With a Little Help from my … Parents ?

Family Networks and Youth Labor Market Entry[*]

by

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April 2, 2007

Abstract

The paper studies the importance of family networks on the labor market. Since family networks appear to be particularly important for young workers we focus on the way such networks affect the transition from school to work. We study if young workers find their first stable jobs in plants where one of their parents is working. We use a Swedish population-wide linked employer-employee data set that also includes detailed information on family ties and detailed information on schools and class composition. Because we are able to follow all students graduating from the school in the same year within the same class and the same field of study (thus the same expected occupation) into their employing plant, where one of their parent can also be employed, we can identify the direct effect of family relationships controlling for confounding factors, in particular those related to location, education, or occupation. Results show that family ties are indeed important for the transition from school to work, in particular for low-educated males who tend to follow their fathers. Then, we show what parental employment characteristics (wage and seniority, in particular) affect referral hiring, how the speed of school to work transition, the wage at hiring, and job duration are impacted by family-referral hires.

[*] We thank seminar participants at Uppsala University, the Nordic Summer Institute in Labor Economics, CREST lunch seminar, ESSLE in Ammersee, CEMFI in Madrid, Winter Meetings of the Econometric Society in Chicago for their remarks, and Giacomo di Giorgi, Ulrike Malmendier, and most particularly Melissa Tartari for helpful comments and suggestions.

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1 Introduction

In this article, we stand at the junction of three literatures. The first two – the intergenerational transmission of income, education and occupations and the factors affecting the school-to-work transition -- are classic questions in labor economics and sociology. The third one, the extent and role of social networks in developed economies, is burgeoning both on the theoretical side (see Montgomery, 1991, or more recently Calvo-Armengol, 2004 and 2006, Calvo-Armengol and Jackson, 2004, Casella and Hanaki, 2005, among many authors, and Jackson, 2005 for a very thorough survey) as well as on the empirical side (see Munshi, 2003; Bayer, Ross and Topa, 2005, Bertrand, Luttmer and Mullainathan, 2000, Fredriksson and Åslund, 2005, 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 works of Rees (1966) and Granovetter (1973).

Our contribution is empirical. We focus on the role of family networks on the transition from school to the first stable job. But, when most analyses remain very loose on the precise person in the network used when finding a job (someone from the family, someone from the same village, a friend), we can track both parents and children exact employer and employment characteristics in each firm or plant in our sample. Hence, we know when a person finds her first stable job in the same plant as her father or her mother. When most analyses have information on the hired side, we have detailed information on the referral – the father or (and) the mother – as well as detailed information on the referred – the daughter or the son. Hence, we are able to measure the relative wage or seniority of the parent who is able to hire her son or daughter within her firm. We are also in position to measure the relative wage of the hired son or daughter in the firm or to see if her occupation is similar to that of the parent. When most analyses have no good control or comparison group, we are able to follow any given student at the time she completes her education together with all her classmates; i.e. all persons within a given school, a given graduation year, and a given field of education that are potential competitors for the same occupations in the same firms. Hence, we can measure the impact of having a parent employed in a given firm when others have none.

Related literature: The "informal" hiring channel is the focus of growing number of 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.

A line of study relies on the neighborhood as the source of information about jobs 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 (2005) 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.

In contrast to these papers, we use extremely precise and error-free measures of family links between the referred (the child) and the referral (the father or the mother). For both of them, we have virtually all information that one classically has in surveys, even though the data we use are administrative. Hence, the father and the mother are our equivalent to the neighborhood in Bayer et al.'s approach. In contrast to these studies, we use an exhaustive sample of all persons who leave school between 1985 and 2002. 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. In the spirit of Laschever, we also define a reference group for each person for whom we examine entry in a first job – 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. Hence, we can use two 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,…). Again, in contrast to all previous studies, we directly measure outcomes at the level of the plant where parents and children are working together, looking also at co-workers and new hires who entered this particular plant by channels other than referral hiring.

Our findings can be summarized as follows. First, having your first stable job in the same plant as, at least, one of your parents is quite frequent. Or, conversely, a plant is more likely to hire one of his employees' children than someone else from the same class. This effect is particularly strong for relatively low-educated males, for Nordic immigrants, in manufacturing jobs. In this process, the father is central for sons when the mother is useful for daughters.[1] Children trained in the same field of study as their father or their mother are more likely to benefit from referral hiring (or equivalently, a plant is even more likely to hire one of his employees' child than some other kid in the child's class when the child and the parent share the same field of study). Referral hiring is most frequent in less competitive industries, in large plants that have a large fraction of low-education workers and many immigrant workers. In addition, parents able to hire their children are high-wage workers and have relatively long tenures at the plant, even controlling for plant fixed effects. However, on the children side, some elements tend to show that being hired by one's parents is not necessarily the outcome of a fully unconstrained choice. First, these children' grades at school tend to be lower than those of their classmates. Second, referral hiring tends to take place when unemployment is high. Finally, the initial wage paid to the child is lower than for equivalent persons entering the plant through other channels. However, this initial mismatch is compensated in the mid-term; these children spend longer spells in their first job than hires without a parent in the plant.

[1] Our results control for self-employment of the parents.

The rest of the paper is structured as follows: First, section 2 discusses the 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

A good starting point when studying the potential role of referral hiring on labor market outcomes, in our context at least, is Montgomery (1991). In this two-period model, workers live one period each, and can be of two types, either high or low ability. There is an equal number of workers in each period and of each type. Finally, firms do not observe workers' type before production (high ability workers produce one unit of output when low ability workers produce zero). On the firm side, each firm has at most one worker and the profit is productivity minus wage and sets the wage before production.

Montgomery adds the following social structure. Each period-1 worker knows at most one period-2 worker. But, period-2 workers may hold multiple ties with period-1 workers. If a period-1 worker holds a social tie, the specific period-2 worker's type is first randomly selected (by assumption, this period-2 worker has the same type as the period-1 worker with probability α strictly greater than ½). Then, the specific worker is chosen among those with the type just selected.

Firm *i* may hire through the market (wage w_{m1}) or through referrals (wage w_{ri}). If a referral hire is offered, the period-1 worker with a social tie conveys the offer to her period-2 acquaintance. Period-2 workers compare wage offers received and, when refusing referral offers, find employment through the market which clears at wage w_{m2}.

The equilibrium schedule induces wage dispersion for the referral wage offers (on all these claims, see Montgomery). In equilibrium, proposition 1 of Montgomery states that "a firm makes a referral offer if and only if it employs a high-ability worker in period 1". Therefore, most workers receiving referral offers are high-ability (because high-ability old workers are connected with high-ability young workers with probability greater than ½).

Now, given free entry of firms and the lack of information on workers' quality, firms hiring through the market make expected zero profit when firms using referrals earn expected positive profit in the second period.

Many extensions are clearly possible and some are mentioned in Montgomery (1991) or in Casella and Hanaki (2005). Interesting for us is the possibility of the existence of two types of technologies in firms, one more ability sensitive than the other. Hence, the high-ability type is more productive in the former whereas the low-ability type is more productive with the latter. Then, referred workers will be assigned preferentially to the ability sensitive technology. It is also likely that referrals are used more in situations where there are less alternative sources of information, such as when unemployment is high.

To summarize the predictions of the above model, we see that workers who make the referrals should be high-ability workers, with longer tenures in the firm (allowing the firm to know worker's ability), in ability-sensitive technologies (potentially because of learning aspects of the job).

According to this model, workers who are hired through referrals should be high-ability too, should be better compensated, and should also stay longer periods of time in the hiring firm. However, because of the learning aspects of such jobs, the wage profile could be steeper but could also start from a low point. Furthermore, other papers tend to emphasize the potential productivity mismatch in referral hiring (Bentolila, Michelacci, Suarez, 2006).

2.2 Empirical model

Our empirical model should help us understand how networks, as measured by parents' employment, affect the search for first stable jobs. In addition, we want to apportion the role of the respective characteristics of the student, of the parents, of the plant of the parents, and of labor market conditions. 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. Below we present the details of our empirical model.

2.2.1 The basic model

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 (2006), we use the following linear model for the probability that graduate *i* starts working in plant *j*:[2]

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

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 we return to a more general case below. Finally, the error term ε captures all other factors within a class that affects the probability that graduate *i* starts working in plant *j*.

If ε and *A* are orthogonal given the class-plant fixed effects β, 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

[2] Note that the probability of a given graduate will start working in a particular plant is likely to be small (even if the parent works there); it thus seems to be a reasonable approximation to formulate the model as a linear probability model.

year, estimation of such a model would therefore require construction of a data set with nearly 200 billion observations.

In order to transform equation (1) into an estimable model, we use a methodology invented by Kramarz and Thesmar (2006). 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 compute, for each plant-class combination, the number of people hired from the class by their parent's plant:

$$n_{cj}^{EA} \equiv \sum_i^{c(i),j} E_{i,c(i),j} A_{i,j} = \beta_{c,j} \sum_i^{c(i),j} A_{i,j} + \gamma \sum_i^{c(i),j} A_{i,j} + u_{c,j}^{A}$$

and the number of children from the class having a parent in the plant,

$$n_{cj}^{A} \equiv \sum_i^{c(i),j} A_{i,j} \ .$$

Taking the ratio of these two numbers, we get

$$(2) \qquad R_{cj}^{A} \equiv \frac{n_{cj}^{E,A}}{n_{cj}^{A}} = \beta_{c,j} + \gamma + \tilde{u}_{c,j}^{A} ,$$

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 sum of 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. This yields

$$n_{cj}^{E,-A} \equiv \sum_i^{c(i),j} E_{i,c(i),j} (1 - A_{i,j}) = \beta_{c,j} \sum_i^{c(i),j} (1 - A_{i,j}) + \sum_i^{c(i),j} \gamma (1 - A_{i,j}) A_{i,j} [= 0] + u_{c,j}^{-A}$$

together with the total number of graduates from the class without parents in the plant,

$$n_{cj}^{-A} \equiv \sum_i^{c(i),j} (1 - A_{i,j}) \, .$$

Proceeding as above, we compute the ratio of these two numbers:

$$R_{cj}^{-A} \equiv \frac{n_{cj}^{E,-A}}{n_{cj}^{-A}} = \beta_{c,j} + \tilde{u}_{c,j}^{-A}$$

Thus, taking the difference between the two ratios eliminates the plant-class fixed effects $\beta_{c(i),j}$:[3]

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

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*.[4] 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 taking the difference in hiring probabilities between pairs in the same class where one has a parent in the plant and the other not.

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?*"

(At least) two main objections can be raised to this 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.

2.2.2 A model with interaction effects

Estimation of equation (3) answers the question of how important parental contacts are on average, but does not provide any insights into when and for whom these contacts matter the most. We therefore expand our original model (equation 1) so as to incorporate effects that may vary with characteristics of the graduate (i), the parent (p), the plant (j), or the labor market (l). This yields the following model with interactions:

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

where we have included parametric 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}.

[3] 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.

[4] 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 more than one parent in the same plant.

Since all terms which are added to the framework of equation (1) are interacted with the presence of a parent in the plant we may proceed as above and get an expanded regression framework equivalent to equation (3) that writes:

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

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) are interaction terms between a parental contact and the measured characteristics, but the underlying model is the same as previously. Thus, estimating the model 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*?

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. As an example, 85 % of those born 1973 graduated from high-school before the age of 20 (see Table 1).

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 year long (with a 4-year version for engineers) whereas vocational programs were 2-year long. All students from the academic programs but, in general not those from the short vocational programs, were eligible for university admission although specific requirements for admissions were common. Due to a reform of the vocational programs in 1994, all Swedish high school students graduating after 1994 receive a 3 year 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 that the Swedish labor market ever faced since World War II: the unemployment rate which was below 5 % since the 1960s (and was below 2 % in the late 1980s) suddenly increased to 8 % in the early 1990s. Explanations for this severe recession are typically based on a combination of bad policies and bad luck (see e.g. Holmlund, 2006). The unemployment rate remained high until the late 1990s when it started to decline and by the year 2002 the unemployment rate had declined to 4 %. The time pattern for youth unemployment showed a similar time pattern (see Figure 1).

The 1990s also saw a rapid expansion of the proportion of the working-age population enrolled in some form of education. Part of this expansion was due to increased participation in regular education but another contributor was the so-called “active policy” measures directed towards the unemployed (and to some extent also to the employed) such as the “adult education initiative”. 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 (see *Figure 2*).

4 Data and description

The paper makes use of a wide range of population wide data sources combined in the Swedish 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. We provide the reader with a fairly detailed overview of our procedure used the various data sources in order to obtain our analysis sample. For further details about the number of observations at different stages of the data generating procedure we refer the reader to the data appendix. The description has two parts; each contains a set of descriptive statistics. The first part describes the general employment data and parental links. The second part focuses on the graduation data.

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.[5] 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.

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[6] 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 to 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.[7]

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[8] and the plant can be linked to various characteristics such as

[5] Statistics Sweden refers to this data base as RAMS.
[6] Defined by the wage paid to janitors employed by municipalities.
[7] For papers using similar strategies see e.g. Edin, Holmlund and Skans (2006) and Åslund and Skans (2005).
[8] We refer to all establishments as “plants”.

industry and location. In some cases (5-6 %) an employee's job can not 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 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.[9] When such correspondences are found we change all the numbers in the data set back in time in order to get consistent data series.

To the constructed worker-plant data we link basic demographic characteristics of individuals such as gender, age, level of completed education and country of birth as well as an indicator of whether a person is self-employed. We also calculate 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 each 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 had 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)[10] and sector (private or public). For each two-digit industry we calculate an employment based Herfindahl-index (*H*) as the sum of squared employment shares in each plant (*j*) which captures the level of competition by industry (*I*) and year (*t*):

$$H_{I,t} = \sum_j \left(Size_j \middle/ \sum_j Size_j \right)^2 .$$

The Herfindahl-index measures the lack of competition as a distance between zero and one, where one corresponds to a situation 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 contain 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. Thus, the data is in general *not* for step-parents, but for biological parents. Missing values (mainly) occur for individuals where the parents

[9] We relax c) when the set of workers is identical between the two years in the two plants.
[10] 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.

are not in the IFAU-population; hence either the parent has an age outside 16 to 65 during our analysis period, 1985-2002, or has not resided in Sweden during this period. There are also a (very) small number of “father-unknown” cases. Overall, missing values in parent codes is nearly exclusively a phenomenon affecting older individuals (where the parents are not in the data) and immigrants arriving without their parents. Thus, because our main purpose is to study the labor market outcomes of young individuals, missing values on parental data is a minor problem, as will be confirmed below.

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 the child and the parent are employed. We do this mainly because we intend to describe the pattern of joint presence at plants among the employed. The numbers refer to the fraction of employed children having a parent (or both) present at the workplace. Furthermore, we only study those aged 40 or below since very few individuals older than 40 have employed parents. The first column of Table 2 shows descriptive regressions on the probability of at least one parent employed at the plant if at least one of them is employed (for different sub-groups). The second and third columns show regressions for the probability of having the mother and father respectively employed at the plant if they are also 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, however, this estimate is imprecise due to the fact that very few foreign born have employed parents in the country. Since recent cohorts have entered the labor market at a slightly older age, age effects and time effects may be confounded; still prevalence of parental networks may have changed over time. To investigate this issue, Figure 3 shows the time pattern from 1985 onwards. Figure 3 uses the 1985 distribution of age, gender, education, immigration status and type of region and weight the subsequent years according to the 1985 distribution to get a pattern purged from changes of individual level variables. We find little evidence of trends, but a clear cyclical pattern, especially for the fractions working with fathers (remember that 1993-1998 are the high-unemployment years).

4.2 Graduation data and first stable jobs

4.2.1 The population of interest

Our population of interest is constructed from the graduation records for the years 1988 to 1995, coming 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).

We create our sample from four different populations defined by their educational attainment:

1. *Compulsory schooling* includes individuals who completed compulsory schooling but did not complete high school. Some of these individuals may have started high school but dropped out for one reason or another.
2. *Vocational high school* includes individuals who complete a two or three year vocational high school education before age 21 without proceeding to university before finding a first stable job (see below).
3. *Academic high school* includes individuals that complete 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 (see below).
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 only use the concept of a class to control for factors that are time, region and occupation specific (how this is done is explained in detail above) and we do *not* use the concept to capture interactions between class mates.

In order to construct the classes we use the most detailed level of the Swedish standardized educational codes ("sun-2000").[11] The field codes are provided with a four digit "hierarchical" structure, so that fields can be described at different levels of precision.[12] 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.

In the case of high schools we proceed similarly, and obtain 146 different vocational educations and 21 academic high school educations respectively. Because these programs are fairly standardized,

[11] We transform codes from the old system to sun 2000 by means of a matrix provided by Statistics Sweden.
[12] The fourth digit is actually a letter, in order to provide a higher level of detail when needed.

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 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.

4.2.3 Other educational variables

Apart from basic demographic characteristics, data contain information on grade point average (GPA) for compulsory and 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 Definition of the first stable job

In order to study parental networks and their role for children labor market insertion, we need to define what “real” or stable jobs are, in particular by opposition with those jobs held when at school (for which parents are likely to help). For this reason, 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 the monthly minimum wage. The reason for these restrictions is that we wish to restrict the analysis to jobs that are fundamentally different from the jobs held during school. As shown in the appendix (Table A3) 44 percent of graduates satisfy these criteria the year after graduation whereas only 7 percent satisfy them the year before graduation.

4.2.5 First stable job of graduates: Sample construction

Here we outline how our analysis sample is constructed. In the data appendix, we present data construction in greater detail along with numbers of observations that were dropped at each stage.

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).

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. We drop all cases where the parent is employed in a plant lacking identifying number. When applying our empirical model, we always compare graduates from the same class in a given year. Therefore, we drop observations for which all graduates from a given class found their jobs in a year and had parents working all in the same plant. 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 worked at the time.

4.2.6 First stable job: Description

Below we describe some of the characteristics of our sample. Figure 4 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. The two high school samples are in between. Figure 6 shows changes over time (by graduation year). Clearly, the worsening of the labor market in the early to mid 1990s coincides with an increased duration of transition from school to work in Sweden, in particular for the low educated.

The appendix (Table A1) provides descriptive statistics for our four samples. Parents’ characteristics are computed for the parents who are employed. When estimating equation (6) we transform the data showed in table 4 according to our empirical model. The data appendix also shows descriptive statistics for these transformed data for all the variables used in the empirical analysis (Table A4).

5 Results

5.1 The basic model – how important are parents?

In this section we estimate the effect on the probability that the first stable job is found at the plant of the parent using equation (3). The referral effect (γ) we estimate captures the excessive probability a graduate has to find his first stable job at the parent's plant after removing the importance of exact education, location, time of graduation and time of finding the first stable job since comparisons are made within class and year of first job. Table 3 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, for male children, and for female children, respectively. First, all estimates are strongly positive. Hence, graduating students are more likely to go in the plant where one of their parents is employed than in any other plant, in comparison with their classmates. The effect is particularly strong for the low-education group. It 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 undergraduate or at the graduate level). And, strikingly, fathers tend to hire their sons when mothers tend to hire their daughters, albeit with a lower intensity.

Table 4 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.

5.2 Robustness of the basic results

Below we discuss a variety of robustness checks, in particular in order to examine how results are affected by some of our initial modeling choices.[13] First, we changed the definition of the *timing* to the first job.[14] 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 does not alter our results; estimates are very similar when defining the comparison group using all individuals from a class, irrespective of their year of first job. We also estimated the model separately for each of the first seven years after graduation. Results show a clear declining pattern over time implying that parent referrals usually take place in the first years after graduation and become less important over time. This result is particularly true for the low-educated; 28 percent (resp. 20 percent) of males (resp. females) with a compulsory school education who find a job within the first year after graduation are being referred by their fathers (resp. mothers).

[13] All the detailed results described in this subsection are available upon request.

[14] 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 similar to those presented in Table 3 were equal to zero.

Second, we performed sensitivity tests in order to assess quality of our 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. However, in order to assess robustness of this identifying assumption, one potential solution could be in using variation over time in the plant at which the parents are employed. Then, it becomes possible to assume, say, that preferences for a given plant are the same for a child's siblings – which are observed in our data – or, put differently, that these preferences are not correlated with the moment *when* the parent works in a particular plant. However, when inspecting the data, we find that parents who change plants between the two dates of entry on the labor market of their children are much less likely to hire any of their children than other parents are. This is not surprising since we show below that parents who are able to have their child hired in their plant are long-tenured workers. But, parents who switch plants, and can be included in the test we just described, have by definition shorter tenure in at least one of the two plants. In addition, the probability (around 2 percent) that someone works in a plant before or after the parent worked there is not likely to be a good estimate of the counterfactual probability that he would have worked there even if the parent had never been employed in that plant. Indeed, children working in a plant before one of her parent may well be used by the parent as referral (reverse causality) or, conversely, parents may help their children getting into a plant, even after leaving it. Both of these factors will lead to an overestimate of the probability that a child works in the same plant as her parent in parent's absentia.

For similar reasons, identifying referral effects by using movements over time for the same individual (even if we included jobs beyond the first job) is not feasible. To understand this, it is useful to compare to Kramarz and Thesmar (2006) who look at CEOs and board members. In their case it is possible to include individual effects and look at changes over time, because board members may hold multiple seats, both in any given period or across periods. By contrast, the average parent of a graduate does not change job very frequently and virtually never hold multiple jobs. Thus, parental mobility cannot be used for identification in our case.

To test 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, we have instead re-estimated the model after dividing each class according to the industry (rather than the plant) in which the parents work, thus comparing each student to others graduating from the same class with *parents employed in similar (same industry), but not identical, plants*. The results are essentially similar, albeit a little smaller, to the ones we presented. We have also performed the same analysis by dividing the class according to the *industry the graduate ends up in*, and again the results are very similar to the ones presented. This suggests that the estimated referral effect is not sensitive to diverging preferences over types of firms within a class.

Third, 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. However, this effect is likely to be small. 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 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 for different total numbers of hires (1, 2-5, 6-10, 11 or more) made by the plant in the relevant year. Here, if there is "crowding out", it should have a strong effect for plants that only hire a unique person – and less of a problem if many new employees are hired. The estimates for plants which hire a unique worker are slightly larger than for those hiring 2 to 5 or 6 to 10 workers, but essentially similar to the estimates for those plants hiring more than 11 workers. In addition, we also find that whenever a graduate is hired in a plant in which the parent of a classmate also works, then it is virtually always true that the classmate is also hired. Furthermore, between 2 and 4 percent of graduates are hired when a classmate with a parent in the plant herself *is* hired. For a more direct test, we have re-estimated the model under the assumption that the increased probability of being hired provided to those with a parent in the plant results in a proportional reduction in the hiring probability shared equally among the classmates.[15] The importance of this correction will, for mechanical reasons, depend on the size of comparison group and thus we do not include it in the main tables. If we compare to classmates in all years in which they find their first job, we find that the correction is negligible; a natural result given that many classmates have a parent in any given plant in some year. If we, on the other hand, use the original specification which partition the class by the year of the first job, we have much smaller classes (i.e. on average 5 for compulsory school graduates) and the estimates are therefore reduced slightly more, but even in this fairly extreme case where we assume that all vacancies are predetermined to be given to one worker within such a small group, the estimates only fall by one-third.

Fourth, the estimates we present are based on plant-level data. It is however possible that parents help their children only 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 referrals is much more limited in the public sector (as will be shown in the following section). The correction is especially important for mothers who work more often than fathers in the public sector.[16] Now, changing our unit of analysis (from plant to firm), given that we only examine the private sector, leaves the estimates essentially unchanged. The difference in estimates between the plant and the firm specifications is less than 1 percent (less than 0.5 percent for the university sample), suggesting that referral hiring is mostly performed at the plant, rather than at the firm. This is true for all educational levels.

Fifth, we have looked at various sub-samples, dividing the data according to various specificities of the parents' educational fields and industries. First, we find that parents in fields (narrowly defined at a three digit level) which have become obsolete (defined by 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. We do however find that parents trained in the same field as their child help more whereas parents working in industries that tend to hire graduates with their child's specialty also help more.

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[15] Formally, let us assume that there is negative effect of classmates having parents in the plant corresponding to $-\gamma \frac{\overline{A}}{1-\overline{A}}$, then, using the same calculations as before we estimate $G_{cj} = \gamma \frac{1}{1-\overline{A}} + u_{c,j}^{G}$

[16] 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.

5.3 Heterogeneous effects - when do parents matter?

We now present results of our analysis of heterogeneous referral effects based on equation (5). All estimates therefore show *when* referral effects are stronger. Table 5 presents estimates for various individual characteristics of the child. The first four columns report estimates for each education group. The fifth column presents estimates when all education levels are grouped whereas the last column presents estimates for a model that also includes a plant fixed effect. The estimates in the sixth column thus 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. Note that the 850,000 contacts are distributed over almost 200,000 plants in the data (see bottom of Table 3) so that each plant has on average 4 to 5 parents of graduates over the 8 years we study. Thus, when plant effects are included, identification comes from plants where more than one parent worked at some point of the analysis period. Clearly, we still have a fairly representative sample in this last case.

Results show that females benefit less from their parents. Nordic immigrants, a group that often fares better on the Swedish labor market than the Swedish-born, benefit more from their parents whereas other immigrant groups are similar to the Swedish-born.[17] And, maybe surprisingly, age at graduation has a negative impact, even controlling for the plant fixed effect, i.e. within a class younger children benefit from their parents' employment more than older ones, when entering their first job. In addition, good grades (a high GPA) do not help entering one's parents' plant, on the contrary: parents may protect weak children; or, by reverse causation, children anticipating that their parents will help them in finding a job, do not work as hard as their classmates and therefore receive low grades. The pattern for mothers and fathers is similar to the one presented above, but interestingly, we see that most of the differences between mothers and fathers disappear when introducing a plant fixed effect. One potential reason for this comes from mothers working more often in the public sector, where referral hiring is practiced to a lesser extent.

Table 6 repeats the exercise for parental characteristics, separating mothers and fathers. We include several unusual and interesting variables, especially in the light of our theoretical model presented in Section 2. More precisely, we include the parent's wage, tenure in the plant, and a measure of coincidence in the field of study between the parent and the child.[18] Estimation results yield strong support to the model: high-wage and high-tenure workers, even controlling for plant fixed effects, induce referral hiring. Furthermore, parents who share the same field of study as their children are more likely to be in position of hiring their children. A potential interpretation was presented in the model section: when on the job training in the first year after graduation is useful for productive efficiency, parents may be more willing to deliver this training to their offspring than other workers in the same plant. Hence, in terms of sorting, within a class of students graduating in the same field of study, those who have parents trained in the same field, or parents who are high-wage and high tenure, are more likely to work in the same plant as their parents. Within a plant, it is also the case that the effect is larger if the parent is the owner. However, it should be stressed that our estimates in general are not driven by the self-employed since none of the results are sensitive to excluding these.

[17] This may be surprising given that ethnic "enclaves" have been found to be important for refugee immigrants in other studies on Swedish data (Edin, Fredriksson and Åslund, 2003). On the other hand, Åslund, Östh and Zenou (2006) found that regional job access matters equally for immigrants and Swedish born. See also Åslund and Skans (2005).

[18] 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 7 gives results for regional characteristics, unemployment, and competition measures. In particular, product market competition tends to be detrimental to referral hiring (by the parents, at least), a result which survives also after including plant fixed effects. Thus, even within a plant, referral hiring is used to a lesser extent when competition increases (i.e. when the Herfindahl index is reduced). Furthermore, high unemployment seems to favor matching of parents and children within plants. Referral hiring is also more common when the child's specialty is more common within hires that flow into the industry where the parent's plant operates (see section 4.2.3 regarding the definition of this education-to-industry variable). It therefore suggests that firms use parent referrals mostly when they select graduates with an education that fits plants' needs. Additional results show that this pattern is reduced when unemployment is high. Thus, when unemployment is high, parent referrals are quite common. But, hired children have an education which is less likely to be adapted to plants' needs.

Finally, Table 8 shows results for plant characteristics. First, referral hiring takes place mostly in large (or in very small) manufacturing plants, in the private sector, in firms with a large fraction of immigrants (consistent with patterns of workplace segregation found in Åslund and Skans, 2006). Employment growth also favors referrals. Note that many of the characteristics are poorly estimated when including the plant fixed effects. This is natural since many of these characteristics (e.g. the industry in which the plant operates) barely change at the plant level. Interestingly, however, we see that the private sector indicator is significant, even in this specification, suggesting that privatized plants increase their use of referrals.

5.4 Do parents provide good or bad jobs?

In this subsection we provide evidence on the quality and content of the jobs provided through parental networks. We do this by studying three outcomes measured at the time of the first job: time to the first job, initial wage, relevance of the industry relative to the education of the graduate. We then proceed to more "long-run" 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 in the same plant 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 still 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 9 first demonstrate that workers who find a job where their parents work, find this job faster than classmates[19] 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

[19] Obviously we do not control fro time to first job in these regressions as we do in the rest of table 9.

their first job at their mothers' plant, but starting wage are not significantly different from classmates if children 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.

In the second panel of Table 9, we look at outcomes three years after finding their first job. Estimates show a very strong positive effect of being referred by parents 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 provide jobs in plants where the expected tenure is long, and b) provide jobs with longer tenure within each plant. Three years after entry in the initial job, parents' referrals have a small positive effect within plants. Finally, the estimated effects on wage growth display a pattern similar to the one observed for starting wages. Mothers provide jobs with lower wage growth, whereas jobs provided by fathers look similar to others, with respect to wage growth. After controlling for plant fixed effects, wage growth for workers entering with the help of their parents looks just slightly different from that observed for other entry channels (in the order of half a percent over the three years, positive for fathers and negative for mothers).

6 Conclusion

In this article, we have examined the impact of parental networks on their children labor market outcomes, as seen from the perspective of the first stable job after graduation from school. We have presented a simple model (Montgomery, 1991) that helps understand some aspects of referral hiring. We have also presented an empirical model that is crucial for implementation and estimation of the sources and effects of parental referral. 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 any child graduating in Sweden over the 80s and 90s.

On many aspects, results are very much in line with Montgomery-type models. We show that having your first stable job in the same plant as, at least, one of your parents is quite frequent. Or, conversely, a plant is more likely to hire one of his employees' children than someone else from the same class. This effect is particularly strong for relatively low-educated males, for Nordic immigrants, in manufacturing jobs. In this process, the father is central for sons when the mother is useful for daughters.[20] Children trained in the same field of study as their father or their mother are more likely to benefit from referral hiring (or equivalently, a plant is even more likely to hire one of his employees' child than some other kid in the child's class when the child and the parent share the same field of study). Referral hiring is most frequent in less competitive industries, in large plants that have a large fraction of low-education workers and many immigrant workers. In addition, parents able to hire their children are high-wage workers and have relatively long tenures at the plant, even controlling for plant fixed effects. However, on the children side, some elements tend to

[20] Our results control for self-employment of the parents.

show that being hired by one's parents is not necessarily the first choice. First, these children' grades at school tend to be lower than those of their classmates. Second, referral hiring tends to take place when unemployment is high. Finally, the initial wage paid to the child is lower than for equivalent persons entering the plant through other channels. However, this initial mismatch is compensated in the mid-term; these children spend longer spells in their first job than hires without a parent in the plant.

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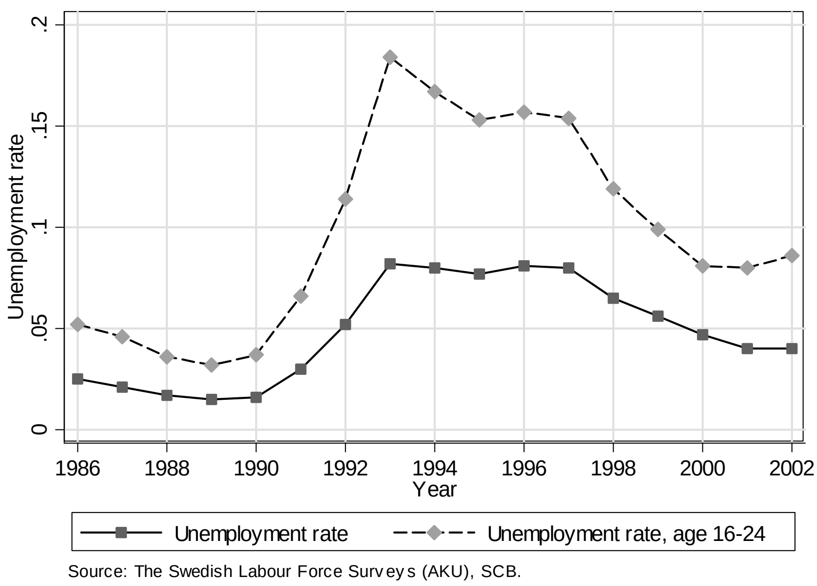

Figure 1: Unemployment rates 1986–2002.

Figure 2: Employment to population rates 1986-2002.

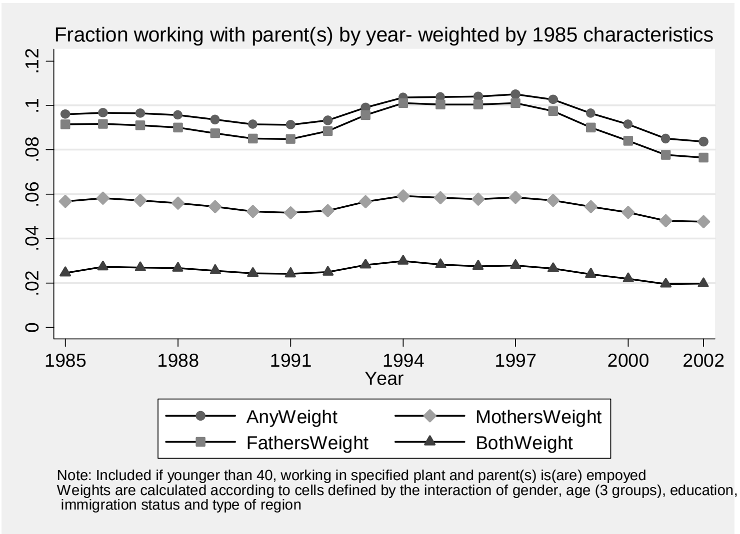

Figure 3: time pattern of fractions working with parents, weighted by 1985 characteristics.

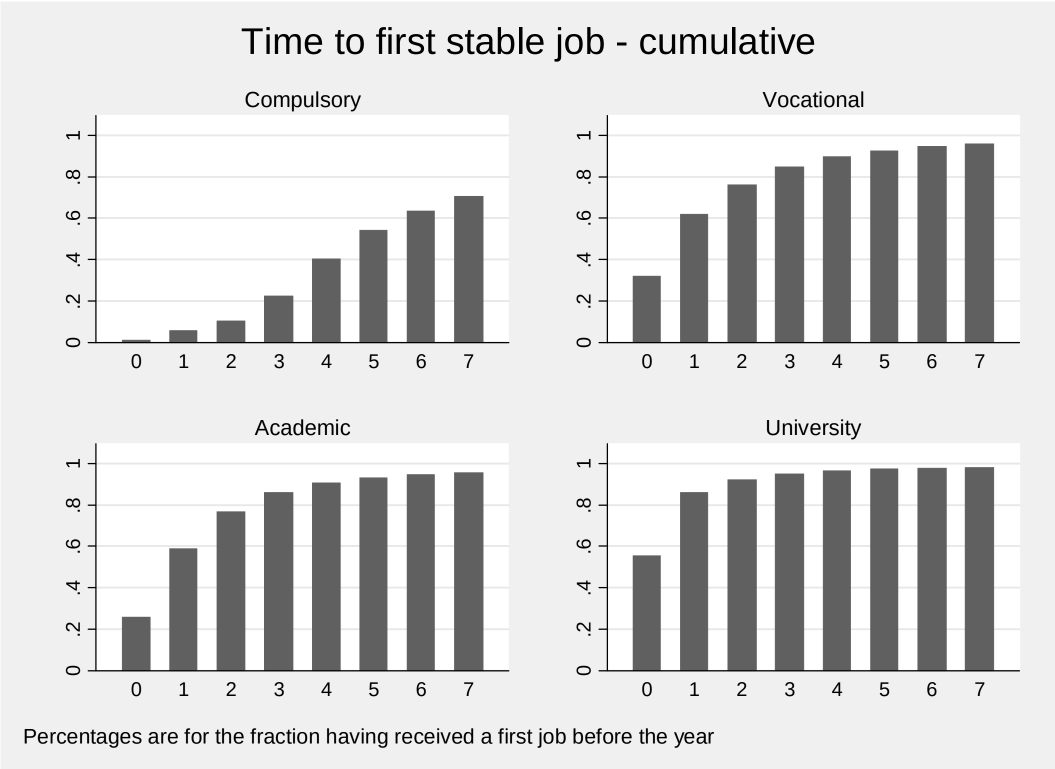

Figure 4

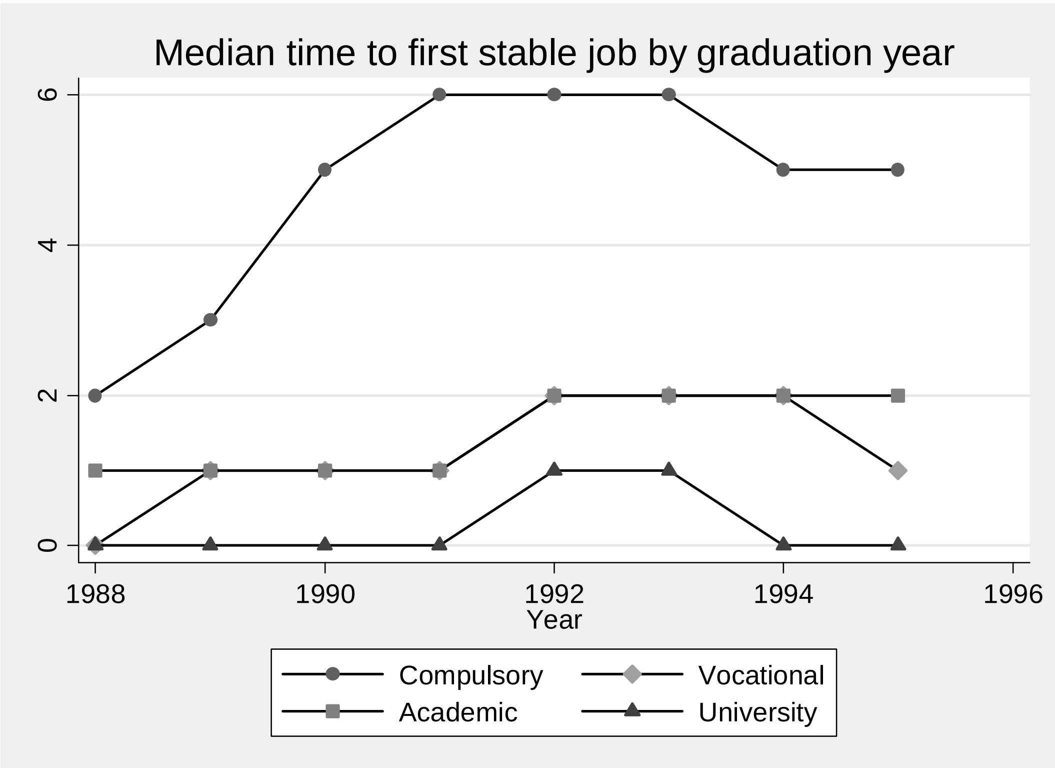

Figure 5

Table 1: The high school programs

Education at age 20:	N_i	Share of total (N_i/N)	Employed at age 20	Tertiary education at age 27
Less than high school	16,234	0.15	0.33	0.08
2-year high school	36,898	0.34	0.46	0.15
3-year high school	46,247	0.43	0.33	0.53
Tertiary education	9,300	0.09	0.17	1
All	108,679	1	0.36	0.37

Note: Groups are defined from completed high school programs. Sample includes all individuals born in 1973 that lived in Sweden in both 1993 and 2000 (excluding 2000 missing values). Employment is for November. “Tertiary education” includes graduates of the 4-year high school engineering program.

Table 2: Probability of having parent(s) at the workplace

	Any parent	Mother	Father	Both
Male	0.024**	-0.017**	0.059**	0.009**
	(0.001)	(0.000)	-(0.001)	(0.000)
Aged 16-24	0.023**	0.013**	0.005**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Aged 35-40	-0.009**	0	0.003**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)
Less than HS	0.041**	0.030**	0.044**	0.017**
	(0.001)	(0.001)	(0.001)	(0.001)
More than HS	-0.045**	-0.026**	-0.046**	-0.013**
	(0.001)	(0.001)	(0.001)	(0.000)
Immigrant	-0.004**	0.007**	-0.004*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Metropolitan	-0.022**	-0.011**	-0.022**	-0.004**
	(0.001)	(0.000)	(0.001)	(0.000)
Constant	0.078**	0.059**	0.056**	0.018**
	(0.001)	(0.001)	(0.001)	(0.000)
Observations	867,824	687,628	609,623	429,427
R-squared	0.02	0.01	0.03	0.01
Restriction	If any parent is employed	If mother employed	If father employed	If both parents

Note: Linear probability model estimates of working with parent(s) if employed in a specified plant and the parent(s) is (are) employed in 2002. Population only includes individuals aged 40 or younger.

Table 3: Parental networks effect on probability of finding the first job in a specific plant

	Compulsory school	Vocational high school	Academic high school	University degree
Mothers				
All				
$\hat{\gamma}$	0.081	0.059	0.068	0.029
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	49,203	154,190	130,473	97,460
Males				
$\hat{\gamma}$	0.066	0.046	0.062	0.022
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**
N	24,106	86,943	59,437	36,311
Females				
$\hat{\gamma}$	0.098	0.074	0.074	0.034
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**
N	17,107	61,754	64,533	57,095
Fathers				
All				
$\hat{\gamma}$	0.104	0.082	0.093	0.031
(s.e.)	(0.001)**	(0.001)**	(0.001)**	(0.001)**
N	51,875	167,131	133,343	92,006
Males				
$\hat{\gamma}$	0.142	0.118	0.127	0.049
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**
N	25,667	93,931	60,456	33,754
Females				
$\hat{\gamma}$	0.05	0.032	0.062	0.02
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.001)**
N	17,774	67,120	65,718	54,473

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

Table 4: Parental Networks and the time to first job

	$t=0$	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$	$t=7$
Mothers								
Compulsory								
γ	0.204	0.099	0.09	0.098	0.08	0.058	0.051	0.049
(s.e.)	(0.013)**	(0.003)**	(0.004)**	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.004)**
N	1,166	7,430	6,593	8,469	8,984	7,611	5,417	3,533
Vocational								
γ	0.069	0.058	0.054	0.043	0.039	0.034	0.038	0.032
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.002)**	(0.003)**	(0.004)**	(0.005)**	(0.008)**
N	55,268	51,979	22,923	12,960	6,112	2,861	1,408	679
Academic								
γ	0.105	0.062	0.049	0.044	0.033	0.037	0.029	0.024
(s.e.)	(0.002)**	(0.001)**	(0.001)**	(0.002)**	(0.003)**	(0.004)**	(0.005)**	(0.007)**
N	37,145	47,693	25,339	11,864	4,883	2,143	945	461
University								
γ	0.032	0.027	0.019	0.022	0.014	0.01		
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.004)**	(0.004)**	-0.006		
N	58,671	31,391	4,832	1,473	696	288		
Fathers								
Compulsory								
γ	0.279	0.152	0.104	0.11	0.099	0.077	0.059	0.043
(s.e.)	(0.012)**	(0.004)**	(0.004)**	(0.004)**	(0.003)**	(0.003)**	(0.003)**	(0.004)**
N	1,463	8,557	7,131	8,985	9,124	7,708	5,395	3,512
Vocational								
γ	0.089	0.076	0.09	0.083	0.062	0.055	0.037	0.03
(s.e.)	(0.001)**	(0.001)**	(0.002)**	(0.003)**	(0.003)**	(0.004)**	(0.005)**	(0.007)**
N	62,509	56,426	23,913	13,205	6,149	2,877	1,387	665
Academic								
γ	0.13	0.084	0.077	0.069	0.056	0.037	0.039	0.025
(s.e.)	(0.002)**	(0.001)**	(0.002)**	(0.002)**	(0.003)**	(0.004)**	(0.007)**	(0.007)**
N	39,134	48,986	25,458	11,691	4,725	2,034	880	435
University								
γ	0.033	0.026	0.036	0.035	0.031	0.023		
(s.e.)	(0.001)**	(0.001)**	(0.003)**	(0.005)**	(0.007)**	(0.010)*		
N	55,488	29,794	4,449	1,316	599	265		

Note: Estimates of parent referral effects. One combination of plant, year of first job and plant of a parent is one observation. Weighted by the number of graduates with parents in plant. Data are for graduates 1988-1995 fiidning a stable job within 7 years of graduation. Only regressions with more than 100 observations are presented. Only plants with parents are included in the data. Standard errors are cluster-corrected for dependencies within class. * (**) Significant at the 1 % (5 %) level.

Table 5: Parental Networks and Graduating Children Characteristics

	Comp.	Voc. HS	Ac. HS	Univ.	All	All
Individual						
Female	-0.021**	-0.024**	-0.024**	-0.008**	-0.020**	-0.018**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nordic Immigrant	0.036**	0.032**	0.040**	0.032**	0.035**	0.015**
	(0.012)	(0.007)	(0.008)	(0.007)	(0.004)	(0.004)
Other Immigrant	0.002	-0.002	0.013**	0.003	0.003	0.001
	(0.005)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
Age at graduation	-0.012**	-0.006**	-0.005**	-0.002**	-0.003**	-0.001**
	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
GPA (1-5)	-0.014**	-0.009**	-0.009**		-0.010**	-0.006**
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
Family						
reference only father						
Only mother in plant	-0.025**	-0.026**	-0.027**	-0.002	-0.021**	-0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Both parents in plant	0.280**	0.177**	0.234**	0.080**	0.182**	0.146**
	(0.009)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
Education						
reference Vocational HS						
Compulsory					0.015**	0.010**
					(0.001)	(0.001)
Academic HS					0.011**	0.020**
					(0.001)	(0.001)
University					-0.020**	-0.007**
					(0.001)	(0.001)
N	97,624	309,587	252,786	182,511	842,508	842,508
Plant fixed effects	No	No	No	No	No	Yes

Note: Estimates of parent referral effects. All regressions include controls for year of graduation. One combination of plant, year of first job and plant of a parent is one observation. Weighted by the number of graduates with parents in plant. Data are for graduates 1988-1995 fiidning a stable job within 7 years of graduation. Only plants with parents are included in the data. Standard errors are cluster-corrected for dependencies within class. * (**) Significant at the 1 % (5 %) level.

Table 6: Parental Networks and Parents' Characteristics

	Comp.	Voc. HS	Ac. HS	Univ.	All	All
Mothers						
Nordic	0.021**	0.014**	0.013**	0.012**	0.015**	0.006**
Immigrant	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Other	0.038**	0.020**	0.021**	-0.001	0.014**	0.006**
Immigrant	(0.006)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Compulsory	0.039**	0.034**	0.031**	0.005**	0.029**	0.012**
education	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Tertiary	-0.044**	-0.029**	-0.041**	-0.015**	-0.030**	-0.011**
education	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Same (1d.)		0.059**	0.012**	0.037**	0.039**	0.041**
field as child		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	0.044**	0.031**	0.036**	0.003*	0.029**	0.028**
Log wage	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	-0.001	0.000	-0.000	0.002**	0.001**	0.001**
Tenure	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	-0.001	-0.038**	-0.038**	-0.018**	-0.032**	0.041**
Self employed	(0.011)	(0.005)	(0.006)	(0.005)	(0.003)	(0.011)
Fathers						
	0.018**	0.020**	0.013**	0.005	0.016**	0.006*
Nordic						
Immigrant	(0.007)	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)
Other	0.011*	0.008**	0.007**	0.001	0.005**	0.002
Immigrant	(0.005)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Compulsory	0.022**	0.033**	0.026**	0.004*	0.024**	0.010**
education	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Tertiary	-0.048**	-0.038**	-0.041**	-0.023**	-0.036**	-0.008**
education	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Same field		0.057**	0.025**	0.029**	0.036**	0.033**
(1d.) as child		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	0.019**	0.028**	0.031**	0.015**	0.026**	0.033**
Log wage	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
	0.001**	0.003**	0.002**	0.003**	0.002**	0.002**
Tenure	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	-0.002	-0.009**	-0.033**	-0.007*	-0.015**	0.081**
Self employed	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.008)
N	96,653	305,525	250,136	180,778	833,092	833,092
Plant fixed effects	No	No	No	No	No	Yes

Note: Estimates of parent referral effects. All regressions include controls for year of graduation, type of education, gender and typ of parental contact (mother father or both). One combination of plant, year of first job and plant of a parent is one observation. Weighted by the number of graduates with parents in plant. Data are for graduates 1988-1995 fiidning a stable job within 7 years of graduation. Only plants with parents are included in the data. Standard errors are cluster-corrected for dependencies within class. * (**) Significant at the 1 % (5 %) level.

Table 7: Parental Networks and Industry-Region Characteristics

	Comp.	Voc. HS	Ac. HS	Univ.	All	All
Region						
	-0.002	-0.004**	-0.005**	-0.001	0.000	0.004
Metropolitan county	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)
	-0.032	0.109**	-0.098*	-0.011	0.122**	0.125**
County unemployment	(0.072)	(0.035)	(0.041)	(0.035)	(0.019)	(0.022)
	-0.031	0.188**	0.390**	0.103**	0.138**	0.161**
Industry-field match	(0.046)	(0.007)	(0.022)	(0.006)	(0.005)	(0.005)
Industry-field match interacted	0.365	-0.397**	-1.935**	-0.297**	-0.438**	-0.346**
with unemployment	(0.802)	(0.124)	(0.371)	(0.101)	(0.079)	(0.082)
Lack of Competition (Herfindahl)						
By 2-digit industry	0.870**	1.802**	2.125**	1.163**	1.601**	0.517**
	(0.160)	(0.089)	(0.101)	(0.087)	(0.053)	(0.193)
N	90,111	267,593	226,089	153,244	737,037	737,037
Plant fixed effects	No	No	No	No	No	Yes

Note: Estimates of parent referral effects. All regressions include controls for year of graduation, type of education, gender and typ of parental contact (mother father or both). Industry-field match measures how common it is that graduates from the field of the graduate's class goes to the industry of the parent's firm. One combination of plant, year of first job and plant of a parent is one observation. Weighted by the number of graduates with parents in plant. Data are for graduates 1988-1995 fiidning a stable job within 7 years of graduation. Only plants with parents are included in the data. Standard errors are cluster-corrected for dependencies within class. * (**) Significant at the 1 % (5 %) level.

Table 8: Parental Networks and Plant Characteristics

	Comp.	Voc. HS	Ac. HS	Univ.	All	All
Plant						
	0.030**	0.027**	0.029**	0.012**	0.026**	0.010**
Private	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
	0.002	-0.004	-0.007**	-0.014**	-0.004**	0.001
New plant	(0.004)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Plant growing from	0.000	0.000**	0.000**	-0.000	0.000**	0.000**
last year	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size <16	0.002	0.001	0.004**	0.005**	0.005**	0.003
(*ref. 16-45*)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	0.015**	0.011**	0.009**	0.004**	0.009**	0.000
Size 46-125	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	0.019**	0.023**	0.021**	0.012**	0.018**	0.001
Size 126-750	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
	0.006	0.019**	0.018**	0.048**	0.021**	0.007
Size 750+	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)
Composition						
Mean age	-0.011**	-0.007**	-0.009**	-0.002**	-0.007**	-0.007**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share primary	0.104**	0.007**	0.024**	-0.004	0.021**	0.018**
education	(0.005)	(0.002)	(0.003)	(0.002)	(0.001)	(0.005)
Share tertiary	-0.016**	-0.057**	-0.033**	-0.002	-0.029**	-0.046**
education	(0.004)	(0.002)	(0.003)	(0.002)	(0.001)	(0.004)
Immigrant share	0.034**	0.025**	0.031**	0.001	0.029**	0.020**
	(0.007)	(0.004)	(0.004)	(0.003)	(0.002)	(0.006)
Average log wage	-0.027**	-0.029**	-0.042**	-0.012**	-0.030**	0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
Industry						
Agriculture	-0.009	-0.008*	-0.054**	-0.001	-0.020**	0.000
(*ref manufact.*)	(0.008)	(0.004)	(0.004)	(0.005)	(0.002)	(0.010)
	0.000	-0.008**	-0.046**	-0.014**	-0.017**	-0.002
Construction	(0.005)	(0.002)	(0.003)	(0.002)	(0.001)	(0.006)
	-0.030**	-0.029**	-0.013**	-0.006**	-0.019**	0.000
Wholesale, retail	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
	-0.024**	-0.035**	-0.031**	-0.009**	-0.025**	-0.004
Financial, corporate	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
	-0.014**	-0.004*	-0.024**	-0.016**	-0.015**	0.008
Education R&D	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)
	-0.035**	-0.028**	-0.055**	-0.003	-0.033**	0.000
Health, Social	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)
	-0.016**	-0.028**	-0.026**	-0.011**	-0.021**	0.008
Personal & Cultural	(0.005)	(0.002)	(0.003)	(0.002)	(0.001)	(0.008)
	-0.022**	-0.029**	-0.040**	-0.019**	-0.030**	0.000
Public admin.	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)
N	96,139	304,451	249,035	179,861	829,486	829,486
Plant fixed effects	No	No	No	No	No	Yes

Note: Estimates of parent referral effects. All regressions include controls for year of graduation, type of education, gender and typ of parental contact (mother father or both). One combination of plant, year of first job and plant of a parent is one observation. Weighted by the number of graduates with parents in plant. Data are for graduates 1988-1995 fiidning a stable job within 7 years of graduation. Only plants with parents are included in the data. Standard errors are cluster-corrected for dependencies within class. * (**) Significant at the 1 % (5 %) level.

Table 9: Effects of finding a job through parental referral

	ln(Time to first job)		ln(Starting wage)		Relevance of industry	
Mother only	-0.162	-0.135	-0.063	-0.072	-0.016	-0.024
	(0.003)**	(0.003)**	(0.003)**	(0.002)**	(0.001)**	(0.001)**
Father only	-0.178	-0.144	-0.002	-0.056	-0.044	-0.019
	(0.003)**	(0.003)**	(0.002)	(0.002)**	(0.001)**	(0.001)**
Both	-0.255	-0.214	-0.061	-0.063	-0.041	-0.025
	(0.005)**	(0.006)**	(0.005)**	(0.004)**	(0.002)**	(0.002)**
	708,961	708,961	708,961	708,961	708,961	708,961
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	0.044	0.029	-0.002	0.009	-0.024	-0.006
	(0.003)**	(0.003)**	(0.003)	(0.003)**	(0.003)**	(0.003)*
Father only	0.102	0.055	0.017	0.013	0.003	0.006
	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.002)	(0.003)*
Both	0.206	0.147	0.056	0.055	0.006	0.032
	(0.006)**	(0.006)**	(0.005)**	(0.006)**	(0.005)	(0.005)**
	606,362	606,362	606,362	606,362	440,382	440,382
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 teh analysis of time to first job). The second model includes plant fixed effects and dummies for the each field and level. 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.

Appendix

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	0.012	0.010	0.008	0.015	0.011
Other imm.	0.068	0.031	0.032	0.029	0.036
Age	16.064	18.399	19.013	25.096	19.739
Age (sd)	0.244	0.622	0.555	2.572	3.253
GPA	2.616	3.052	3.121	3.000	3.003
GPA (sd)	0.742	0.598	0.562	0.000	0.563
Mean class size	18.373	28.205	41.192	43.582	66.328
Class size (sd)	10.799	22.537	28.774	39.172	42.855
Class size by year of first job	5.235	11.124	13.240	28.353	14.736
(sd)	3.469	11.022	11.631	30.303	18.558
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	0.671	0.762	0.804	0.691	0.746
Mother Employed	0.665	0.742	0.810	0.740	0.750
Both Employed	0.487	0.594	0.676	0.571	0.598
Both in same Plant	0.037	0.046	0.054	0.048	0.048
N (graduates)	83545	238543	178338	141161	641587
Employed parents with known Plant-ID					
Mother Nordic Immigrant	0.069	0.055	0.049	0.035	0.050
Mother Other Immigrant	0.064	0.050	0.068	0.172	0.084
Mother Compulsory	0.308	0.319	0.210	0.197	0.257
Mother Tertiary	0.193	0.158	0.325	0.427	0.273
Mother in same field	0.071	0.119	0.134	0.175	0.131
Mothers log Wage	9.425	9.265	9.375	9.384	9.343
Mothers log Wage (sd)	0.389	0.357	0.383	0.401	0.384
Mothers tenure	3.661	3.353	3.538	3.957	3.579
Mothers tenure (sd)	3.700	3.008	3.045	3.079	3.129
Mother self employed	0.021	0.023	0.019	0.021	0.021
N (mothers)					
Father Nordic Immigrant	0.051	0.042	0.034	0.024	0.037
Father Other Immigrant	0.094	0.097	0.118	0.271	0.139
Father Compulsory	0.411	0.434	0.265	0.232	0.340
Father Tertiary	0.149	0.119	0.287	0.388	0.228
Father in same field	0.026	0.187	0.272	0.208	0.198
Fathers log Wage	9.716	9.604	9.776	9.804	9.710
Fathers log Wage (sd)	0.432	0.395	0.450	0.500	0.448
Fathers tenure	4.407	3.934	3.926	4.207	4.043
Fathers tenure (sd)	4.129	3.219	3.194	3.127	3.317
Father self employed	0.070	0.076	0.056	0.056	0.065
N (fathers)	103264	331140	271860	191467	897731

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 the regressions.

Table A2 Creation of February job data

	1988		1995		Parents in graduation year	
	Individuals	**Fraction**	**Individuals**	**Fraction**	**Individuals**	**Fraction**
Population	5,334,727	1	5607753	1	1,267,516	1
Employment according to statistics Sweden						
November	4,347,401	0.815	3796432	0.677	1,042,655	0.823
Anytime	4,807,023	0.901	4558659	0.813	1,094,923	0.864
Data creation						
Jobs	8,149,152	1.528	6982150	1.245	1,820,539	1.436
Jobs with plant-ID	6,562,635	1.230	5851746	1.044	1,364,409	1.076
Plants	509,571	0.096	494951	0.088	288,081	0.227
Ind. with jobs	4,974,115	0.932	4696508	0.838	1,006,670	0.794
...in February	4,588,783	0.860	4202953	0.749	859,530	0.678
and earnings>cut-off	3,595,163	0.674	3271469	0.583	772,074	0.609
and identified Plant	3,306,485	0.620	3058067	0.545	719,634	0.568
Ind. w. mult. Jobs	66,567	0.012	48186	0.009	168,559	0.133

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	0.837	0.871	0.879
Number of Jobs per graduate	1.478	1.458	1.441	1.460
Jobs at least 4 months	0.650	0.728	0.786	0.814
and 3 monthly wages	0.074	0.443	0.521	0.600
Known Plant-ID	0.067	0.399	0.479	0.561
Multiple jobs	0.002	0.024	0.026	0.038

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

Table A4: Description of transformed regression data - all education

Variable	Obs	Mean	Std. Dev.	Min	Max
Hired by parent	842508	0.064	0.244	0	1
Hired by classmates parent	842508	0.003	0.037	0	1
Network effect	842508	0.061	0.241	-1	1
Individual					
Female	842508	0.491	0.498	0	1
Nordic Immigrant	842508	0.006	0.077	0	1
Other Immigrant	842508	0.022	0.145	0	1
Age at graduation	842508	19.693	3.088	16	30
GPA	842508	3.040	0.548	1	5
Only mother in Plant	842508	0.476	0.498	0	1
Both parents in Plant	842508	0.032	0.175	0	1
Compulsory	842508	0.116	0.320	0	1
Academic High School	842508	0.300	0.458	0	1
University	842508	0.217	0.412	0	1
Mothers - measured relative to mean among mothers (by education)					
Nordic Immigrant	842508	0.000	0.153	-0.069	0.965
Other Immigrant	842508	0.000	0.195	-0.172	0.950
Compulsory education	842508	0.001	0.308	-0.319	0.803
Tertiary education	842508	0.000	0.306	-0.427	0.842
Same (1d.) field as child	842508	-0.001	0.229	-0.175	0.881
Log wage	842508	-0.001	0.282	-1.284	3.584
Tenure	839218	-0.010	2.211	-3.957	13.647
Self employed	842508	0.000	0.105	-0.023	0.981
Fathers - measured relative to mean among fathers (by education)					
Nordic Immigrant	842508	0.000	0.134	-0.051	0.976
Other Immigrant	842508	0.000	0.244	-0.271	0.906
Compulsory education	842508	0.000	0.335	-0.434	0.768
Tertiary education	842508	0.000	0.293	-0.388	0.881
Same (1d.) field as child	842508	0.000	0.280	-0.272	0.813
Log wage	842508	-0.002	0.333	-1.685	4.595
Tenure	836165	-0.009	2.385	-4.407	13.074
Self employed	842508	0.001	0.181	-0.076	0.944
Region and competition					
Metropolitan county	842508	0.39	0.49	0	1
County Unemployment rate	749067	0.05	0.03	0.008	0.128
Industry field match	819145	0.08	0.16	0	1
Herfindahl	828684	0.00	0.01	0.000	0.077
Plant					
Private	842508	0.513	0.500	0	1
New Plant	842508	0.037	0.190	0	1
Plant growing	842508	-0.170	111.361	0	1
Size 1-15	842508	0.298	0.457	0	1
Size 46-125	842508	0.201	0.401	0	1
Size 126-750	842508	0.196	0.397	0	1
Size 750+	842508	0.101	0.301	0	1
Plant mean age of employees	842122	42.943	4.847	19	68
Plant share of primary ed.	842508	0.249	0.233	0	1
Plant share of tertiary ed.	842508	0.277	0.274	0	1
Plant share of immigrants	842508	0.108	0.131	0	1
Plant average log wage	842508	9.879	0.260	8.900	13.076
Agriculture/forrestry	829833	0.021	0.144	0	1
Manufacturing	829833	0.205	0.404	0	1
Construction	829833	0.061	0.240	0	1
Wholesale or retail	829833	0.189	0.392	0	1
Financial, corporate services	829833	0.099	0.299	0	1
Education, R&D	829833	0.102	0.302	0	1
Health, Social work	829833	0.204	0.403	0	1
Personal, Cultural, Sanitation	829833	0.049	0.215	0	1
Public administration	829833	0.070	0.254	0	1