially weaker if the parent has left the plant, and (except for university graduates) at some other plant within the same firm.
- Fifth, similarity between the child and the parent reinforce the network effect, in particular fathers (mothers) matter more for sons (daughters) and the network effect is stronger when children have an education similar to that of their parents and when the industry of the parent is more relevant for the type of education the child has followed.[2]
- Sixth, gender matters: boys follow parents more than girls and paternal links matter more than maternal links. The finding that networks matter more for males concur with results from previous research on weak ties (e.g. in Bayer et al, 2008), but a novel finding is that the gender effect on the demand side is primarily driven by the type of employing plant: within plants, the gender of the parent matters much less. On the supply (child) side, boys benefit from parental networks more than girls, even within plants.

[2] This analysis accounts for the direct effect of similarity by using classmates whose parents also have the same type of education as their parents to estimate the counterfactual probability of entering the plant.

- Seventh, information appears to be a key driver of family network effects. Occupations in which parental hiring is widely used are those with many outgoing students and relatively broad scope of potential receiving firms in the municipality (not bakers or masons or any other craft but skilled metal workers or energy workers) together with a large number of potential employers in the municipality.
- Eighth, we show that the parent is indeed the agent of the match: a) the plant hires more graduates in the exact year in which an employee's child graduates from school; b) wage growth of the parents whose children are recruited are higher than that of their coworkers before the time of recruitment, but becomes lower in the exact year the plants hire their children.
- Finally, when analyzing the consequences of parental networks for subsequent labor market outcomes we find that the initial wage paid to the child is lower than for equivalent persons entering the plant through other channels. However, this is partially compensated in the mid-term; these children spend longer spells in their first job than hires without a parent in the plant. For firms, parental hiring thus appears to be one way of reducing (young) workers subsequent turnover.

The rest of the paper is structured as follows: First, section 2 discusses some elements of theory and the empirical model. Section 3 provides a brief background of Swedish institutions and the labor market conditions at the time of study. Section 4 gives a detailed description of the used data and how it has been constructed. Section 5 provides empirical results and Section 6 concludes.

2 Theory and empirical model

2.1 Theory

In this subsection, we briefly outline the potential roles of networks in labor markets. In particular, we try to focus on the specific role of parents, the strong ties, versus weaker ties, the classmates or the neighbors at the moment of entry onto the labor market. We examine in turn various functions.

Strong ties and Weak ties: In a seminal contribution built on Granovetter (1973), Boorman (1975) models the time spent by a job searcher in maintaining respectively her strong and her weak ties. Without going deep into his model, Boorman assumes that strong ties take more time to maintain than weak ties. The tradeoff is therefore between a limited number of strong ties and a larger number of weak ties. Information from a social contact goes first to her strong ties, then if none or if all are already employed, to her weak ties. One clear consequence is that when unemployment is high or when the strong ties of some contact are more likely to be unemployed (because they have low-education; for instance), information will not reach the weak ties. Conversely, strong ties are more helpful when unemployment is high or when the job searcher has low-education.[3] Clearly, the number of weak and strong ties matters in this problem: a lower number of the former (at entry on the labor market, with no labor market experience one has few contacts) makes the strong ties relatively more useful.

2.1.1 Roles of (parental) networks when searching for a job

Informing the job searcher: In a situation where job openings are rare, dispersed, or difficult to locate, a job searcher will use family informants more intensively. In addition, networks may help the job searcher to learn about the quality of the jobs in the contact firms. This effect should be even stronger for young workers examined in this paper who generally have little first-hand knowledge of the labor market.

Informing the firm about the job searcher's quality: In this context, the presence of unobserved heterogeneity and potential adverse selection may explain why firms use referring (Montgomery, 1991). For this line of research, quality of the applicants is what matters for the firm. However, other papers tend to emphasize the potential productivity mismatch in referral hiring (Bentolila, Michelacci, Suarez, 2010). In this case, referral hiring should be associated with lower wages for those hired through referrals than for those hired through normal channels.

2.1.2 Holding a job with the help of a network

In Montgomery (1991), workers who provide contacts should be high-ability workers, with longer tenures in the firm (allowing the firm to know workers' ability). Furthermore, workers who are hired through referrals should be high-ability too, should

[3] Jackson (2008) summarizes Boorman (1975) and shows the limits of this model. Still, given the empirical nature of our work, our short presentation is sufficient.

be better compensated, and should also stay longer periods of time in the hiring firm. The analysis of outcomes beyond the moment of hiring for those workers, both informant and informed, within firms that use referrals is absent from this strand of the literature. However, the references mentioned above, from the development literature, show that moral hazard is a central issue resolved through delegated or peer monitoring. In our context, a similar solution can be found for three actions that are subject to moral hazard. First, the referral may have lied on the referred type (using Montgomery's perspective). Second, more classically, the referred may not select the appropriate level of effort. In this last case, the referral provides a natural peer when implementing some form of monitoring.[4] Third, if turnover is costly, the referral might be expected to induce the referred worker to stay longer periods of time.[5] In all cases, punishment of the deviating individual remains an issue that we will try to address.

2.2 Empirical models and identification strategies

Our empirical models should help us understand how networks affect the search for the first stable job of new graduates. Here we describe the set-up for family networks but the principles directing our analysis of classmates' and neighbors' networks are exactly similar. Because we try to capture causal effects of parental presence at a plant, we need an empirical model that accounts for the fact that there is a (counterfactual) probability that the graduate would have ended up in her parent's plant, **even if the parent had not worked there**. We use *classmates* to construct such a counterfactual. Our empirical models should also help us understand the direct effect of "parental hiring". First, we must measure the children outcomes and compare them with those that entered a given plant with no parent around. Second, we want to capture the impact on parents if "parental hiring" was not successful. In addition, we want to apportion the role of the respective characteristics of the student, of the parents, of the plant of the parents, of the children and parents fields of study and occupations, and of labor market conditions but we leave the description of that extension to the empirical part of the paper. Below we present the details of our empirical models, starting with the basic model that will help us assess the existence and the magnitude of parental networks in hiring.

[4] For instance, Millo and Pasini (2007) mix Arnott and Stiglitz (1991), who study the effect of the presence of non-market insurance on market insurance when moral hazard is a concern, with Vega-Redondo (2006), who looks at stability in social networks. They show that more cohesive networks allow for a better control of moral hazard.

[5] Discouraging turnover could also be modeled using Montgomery's model if the types are not low versus high quality but low versus high mobility.

2.2.1 The set-up

Whether a high-school or university graduate finds her first stable job in a particular firm depends on how well her skills and social networks overlap with those needed by the firm. In order to estimate the effects of a particular network (in our case provided by the parents-children relations), we need a model which accounts for all potential sources of overlap between skills of the graduate and characteristics and needs of the firm.

Consider a set of graduates, indexed by *i*, each graduating from a particular class, *c*(*i*). The class defines a specific location (school), a time (year of graduation) and an occupation (the specifics of the education, the field of study). Each graduate may start working in any of the plants (indexed by *j*) present in the economy. Using a formulation similar to Kramarz and Thesmar (2011), we analyze the following linear model for the probability that graduate *i* starts working in plant *j*:

$$(1) \qquad E_{i,c(i),j} = \beta_{c(i),j} + \gamma A_{i,j} + \varepsilon_{i,j} \,,$$

where $E_{i,c(i),j}$ is an indicator variable taking the value one if individual *i* from class *c(i)*, starts working in plant *j*. $A_{i,j}$ is an indicator variable capturing whether a parent of the graduating student *i* works in plant *j*, $\beta_{c(i),j}$ is a match effect that captures the propensity that graduates from a given class may end up working in a particular plant (skills, size,…). In this model, because we control for the match specific effect just described, our parameter of interest measuring the network effect is captured by γ. For now, we assume that γ is a constant, but in the results section, we present useful extensions. Finally, the error term ε captures all other factors within a class that affects the probability that graduate *i* starts working in plant *j*. We assume that $E(\varepsilon_{i,j} \mid A_{i,j}, c(i) \times j) = 0$ where the product between *c(i)* and *j* captures the controls for the interaction between the class and the plant effects.

If ε and *A* are orthogonal given the class-plant fixed effects β as assumed just above, we are, in theory, able to obtain a consistent estimate of γ. The practical problem of estimating equation (1) is however non-trivial. Estimation of (1) as such would require a data set with one observation for each combination of individual and plant. As our data set contain over 600,000 graduates and over 300,000 plants per year, estimation of such a model would therefore require construction of a data set with nearly 200 billion observations.

In practice we estimate two transformations of equation (1), based on two identification strategies. The first transformation results in a *within-class model* where we compare the average hiring probabilities of linked (A=1) and unlinked (A=0) graduates by class-plant combination. The second transformation assumes that the class-plant effect (β) is constant over time which allows us to estimate a plant level *timing model*. The model compares the plant's probability of hiring workers from the (time-constant) "class type" (a school-field of study combination) before and after the graduation of a linked child (i.e. with a parent in the plant).

2.2.2 Identification using within-class comparisons

In order to transform equation (1) into an estimable model, we use a methodology invented by Kramarz and Thesmar (2011). First, we restrict the sample under study to cases where there is within plant-class variation in *A*. Hence, we exclude plant-class combinations in which no parent of the class's graduates are employed as well as classes where all parents work in the same plant. However, this is not sufficient to make the model estimable. We thus aggregate the model by computing, for each plant-class combination, the ratio of the fraction of graduates with parents in the plant who were hired

$$(2) \qquad R_{cj}^{A} \equiv \frac{\sum_{i}^{c(i),j} E_{i,c(i),j} A_{i,j}}{\sum_{i}^{c(i),j} A_{i,j}} = \beta_{c,j} + \gamma + \tilde{u}_{c,j}^{A} .$$

In words, equation (2) relates the fraction of graduates from class *c* with parents in plant *j* who were hired by this particular plant to parameters of equation (1). However, because the match specific effect $\beta_{c(i),j}$ is still present in the equation, the model is still not estimable. Therefore, we now calculate the corresponding ratio for graduates from each class hired by a plant in which *none* of their parents is working. Note that because of our sample restriction, it implies that at least one student from the same class has a parent working in that same plant.[6]

$$R_{cj}^{-A} \equiv \frac{\sum_{i}^{c(i),j} E_{i,c(i),j}(1-A_{i,j})}{\sum_{i}^{c(i),j}(1-A_{i,j})} = \beta_{c,j} + \tilde{u}_{c,j}^{-A}$$

Thus, taking the difference between the two ratios eliminates the plant-class fixed effects $\beta_{c(i),j}$:

$$(3) \qquad G_{cj} \equiv \frac{n_{cj}^{E,A}}{n_{cj}^{A}} - \frac{n_{cj}^{E,-A}}{n_{cj}^{-A}} = \gamma + u_{c,j}^{G} .$$

Note that $u_{cj}^{G} = \sum_{i}^{c(i),j} \varepsilon_{i,j} A_{i,j} \Big/ \sum_{i}^{c(i),j} A_{i,j} - \sum_{i}^{c(i),j} \varepsilon_{i,j}(1-A_{i,j}) \Big/ \sum_{i}^{c(i),j} (1-A_{i,j})$ so that $E(u_{cj}^{G}) = 0$ if the original error term is uncorrelated with *A*.

The variable *G* is computed for each plant-class combination as the fraction of those hired in the plant from the class *among those with a parent in a plant* **minus** the fraction of those hired in the plant from the same class *among those without a parent in the plant*.[7] It is worth stressing that *G* is computed as the difference between two probabilities: working in a specific plant for those with a parent in the plant and working in the same plant for those without a parent there. Conceptually this computation is very close to, but more efficient than, taking the difference in hiring probabilities between pairs in the same class where one has a parent in the plant and the other not.[8]

[6] Note that the restrictions we use imply that we drop plants where no parents work. Given our very broad data set (described below) we do however keep observations describing a very large part of the labor market. In total we have observations from 150,000 establishments (see Table 6b below) which is about half of all establishments in the economy. In addition, since the sample is drawn on the employee side, lost establishments are typically very small.

[7] When estimating (3) we weight all regressions by the number of parents (from the class) in each plant in order to get representative estimates, but this weighting is not essential since it is rare that several graduates from the same class have parents in the same plant.

[8] Melissa Tartari, in a discussion of our paper, rightly suggested that looking at pairs of classmates with one parent working in a plant, when the other parent does not, suffices for estimating γ. Other transformations of the data that allows identification and estimation of γ must exist; we do not investigate them here.

Estimating γ from G allows us to answer the question "how much more likely is the average plant to hire a child of one of its employees than someone else from the child's class?" Equivalently it answers the question "how much more likely is it for a graduate of a given class to start working in a plant where her parents are employed than it is for her classmates?". Note that both of these questions refer to the importance of existing links, i.e. the estimates are defined for graduates with employed parents and, equivalently, for plants with (parental) links to graduates.

(At least) two main objections can be raised to the above identification strategy. First, classmates may not be a valid control group. Our estimates will be biased if a worker with a parent in a plant would have had a higher probability than his classmates of working in the plant even if the parent had not worked there. Second, there may be "crowding-out" of classmates in their hiring probabilities. If there is competition over vacancies, when someone in a class has a parent in a specific plant, the probability of working there for classmates without a parent in the plant may well be reduced. Both of these possible concerns will lead us to overestimate the importance of family networks. We will return to these questions in the empirical section, discuss them extensively, and present various robustness checks within this framework to assess their importance.

2.2.3 Identification using the timing of graduation

An alternative identification strategy relies on the following idea. When a student graduates in a given year, for the plant that employs his/her parent this event constitutes a potential exogenous supply shock directed to this specific plant in this specific year. We rely on this variation to estimate a model that relates the plant's recruitments of *any* worker (resembling the child of an employee) to the timing of the child's graduation. In this case, we define the type of worker by the combination of school and field (but, obviously not the year of graduation). We then calculate for each year (going from 5 years before to 5 years after graduation) the fraction of graduates (of the type) who enter the linked plant.

Essentially, we think of the graduation year of the child as creating an idiosyncratic link between the plant where the parent works and the type of worker defined by the child's characteristics. In this alternative strategy, we ask whether this new link affects actual recruitments or not. More precisely, it measures whether firms hire a larger fraction of the available workers with a given set of characteristics at the moment of graduation of an employee's child (endowed with these characteristics), rather than before.

3 Institutional background

3.1 The Swedish educational system

The Swedish educational system is tuition-free at all levels. Children are, with few exceptions, required to start school in August during their 7th year and attend 9 years of compulsory schooling. After finishing 9th grade (during their 16th year) most students choose to start high-school and about 85 percent of a cohort graduates.

High school students are enrolled in one of several possible "programs". Admissions to the programs are based on the compulsory school grade point average (GPA) whenever there are more applicants than can be admitted. Programs are either "Academic" or "Vocational". Academic programs provide general education with some (broad) specialization such as "Science" or "Social Sciences" whereas Vocational programs provided specific training into occupations through programs such as the Construction worker program or the Office assistant program. Up to 1994, Academic programs could either be 2 or 3 years long (with a 4-years version for engineers) whereas vocational programs were 2-years long. All students from the academic programs but, in general not those from the short vocational programs, were eligible for university admission. Due to a reform of the vocational programs in 1994, all Swedish high school students graduating after 1994 receive a 3 years long education that qualifies for university studies. However, the transition rates from vocational programs to higher education remain very low.

3.2 The business cycle

Our period under study goes from 1988 to 2002. This includes the most turbulent period ever faced by the Swedish labor market since the 1930s. The unemployment rate which had been below 5 % since the 1960s (and was below 2 % in the late 1980s) suddenly increased to 9.5 % in the early 1990s (see Figure 1).[9] The unemployment rate remained high until the late 1990s when it started to decline and by the year 2001 the unemployment rate had reached 5 % again. Youth unemployment showed a similar time

[9] The recession started with the adverse effects of high inflation combined with a fixed exchange rate. It was accompanied by high interest rates, a rapid fall in private spending due to a tax reform, and a collapsing real estate market. Starting in 1993 there was also a large reduction in public sector employment (see e.g. Holmlund, 2006).

pattern. The 1990s also saw a rapid expansion of the proportion of the working-age population enrolled in some form of education. Upper secondary education was prolonged for students on vocational programs and the number of students in tertiary education was dramatically increased. As a result, the employment to population ratio did not recover as much as the unemployment rate after the recession, the difference being especially strong for younger workers.

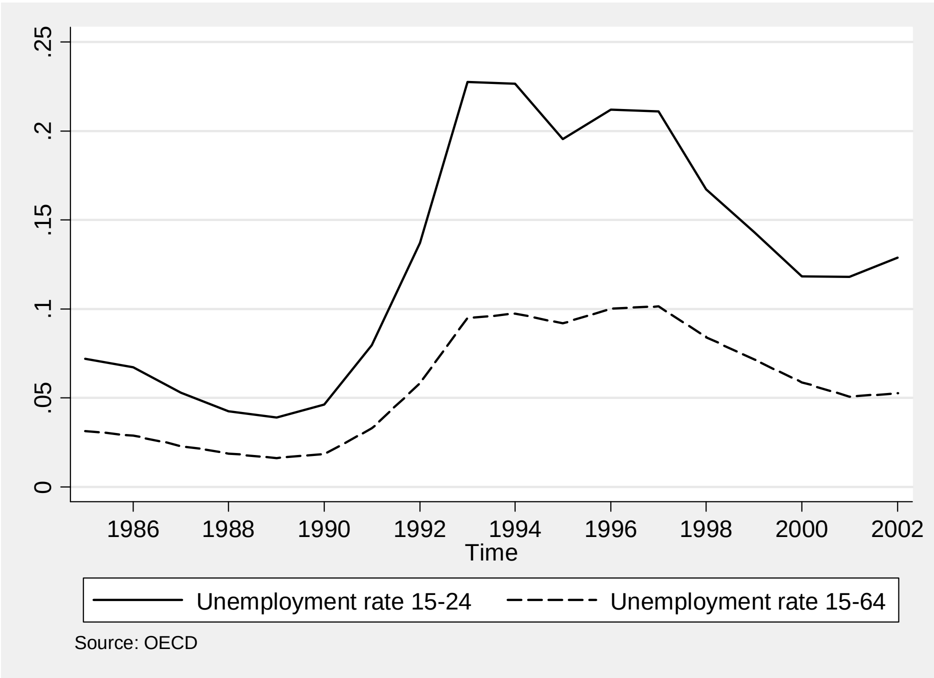

Figure 1 Unemployment 1985–2002

4 Data and description

The paper makes use of a wide range of Swedish population-wide data sources combined in the “IFAU database”. Part of the data comes from a linked employer-employee data set covering the entire Swedish economy between 1985 and 2002. In addition, the paper uses links between children and their biological parents. Furthermore, we use detailed information from graduation records stemming from different levels of schooling. These records contain information, not only on the exact type of education, but also give details on the exact school at which graduation took place. Combining these various data sources into a working data set is a complex procedure. Appendix A provides a fairly detailed overview of the procedure we used in creating our final data set.

4.1 Establishment and parental link data

4.1.1 Establishment data

The linked employer-employee part of the data set is originally based on tax records filed by firms and collected by Statistics Sweden.[10] The data contain annual information on all 16–65 year-old employees receiving remuneration from Swedish employers (both private and public) between 1985 and 2002. These annual data sets contain information on each individual's earnings received from each single employer as well as the first and last remunerated month during the year. We use these data to find each workers primary job in February each year. The job is defined by a wage and a plant.[11]

Throughout the analysis we exclude workers in the agricultural-forestry sector and children of self employed parents. These restrictions are however not essential for any of the results.

We link basic demographic characteristics to the data set. These include gender, age, level of completed education, and country of birth as well as an indicator of whether a person is self-employed or not. We calculate plant size as the number employees and construct variables capturing average wage and the fraction of employees having various characteristics within each plant. Wages are deflated by the average wage within the sample for that year to account for both inflation and real wage growth. Tenure is calculated as the number of consecutive years (since 1985 at most) that the person has worked in the same plant. We further add some generic plant characteristics such as county of the plant (there are 24 counties in Sweden), industry (38 two-digit codes and 9 one-digit codes)[12] and sector (private or public). For each two-digit industry we calculate an employment based Herfindahl-index (H)[13] measuring the lack of dispersion as a distance between zero and one, where one corresponds to a situation

[10] Statistics Sweden refers to this data base as RAMS.
[11] We refer to all establishments as "plants".
[12] Due to a change in the industry classification system in 1992 this "reduced" two-digit level is the finest level at which we can have consistent industry codes over the period.
[13] Calculated as the sum of squared employment shares in each plant (j) which captures the level of competition by industry (I) and year (t): $H_{I,t} = \sum_j \left(Size_j \Big/ \sum_j Size_j \right)^2$

with one dominant plant and zero corresponds to a situation with an infinite number of plants, each with an infinitesimal market share.

4.1.2 Parent-child links

The overall data set contains links between all parents and children present in the data set. The information is based on registers of legal parents, thus the links are between children and their biological parents *or* if applicable, their adoptive parents. Missing values are rare (less than 3 percent in the various samples, see table A1) mainly occur either if the parent was older than 65 already in 1985 or did not reside in Sweden at all during 1985-2002. There are also a (very) small number of “father-unknown” cases.

4.1.3 Description: Parent-establishment links in the overall data

Here we describe the pattern of parent-child joint employment that can be found in the overall establishment data. We use the information on employment that was described above and add links between parents and children as well as basic demographic characteristics. We restrict the description to parent-child pairs in which both parties are employed. Furthermore, we only include cases where the children are aged 40 or below. The first column of Table 1 shows descriptive regressions on the probability of at least one parent employed at the plant if at least one of them is employed using data for 2002. The second and third columns show regressions for the probability of having the mother and father respectively employed at the plant if the relevant parent also is employed. The last column shows regressions for having both parents in the plant if both are employed.

The results show that being male, young, low educated and living in a rural area makes it more likely that a person is working with his parents. Differences between immigrants and Swedish born are only minor although the estimate is imprecise due to the fact that too few foreign born employees have parents that are employed (in Sweden). Figure 2 shows the time pattern from 1985 onwards using the 1985 distribution of age, gender, education, immigration status and type of region as weights in order to purge the time pattern of changes in individual characteristics. We find little evidence of trends, but a clear cyclical pattern with a much higher frequency of working together during the high unemployment years (i.e. 1993-1998, see Figure 1 above).

Table 1 Probability of having parent(s) at the workplace

	Any	Father	Mother	Both
Male	0.032**	0.056**	-0.015**	0.009**
	(0.001)	(0.001)	(0.001)	(0.000)
Young	0.018**	0.005**	0.011**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Old	0.004**	0.005**	0.003**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
LowEd	0.063**	0.048**	0.033**	0.017**
	(0.002)	(0.002)	(0.001)	(0.001)
HighEd	-0.064**	-0.048**	-0.028**	-0.013**
	(0.001)	(0.001)	(0.001)	(0.000)
Immigrant	-0.005*	-0.005*	0.004*	0.004**
	(0.002)	(0.002)	(0.002)	(0.001)
Metro	-0.028**	-0.021**	-0.011**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.000)
Constant	0.104**	0.060**	0.062**	0.018**
	(0.001)	(0.001)	(0.001)	(0.000)
Observations	384,858	384,858	384,858	384,858
R-squared	0.03	0.03	0.01	0.01

Note: Linear probability model estimates for working with parent(s) in a specific plant if employed and the parent(s) is (are) employed. Data is for 2002. Population only includes (children) aged 40 or younger. * (**) Significant at the 5 (1) % level.

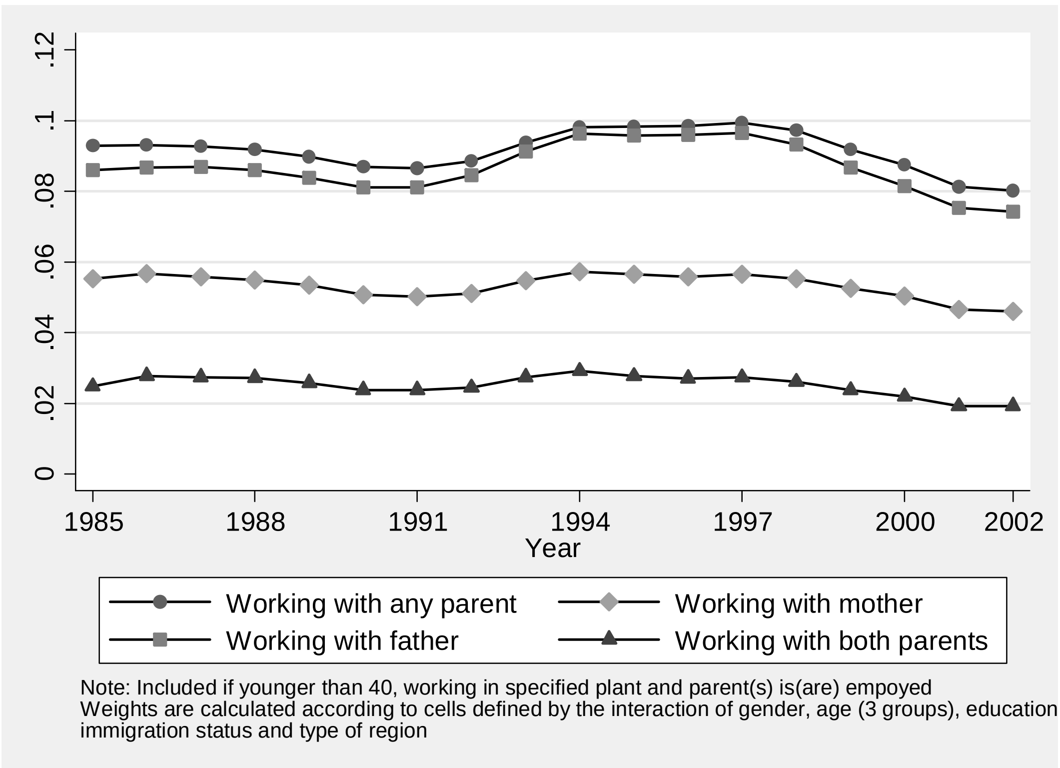

Figure 2 Time pattern of fractions working with parents, weighted by 1985 characteristics.

Although this description is suggestive, it has its limitations in terms of understanding network effects. These limitations highlight why our identification strategy is useful: from these statistics we cannot know if parents work with children because they are similar (e.g. in terms of education and where they live) or because of the existence of networks. Even if we could, we would not be able to differentiate between the supply and demand sides of the market since we do not know who hired whom. Our solutions to these problems are to focus our main analysis on graduates' first jobs and to make the within-class and timing comparisons outlined in Section 2.

4.2 Graduation data and first stable jobs

4.2.1 The population of interest

Our population of interest is constructed from graduation records from all three major levels of schooling in the Swedish system (see Section 3 for details on the schooling system): We use data on all individuals graduating from Compulsory schools (9 years of schooling), High Schools (11, 12 or 13 years) or Universities (15 years or more) during 1988 to 1995.

We study four different populations defined by their educational attainment:

1. *Compulsory schooling* includes individuals who completed compulsory schooling but did not complete high school.
2. *Vocational high school* includes individuals who completed a two or three year vocational high school education before age 21 without proceeding to university before finding a first stable job.
3. *Academic high school* includes individuals that completed a two, three or four year long academic high school program before age 21 and who do not proceed to university before finding a first stable job.
4. *University* includes graduates from a university (college) education that is at least 3 year long. Only those graduating before age 30 are included. This sample also includes graduates from various post high school educations within health care (if they are at least three years long) such as nursing school graduates.

4.2.2 Defining classes and classmates

Our identification strategy essentially builds on comparisons between graduates coming from the same school, graduating at the same time, and within the same field of education. We refer to the combination of school, graduation time, and field as a "class". Even though this measure does not necessarily correspond to an exact class as such, the definition serves our purposes well since we mainly use the concept of a class to control for factors that are time, region and occupation specific (how this is done was explained in section 3 above) and we do not mainly use the concept to capture social interactions between classmates.[14] In Appendix A we explain in detail how the class concepts are defined for each of the four different groups of graduates.

4.2.3 Other educational variables

Apart from basic demographic characteristics, data contain information on grade point average (GPA) for compulsory school graduates and the two sets of high school graduates. Each grade is set on a scale of 1 to 5 by the teacher (in some cases with the help of nation-wide tests) so that grades should have a national average of 3 and a standard deviation of 1.

We further construct two key variables describing the similarity between the education of a graduate and the education of his or her parent and the industry of the parent: First, we construct an indicator equal to 1 when the graduate and the parent share the same 1-digit field of education (irrespective of level). Second, for each type of education (field and level), but over all schools and years, we measure the fraction of graduates finding a job in each of the 38 different industries. This measure of average education-industry flows is used to capture how relevant an industry is for a graduate with a specific education. This measure is then used to quantify how expected or unexpected is a graduate's choice of industry, given his or her education.

4.2.4 Neighborhoods

Our data on neighborhoods are based on Statistics Sweden's definition of SAMS (Small Area Market Statistics) which refers to a homogeneous neighborhood in terms of building structures (not resident characteristics). The median resident has 450 working age neighbors within his or her SAMS.

4.2.5 Definition of the first stable job

In order to study parental networks and their role for children's labor market insertion, we need to define what "real" or stable jobs are, in particular in contrast to those jobs held when at school (for which parents are likely to help even more). For this reason,

[14] Although we do discuss robustness checks where we try to account for the possibility of such effects, through friendship networks.

we define a “stable job” as a job which lasts for at least 4 months during a calendar year and which produces total (annual) earnings of (at least) 3 times an average janitor’s wage which we use as a proxy for a “minimum wage” (Sweden have no legislated minimum wage). As shown in the Data Appendix (Table A3) 53 percent of graduates satisfy these criteria the year after graduation.

Figure 3 shows the time elapsed in order to find a first stable job for the different types of educational attainment. The figure clearly highlights that there are large differences between the different samples. It is clear that it takes a substantial amount of time before Compulsory school graduates finds their first stable job, whereas University graduates in general find jobs very shortly after graduation. When analyzing the time pattern we found, unsurprisingly, that the negative labor market shocks in the early to mid 1990s coincides with an increased duration between graduation and work, in particular for the low educated (results are available on demand).

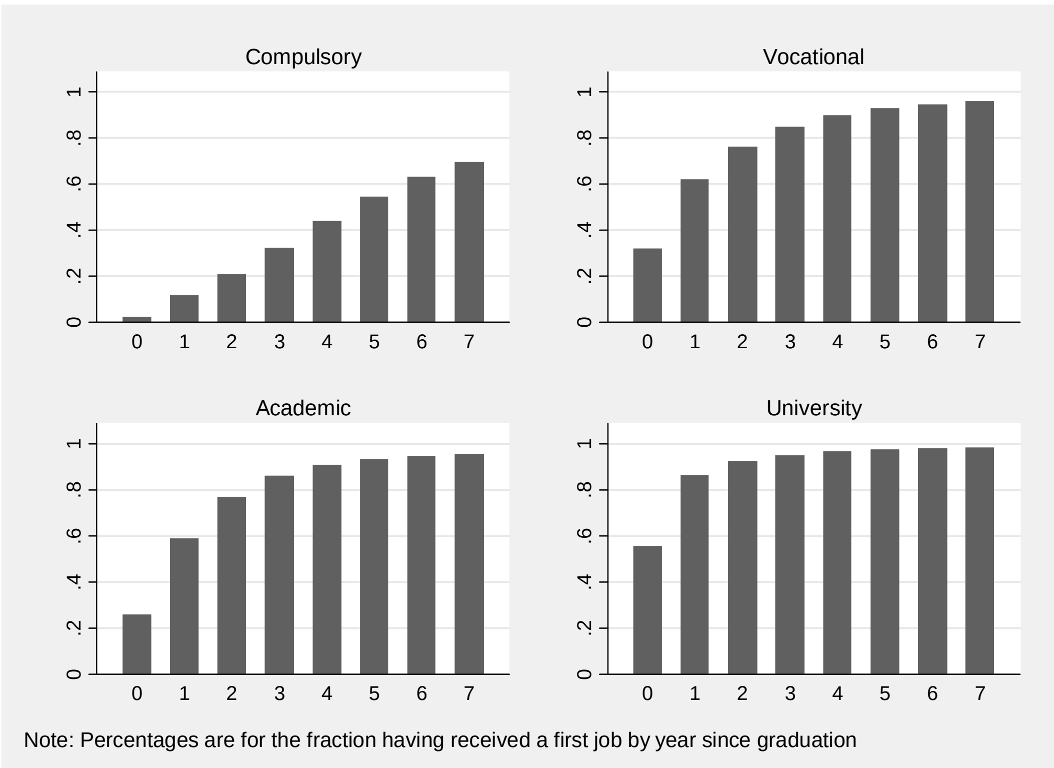

Figure 3 Time to first stable job – cumulative

Appendix A provides descriptive statistics. Table A1 describes children and parents in the four education groups where parents' characteristics are computed conditional on employment. Table A2 describes the construction on data on jobs held by parents. Table A3 presents statistics for the creation of the graduates' first stable jobs. When estimating equation (6) we transform the data according to our empirical model and Table A4 shows descriptive statistics for these transformed data for all the variables used in our heterogeneity regressions.

5 *Results*

5.1 Using within-class variations – how important are parents?

In this section we estimate the probability that the first stable job is found at the plant of the parent using equation (3). The parental hiring effect (γ) we estimate captures the excess probability a graduate has to find her first stable job at the parent's plant after removing a specific effect capturing the interaction of the exact education, location, time of graduation (the class, to summarize), year of the first stable job, and the hiring plant since comparisons are made within the combination of class, year of first job, and plant. As mentioned above, self employed parents and parents in the agricultural-forestry sector are excluded throughout.

Table 2 presents the estimation results. We present estimates of γ for mothers and fathers separately, respectively in the first panel and in the second panel. Each column presents separate estimates for the four education groups. Finally, for each panel, we present estimation results for children of both sexes jointly, as well as for male and female children separately.

All estimates are strongly positive and significant. Hence, graduating students are much more likely than their classmates to go in the plant where one of their parents is employed. It should be noted already at this stage that the estimates of the model, in general, are very close to the raw mean probabilities for starting to work in the parents plant, in other words the counterfactual probability of working in the specific plant is very low (estimated to be around half a percent).[15] This is highlighted in Table A5 in Appendix A, where we also show the different components leading up to the estimates.

[15] To understand this, notice that it is essentially impossible to predict the employing plant of any graduate so the baseline probabilities captured by the fixed effects in equation (1) are very small, at least compared to the estimates

Table 2 Parental networks effect on probability of finding the first job in a specific plant, baseline within-class estimates

	Compulsory school	Vocational high school	Academic high school	University degree	All
Fathers					
All					
$\hat{\gamma}$	0.104	0.081	0.095	0.020	0.076
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N	46,872	151,208	124,279	85,366	407,725
Males					
$\hat{\gamma}$	0.142	0.117	0.129	0.033	0.110
(s.e.)	(0.002)**	(0.001)**	(0.002)**	(0.001)**	(0.001)**
N	23,106	84,797	56,842	31,560	196,305
Females					
$\hat{\gamma}$	0.052	0.033	0.064	0.011	0.039
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N	16,093	60,902	60,844	50,252	188,091
Mothers					
All					
$\hat{\gamma}$	0.079	0.057	0.068	0.020	0.055
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N	47,374	149,733	127,387	94,940	419,434
Males					
$\hat{\gamma}$	0.063	0.044	0.061	0.014	0.046
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N	23,187	84,341	58,152	35,358	201,038
Females					
$\hat{\gamma}$	0.097	0.074	0.074	0.023	0.062
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	16,456	60,059	62,927	55,608	195,050

Note: Estimates of parental network effects. An observation is a combination of class, plant, and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 findning a stable job within 7 years of graduation. Standard errors are cluster-corrected for dependencies within class. **Significant at the 1 % level.

The estimated network effect is particularly strong for the low educated. As an example, the estimates for graduates who enter the labor market without any post-compulsory school education suggest that the probability of working in a specific plant is increased by 8 percentage points by the mere fact that the mother works there. The corresponding estimate for the plant where the father works is 10 percentage points. The effect is also quite large for students graduating from Vocational or Academic high-schools. It is much lower though for students graduating from the university (at the

of interest: the average plant has about 50 employees, thus, starting to work in any particular plant is very rare. Fortunately, our empirical model gives us the tools to compare the realized and counterfactual outcomes in this type of situations.

undergraduate or at the graduate level). And, strikingly, fathers tend to "hire" their sons when mothers tend to "hire" their daughters, even though the latter happens with a lower intensity.

Table B1 presents similar results for each year after graduation. Hence, the first column shows results in the graduation year. Then, results for one year, two years, or more, after graduation are given in the next columns. Again results are presented for mothers and fathers separately as well as by education group. It is important to remember that each child is present only once in the analysis. Hence, for example, estimates shown in column "*t=1*" are obtained for those children who find a job one year after graduation. The comparison group is made up of classmates who find a job after the same number of years. Results show that the effect is stronger just after graduation for most groups (see in particular those graduating from compulsory schools). It is slowly decaying afterwards, never disappearing even after seven years. However, clear exceptions are children graduating from vocational high-school, who have roughly the same likelihood of finding their first job in a plant where their father works just after graduation or three years after graduation. In addition, and not surprisingly, the number of children who find a job in more than 2 or 3 years after graduation is small for all groups but the low-education (with only compulsory schooling).

5.2 Robustness checks

We have performed a variety of robustness checks, in particular in order to examine how results are affected by some of our initial modeling choices. All the detailed results described in this subsection are either presented in Table 3, in Appendix B, or are available upon request.

First, we performed sensitivity tests in order to assess the quality of our main identifying assumption that classmates are a valid control group. The consistency of the estimates relies on the assumption that there is no unobserved factor which makes a child more likely to work in the same plant as her father or mother (in comparison with other students in her class) other than the parent working there. Such a factor could be an unobserved taste for that particular plant. This is indeed difficult to test. As an attempt to falsify the assumption we did three different robustness checks: We partitioned each class by the industry in which their parents worked so that we only compared one graduate to other graduates with *parents employed in similar (same industry), but not identical, plants*. The results are essentially similar to, albeit a little smaller than, the results presented above (Table 3). We then performed the same analysis by partitioning the class according to the industry the graduate ends up in and again the results (Table 3) are very similar to the ones presented in Table 2. This shows that graduates end up in their parents' plants more often than other graduates from the same class *who start working in similar (same industry), but not identical, plants*. Third, the taste for a particular plant may reveal a common taste or skill shared by the parent and the child, denoted α_i. Its presence would bias our above estimates since it would be correlated with $A_{i,j}$ and included in the residual $\varepsilon_{i,j}$ without any way of controlling for it. In particular, our within-class-plant transformation which leads to equation (3) does not eliminate it as soon as some students in the class share such a taste with their parent when others do not. Hence, one strategy is to restrict attention to those students that are most likely to share this taste. Therefore, we re-estimated equation (3) but we only included graduates who had the *exact same education as their parent*. [16] We perform this test for three levels of aggregation of education categories, 1-digit, 2-digits, and 3-digits. Results are presented in the Appendix Table B2. Again, we find extremely similar results, with slightly larger estimated effects, and a little less precise when we use 3-digits education categories.[17] Because we only have children who share some α_i component with their parents, the quasi-differencing procedure embedded in equation (3) should eliminate the bias. Overall, these results suggest that the estimated effect is not strongly sensitive to diverging preferences over types of firms within a class.

[16] We thank Raquel Fernandez and Daron Acemoglu for suggesting this procedure.
[17] Using a 3-digits match reduces the sample considerably so in this specification we did not condition on the school, but instead used graduates from the same education, the same *municipality* (except university sample), and the same year.

Table 3 Parental networks effect on probability of finding the first job in a specific plant, robustness of within-class model

	Baseline estimates	Only classmates with parents in same industry	Only classmates with parents in same industry and within-firm wage quartile	Only classmates going to the same industry
Fathers				
$\hat{\gamma}$	0.076	0.065	0.065	0.044
(s.e.)	(0.000)**	(0.001)**	(0.001)**	(0.001)**
N	407,725	123,458	50,262	202,293
Mothers				
$\hat{\gamma}$	0.055	0.041	0.040	0.043
(s.e.)	(0.000)**	(0.001)**	(0.001)**	(0.001)**
N	419,434	196,825	97,546	210,017
	Firm hires 1 worker	Firm hires 2-5 workers	Firm hires 6-10 workers	Firm hires 11+ workers
Fathers				
$\hat{\gamma}$	0.094	0.087	0.064	0.078
(s.e.)	(0.002)**	(0.001)**	(0.002)**	(0.001)**
N	17,001	50,206	24,664	148,223
Mothers				
$\hat{\gamma}$	0.056	0.050	0.041	0.065
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**
N	14,022	56,634	32,002	163,785
	Private plants	Firm level analysis (only private)	Old (t-3) plant of parent	Old (t-3) plant of parent, if plant grows
Fathers				
$\hat{\gamma}$	0.099	0.104	0.016	0.025
(s.e.)	(0.001)**	(0.001)**	(0.000)**	(0.001)**
N	264,916	258,386	78,468	42,969
Mothers				
$\hat{\gamma}$	0.103	0.108	0.014	0.023
(s.e.)	(0.001)**	(0.001)**	(0.000)**	(0.001)**
N	146,861	142,915	88,136	47,180

Note: Estimates of parental network effects. An observation is a combination of class, plant, and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 findning a stable job within 7 years of graduation. Standard errors are cluster-corrected for dependencies within class. **Significant at the 1 % level.

Restricting attention to children with the exact same education as their parent tries to capture the idea that children may be better informed of certain job characteristics thanks to the occupations of their parents. This analysis shuts down such "supply side" explanations since all children in a class with the exact same education as their parents are on equal footing. We would also like to analyze situations where parents have the same positions within the firms but our data lack information about occupations. Therefore, we instead measured the effects within groups of parents with similar positions by dividing each class by the 2-digit industry and the within-firm wage quartile of the parents' firm and re-estimated our equation. The results, presented in Table 3 (first panel, third column), show absolutely no change in the estimated effects. Hence, when we compare the role of parents with similar positions in similar firms, network effects are again present.

Second, our identification rests on the assumption that classmates provide a valid control group for each graduate. But, if vacancies are rationed, it is possible that a worker who gets hired by a parent "takes" a vacancy away from the classmates. If this happens our estimates will be upward biased. To see this, let us rewrite equation (1) with the possibility that classmates are potential competitors for the same job:

$$E_{i,c(i),j} = \beta_{c(i),j} + \gamma A_{i,j} + \tilde{\gamma} A_{-i,j} + \varepsilon_{i,j}$$

where $A_{-i,j}$ denotes parental employment for all other children in the class in this plant *j*. Then, taking first difference, between two classmates, *i* and *i'*, yields

$$E_{i,c(i),j} - E_{i',c(i'),j} = \gamma (A_{i,j} - A_{i',j}) + \tilde{\gamma} (A_{-i,j} - A_{-i',j}) + \varepsilon_{i,j} - \varepsilon_{i',j}$$

Assuming that only two pupils belong to the class, with *i* having a parent in *j*, whereas *i'* does not, then the two variables, $(A_{i,j} - A_{i',j})$ and $(A_{-i,j} - A_{-i',j})$ are negatively correlated, with correlation -1. Hence, our estimation would yield $\gamma - \tilde{\gamma}$ rather than γ. Given that $\tilde{\gamma}$ is likely to be negative because of this crowding-out effect due to limited vacancies, then our estimate would be biased upwards.

However, this effect is likely to be small. Indeed, as seen above, the parental hiring effect is sizeable but not huge, and the “crowding out” of classmates employment probabilities should be shared by *all* the classmates. Hence, the effect per classmate should therefore be very small. We have nevertheless performed three sets of robustness checks to see if this conjecture holds. First, we have estimated a separate effect in the (few) cases when there is more than one parent from a particular class in a given plant. The effect (unreported, but available upon request) is very similar to our main estimates suggesting that different graduates with parents in the same plant do not decrease each others’ probabilities of being hired. Second, we have estimated the model separately by total numbers of hires (1, 2-5, 6-10, 11 or more) made by the plant in the relevant year. Results are shown in Table 3, second panel. Here, if there is “crowding out”, the effect should be strong for plants that only hire a unique person – whereas crowding out should be less of a problem if many new employees are hired. The estimates for plants that hire a unique worker are slightly larger than for those hiring 2 to 5 or 6 to 10 workers, but are essentially similar to the estimates for those plants hiring more than 11 workers. In addition, we re-estimated the model of equation (3) relaxing the definition of the comparison group, using either graduates from other years, or graduates from other schools in the same municipality (except for university) but in the same year. The (unreported, again available) results were essentially unchanged.

Third, the estimates we present are based on plant-level data. It is however possible that some parents not only help their children to enter their own plant but also other plants within the same firm. This could be particularly true for the highly educated (for instance, someone trained in law might not find an appropriate job in the local plant where her parents work but in the main office). In order to study the effects at the firm level, we need to restrict the analysis to the private sector. Looking at private plants increases the estimates quite a lot because the use of networks is much more limited in the public sector (as will be shown in the following section). The correction is especially important for mothers who more often than fathers work in the public sector.[18] Now, changing our unit of analysis (from plant to firm), given that we only examine the private sector, leaves the estimates essentially unchanged (Table 3, last panel). The difference in estimates between the plant and the firm specifications is less

[18] We show below that the there are no gender differences in the use of referrals if one accounts for the characteristics of the plant of the parent.

than 1 percent (less than 0.5 percent for the university sample), suggesting that parental hiring is mostly performed at the plant, rather than at the firm. This is true for all educational levels.

Fourth, we changed the definition of the *timing* to the first job.[19] Our baseline specification compares all those within a class who find a job within the same year, in order to be sure that our results are not driven by time effects or differences in overall hiring probabilities. Changing the definition and extending the comparison group to involve all graduates who find a first job at some point during the 7 years following graduation, rather than using only those finding a job in the same year, does not alter our results (unreported, available upon request).

Fifth, we have looked at the probability of being hired in a plant where the parent *used to* work rather than where the parent is currently working. We took all the cases where the parent was employed by a different plant three years before the year under consideration, the plant still existed, and the plant hired at least *someone* (not necessarily a graduate). Results are shown in Table 3, third panel - columns 3 and 4 - for different conditioning sets (results by education are not reported but are available upon request). We find some evidence that the effects remain after the parent has left the plant but the magnitudes of these effects are, in all cases but one (unreported, again available), considerably smaller than the effects when the parent is still present. The one exception is the university sample. In this case the effect is nearly as large when the parent has left the plant as when the parent was present.

Sixth, we have looked at various sub-samples, dividing the data according to various specificities of the parents' educational fields and industries. We find in particular that parents in fields (narrowly defined at a three digit level) which have become obsolete (defined as having more than twice as many parents than children) do not, on average, help children more or less than parents in fields that are still expanding (unreported but available).

Seventh, we changed the control group to only include classmates living in the same neighborhood, and/or with parents living in the same neighborhood. Naturally this reduced the sample dramatically for the university sample. The estimates found in

[19] In fact, we performed an even more basic robustness check before this one. We randomly allocated parents and children within a class and re-estimated our model. All coefficients in the specifications presented in Table 2 were equal to zero.

Table B3 in the appendix are, on average, reduced by a very small amount, but the pattern is stable cross educational levels. We have experimented with various models accounting for sorting over places residence and/or location of the parent's place of work but the results are remarkably robust. We return to models estimating the impact of residential proximity in the weak tie analysis below.

Eighth, we looked at siblings (i.e. brothers and sisters) and found that the presence of a sibling at a firm hiring one of our graduates is low, around 3.1% in the first job (for parents, the proportion is 6.7%, Table A4, first row). We will return to the impact of siblings in our analysis of later outcomes.

5.3 Do employee-graduate links affect plant-level hiring? The timing model

The timing model offers a different identification strategy for our effects of interest. It also allows us to further address concerns about crowding-out or spill-over effects between students in the same class. As described in Section 2, the timing model focuses on plants' recruitments before and after graduation of a child linked to an employee (a father or a mother) at the plant. We use data on all graduates from the same school and type of education as that of an employee's child, and look at recruitments before and after the graduation year of the child.[20] Identification here relies on within-plant variation over time for graduates of a given school and field across the years (by contrast with the time varying-definition of a class used in the previous model). Figure 4 shows the probability of hiring a graduate of the same type as the graduating child over time before and after the graduation year. Results presented in Table 4 give the precise numbers and standard errors. This hiring probability is low and stable before the graduation of the linked child, but then increases dramatically at graduation and subsequently declines. Indeed, a gradual decline after the graduation year is what we should expect since not all graduates find their first job immediately. As shown in Figures B1 and B2 in Appendix B, the rate of decline is rapid for university graduates (who find jobs fast, as indicated by Figure 3 above) and slow for compulsory school graduates (who find jobs slowly).

The models we estimate here include the full effect of the link, which include any within-class spill-over or crowding-out effects. But the strategy may be affected by

[20] For reasons of computational convenience we exclude the few cases where there are multiple years during our sample period where links are created between the same type of class and plant.

inter-temporal substitution if plants postpone recruitments until a linked worker's child graduates. However, the fact that there is no visible (or statistically significant) decline over time before graduation suggests that inter-temporal crowding out is not an important phenomenon unless plants are willing to postpone recruitments a full five years until the linked child graduates.

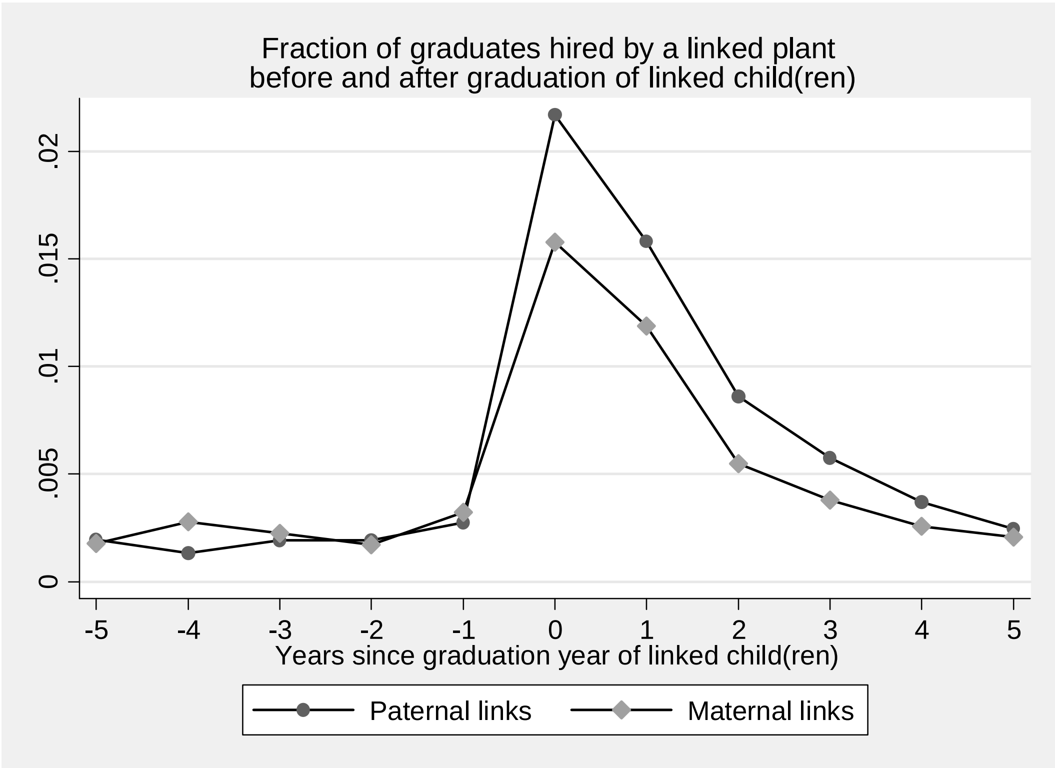

Figure 4 Fraction of graduates hired by a linked plant before and after graduation of linked child(ren)

Table 4 Parental links and plant level hiring

	Fraction of graduates "at risk" hired		Number of hires from linked school-field		Total number of graduates hired	
	Fathers	***Mothers***	***Fathers***	***Mothers***	***Fathers***	***Mothers***
Graduation year (GY)	0.019	0.013	0.030	0.023	0.031	0.024
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**
GY+1	0.013	0.009	0.024	0.016	0.024	0.021
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**
GY+2	0.006	0.004	0.012	0.006	0.010	0.007
	(0.001)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**
GY+3	0.004	0.002	0.006	0.003	0.002	0.002
	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.001)	(0.002)
GY+4	0.002	0.001	0.003	0.000	0.001	-0.002
	(0.000)**	(0.001)*	(0.001)	(0.001)**	(0.001)	(0.002)
GY+5	0.000	0.000	0.000	-0.001	-0.003	-0.003
	(0.000)	(0.000)	(0.001)	(0.001)*	(0.002)*	(0.002)
Constant	0.002**	0.002**	0.007	0.005	0.049	0.066
(average plant fixed effect)	(0.000)	(0.000)	(0.001)**	(0.001)**	(0.001)**	(0.002)**
Sum of effects (0-3)	0.042 (0.002)**	0.028 (0.001)**	0.072 (0.002)**	0.048 (0.002)**	0.068 (0.004)**	0.053 (0.004)**
Sum of effects (0-5)	0.044 (0.002)**	0.029 (0.002)**	0.075 (0.003)**	0.046 (0.002)**	0.065 (0.006)**	0.048 (0.006)**
Sample	All plants	All plants	**Small (< 16 employees) plants**			
N		2,614,984		477,670		477,670
Plant FE:s	Yes	Yes	Yes	Yes	Yes	Yes

Note: Sample include five years before and five years after graduation, excluding years in which the plant did not exist and plants which more than doubles or halves its labor force since the preceding year. An observation in the first two columns is a combination of type of class (school and field), plant, and year. Dependent variable in first two columns is the hired fraction of all graduates from the same school as the child of the employee finding of their first job during the year, estimate is for the fraction of these graduates that have a father/mother in the plant. An observation is a plant in the third to sixth column. Dependent variable in the third and fourth column is the number of hired workers from any school-field combination in which the plant is linked via a father/mother. Explanatory variables are the number of these children who graduate in the observation year (+ 1 to 5). Dependent variable in the 5th to sixth column is the number of hired graduates overall (i.e. from any track) during the year. Standard errors are cluster-corrected for dependencies within plants.

In order to find the full effect on plant level recruitments, we use the pre-graduation years as a baseline and sum the effects found in the post-graduation years. The summation of the estimates suggests that the firm hire 4.6 percent of graduates as a result of the father-links and 3 percent of graduates as a result of the mother-links (Table 4). These estimates do not change if we allow for pre-graduation trends.

An interesting follow-up question is whether links induce plants to hire more workers overall, or if they mainly redirect their hiring intentions. In order to analyze this question, we focus on small plants (defined as having on average less than 16 employees during the sample period) where the shocks to total networks are likely to be most pronounced. Here we aggregate the data to the plant level and look at the number of links to graduates the plant has and relate this to the total number of recruitments of graduates (in their first jobs, but from any level of schooling). As above we rely on timing at graduation for identification. We separately estimate the number of recruitments of the linked type and the number of recruitments of graduates overall. Consistent with the overall finding, the evidence suggests a positive post-graduation effect on the propensity to hire workers of the linked type. Moreover, we also find an effect on overall recruitments of graduates, which suggests that stronger networks to graduating students induce (at least small) plants to hire more graduates.[21] Indeed, the estimated constants suggest that the average plant hires about 10 times as many graduates from other types of schooling in the pre-graduation years whereas the effects of graduation on the number of recruitments are of nearly identical size in both specifications which suggests that parental links increase the hiring probabilities of the linked children without reducing the hiring probabilities of other graduates.

Overall, the evidence presented in this section supports the results of a significant impact of the parent-child links on the child's probability of being hired by the plant of the parent. The results further suggest that (small) plants hire more graduates overall in the years when the children of employees graduate. Thus, the network effect does not appear to be the result of a reshuffling of vacancies between different graduates entering the labor market at the same time, or between similar graduates over time, but rather the result of new vacancies being opened (or made available to inexperienced workers at least). Finally, and importantly for our strategy, the timing model is one element showing that the parent is the agent of the match as postulated.

[21] Note that we cannot analyze the propensity to hire workers overall since the sampling of parents essentially means drawing "random" workers within plants, a strategy which over-samples plants in years when they have many employees. This generates a spurious hump shape in plant size peaking in the sampling year (i.e. the year of graduation).

5.4 Weak tie estimates

In order to contrast our main results which focus on the role of strong social ties as defined by parent-child links we investigate the role of other links which could proxy weaker ties. Although it is difficult to find an exhaustive set of ties (weak or strong), we are able to analyze the role of a number of types of ties. We start by analyzing the role of classmates' parents, by comparing the probability of being hired by a classmates' parent's plant relative to being hired by the plant of a graduate's parent coming from a *different* cohort from the *same* school and field. Then, we analyze the role of neighborhoods by comparing the probability of working with a classmates' parent as a function of geographical proximity (neighbors within the class versus non-neighbors within the class). Finally, we analyze the direct effect of classmates by comparing across educational cohorts within the same field and school (although we are unable to identify who is the agent of the match in this final context and thus will overstate the magnitudes, see e.g. Manski 1993). The estimates are presented in Table 5. Note that we change the units of analysis to the level of the field-school, or class-year-neighborhood, which explains the much smaller sample sizes.

In the first part of Table 5 we show how classmates' parents affect the probability of working in a specific plant. In the specification we analyze how the probability of a first job is affected by class proximity (hence, working in the plant of a classmate's parent). The empirical strategy is similar to that of the main analysis, but the network indicator (*A* in equation (1)) in this case is equal to 1 when a classmate's parent works in the plant and the fixed effect which defines the comparison group comprises all combinations of school, field, and plant of a parent (rather than class and plants of a parent). The effects are therefore identified through differences in probability of working with parents of classmates relative to working with parents of students who graduated in a previous or a later cohort from the *same* field and the *same* school. The estimates are all very close to zero. Hence, classmates' parents do not play the role of one's own parents.

The second part analyzes the role of proximity by splitting each class by neighborhood and analyzing whether it is more likely to start working with a neighboring classmate's parent than in the plant of other classmates' parents, again using the same model as in the main analysis. Here we exclude parents and children who start working together and parents who work in another municipality, and (for computational convenience) restrict the sample to plants where only one parent within the class works.

Table 5 Weak tie network effects

	Compulsory school	Vocational high school	Academic high school	University degree	All
Classmates' parents (relative to parents' of other cohorts, same field and school)					
Fathers					
$\hat{\gamma}$	-0.001	0.001	0.000	0.000	0.000
(s.e.)	(0.001)*	(0.001)	(0.002)	(0.001)	(0.001)
N (classes)	6,202	13,772	7,713	5,560	33,247
Mothers					
$\hat{\gamma}$	0.002	0.002	0.001	0.001	0.001
(s.e.)	(0.001)*	(0.001)*	(0.001)	(0.001)	(0.000)**
N (classes)	6,114	13,791	7,787	5,769	33,461
Neighboring classmates' parents (relative to other classmate's parents)					
Fathers					
$\hat{\gamma}$	0.008	0.007	0.005	0.004	0.006
(s.e.)	(0.002)**	(0.002)**	(0.001)**	(0.003)	(0.001)**
N (class/neighb)	2,986	6,591	6,861	1,178	17,616
Mothers					
$\hat{\gamma}$	0.003	0.012	0.006	0.007	0.007
(s.e.)	(0.002)	(0.001)**	(0.001)**	(0.003)**	(0.001)**
N (class/neighb)	4,749	9,830	10,494	1,579	26,652
Classmates (relative to other cohorts, same field and school)					
Males					
$\hat{\gamma}$	0.006	0.014	0.005	0.006	0.008
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N (classes)	6,605	14,148	7,936	5,594	34,283
Mothers					
$\hat{\gamma}$	0.005	0.013	0.004	0.005	0.008
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**
N (classes)	6,696	14,253	8,082	5,787	34,818

Note: Estimates of weak tie network effects. Weighted by the number of graduates in the class or class-neighborhood. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Excluding children who starts working with their own parents and, for neighbor analysis, parents who work in a different municipality. Standard errors are cluster-corrected at the level of the fixed effect, i.e. for dependencies within field and school (and year for the neighborhood analysis). **Significant at the 1 % level.

The results indicate small, but mostly significant, network effects arising from being neighbors. Most estimates are between a half and one percent, which is in the vicinity of the baseline probability of working with any given parent of another graduate from the same class (neighbor or not). Interestingly, we do not see the clear pattern of diminishing network effects for graduates of higher levels of education. For fathers, the effects decreases very moderately with education and neighboring mothers are in fact twice as important for university graduates as they are for compulsory school graduates.

Roughly, the results indicate that, neighbors matter about as much for the low and high-educated, while the own parent is 10-20 times as important as a neighboring classmate's parent for least educated (comparing results in Table 2 and Table 5), but less than 4 times as important for the university graduates. This is consistent with the presumption that ties' strength is relatively more important for "weak" graduates.

Finally, we analyze the direct role of classmates (leaving parents' role aside). Here we estimate the difference in probability of finding the first job at the same plant as someone in the same class relative to those in other cohorts, but same field and school. It is important to note that this analysis suffers from some serious shortcomings. Most notably, we cannot isolate which agent is responsible for the match, and the estimates will therefore suffer from a "reflection" type problem where we are likely to inflate the estimates since two classmates who start working together will be classified as having recruited each other. Thus, we should consider the estimates as indicative upper bounds of the effects of classmates in the job finding process. Again, we find considerably smaller effect than in the main analysis, and, again, we do not find the clear pattern of smaller effects for more educated youths.

5.5 Heterogeneous effects in the within-class model––when do strong ties matter?

Estimation of equation (3) answers the question of how important parental contacts are on average, and for different subsamples. The evidence suggests that strong ties networks are more important for less educated youths. But in order to identify whether the heterogeneity is due to the educational performance of the child, due to the education or labor market status of the parent, or due to the regional characteristics or the nature of the firms in which parents of low educated children tend to live and work we need a richer model. We therefore expand our original framework (equation (1)) so as to incorporate effects that may vary with characteristics of the graduate (*i*), the parent (*p*), the labor market (*l*) or the plant (*j*),. This yields the following model:

$$E_{i,j} = \beta_{c(i),j} + [\gamma^{i} X_{i} + \gamma^{p} X_{p(i)} + \gamma^{l} X_{l(j,t)} + \gamma^{j}]A_{i,j} + \varepsilon_{i,j}\,, \tag{4}$$

where we have included observed characteristics (*X*) of graduates and parents as well as time-varying labor market conditions. We also allow for each plant to have a unique propensity to hire graduates with parents in the plant by incorporation of a plant fixed effect γ^j .

Since all terms we add to the framework of equation (1) are interacted with the presence of a parent in the plant we may proceed as in Section 3 to get an expanded regression framework equivalent to equation (3):

$$(5) \qquad G_{cj} = \gamma_0 + \gamma^i \overline{X}_i^A + \gamma^p \overline{X}_{p(i)}^A + \gamma^l \overline{X}_{l(j,t)}^A + \gamma^j + u_{c,j}^G$$

where a ‘bar’ and superscript *A* denotes the average within class/plant for those with a parent in the plant. Consequently, $\overline{X}_i^A$ is the average of the individual characteristics among graduates from a given class with a parent in that plant.

All terms in equation (5) come from the interaction between a parental contact and the measured characteristics, but the underlying model is the same. Thus, estimating equation (5) answers the question: *when, where, and for whom do parent-child networks matter at entry in the children’ first stable job after graduating from school*? All estimates therefore show *when and for whom* the effects are stronger.

Because estimates turn out to very rarely differ with education, we only report pooled estimates over all levels of education. More important though, we present estimates with and without plant fixed effects. The estimates from models with plant fixed effects compare cases where graduates from different classes have parents in the same plant (possibly in different years), to see which graduates are more likely to be hired *conditional* on the plant the parent works at. This accounts for the possibility that plants have different propensities to hire children of their employees. Thus, when plant effects are included, identification comes from plants where more than one parent worked at some point of the analysis period. Note that the 850,000 contacts are distributed over almost 200,000 plants in the data so that each plant has on average 4 to 5 parents of graduates over the 8 years we study. Clearly, we still have a fairly representative sample also in this case.

Table 6a Parental Networks and heterogeneity

	All	**All - Plant FE**		**All**	**All - Plant FE**
			Family link		
Graduate			*reference only father*		
Female	-0.024	-0.021	Only mother in plant	-0.014	-0.006
	(0.001)**	(0.001)**		(0.001)**	(0.001)**
Nordic Immigrant	0.005	0.006	Both parents in plant	0.164	0.127
	(0.004)	(0.005)		(0.003)**	(0.003)**
Other Immigrant	-0.001	0.002			
	(0.002)	(0.002)	***Education of graduate***		
Age at graduation	-0.001	-0.002	*reference Vocational HS*		
	(0.000)**	(0.000)**	Compulsory	0.034	0.032
GPA (1-5)	-0.006	-0.007		(0.001)**	(0.001)**
	(0.001)**	(0.001)**	Academic HS	0.029	0.028
				(0.001)**	(0.001)**
			University	-0.022	-0.023
				(0.001)**	(0.002)**
Fathers			***Mothers***		
Nordic Immigrant	0.001	0.005		0.004	0.006
	(0.003)	(0.003)	Nordic Immigrant	(0.002)*	(0.002)*
Other Immigrant	0.008	0.006		0.017	0.012
	(0.001)**	(0.001)**	Other Immigrant	(0.001)**	(0.002)**
Compulsory education	0.009	0.008		0.008	0.008
	(0.001)**	(0.001)**	Compulsory education	(0.001)**	(0.001)**
Tertiary education	-0.009	-0.012		-0.011	-0.013
	(0.001)**	(0.001)**	Tertiary education	(0.001)**	(0.001)**
Same (1d.) field as child	0.023	0.024		0.009	0.012
	(0.001)**	(0.001)**	Same (1d.) field as child	(0.001)**	(0.001)**
Log wage	0.046	0.045		0.048	0.041
	(0.001)**	(0.001)**	Log wage	(0.001)**	(0.001)**
Tenure	0.002	0.002		0.002	0.001
	(0.000)**	(0.000)**	Tenure	(0.000)**	(0.000)**

Note: Estimates of interacted network effects, the model also includes covariates in table 5b and graduation year dummies. An observation is a combination of class, plant and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Standard errors are cluster-corrected for dependencies within class. ** (*) Significant at the 1 (5) % level.

For whom do parents matter?: Table 6a presents estimates for various individual characteristics of the child. The estimates confirm that the networks matter more for the less educated, even accounting for characteristics of the parent, the plant and the location. This is true also in the case of the plant fixed effects model. Thus, network effects, (conditional on parental education, tenure and wage) are larger the less educated the child is, even when comparing parents who work within the same plant. In addition, poor grades (a low GPA) increase the size of the network effect. We have re-estimated the model replacing grade by the position of the child in the within-class grade distribution yielding similar results. In addition, we have also looked at *siblings*, showing that a given parent is more likely to hire the child with the weaker grades.[22] We see only small differences between immigrants and natives and perhaps surprisingly, age at graduation has a negative impact, even controlling for plant fixed effects, i.e. within a class younger children benefit from their parents' employment more than older ones, when entering their first job.. Overall, however, the evidence suggests that the effects of strong social ties are more important the weaker the position of the child.

Further results confirm that females benefit less from their parents. In accordance with the results presented earlier, we find that paternal links are more important than maternal links. Importantly however, we see that most of the differences between mothers and fathers disappear when introducing plant fixed effects. Hence, within a plant, parents' sex (on the demand side) plays a much more limited role. Mothers mainly work in plants which resort less to parental links. Apparently, part of the initial difference comes from mothers working more often in the public sector, where referral hiring is used much less intensively (see below).

Who are the parents who matter? : Table 6a also displays the impact of parental characteristics, separately for mothers and fathers. Let us stress again the specificity of this analysis. We study which characteristics of the incumbent workers affect the probability that the firm will hire one of the incumbent's children, holding the characteristics of the child constant. First, similarly as the demand side analysis above, low educated workers on the supply side make more use of the networks. Incumbents with a lower education have a higher probability of using their network (for a given

[22] All results not shown here are available from the authors.

education of the child) *within plant*. One possible explanation for this is that similarity in level of education reinforces the network effect.

Further, results support this notion. In agreement with results shown above, parents who share (broad) field of study with their children are more likely to be working in the same plant as their children. Thus, family links are more important when skills also overlap. We also find that a given parent with multiple children is more likely to hire the child endowed with the same field of education as his/her (detailed results available upon request).

We also study the parent's wage, tenure at the plant.[23] Estimation results yield strong support to some elements of Montgomery's model (but not to all, see just below) in the sense that well-attached workers appear to be more important: children of high-wage and high-tenure workers, even controlling for plant fixed effects, are more likely to be hired (in comparison with their classmates). Interestingly however, we also find, in apparent contradiction with Montgomery's model, that the interaction between parents' wage and the grades of the child is negative: parents who are paid high wages are more likely to hire children with relatively poor grades (detailed results available upon request). Indeed, his model tells us that referrals help firms to hire high-quality applicants. However, if parents do know something unobserved by the firm (the real productive quality of their child as opposed to scholarly grades), this result is still interpretable along the lines of the Montgomery model.

Overall the results show that within a class of students graduating in the same field of study, those who have parents trained in the same broad field, or parents who are high-wage and high tenure, are more likely to start working in the same plant as their parents. Note that all of our displayed estimates exclude self-employed parents but when including them we find that children of self-employed parents (not surprisingly) more often follow their parents than children of other employees in the same plants.

[23] Since tenure only cannot be measured before 1985 it is not a perfect measure, especially so for the earlier cohorts. Hence the estimates may be biased downwards but since all comparisons are made within cohorts there is no reason to believe that measurement errors should be correlated with our outcomes.

Table 6b Parental Networks and heterogeneity

	All	**All - Plant FE**		**All**	**All - Plant FE**
Industry-region			***Plant char.***		
Metropolitan county	-0.001	0.004	Private	0.023	0.010
	(0.001)	(0.011)		(0.001)**	(0.003)**
County unemployment	0.183	0.17	New plant	0.017	0.010
	(0.017)**	(0.023)**		(0.002)**	(0.002)**
Industry-field match	0.136	0.13	Plant growing from last year	0.015	0.012
	(0.002)**	(0.003)**		(0.001)**	(0.001)**
Industry-field match* unemployment	-0.271	-0.268	Size <16 (ref 16-45)	0.006	0.006
	(0.064)**	(0.075)**		(0.001)**	(0.002)**
Market concentration (Herfindahl)	-0.238	0.476	Size 46-125	0.009	-0.001
	(0.055)**	(0.213)*		(0.001)**	(0.002)
			Size 126-750	0.018	-0.002
				(0.001)**	(0.002)
			Size 750+	0.020	0.005
				(0.001)**	(0.004)
Worker composition at plant			***Industry of plant***		
Mean age	-0.006	-0.006	Construction (*ref manufact.*)	0.021	0.000
	(0.000)**	(0.000)**		(0.002)**	(0.007)
Share primary education	0.022	0.028	Wholesale, retail	-0.003	0.004
	(0.002)**	(0.006)**		(0.001)*	(0.008)
Share tertiary education	-0.010	0.001	Financial, corporate	-0.008	-0.004
	(0.002)**	-0.005		(0.001)**	(0.007)
Immigrant share	0.023	0.019	Education R&D	-0.005	-0.005
	(0.003)**	(0.007)*		(0.002)**	(0.008)
Average log wage	-0.093	-0.126	Health, Social	-0.047	-0.036
	(0.002)**	(0.004)**		(0.002)**	(0.008)**
			Personal & Cultural	-0.005	-0.003
N	788,028	729,124		(0.002)**	(0.010)
N (parents)	823,516	754,150	Public admin.	-0.014	-0.009
N (plants)	157,518	88,286		(0.001)**	(0.008)

Note: Estimates of interacted network effects, the model also includes covariates in table 5a and graduation year dummies. An observation is a combination of class, plant and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Standard errors are cluster-corrected for dependencies within class. ** (*) Significant at the 1 (5) % level.

In which types of plants do parents who matter work?: Table 6b presents results from the same regressions focusing on regional characteristics, unemployment, and market conditions. In particular a fragmentation of the market as measured by the Herfindahl index in the industry is associated with more referral hiring in the cross-section however, when plant fixed effects are introduced the result is reversed. Thus, referral hiring is used more intensely within plants when fragmentation in the industry is reduced (i.e. when the Herfindahl index in the plant industry increases over time).

Importantly, high unemployment seems to favor matching of parents and children within plants. Networks are also used more commonly when the industry of the parent is a more logical destination (hence more “relevant”) for the typical graduate with the type of education that the child has (see section 4.2.3 regarding the definition of this education-to-industry variable). It therefore suggests that networks are used mostly when workers with types of education that fits the plants’ typical needs are hired, thus again pointing towards the reinforcing effect of similarity between the child and the potential destination (note though, again, that the effect is estimated relative to classmates who have the same type of training). Results on the interaction between the industry-field match and unemployment show that this pattern is strongly reduced when unemployment is high. Thus, when unemployment is high, networks are used more often. And, hired children have an education which is less likely to be in line with the plants’ typical recruitment patterns.

Finally, Table 6b also shows results for plant characteristics. First, “family” hiring takes place mostly in large (or in very small) plants, in manufacturing industries, in the private sector (consistent with Table 3), and in firms with a large fraction of immigrants (consistent with patterns of workplace segregation found in Åslund and Skans, 2009). Employment growth also favors referrals.[24]

Parental networks, occupations, and the role of information: To get a better sense of the causal role of parents and the underlying mechanisms, in particular the role of information, we analyze the characteristics of the occupations/educations that are most (or least) frequently obtained through parents. Because the education categories (with closely related associated occupations) are very well defined for the vocational

[24] Not surprisingly, many estimates are imprecise when including the plant fixed effects since many of the associated variables barely change at the plant level. Interestingly, however, we see that the private sector indicator is significant, even in this specification, indicating that privatized plants tend to increase their use of referrals.

high school sample (examples are masons, restaurants, telecommunications, secretary…), we restrict attention in this paragraph to the vocational high-school sample. We start by estimating a network effect for each combination of municipality and occupation (more precisely, the detailed education received in vocational high school).[25] The resulting estimates are used as endogenous variables in a second stage where we try to explain the relative magnitude by educational and regional characteristics.

Table 7 Use of parent networks by municipality/poccupation among vocatinal high school graduates

	a	b	c	d	e	f
1000s of employing plants	0.068	0.026	0.027	0.040	0.023	0.009
	(0.013)**	(0.009)**	(0.007)**	(0.006)**	(0.007)**	(0.002)**
1000s of workers	-0.017	-0.010		-0.013	-0.011	
	(0.004)**	(0.003)**		(0.003)**	(0.003)**	
Constant	0.061	0.063	0.061	0.062	0.065	0.061
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	3,228	3,228	3,228	3,228	3,228	3,228
Municipality fixed effects	Yes	No	Yes	Yes	No	Yes
Size weights	No	No	No	Yes	Yes	Yes

Note: The table shows regressions where we explain the municipality/occupation specific use of parent networks by number of employing plants by education and municipality. The number of plants is calculated for 1995 by education and municipality using the full stock of employees (unweighted average # of plants is 78, weighted average is 228, max is 3893). Network effects (i.e. the dependent variable) is estimated using all years (the same model as in table 2). ** Significant at the 1 % level.

To measure how diverse the receiving market for each occupation-education is within the municipality, we compute the number of plants that employ at least one worker with such an occupation-education (using the full stock of employees in the 1995 data). We also compute the number of workers, in each municipality having each type of education (again, in the year 1995). We use the number of plants and number of workers as the main explanatory variables in models with or without municipality effects, with or without a control for the number of workers, with or without weights (number of employed parents). Results are presented in Table 7. The results are robust to the various controls and the message clear: Hiring through parental contacts is more common for occupations that are used in a large number of plants. Put differently, the

[25] Resulting estimates are available from the authors.

less *specific* the type of education is in terms of which plant hires the workers, the more prevalent is the use of networks. We have re-estimated the model after characterizing occupational dispersion by a segregation index (exposure) instead, receiving a similarly clear picture – the rarer the occupation of the graduate is at his future employer (e.g. receptionists) the stronger is the network effect.

We interpret these results as showing that networks are used less frequently when the set of potential hiring firms is small (hence, easier for the graduate to find). An interpretation in terms of information seems reasonable: firms need matchmakers when many applicants arrive for jobs that are less specific to that firm (for which relations with (vocational) high schools are less likely to have been developed). Furthermore, students also need parents help when there are many firms that are susceptible of employing them. The parents' employer is a natural focal point in this coordination problem. Conversely, graduates with a more specific education, (e.g. a carpenter) can easily identify firms that employ them but those with a more general type of education (electricians, manufacturing workers…) might face more potential employers and therefore need networks to a greater extent.

5.6 Strong social tie recruitments and other outcomes

In this subsection we provide evidence on the quality of the jobs provided through parental networks. We also document the effect (on wage growth) on parental outcomes of having a child hired in the "parental" plant. We analyze the quality of the jobs by studying three outcomes measured at the time of the first job: time since graduation, initial wage and relevance of the industry relative to the education of the graduate. We then proceed to median term outcomes, measured three years after the first job was found. In this case we restrict the sample to those finding a first job within four years from graduation. These outcomes are the probability of being employed three years after entry, the probability of working in the *same* plant 3 years after entry, as well as wage growth during the three years after entry. Of course, we can only measure wage growth for those who are employed (in some firm) three years after entering their first job. We present results for two models, one which includes fixed effects for each combination of class and time to first job, and one which controls for educational characteristics as well as a plant fixed effects (we have estimated a model with class fixed effects and plant characteristics, giving very similar results to the one with plant fixed effects only). Interpretations of these two models are slightly different. The first model looks at the relationship between finding a first job at a parent's plant and our outcomes of interest. In this specification, the estimate may well include effects due to unobserved plant characteristics. The second model, because it includes plant fixed effects, allows estimates to be measured in difference from other graduates finding their first job in the same plant, but through channels other than parents referral hiring. The model thereby isolates the effect of getting a job through a parent, within a given plant. All models control for grades, gender, and immigration status.

Results presented in Table 8 first demonstrate that workers who find a job where their parents work, find this job faster than classmates[26] and also faster than others who start working in the same plant, after accounting for educational characteristics. Second, starting wages are lower for those who get their first job at their mothers' plant, but starting wage are not much different from classmates if they find their first job through their fathers. However, when controlling for the plant (observed or unobserved) characteristics at which the first job was found, wages are always lower than for jobs found through other channels, irrespective of the parent who helped find the job (note that we obtain similar results when we estimate the model within class and add observed plant characteristics). Children following their parents receive a low (within-plant) wage, but fathers provide access to high-wage plants. Third, graduates, getting their first jobs through their parents, find these jobs in less "relevant" industries than those their classmates find. Therefore, they enter industries in which individuals endowed with their type of education most generally do not find their first jobs. This result also holds within plant.

[26] Obviously we do not control for time to first job in these regressions as we do in the rest of Table 8.

Table 8 Effects of finding a job through parental or sibling referral

	ln(Time to first job)		ln(Starting wage)		Relevance of industry	
Mother only	-0.180	-0.136	-0.056	-0.058	-0.02	-0.028
	(0.003)**	(0.004)**	(0.003)**	(0.003)**	(0.002)**	(0.001)**
Father only	-0.197	-0.149	0.011	0.008	-0.043	-0.024
	(0.003)**	(0.004)**	(0.003)**	(0.003)*	(0.001)**	(0.001)**
Both	-0.264	-0.223	-0.039	-0.042	-0.038	-0.029
	(0.006)**	(0.008)**	(0.006)**	(0.006)**	(0.002)**	(0.002)**
Sibling	-0.101	-0.077	0.029	0.027	-0.023	-0.010
	(0.004)**	(0.004)**	(0.004)**	(0.004)**	(0.001)**	(0.001)**
N	573,060	573,060	573,060	573,060	573,060	573,060
Class Fe	Yes	No	Yes	No	Yes	No
Ed. char	--	Yes	--	Yes	--	Yes
Plant FE	No	Yes	No	Yes	No	Yes

	Outcomes after three years (only if first job within 4 years)					
	In same plant		Employment		Wage growth (3 years)	
Mother only	0.047	0.030	0.006	0.009	0.049	0.060
	(0.005)**	(0.004)**	(0.004)	(0.004)*	(0.006)**	(0.004)**
Father only	0.103	0.053	0.025	0.018	0.025	0.056
	(0.004)**	(0.003)**	(0.004)**	(0.003)**	(0.005)**	(0.004)**
Both	0.204	0.136	0.072	0.063	0.067	0.083
	(0.008)**	(0.007)**	(0.007)**	(0.007)**	(0.009)**	(0.008)**
Sibling	0.087	0.051	0.032	0.028	-0.002	0.014
	(0.005)**	(0.004)**	(0.004)**	(0.004)**	(0.006)	(0.004)**
N	521,642	521,642	521,642	521,642	380,666	380,666
Class Fe	Yes	No	Yes	No	Yes	No
Ed. char	--	Yes	--	Yes	--	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Note: Estimates are for the conditional association between getting the the first job at the plant of parents and subsequent outcomes. Relevance of industry measures the fraction of all graduates with the same education who found the first job in that industry. Outcomes 3 years later are for the sample that got the first job within 4 years. The first model includes a fixed affect for each class and year of first job (only for class in the analysis of time to first job). The second model includes plant fixed effects and dummies for each field and level of education. All regressions control for immigration status, gender and GPA (except for university graduates). Data are for graduates 1988-1995. Standard errors are cluster-corrected for dependencies within class. ** (*) Significant at the 1 % (5 %) level.

In the second panel of Table 8, we look at outcomes three years after finding their first job. Estimates show a very strong positive effect of entering the plant where a parent works on the probability of staying in their first plant for at least three more years. This effect remains strong and significant, albeit roughly halved, when including plant fixed effects, suggesting a) that parents match children to jobs in plants where the expected tenure is long, and b) provide jobs with longer tenure within each plant.

Parental matches are also associated with slightly increased overall employment probabilities three years later. Finally, the estimated effects on wage growth display a pattern of effects suggesting that wage growth is faster for the youths who start working with their parents, even within plant. In effects this compensates for the lower starting wages. When re-estimating the model controlling for starting wages (results are available on request) the pattern is much less pronounced, after controlling for plant fixed effects, wage growth for workers entering with the help of their fathers looks just slightly higher than that observed for other entry channels whereas the estimates for jobs obtained through mothers remain unchanged**.**

Table 8 also includes an indicator for having a sibling (brother or sister) in the same plant, despite the low occurrence of such co-presence noted before (3 percent). The effects of siblings are in most models similar to that of parents, although the wage pattern differs by being positive for starting wages, but without the positive wage growth effects in the three years horizon.

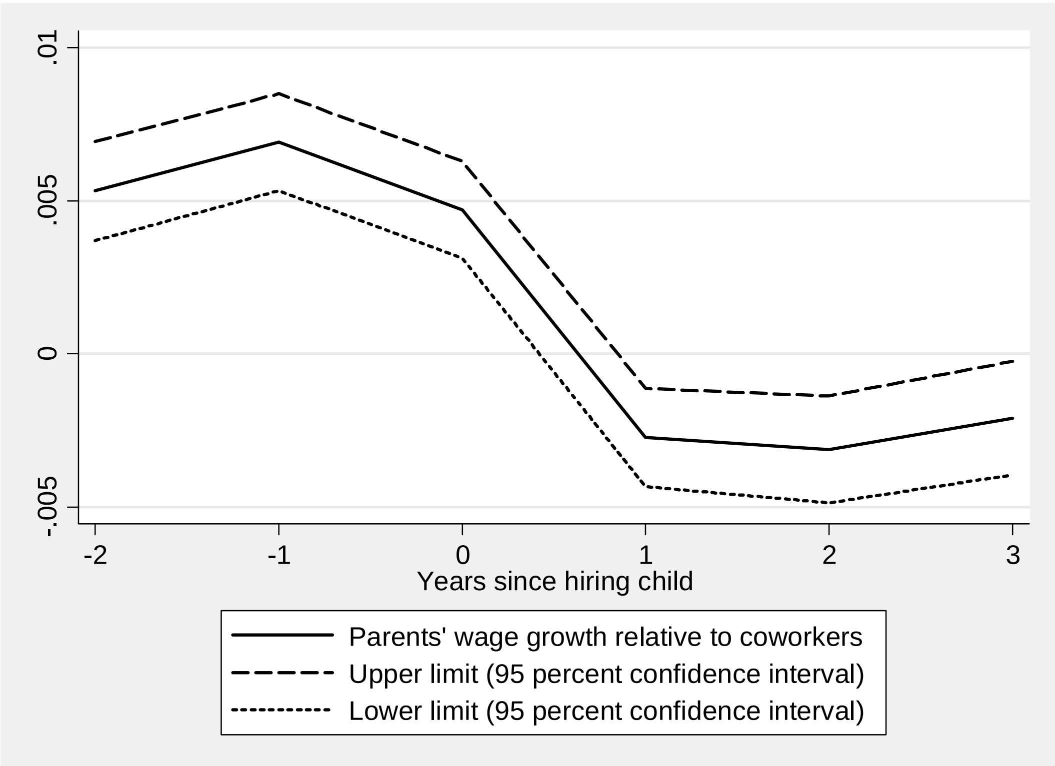

Figure 5 Wage growth (log difference) of recruiting parents relative to other stable co-workers (at least 35 years old and five years of ensuing tenure).

Finally, in Figure 5, we display the wage growth of parents before and after the recruitment of a graduate into the plant of the parent. The Figure displays the wage growth relative to that of other stable workers (aged at least 35 and with at least 5 years of tenure before leaving) in order to give an appropriate baseline and in order to exclude the recruited children from the calculation. The Figure shows that wage growth among the recruiting parents is above the mean wage growth before the child is hired, which is consistent with the picture emerging from the heterogeneity analysis. This extra wage growth does however stop at the exact time of recruitment of the graduate. We have analyzed the wage growth pattern of the other parent as well and we do find some indications of falling wage growth around the time of the child's first job (suggesting a labor supply reaction), but without the sharp pattern around the time of hiring shown in Figure 5. The pattern shown in the Figure suggests that parents either over-perform before the (possible) recruitment in order to provide a positive signal, or that child's recruitment is a substitute for their own wage increases. In any case, this result (as well as the results from the timing model) indicates real effects for the parent (and the parent's firm) around the time of the child's hiring (and graduation) which support the notion that the parent is indeed the agent of the match.

6 Conclusion

In this article, we have examined the impact of parental networks at the moment of entry on the labor market. We have presented a set of empirical models that allows the identification and the estimation of the magnitudes, sources, and effects of family based networks. For estimation, we used a unique data set constructed from various administrative data sources linking information on parents and children, giving the plant identifier of both parents and children, and identifiers of all classmates of all children graduating from any level of regular schooling in Sweden over a seven years period. We show that having your first stable job in the same plant as one of your parents is quite frequent. Or, conversely, a plant is substantially more likely to hire one of his employees' children than someone else from the same class.

We show that strong social ties as captured by family ties matter more, the weaker the position of the child. This is a robust finding which appears in many dimensions, in particular lower education, poorer grades, and higher unemployment increases the relative importance of strong social ties. This heterogeneity withstand models which account for other forms of (potentially correlated) heterogeneity on the parent, region, and plant side, most notably when comparing different parents employed within the same plant. We also show that the effects of weak ties are more equally distributed over weak and strong children implying that strong ties are relatively more important for poor performing children. Consistent with the strong ties hypothesis, we find that parents have to be present in the plant at the time of hiring, the effects become small once the parent has left the plant, and other plants within the parents' firm play virtually no role.

However, not all potential agents of the match matter equally. Those that do are mostly high-wage workers and have relatively long tenures at the plant, even controlling for plant fixed effects. The fact that parents with a strong position matter more is a result very much in line with Montgomery (1991). However, our results on the children observable characteristics do not fully support this type of models.

We also find that several dimensions of similarity reinforce the networks effects. The effects are stronger for parents with a similar field of education as that of their child, parents who work in industries for which the education of the child is useful, and the parent with the same gender as the child. Crucially, all such dimensions of heterogeneity increase the estimated effects relative to a control group of classmates who also share the same links to the plant (thus removing any direct effect of similarity).

Particularly telling is the fact that the occupation-education categories for which parents appear to matter the most are the ones that are least specific, and where destinations are harder to predict: not masons or cooks but secretarial work, sales, or administrative jobs. Hence, children in fields that are less well-defined, used in many different industries or plants, appear to be helped by their parents in order to locate, and get, their first jobs.

Finally, the initial wage paid to the child is lower than for equivalent persons entering the plant through other channels, again controlling for plant fixed effects. However, this is compensated in the mid-term; these children spend longer spells in their first job than hires without a parent in the plant. Firms thus appear to benefit from parental hiring, not by selecting better applicants, as suggested in Montgomery (1991), but by keeping these young hires for longer periods of time.

The identification strategies induced by our two empirical models capture the differential supply shocks that affect the different potential employing firms leaving firms' labor demand unaffected. Indeed, by comparing children from the same classroom with the same education potentially shared with that of their parents, we capture the differential connections between children and firms. Furthermore, by showing how the timing of graduation of children of their employees directly affect their hiring behavior; we see that firms adapt their recruitment patterns to directed supply shocks. Finally, the effect of having her child hired at one's own plant is being felt by the parent: wage growth gets negatively affected. These two elements demonstrate that parents are indeed the strong tie between the firm and the job-seeking child.

References

Arnott, R and J E. Stiglitz. (1991), "Moral Hazard and Non-Market Institutions: Dysfunctional Crowding Out or Peer Monitoring," *American Economic Review*, 81 (March), 179-90.

Åslund O., L. Hensvik and O. N. Skans "Seeking Similarity: How Immigrants and Natives Manage at the Labor Market", Working Paper 2009:24, IFAU, Uppsala.

Åslund, O., and O. N. Skans (2009), "Will I See you at Work? Ethnic Workplace Segregation in Sweden 1985-2002," *Industrial and Labor Relations Review*, vol 63, issue 3, article 6.

Ballester C., Calvó-Armengol, A., and Y. Zenou (2006), "Who's Who in Networks. Wanted: the Key Player", *Econometrica*, 74, 1403-1417.

Bandiera O., Barankay, I., and I. Rasul (2009), "Social Connections and Incentives: Evidence from Personnel Data" *Econometrica* vol. 77(4), 1047-1094.

Bayer, P., Ross, S. L., and G. Topa (2008), "Place of Work and Place of Residence: Informal Hiring

Networks and labor Market Outcomes" *Journal of Political Economy*, vol. 116(6) no 6, 1150-1196.

Beaudry P and J DiNardo (1991), "The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data," *The Journal of Political Economy*, Vol. 99, 4, 665-688.

Bentolila, S., Michelacci, C., and J. Suarez (2010), "Social Contacts and Occupational Choice," *Economica*¸ 77(305), 20-45.

Bertrand, M., Luttmer, E. F. P., and S. Mullainathan (2000), "Network Effects and Welfare Cultures," *Quarterly Journal of Economics*, 115, 1019-1056.

Bewley, T. F. (1999), *Why Wages Don't Fall During a Recession*, Cambridge: Harvard University Press.

Boorman S A (1975) "A Combinatorial Optimization Model for Transmission of Job Information Through Contact Networks" Bell journal of Economics 6, 216-49.

Calvó-Armengol, A. (2004), “Job Contact Networks,” *Journal of Economic Theory*, vol. 115, 191-206.

Calvó-Armengol, A., and M. O. Jackson (2004), “Social Networks in Determining Employment and Wages,” *American Economic Review*, vol. 94(3), 426-454.

Calvó-Armengol, A. and M.O. Jackson (2007), “Social Networks in Labor Markets: Wage and Employment Dynamics and Inequality,” *Journal of Economic Theory*, 132, 27-46.

Calvó-Armengol, A., Verdier, T., and Y. Zenou (2007), “Strong ties and weak ties in employment and crime”, *Journal of Public Economics*, 91, 203-233

Cappellari, L., and K. Tatsiramos (2011), “Friends’ Networks and Job Finding Rates,” mimeo.

Casella, A., and T. Hanaki (2008), “Information Channels in Labor Markets. On the Resilience of Personal Referrals,” *Journal of Economic Behaviour and Organization*, vol 66(3-4), 492-513, June.

Cingano F., and A. Rosolia (2008), “People I know: Job Search and Social Networks” CEPR Discussion paper 6818.

Conning J. (2005), “Monitoring by Peers or by Delegates? Joint Liability Loans and Moral Hazard,” Hunter College Department of Economics Working Papers 407.

Corak, M., and P. Pirano (2010), “Intergenerational Earnings Mobility and Inheritance of Employers,” IZA working paper 4876.

De Schweinitz, D. (1932), *How Workers Find Jobs: A Study of Four Thousand Hosiery Workers in Philadelphia*, Philadelphia: University of Philadelphia Press.

Dustmann, C., Glitz, A., and U. Schönberg (2010), “Referral-based Job Search Networks,” mimeo, paper presented at the 2010 SOLE meetings.

Fredriksson, P., and O. Åslund (2009), "Peer effects in welfare dependence--Quasi-experimental evidence", *Journal of Human Resources*, 44(3), 798-825.

Ghatak, M., and W. T. Guinnane (1999), “The economics of lending with joint liability: Theory and practice,” *Journal of Development Economics*, vol. 60, 195-228.

Ghatak M. (2000), "Screening by the Company You Keep: Joint Liability Lending and the Peer Selection Effect," *Economic Journal*, vol.110, Issue 465, July.

Granovetter, M. (1973), "The Strength of Weak Ties," *American Journal of Sociology*, 78 (May), 1360-1380.

Granovetter, M. (1983), "The Strength of Weak Ties: A Network Theory Revisited," *Sociological Theory*, 1: 201–233

Holmlund, B. (2006), "The Rise and Fall of Swedish Unemployment," in M Werding (ed), *Structural Unemployment in Western Europe: Reasons and Remedies*, MIT Press 2006.

Ioannides, Y. M., and L. D. Loury (2004), "Job Information Networks, Neighborhood Effects and Inequality," *Journal of Economic Literature*, 42 (4), 1056.1093.

Jackson, M. O. (2004), "A Survey of Models of Network Formation: Stability and Efficiency," in G. Demange and M. Wooders (Eds.), *Group Formation in Economics; Networks, Clubs and Coalitions*, Chapter 1. Cambridge U.K.: Cambridge University Press.

Jackson M O (2008) *Social and Economic Networks*, Princeton University Press, Princeton NJ.

Kahn, L. (2010), "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 17, 2.

Keane, M. P. and K.I. Wolpin, (1997). "The Career Decisions of Young Men," *Journal of Political Economy*, 105(3), 473-522.

Kramarz, F., and D. Thesmar (2011), "Social Networks in the Boardroom," CEPR Discussion Paper 5496, revised.

Laschever, R. (2005), "The Doughboys Network: Social Interactions and Labor Market Outcomes of World War I Veterans," Northwestern University working paper.

Manski C. F. (1993), "Identification of Endogenous Social Effects: The Reflection Problem" *Review of Economic Studies*, vol. 60, 531-542.

Millo G. and G. Pasini (2007), "Does Social Capital Reduce Moral Hazard? A Network Model for Non-Life Insurance Demand," University Ca' Foscari of Venice, Dept. of Economics Research Paper Series No. 59/WP, (August).

Montgomery, J. (1991), "Social Networks and Labor-Market Outcomes – Toward an Economic Analysis" *American Economic Review,* vol. 81, 5, 1408-1418

Munshi, K. (2003), "Networks in the Modern Economy: Mexican Migrants in the US Labor Market", *Quarterly Journal of Economics,* 549-599

Rees, A. (1966), "Information Networks in the Labor Market," *American Economic Review,* vol. 56, 1/2, 559-566

Skans O. N., P-A Edin and B. Holmlund (2009), "Wage Dispersion Between and Within Plants: Sweden 1985-2000" in Lazear E and K Shaw (ed) *The Structure of Wages,* University of Chicago Press, Chicago.

Topa, G. (2001), "Social Interactions, Local Spillovers and Unemployment," *The Review of Economic Studies*, 68, 261-295.

Vega-Redondo, F. (2006), "Building up social capital in a changing world," *Journal of Economic Dynamics and Control,* 30.

Appendix A: Data

A1 The establishment data

By dividing total remuneration by the number of months between the first and the last entry, we get a measure of monthly wages received from each employer. We use this measure of wages to define employment in a procedure which closely resembles how Statistics Sweden calculates employment from these data. We define a person as being employed if an employment spell a) covers February b) generates at least 50 % of a minimum monthly wage[27] c) for individuals having several jobs satisfying these criteria during one year, we only keep the job generating the highest income.

There are two main differences with Statistics Sweden's procedure. First, we study employment in February rather than November. We select this month in order to characterize where parents work at the *beginning* of each year. Second, we use a slightly higher wage threshold in order to minimize measurement errors in wages for employees working very few hours.[28]

The procedure provides us with a data set containing one February job per worker and year. The job is defined by a wage and a plant[29] and the plant can be linked to various characteristics such as industry and location. In some cases (5-6 %) an employee's job cannot be located at a specific plant, mostly because plants are defined by physical addresses and some jobs do not take place at a specified address. Examples of such jobs include home care, some construction workers, some sales persons, security personnel and workers lacking "normal" contracts such as artists, board members, and people mostly working at home. We consider the establishment information for these individuals as missing.

Throughout the analysis we use administrative identifiers to define physical establishments. However, the administrative numbers may change over time if there is a change in ownership or industry affiliation. Since part of the analysis builds on following plants over time we correct for this by linking plants with different identifiers but (almost) the same set of employees in order to minimize the impact of such changes. A plant with code "A" in year 1 is considered to be the same as a plant with code "B" in year 2 if a) more than 50 % of employees in plant A in year 1 works in plant B in year 2

[27] Defined as the wage paid to janitors that are employed by municipalities.
[28] For papers using similar strategies see e.g. Skans, Edin, Holmlund (2009) and Åslund and Skans (2009).
[29] We refer to all establishments as "plants".

and b) more than 50 % of those at plant B in year 2 worked at plant A in year 1 and c) at least 3 people worked in both plant A in year 1 and in plant B in year 2.[30] When such correspondences are found we change all the numbers in the data set back in time in order to get consistent data series.

A2 Defining classes and classmates

In order to construct the classes we use the most detailed level of the Swedish standardized educational codes ("sun-2000").[31] The field codes are provided with a four digit "hierarchical" structure, so that fields can be described at different levels of precision.[32] Since the same field of specialization can be provided at different levels, such as two or three year-long high-school training in construction work or bachelors/master degrees in economics, we always interact the field codes with the level codes in order to get our definition of a class (so that e.g. bachelor and masters degree graduates are coded differently).

As we show below, the class concepts differ slightly between the four different groups of graduates. Since the concept of a class is the basis for our identification, it is important to understand how these are constructed. Therefore, we now discuss in some detail how the classes are defined for each type of educational attainment.

For graduates from universities, we define a class by combining information on the graduation year and semester (fall or spring) and a code for the examining university or college. There are graduates from 88 different schools in the data. The field codes are quite precise; examples of specific fields are "Economics/economic history", "Law", "Medical Doctor, specialized in radiology", "Nurse, specialized in geriatrics", "Teacher in Math/Data/Science", "Science, Chemistry", "Civil Engineer, Chemistry". When we interact the field and level codes we get over 300 types of university educations within our analysis sample (see Table A1 below).

In the case of high schools we proceed similarly, and obtain 106 different vocational educations and 25 academic high school educations respectively. Because these programs are fairly standardized, we have a relatively small number of academic high school educations (as the name implies, these are mainly general courses aiming at the transition into higher education). The main academic programs are divided into "Social

[30] We relax c) when the set of workers is identical between the two years in the two plants.
[31] We transform codes from the old system to sun 2000 by means of a matrix provided by Statistics Sweden.
[32] The fourth digit is actually a letter, in order to provide a higher level of detail when needed.

Sciences or Humanities”, “Science”, “Economics”, and “Engineering”. The engineering program is more job-oriented than the other programs and many different specialties are provided (e.g. construction, machinery or electronics), in which case the graduates are coded according to their specialty. The engineering program also provides the opportunity to study for 4-years (coded separately).

The level of detail in the field of study is obviously much greater for vocational programs. Here, each program is directed to a specific occupation. The graduates are coded in fields such as “Construction work”, “Auto mechanics”, “Social work, child care”, “Trade and office assistants”, “Electricians, installations”, “Electricians, data, and telecommunication” ... In this case, there are also different levels since vocational programs can be either two or three years long.

Graduates from compulsory education do not belong to specific fields. Education in the compulsory schools is quite standardized even though some courses are chosen by the individuals. Compulsory school graduates may in many cases have started high school but dropped out, but we do not know what kind of training they may have received there. We however treat members of this group as unskilled, with no field of specialization. Thus a compulsory school “class” is defined as graduates from one compulsory school in a given year that either did not proceed to high school or dropped out if they did.

Table A1 Descriptive statistics of graduates and parents

	Comp.	Vocational	Academic	University	All
All graduates					
Female	0.435	0.421	0.524	0.602	0.491
Nordic immigrant	0.011	0.010	0.008	0.015	0.011
Other imm.	0.067	0.031	0.032	0.029	0.035
Age	16.063	18.399	19.013	25.096	19.746
Age (sd)	0.242	0.622	0.555	2.572	3.252
GPA	2.650	3.053	3.121	3.000	3.008
GPA (sd)	0.682	0.598	0.562	0.000	0.549
Mean class size	19.8	29.5	42.4	44.6	35.2
Class size (sd)	10.4	22.4	28.7	39.3	29.1
Class size by year of first job	5.2	11.1	13.2	28.4	14.8
(sd)	3.5	11.0	11.6	30.3	18.6
Number of fields	1	106	25	321	453
Father identified	0.974	0.985	0.987	0.973	0.981
Mother identified	0.995	0.998	0.998	0.983	0.994
Both identified	0.971	0.984	0.986	0.972	0.980
Father Employed	0.673	0.762	0.804	0.691	0.747
..in known plant*	0.580	0.652	0.714	0.610	0.651
Mother Employed	0.666	0.742	0.810	0.740	0.751
..in known plant*	0.590	0.651	0.742	0.681	0.675
Both Employed	0.383	0.458	0.563	0.479	0.482
Both in same Plant	0.029	0.034	0.045	0.038	0.037
N (graduates)	82,341	238,521	178,324	141,161	640,347
Employed parents with known Plant-ID, excluding agriculture and self employed					
Mother Nordic Immigrant	0.070	0.056	0.049	0.035	0.051
Mother Other Immigrant	0.063	0.050	0.067	0.171	0.084
Mother Compulsory	0.305	0.315	0.207	0.192	0.253
Mother Tertiary	0.193	0.161	0.329	0.433	0.277
Mother in same field	0.000	0.120	0.135	0.177	0.132
Mothers log Wage	9.430	9.272	9.380	9.391	9.349
Mothers log Wage (sd)	0.386	0.354	0.381	0.398	0.381
Mothers tenure	3.921	3.569	3.755	4.180	3.801
Mothers tenure (sd)	3.835	3.088	3.114	3.118	3.203
N (mothers)	48,608	155,161	132,322	96,166	432,257
Father Nordic Immigrant	0.051	0.043	0.034	0.025	0.038
Father Other Immigrant	0.092	0.095	0.116	0.264	0.136
Father Compulsory	0.400	0.422	0.254	0.220	0.327
Father Tertiary	0.156	0.126	0.298	0.404	0.239
Father in same field	0.000	0.192	0.281	0.215	0.205
Fathers log Wage	9.747	9.639	9.808	9.841	9.745
Fathers log Wage (sd)	0.418	0.373	0.432	0.481	0.429
Fathers tenure	4.884	4.286	4.239	4.516	4.388
Fathers tenure (sd)	4.316	3.312	3.269	3.161	3.406
N (fathers)	47,784	155,539	127,358	86,130	416,811
N (parents)	96,392	310,700	259,680	182,296	849,068
N (plants)	47,580	93,886	84,964	60,553	157,586

Note: Description of all graduates and employed parents with known Plant-ID:s. See Table A4 for a description of the transformed data used in heterogeneity regressions. * Also exclude self employed parents and parents employed in the agriculture and forestry industry.

A3 First stable job of graduates: Sample construction

For each graduate we look for the first stable job they have after graduation. Some of the university graduates had stable jobs before starting (or less commonly, during) university but these jobs are ignored. In order to get symmetry between the graduation cohorts we only include those that find a first stable job within 7 years after graduation (remember that the last graduating cohort is 1995 and data stop in 2002).

Table A2: Creation of job data (parents)

	All 16-65 (1988)		All 16-65 (1995)		Parents in graduation year	
	N	Fraction	N	Fraction	N	Fraction
Population (individuals)	5,334,727	1	5,607,753	1	1,265,142	1
Employment according to Statistics Sweden						
November	4,347,401	0.815	3,796,432	0.677	1,041,078	0.823
Anytime during the year	4,807,023	0.901	4,558,659	0.813	1,093,199	0.864
Data creation						
Jobs	8,149,152	1.528	6,982,150	1.245	1,817,233	1.436
Jobs with Plant-ID	6,562,635	1.230	5,880,534	1.049	1,363,349	1.078
Plants*	304,949	0.057	332,370	0.059	262,221	0.207
Individuals with jobs	4,974,115	0.932	4,696,508	0.838	1,004,948	0.794
…in February	4,588,783	0.860	4,202,953	0.749	858,313	0.678
..and earnings>cut-off	3,595,163	0.674	3,271,469	0.583	771,054	0.609
..and identified plant	3,306,485	0.620	3,058,382	0.545	718,751	0.568
..not self emp. or agriculture	3,137,681	0.588	2,900,262	0.517	681,861	0.539
Individuals with multiple jobs	53,126	0.010	42,275	0.008	158,820	0.126

Note: The "N" columns give the number of individuals, jobs or plants. The "Fraction" columns show "N" as a share of the total population (as given in first row). *Excluding self employed and agriculture/forrestry.

We then look for the plant in which each of the parents was employed in February during the year when the graduate found her first stable job. When applying our empirical model, we compare graduates from the same class finding their first stable job in a given year. Therefore, we drop observations for which all graduates from a given class found their jobs in a year and all had parents working in the same plant (since in these cases there is no variation within the fixed effect). In practice, this almost exclusively means dropping graduates who were alone in their class in finding a job in a particular year.

Our data set contains graduates, identifiers of their class (and thus their "field"), their personal characteristics, as well as the year he or she found her first stable job, as well identifiers for each student's mother and father. The identifiers are then used to check whether the plant in which the graduate finds her first stable job is a plant in which any of the parents to the classmates worked at the time.

Table A3 Creation of graduates' first job data

	Time (t) after graduation			
	t = -1	t = 1	t = 3	t = 5
Graduates with any job	0.864	0.885	0.881	0.873
Number of Jobs per graduate	1.478	1.590	1.439	1.417
Jobs at least 4 months	0.650	0.800	0.812	0.817
and 3 monthly wages	0.074	0.532	0.600	0.630
Known Plant-ID	0.067	0.479	0.551	0.590
Multiple jobs	0.002	0.029	0.032	0.040

Note: Colum for t = -1 excludes compulsory since no information is available before age 16

Table A4: Description of transformed regression data for Tables 6a and 6b

Variable	N	Weighted	Mean	Std. Dev.	Min	Max
Hired by parent	788,022	812,750	0.064406	0.241	0	1
Hired by classmates parent	788,022	812,750	0.004797	0.045	0	1
Network effect	788,022	812,750	0.059609	0.237	-1	1
Individual characteristics						
Female	788,022	812,750	0.492	0.495	0	1
Nordic Immigrant	788,022	812,750	0.006	0.077	0	1
Other Immigrant	788,022	812,750	0.022	0.144	0	1
Age at graduation	788,022	812,750	19.692	3.072	16	30
GPA	788,022	812,750	3.046	0.533	1	5
Only mother in Plant	788,022	812,750	0.497	0.496	0	1
Both parents in Plant	788,022	812,750	0.029	0.164	0	1
Compulsory	788,022	812,750	0.114	0.317	0	1
Academic HS	788,022	812,750	0.305	0.461	0	1
University	788,022	812,750	0.215	0.411	0	1
Mothers - measured relative to mean among mothers by child's education						
Nordic Immigrant	788,022	812,750	0.000	0.155	-0.070	0.965
Other Immigrant	788,022	812,750	0.000	0.195	-0.171	0.950
Compulsory education	788,022	812,750	-0.001	0.308	-0.315	0.808
tertiary education	788,022	812,750	0.001	0.310	-0.433	0.839
Same (1d.) field as child	788,022	812,750	0.000	0.233	-0.177	0.880
Log wage	788,022	812,750	0.045	0.264	-1.113	3.518
Tenure	788,022	812,750	0.004	2.290	-4.180	13.431
Fathers - measured relative to mean among fathers by child's education						
Nordic Immigrant	788,022	812,750	0.000	0.132	-0.051	0.975
Other Immigrant	788,022	812,750	0.000	0.236	-0.264	0.908
Compulsory education	788,022	812,750	-0.001	0.322	-0.422	0.780
Tertiary education	788,022	812,750	0.001	0.290	-0.404	0.874
Same (1d.) field as child	788,022	812,750	0.000	0.276	-0.281	0.808
Log wage	788,022	812,750	0.045	0.292	-1.515	4.439
Tenure	788,022	812,750	0.007	2.397	-4.884	12.761
Region and competition						
Metropolitan county	788,022	812,750	0.488	0.500	0	1
County Unemployment rate	788,022	812,750	0.048	0.030	0.008	0.128
Industry field match	788,022	812,750	0.086	0.180	0.000	1.000
Herfindahl	788,022	812,750	0.004	0.007	0.000	0.077

(Table continues on next page)

Table A4 (Continued)

Plant						
Private	788,022	812,750	0.491	0.500	0	1
New Plant	788,022	812,750	0.031	0.172	0	1
Plant growing	788,022	812,750	0.429	0.495	0	1
Size 1-15	788,022	812,750	0.258	0.437	0	1
Size 46-125	788,022	812,750	0.208	0.406	0	1
Size 126-750	788,022	812,750	0.206	0.405	0	1
Size 750+	788,022	812,750	0.119	0.324	0	1
Plant mean age of employees	788,022	812,750	42.7	4.6	21	65
Plant share of primary ed.	788,022	812,750	0.238	0.212	0	1
Plant share of tertiary ed.	788,022	812,750	0.290	0.272	0	1
Plant share of immigrants	788,022	812,750	0.104	0.116	0	1
Plant average log wage	788,022	812,750	9.517	0.275	8	13
Manufacturing	788,022	812,750	0.218	0.413	0	1
Construction	788,022	812,750	0.056	0.231	0	1
Wholesale or retail	788,022	812,750	0.184	0.387	0	1
Financial, corporate services	788,022	812,750	0.098	0.297	0	1
Education, R&D	788,022	812,750	0.105	0.307	0	1
Health, Social work	788,022	812,750	0.219	0.414	0	1
Personal, Cultural, Sanitation	788,022	812,750	0.047	0.212	0	1
Public administration	788,022	812,750	0.073	0.259	0	1

Note: Weights are according to the number of graduates with parents in each plant.

Table A5 Components in the estimated network effects of Table 2

	Compulsory school	Vocational high school	Academic high school	University degree	All
Fraction hired by fathers	0.1114	0.0890	0.0990	0.0218	0.0807
Hired by classmates father	0.0067	0.0074	0.0037	0.0019	0.0050
Estimated network effect	0.1044	0.0814	0.0952	0.0199	0.0755
Fraction hired by mothers	0.0867	0.0653	0.0715	0.0233	0.0603
Hired by classmates mother	0.0070	0.0083	0.0037	0.0035	0.0057
Estimated network effect	0.0794	0.0570	0.0678	0.0198	0.0545

Note: Rows correspond to R^A, R^{-A} and G of equation 2 to 3. For further details, see note to Table 2.

Appendix B Additional figures and tables

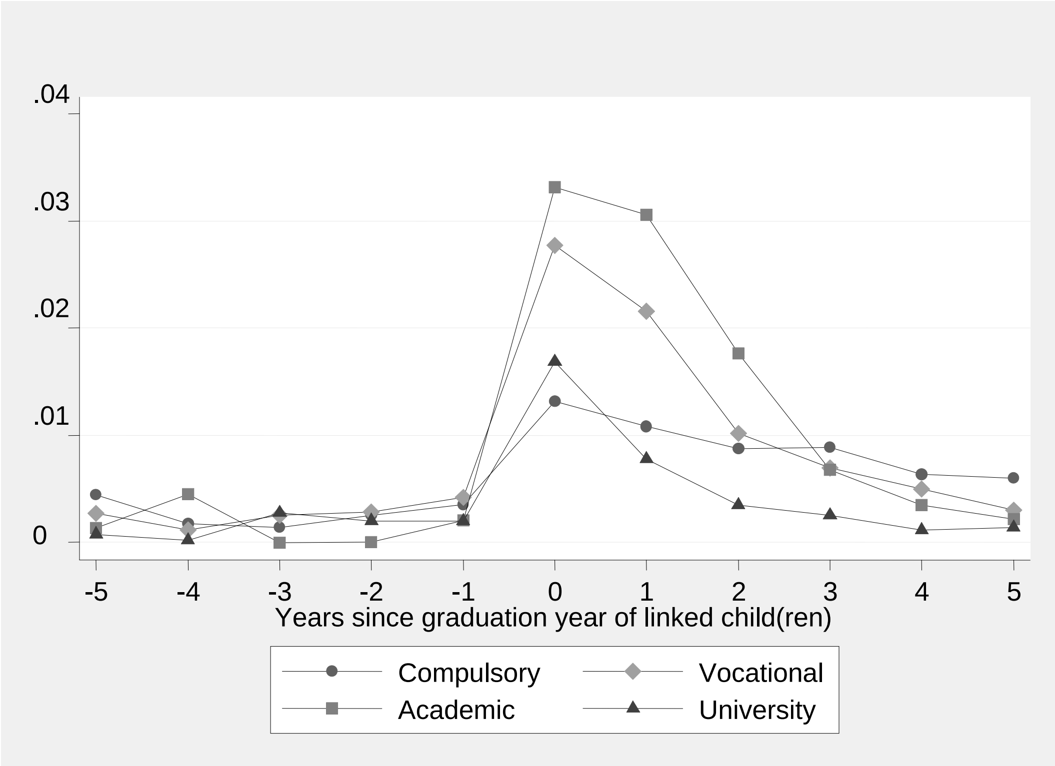

Figure B1 Fraction of graduates hired by a paternal-linked plant before and after graduation of linked child(ren), by education

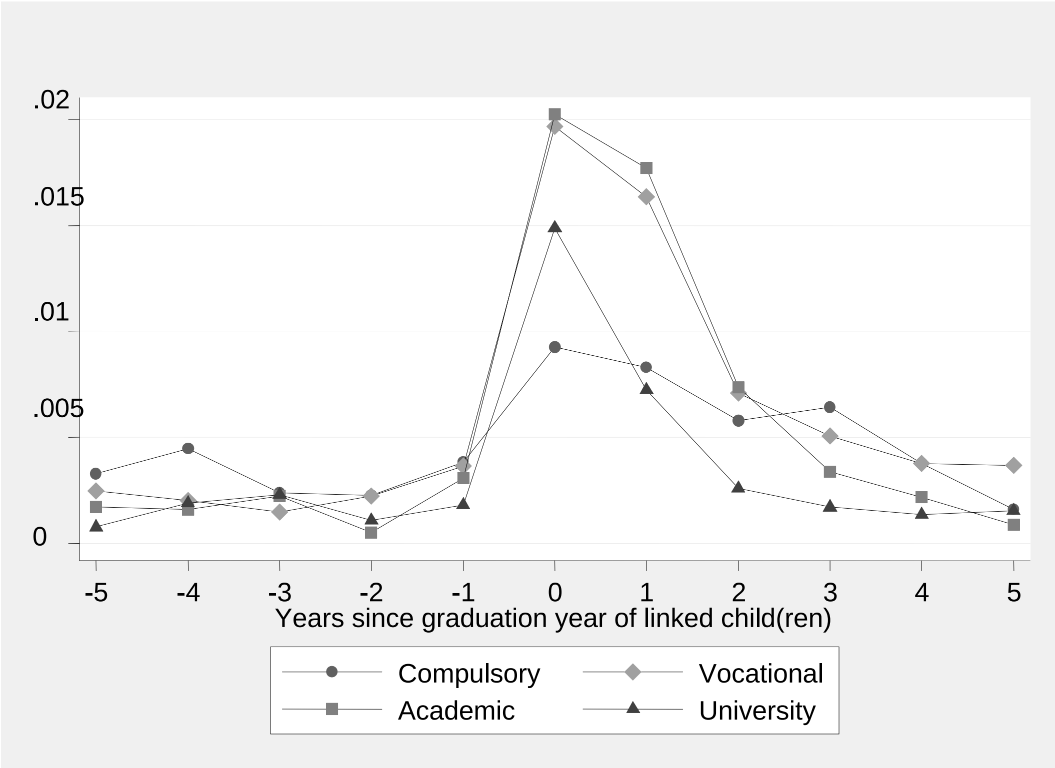

Figure B2 Fraction of graduates hired by a maternal-linked plant before and after graduation of linked child(ren), by education

Table B1 Parental Networks and the time to first job, within-class estimates

	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7
Fathers								
Compulsory								
γ	0.291	0.152	0.103	0.112	0.099	0.078	0.058	0.040
(s.e.)	(0.013)**	(0.004)**	(0.004)**	(0.004)**	(0.003)**	(0.003)**	(0.004)**	(0.004)**
N	1,299	7,603	6,414	8,163	8,296	7,006	4,913	3,178
Vocational								
γ	0.089	0.075	0.089	0.081	0.060	0.053	0.038	0.032
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.003)**	(0.003)**	(0.004)**	(0.005)**	(0.007)**
N	56,173	51,018	21,762	12,091	5,649	2,624	1,283	608
Academic								
γ	0.133	0.086	0.079	0.071	0.056	0.038	0.038	0.023
(s.e.)	(0.002)**	(0.001)**	(0.002)**	(0.003)**	(0.004)**	(0.004)**	(0.007)**	(0.008)**
N	36,449	45,550	23,818	10,931	4,434	1,901	810	386
University								
γ	0.024	0.012	0.022	0.024	0.020	0.004		
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.004)**	(0.006)**	(0.004)		
N	51,414	27,637	4,176	1,244	556	250		
Mothers								
Compulsory								
γ	0.196	0.094	0.089	0.096	0.079	0.057	0.050	0.048
(s.e.)	(0.013)**	(0.003)**	(0.004)**	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.004)**
N	1,110	7,118	6,378	8,169	8,662	7,346	5,223	3,368
Vocational								
γ	0.067	0.056	0.053	0.042	0.038	0.032	0.035	0.036
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.002)**	(0.003)**	(0.004)**	(0.005)**	(0.007)**
N	53,505	50,445	22,345	12,644	5,947	2,797	1,382	668
Academic								
γ	0.105	0.061	0.048	0.043	0.031	0.035	0.028	0.018
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.002)**	(0.003)**	(0.004)**	(0.005)**	(0.006)**
N	36,242	46,516	24,784	11,626	4,784	2,086	912	437
University								
γ	0.023	0.016	0.011	0.011	0.006	0.000		
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.003)**	(0.003)*	(0.000)		
N	57,074	30,618	4,728	1,448	683	281		

Note: Estimates of parental network effects. An observation is a combination of class, plant, and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Only regressions with at least 100 observations are shown. Standard errors are cluster-corrected for dependencies within class. ** (*) Significant at the 1 (5) % level.

Table B2 Parental networks effect on probability of finding the first job in a specific plant, depending on whether field of study matches that of parent

	Same 1-digit field	Same 2-digit field	Same 3-digit field	Different 1-digit field	Different 2-digit field
Vocational					
Fathers					
$\hat{\gamma}$	0.121	0.137	0.169	0.072	0.073
(s.e.)	(0.002)**	(0.003)**	(0.011)**	(0.001)**	(0.001)**
N	21,850	13,234	1,426	119,735	131,158
Mothers					
$\hat{\gamma}$	0.089	0.104	0.132	0.052	0.053
(s.e.)	(0.003)**	(0.004)**	(0.006)**	(0.001)**	(0.001)**
N	13,404	8,761	4,544	131,417	137,463
Academic					
Fathers					
$\hat{\gamma}$	0.117	0.119	0.107	0.087	0.088
(s.e.)	(0.002)**	(0.002)**	(0.003)**	(0.001)**	(0.001)**
N	29,045	23,958	15,313	89,541	94,906
Mothers					
$\hat{\gamma}$	0.094	0.096	0.101	0.061	0.061
(s.e.)	(0.002)**	(0.002)**	(0.003)**	(0.001)**	(0.001)**
N	20,970	19,963	14,649	102,492	103,754
University					
Fathers					
$\hat{\gamma}$	0.025	0.032	--	0.020	0.020
(s.e.)	(0.002)**	(0.003)**		(0.001)**	(0.001)**
N	27,888	10,403		61,795	79,692
Mothers					
$\hat{\gamma}$	0.023	0.031	--	0.022	0.022
(s.e.)	(0.003)**	(0.007)**		(0.002)**	(0.002)**
N	1,976	575		97,802	99,525

Note: Estimates of parental network effects. An observation is a combination of class, plant, and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Only regressions with at least 100 observations are shown. Regressions based on those within the class who have the same (or different) field of education as their parent. Standard errors are cluster-corrected for dependencies within class. ** (*) Significant at the 1 (5) % level.

Table B3 Parental Networks Effect on the Probability of Finding the First Job in a Specific Plant, Baseline Within-Class and Neighborhood estimates

	Compulsory school	Vocational high school	Academic high school	University degree	All
Fathers					
All					
$\hat{\gamma}$	0.111	0.074	0.087	0.013	0.081
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	39,485	67,195	71,456	18,644	196,780
Males					
$\hat{\gamma}$	0.151	0.110	0.117	0.021	0.116
(s.e.)	(0.003)**	(0.002)**	(0.002)**	(0.002)**	(0.001)**
N	19,156	32,916	24,499	5,513	82,084
Females					
$\hat{\gamma}$	0.056	0.032	0.061	0.009	0.045
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	12,878	26,523	31,182	9,134	79,717
Mothers					
All					
$\hat{\gamma}$	0.081	0.053	0.063	0.012	0.058
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	39,868	66,359	73,455	20,687	200,369
Males					
$\hat{\gamma}$	0.065	0.041	0.055	0.009	0.048
(s.e.)	(0.002)**	(0.001)**	(0.002)**	(0.001)**	(0.001)**
N	19,204	32,577	25,067	6,143	82,991
Females					
$\hat{\gamma}$	0.102	0.067	0.068	0.013	0.067
(s.e.)	(0.003)**	(0.002)**	(0.001)**	(0.002)**	(0.001)**
N	13,105	26,035	32,224	10,067	81,431

Note: Estimates of parent network effects. An observation is a combination of class, plant, and year of first job. Weighted by the number of graduates with parents in the plant. Data are for graduates 1988-1995 finding a stable job within 7 years of graduation. Standard errors are cluster-corrected for dependencies within class. **Significant at the 1 % level.

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