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ABSTRACT

Assortative Matching and Gender*

Exploiting the richness of the Danish register data on individuals and companies, we are able to provide an overall assessment of the assortative matching patterns arising in the period 1996-2005 controlling for firms and individual characteristics. We find strong differences between men and women in assortativity. While positive assortative matching in job-to-job transitions emerges for good female workers, good male workers are more likely to be promoted. These differences are not present in female friendly firms which have high profits and where good female workers tend to find jobs. Complementary analysis on job-to-unemployment and job-to-self-employment transitions reveals a lower employer's willingness to retain women. Overall, we find strong evidence of glass-ceilings in certain firms preventing women to climb the carrier ladder and pushing them to look for better jobs offered by more female friendly firms.

JEL Classification: J16, J24, J62

Keywords: assortative matching, gender gap, glass ceiling, sticky floor

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1 Introduction

Gender differences in labor market outcomes are present and persistent in many countries. Furthermore, it turns out that studying the matching profiles that emerge in an economy is important in understanding wage gaps since they come about through segregation in lower-paying occupations, in less productive establishments and in lower paying occupations within establishments (Bayard, Hellerstein, Neumark and Troske, 2003; Hellerstein and Neumark, 2008; Merlino, 2012).

The reason why these differences occur is debated. While some find evidence for the existence of discrimination (Bowlus and Eckstein, 2002; Flabbi, 2010), also biological differences are important (Ichino and Moretti, 2009); some find that promotion rates are lower for women (Albrecht, Björklund and Vroman, 2003), but also that women receive small wage increases after promotions (Booth, Francesconi and Frank, 2003).

To assess the importance of the different channels, in this paper we measure sorting, i.e., to which extent good workers go to good firms, for men and women using Danish employers-employee matched data. In particular, we study how different type of transitions (job-to-job, promotions, into self-employment and into unemployment) are affected by workers' type, and how this relationship changes for male and female workers. Thanks to the richness of Danish data, we can follow workers along their career and we can exploit within-firm wage variation and differences in profits between companies to respectively rank employee and employer types, a methodology recently proposed by Bartolucci and Devicienti (2012).

Our empirical analysis on several aspects of both internal and external labour market transitions considerably extends previous investigations on this topic as, to the best of our knowledge, no other work has provided such a clear and comprehensive description and explanation of gender differences in sorting. While we find evidence of positive assortative matching in job-to-job transitions, the strength of sorting is much stronger for female workers. The opposite is true when we look at promotions, where better women are less likely to get promoted than men. The picture that emerges is that good female workers are more likely to move to a good female friendly firm to escape the glass ceilings they face in the average firm. Quite interestingly, these female-friendly firms obtain a higher profitability than those firms where good female workers are discouraged.

This gives a strong rationale for policy interventions, since discriminatory firms pay in terms of productivity their gender bias in promotion choices. Furthermore, our findings are consistent with the fact that, even in a context characterized by flexible labour market and generous family friendly schemes, like the Danish one, there still exists a persistently large gender gap in top job positions and promotions. According to the Global Gender Gap Report (2011), Denmark is ranked as number 7 (of 134 countries) on the overall Gender Gap Index, but it takes position 68 on the gender gap for representation among legislators, senior officials and managers. Although the Nordic model has succeeded in maintaining a high rate of female employment, some unintended boomerang effects plausibly associated with the high generosity of parental leave policies[1] seem to emerge and impede women to progress in their carrier ladders, as pointed out by Gupta, Smith and Verner (2008) as well.

From the seminal contribution of Becker (1973), several studies have investigated whether good workers go to good firms, i.e. whether positive assortative matching arises. Answering this research question matters especially for the allocation of resources in the labor market and the efficiency of the production process. For instance, if the production is characterized by strong complementarities then frictions preventing the right matches between workers and firms are associated with substantial efficiency

[1] Women are entitled to be out of the labor force in shorter or longer spells during the child bearing and rearing periods.

losses. Conversely, these losses do not occur from randomly allocating workers to jobs when complementarities in production are nearly absent. The nature (sign and strength) of sorting (assortativity) may also have profound implications in shaping labor market policies such as the design of unemployment insurance schemes that provides (dis)incentives to workers in looking for the "right" job rather than accepting the first offer (Acemoglu and Shimer, 2000).

Theory on sorting in the labor market tells us that different equilibrium matching patters are possible, depending on the supermodularity of the production function, transferability of the utility function, heterogeneity and endogeneity of search costs and type dependency of a vacancy value (Sattinger, 1995; Shimer and Smith, 2000; Legros and Newman, 2002; Atakan, 2006; Legros and Newman, 2007). Thus, what kind of matching patters does generally arise is mainly an empirical question. Since the seminal study of Abowd, Kramarz and Margolis (1999), and with the increasing availability of linked employer-employee databases, a large set of empirical works has extensively contributed to the analysis of assortativeness, with particular focus on the importance of worker and firm types. Both heterogeneity sides refer to the concept of productivity and are driven by different factors, some of them are observable whereas others are unobservable, and therefore hard to measure. Being the definition of firm and worker types not straightforward, a general and final agreement on how testing the nature of sorting (relationship between such types) has not emerged yet.

In this article, we follow a recent approach developed by Bartolucci and Devicienti (2012), that is based on two main identifying assumptions: monotonicity of agents' payoffs in their (own) types and existence of mismatches in the equilibrium distribution of workers and firms. Specifically, exploiting within-firm wage variation and differences in profits between companies it is possible to respectively rank employee and employer types. This approach is "as agnostic as possible with regards to the labor market model generating the data" (Bartolucci and Devicienti, 2012).

If there is an overall tendency towards positive assortative matching in the labor market, one could use differentials in the strength of this tendency to assess the sources of labor market outcomes across genders. Indeed, Merlino (2012) pointed out that looking at equilibrium matching profiles is key in understanding labor market outcomes of disadvantaged workers. Taking this into account is important to design policies aiming at reducing gender gaps.

Several studies have pointed out different mechanisms on the emergence of labor market differences. These mechanisms have different implications for career developments of women, which is useful to make sense of our empirical findings. One of the most well-known metaphors to describe career gender gaps is the "glass ceilings hypothesis", a term first used by Gay Bryant (Frenkiel, 1984) which refers to the situation in which women are not promoted. In that case, we should find no tendency for women towards positive assortative matching. A related theory has been proposed by Booth et al. (2003), who coined the term "sticky floors" to refer to the situation where women do not face discrimination in promotions, but they receive smaller wage improvements than men after promotions, because they have worse market opportunities than men. Conversely, Lazear and Rosen (1990) assumed that women have better non-market opportunities than men: this would translate in women being less likely to be promoted than men in all firms but more likely to receive higher wages if promoted and are more likely to quit to non-market opportunities.

Another factor is that women are less productive (or, their productivity is less observable) at the beginning of their career due to a rate of absenteeism higher than male workers (Ichino and Moretti, 2009). According to these theory, gender gaps should disappear for older workers and at the top of the wage distribution. A similar story is that women have stronger preferences for hour flexibility due to parenting and other activities in the household (Flabbi and Moro, 2012). This would imply substantial differences in the wage distribution across genders, but negligible on unemployment differentials.

Exploiting the richness of the Danish register data on individuals and companies, we are able to provide an overall assessment of the assortative matching process in the labor market for different categories of firms and workers to assess the relevance of the different causes behind gender gaps. We trace mobile workers (movers) involved in job-to-job, job-to-self-employment and job-to-unemployment transitions to evaluate the relationship between their last wage earned and the recruitment in a company characterized by high profitability, the start of an own business, and the entry in unemployment, alternatively. Furthermore, we complement the analysis by looking at promotions of workers already employed in a given firm (stayers) to understand how employees' last labor income is linked to the probability of moving to higher job-positions.

For the purposes of this study, population data source such as the Danish individuals and firm register data is particularly appropriate. This is because it covers an extremely large number of workers employed in different firms and occupations in a relatively long period of time. In addition, assortativity between firms and workers in Denmark is not influenced by rigidities and frictions imputable to institutions in the labor market, which is characterized by: i) high labor mobility, promoted by a high degree of flexibility; ii) large female participation, attributable to the Nordic welfare state model and the presence of family friendly policies (Gupta et al., 2008); and iii) a very decentralized wage bargaining system.

We find evidence of positive assortative matching, which increases its strength with age, educational and occupational levels. Our key finding is the strong difference in assortative matching between men and women. Whereas the former are characterized by insignificant or negligible positive sorting, the latter present a stronger and significant positive assortative matching process. These differences are stable as they arise over a number of different specifications and tests referring to the sample of movers.

As a complementary support to this evidence, we find substantial differences between men and women in the propensity to become self-employed or experience open unemployment period in favor of women, meaning that the stronger female job-to-job assortativity may be also related to the lower employer's willingness to retain women. Results on promotion patterns do not only corroborate but also reinforce the gender gap finding. They in fact suggest that women are subject to discriminating promotion policies, and for such a reason then they try to overcome gender barriers by searching for a better job offered by fairer firms. A further important result arises from the comparison between male and female promotion rates in the highly profitable firms where women tend to find job: in these, no differences arise in terms of gender.

Overall, our findings support a refined version of the glass ceilings hypothesis: there are firms both with and without glass ceilings: since in the former there is no tendency towards positive assortative matching for good female workers, these workers go to firms without glass ceilings to advance in their career. These firms obtain higher profits, also because they are able to recruit good workers for cheaper wages, given that disadvantaged workers have worse market options.[2]

The structure of the remainder of the paper is as follows. Section 2 briefly overviews the main literature in this field. The data are described in detail in Section 3. Section 3 describes the Danish institutional background while section 4 presents the estimation strategy. Section 5 presents and discusses the empirical findings and Section 6 concludes.

[2]Note that there might be several reasons why discriminatory firms might survive competition from non-discriminatory firms. First, social enforcement might make deviations not to discriminate non-profitable. Second, certain firms might have clients with discriminatory tastes. Third, search frictions may make social enforcement easier.

2 Literature Background

From the work of Becker (1973), the phenomenon of sorting in the labor market has been largely investigated theoretically in the economic literature, but, from an empirical perspective, a number of insights and puzzles arises.[3] With the increasing availability of employer-employee datasets, many scholars have tested the positive assortative matching (henceforth, PAM) hypothesis. A central study in such a context is Abowd et al. (1999) (henceforth, AKM). Estimating individual worker and firm fixed effects, AKM find small or negative correlation between these fixed effects and interpret it as evidence of no or negative role of sorting in the labor market. Similar studies have thereafter been conducted for different countries. Whether some of them (Abowd, Creecy and Kramarz, 2002; Gruetter and Lalive, 2004; Andrews, Gill, Schank and Upward, 2008) seem to be in line with AKM's conclusions, others (Abowd and Kramarz, 2003; Woodcock, 2008) do not.

However, relevant shortcomings emerge from AKM's contribution as the latter tests the sorting hypothesis by using identifying assumptions which rule out key mechanisms, such as endogenous search intensity. This can induce sorting in models with production function complementarities (Bagger and Lentz, 2008). Further, the correlation between worker and firm fixed effects may be biased due to non-monotonicity of wages in firm type, e.g. frictions in posting new vacancies[4] or in the hiring process between competing firms[5]).

Mendes, van den Berg and Lindeboom (2010) test sorting hypothesis by assuming that all information on worker types is contained in the observables, and firm types can be obtained through a production function estimation approach. Specifically, estimating a translog approximation by fixed-effects methods, they determine the firm-specific

[3]See Christensen, Lentz, Mortensen, Neumann and Werwatz (2005) for a survey of the literature.
[4]See Postel-Vinay and Robin (2002), and Cahuc, Postel-Vinay and Robin (2006).
[5]See Lopes De Melo (2009) and Eeckhout and Kircher (2010).

productivity, and relate this to the skills of the workforce. This estimation strategy presents two main limitations, however: (i) the estimation of the production function is based only on within-firm variations, and (ii) observable characteristics just partly explain the wage distribution.

Indeed, Eeckhout and Kircher (2011) argue that from wage data alone it is virtually impossible to identify the ranking of firms and then the sign of sorting: whether more able workers derive their higher marginal product from more productive firms. Thus, they develop a method in which the cost of search is extracted from the range of wages paid [6] and the fraction of the firm population that an agent is willing to match with identify the strength of the complementarity (sorting) as expressed by the (absolute value of the) cross-partial of the production function. Lopes De Melo (2009) improves AKM's approach testing assortativity by looking at the correlation between a worker fixed effect and related average coworkers' fixed effects. Both approaches though face the limitation that they cannot detect the sign of sorting.

In our opinion, the most interesting recent contribution in the empirical literature is due to Bartolucci and Devicienti (2012). They provide an estimation strategy grounded on agents' payoff monotonicity on their (own) types and the presence of some mismatches between workers and firms in the equilibrium distribution. The latter condition is crucial as perfect sorting would make empirically indistinguishable both sources of heterogeneity. Using an employer-employee dataset, Bartolucci and Devicienti (2012) exploit within-firm variation in wages to order worker types (within firms) and profits to rank firm types.

While we are the first to use the empirical strategy developed by Bartolucci and Devicienti (2012) to study gender gaps in labor market outcomes, clearly we are not the first to try to use career development to disentangle between different theories of

[6] The highest observed wage is assumed to be the frictionless wage and they use it to order worker type. Likewise, firms are ranked with respect to the level of wages that they pay. The difference between the highest and lowest wage is the cost of search.

gender gaps. Most notably, Booth et al. (2003) found support of their model of sticky floors where men and women are equally likely to be promoted but women face lower wage increases. Nonetheless, they did not have information about firms though, since they did not use matched employer-employee data. Hence our study represents a big advancement with respect to theirs. More recently, George-Levi Gayle (Forthcoming) focused on CEO of publicly listed firms to track the career of top CEO's and found that women are more likely to become CEO once they did not exit that occupation. Our findings are in line with theirs, but we provide a more general and detailed analysis since we do not restrict our attention to CEO's and we look at all transitions.

3 Data and institutional background

3.1 Data

The dataset is a merged employer-employee unbalanced panel sample of Danish firms observed over the period 1996-2005. The key features of our data, provided by Statistics Denmark, is the total coverage of employees and firms, and the match between the employee and firm records. Both these features make the data particularly suitable for our purposes, since they enable us to detect moving workers in each year and their sending and receiving firms (Parrotta and Pozzoli, 2012).

Firm-level data[7] include sales, employment, value added, materials, profits, fixed assets and two-digit NACE identifier.[8] All companies in the sample have more than 20

[7]Firm-level statistics have been gathered in several ways. All firms with more than 50 employees or profits higher than a given threshold have been surveyed directly. The other firms are recorded in accordance with a stratified sample strategy. The surveyed firms can choose whether to submit their annual accounts and other specifications or fill out a questionnaire. To facilitate responses, questions are formulated similarly to those in the Danish annual accounts legislation.

[8]The final sample includes the following industries: manufacturing of food, beverages and tobacco; manufacturing of textiles and leather; manufacturing of wood products and printing; manufacturing of chemicals and plastic products; manufacturing of other non-metallic mineral products; manufacturing of basic metals and fabricated metal products; manufacturing of furniture; manufacturing n.e.c.; construction; sale and repair of motor vehicles, sale of automotive fuel; wholesale except for motor

employees and are private firms, i.e. they are not part of the public sector. Furthermore, all firms with imputed accounting variables are dropped from the analysis.

The individual-level data are available from 1980 onwards, covers the working age population and includes wage, age, gender, marital status, number of children, experience, tenure, highest completed education, occupation and information on the family background characteristics. Apart from deaths and permanent migration, there is no attrition in the dataset. The labor market status of each person as of November 30 is recorded as the relevant datum for each person for that year. So if a worker changed jobs, we only observe the year in which it occurred.[9] However, we observe whether a worker experiences unemployment and the duration (number of weeks) of the overall unemployment period in a calendar year.

In the analysis that follows, we only include individuals with a positive annual salary[10] and individuals younger than 60. Furthermore, apprentices and part-time employees are excluded from the main analyses. Our empirical estimations are finally based on two samples. The first sample only considers those workers who, within 1996-2005 period, switched from a firm (sending firm, according to our terminology) to another one (current firm) in the dataset, at least once. An important challenge regarding this dataset is that, as a result of changes of ownership, there appears to be some false transitions in the data. In order to minimize miscoded turnover, transitions involving more than 50 per cent of the size of the same sending firm are excluded from the final sample. In total this sample includes 379,836 observations, 124,861 job switchers, i.e. 22 per cent of the original sample, and approximately 8,500 firms. The

vehicles; retail trade of food; department stores; retail sale of pharmaceutical goods and cosmetic articles; retail sale of clothing and footwear; other retail sale, repair work; hotels and restaurants; land transport and transport via pipelines; water transport; air transport; supporting transport activities; post and telecommunications; finance; insurance; activities auxiliary to finance; real estate activities; renting of transport equipment and machinery; computer and related activities; research and development; consultancy activities; and cleaning activities.

[9] For individuals for multiple jobs, only the main occupation is considered.

[10] We exclude from the original sample the extreme observations of the annual salary, i.e. those lower than 1th percentile and higher than 99th percentile of the salary distribution.

second sample considers only those individuals who have always remained with the same employer over the sample period and includes 2,449,905 observations, 303,930 "stayers" and nearly 9,000 firms.

3.2 Descriptive statistics

Table 1 lists descriptive statistics for both samples and measured at both the worker and firm level, separately by gender. The average male (female) job switcher is 35 (34) years of age and has 14 (11) years of experience. The average tenure for both women and men is around 3 years. The majority has a secondary or post-secondary diploma, 5 (7) percent of male (female) job changers has at least a university degree while 30 (37) percent has primary education. Most of men and women are classified as blue collars (73-75 percent), followed by middle manager (22-25 percent). Significantly more male switchers have managerial jobs compared to their female counterpart (4.2 percent versus 1.8 percent). For both genders, around 5 percent is foreigner, nearly 14 percent has at least a child of 0-3 years of age and about 4 percent has at at least a parent working as a manager at the time of the job transition or before, i.e. 4 percent has a familiar network, i.e., at least one parent holding managerial positions. In comparison, the average stayer is fairly older and experienced and with slightly lower educational and occupational level. The average stayer is also more likely to be married and less likely to have a child between 0-3 years of age and a familiar network, no matter the gender of the individual. The percentage of foreigners are reasonably comparable across the two samples. During the time period covered by our sample, the wage of an average male (female) job switcher was around 220 (172) thousand Danish Krones, or about 29,5 (23) thousand Euros, per annum. The salary of an average stayer was about 20 percent above that. Turning to the firm-level characteristics, the average size and share of women are fairly similar across the two samples, while the profits per worker are higher in the sample of stayers, no matter the gender of the employee.

Table 2 includes instead the mean of all the outcome dependent variables used in our empirical analysis. For the sample of job switchers, we calculate an indicator function that takes value one if the worker moves to a receiving firm which is with better quality than the sending one, and zero if the worker moves to a receiving firm with worse quality than the sending one. As suggested in Bartolucci and Devicienti (2012), firms quality is primarily defined in terms of profits. Given that the measure of profits is firm and time specific and it can be affected by transitory productivity shocks or measurement error, we also calculate a set of indicator variables based on either a substantial improvement in profits, i.e. the profits differential between sending and receiving firms is at least 10 percent large, or on the average profits across time. Furthermore, given that job switchers may have not been able to find out about the entire evolution of profits over time, we also define the firm quality on the basis of the past average profitability (Bartolucci and Devicienti, 2012). Finally, the alternative indicators mentioned before are also all calculated on the basis of profit measures per worker and firm-value added in levels and per worker. The means of these outcome variables, reported in Table 2, allow us to conclude that women and men have very similar probabilities of moving to a receiving firm with better quality, no matter the definition of firm quality we refer to. For the sample of stayers, we also look at the probability of promotion to a better occupational level and to a managerial position, as additional outcome variables. Women are generally less likely to be promoted than men. This is in line with the glass-ceiling hypothesis, whereby women otherwise identical to men can only advance so far up the occupational ladder (Arulampalam, Booth and Bryan, 2007). The last two outcome variables, included in our empirical analysis, are the probabilities of moving from the state of employment to the state of unemployment and self-employment, respectively.[11] On average, women are more (less) likely to

[11] The state of unemployment and self-employment are measured as destination state by looking at the longest spell in the year following the transition.

be unemployed (self-employed) compared to men.

3.3 Institutional background

As the institutional constraints might hamper the degree of assortativeness and sorting in the labor market, we outline the main features of the Danish labor market, represented by the combination of high flexibility and social security, the role of family-friendly policies and decentralized wage setting.

Cornerstones of the Danish "flexicurity" model are the high level of labor mobility and the generosity of social security schemes. In particular, the absence of severance pay legislation lowers hiring and firing costs, reducing frictions in labor market and then facilitating firms in adjusting the quality and size of their workforces. Moreover - although not protected by stringent employment rules - workers bear relatively low costs of changing employer and they have easy access to unemployment insurance or social assistance benefits. Danish replacement ratios are in fact among the most generous in the world. As a consequence, a notable part of the observed labor mobility is also associated with wage mobility (Eriksson and Westergaard-Nielsen, 2009).

A further key feature of the Danish labor market is the wide coverage of publicly provided childcare that combined with the length and flexibility of parental leave schemes has favored female labor market participation and full-time employment, without dramatic consequences on the fertility rate (OECD, 2005). In fact, Denmark and the other Nordic countries (Finland, Iceland, Norway and Sweden) have traditionally been considered as forerunners in designing family-friendly policies. Female participation went hand in hand with the expansion of the welfare state and many jobs held by women were part-time occupations in the public sector. Nowadays, a notable proportion of women is employed in the private sector and works full-time. However, the widespread take-up of parental leave schemes almost exclusively by mothers might have created some "boomerang effects on women's wage and job position within firms (Gupta et al., 2008; Smith, Smith and Verne, 2011).

For the purposes of our analysis, a brief description of the wage bargaining in the Danish private sector is important as well as the former ones. As other OECD countries, Denmark experienced a shift in wage bargaining from a highly centralized to considerably decentralized system. Since early 90s an increasing share of wage bargaining moved down to the firm (individual employee) level. That increased the weight of the employer and employee roles and effects in the resulting internal firm wage structure. As found in Shaw and Lazear (2008), within-firm wage variability in Denmark represents even more than 80% of the total variability observed among all workers.

4 Estimation strategy

Our empirical analysis is based on a reduced form model developed from the theoretical framework formalized in Bartolucci and Devicienti (2012). Specifically, we estimate the following probability model, conditional on a movement, i.e. for the sample of movers:

$$\begin{aligned} move\_up_{ijr} &= \alpha_0 + \alpha_1 wage\_lag(e_i, f_j) + \alpha_2 (wage\_lag(e_i, f_j) * gender_i) \\ &\quad + \alpha_3 gender_i + x'_{ij}\beta + z'_j\gamma_1 + z'_r\gamma_2 + u_j \end{aligned} \tag{1}$$

where $move\_up_{ijr}$ is a dummy variable equal to 1 if employee i, who has worked in the sending firm j, moves to a better receiving firm r. The same variable is equal to 0, if employee i moves to a worse firm r. As explained in the previous section, we apply alternative definitions and measures of firm's quality and ranking. The term $wage\_lag(e_i, f_j)$ is the log of wage earned in the sending firm j, by employee i, which is a function of her and employer j types, respectively e_i and f_j. Assuming that employees' wages are monotone in their types allows to use within-firm variation on wages to rank workers. As suggested in Bartolucci and Devicienti (2012), the existence and the sign of assortativeness is tested by investigating whether the coefficient α_1 is different from zero. More specifically, if $\alpha_1 > 0$, there is evidence of positive assortative matching. The main focus of this paper is to test whether the degree of assortativeness varies by gender, by looking at whether the coefficient α_2 is statistically significant and different from zero. As wages of women may not be directly comparable with those of men and their ranking may be biased due to this intrinsic incomparability, we also estimate equation (1) separately by gender and we test whether α_1 significantly varies across the female and male sub-samples. The vector x_{ij} consist of relevant worker characteristics, as age, tenure, work experience, ethnicity, marital status, parental status, education, occupation and network dummy, i.e. having had at least a parent employed as a manager. Finally, the vectors z_j and z_r includes the share of women and the size of respectively the sending and receiving firm, whereas u_j captures firm j fixed effects.

Turning to the sample of stayers and their probability to be promoted, a similar model is implemented:

$$\begin{aligned} move\_up_{ij} &= \alpha_0 + \alpha_1 wage\_lag(e_i, f_j) + \alpha_2(wage\_lag(e_i, f_j) * gender_i) \\ &\quad + \alpha_3 gender_i + x'_{ij}\beta + z'_j\gamma + u_{cj} \end{aligned} \tag{2}$$

where $move\_up_{ij}$ is a dummy variable equal to 1 if employee i, who has worked within a specific occupation in firm j , gets promoted to a higher occupational level. The the term u_{cj} captures within-firm occupational fixed effects.[12] As in the previous model, the vector x_{ij} and z_j include worker and firm characteristics.

To complement the analysis on assortativity patterns and for a better understanding of its findings, we run model (1) also for transitions from employment to either unemployment or self-employment.

[12] Three main occupational groups are considered: managers, middle-managers and blue-collar workers

5 Results

Given the large amount of results and for sake of clarity, we discuss them into three separate paragraphs. The first one describes sorting in job-to-job transitions, the second gives account of promotion patterns, and the last one looks at both job-to-self-employment and job-to-unemployment transitions. Each sub-section complements the others and provides support to the hypothesis that there are some firms where female workers face glass ceilings.

5.1 Job-to-job transitions

Results referring to job-to-job transitions are reported from Table 3 to Table 10. Table 3 includes our main results that show a general positive assortativity between workers and firms (i.e. there is a significantly positive association between the logarithm of past wage earned in the previous firm and the probability to move to better firm). Although very statistically significant, the size of this elasticity is relatively low as it fluctuates between 0.005 and 0.012, depending on the definition of "better firm" we use. Specifically, the assortativity coefficient gets typically larger if we consider profit rather than value added for the definition of firm type and when workers switch to a firm with higher average or past profits. Interestingly, whereas on average women seem to be less likely to move to better firms, their assortativity appears substantially stronger than men's assortativity, as indicated by the estimated coefficient on the interaction term. Furthermore, the conditional probability to move to a better firm is positively (negatively) associated with the presence of a larger share of women in the receiving (sending) firm. These empirical associations suggest that women are usually more represented in companies characterized by higher profits or value added levels. Transitions to better firms are also more likely when a worker is married, native or holds a tertiary education. The relationship with age and tenure looks positive but low, and the fact of having at least a child, or a parent with past managerial experience are not precisely estimated.

In Table 4, we replace the past log level wage earned with employee fixed effects estimated from a wage equation à la AKM, in the first two columns, and strengthen the conditions on profits and value added to define transitions towards better firms, in the remaining columns. It turns out that the conditional probability of being recruited in a better firm is also positively correlated with worker fixed effects and, as in the previous table, this correlation is stronger for women, implying that the sign of assortativity matching and the gender effect are both confirmed when using the alternative definition of worker ranking suggested by AKM. These findings are corroborated also by the use of more stringent criteria on the indicator function, i.e. the profits or value added differential between sending and receiving firms should be at least 10 percent large. Parameters on other variables lead to similar interpretations as in Table 2.

To further investigate gender differences in assortativity, Table 5 reports results by gender. As expected, notable differences in sorting patterns emerge between women and men. Whereas PAM is typically low and insignificant for men, women show a stronger and much more stable assortativity coefficient, which grows by restricting the criteria on firm performance. In addition, a robustness check on the definition of worker ranking à la AKM, reported in the last two columns, leads to similar conclusions. Hypothesis testing, reported at the bottom of the table, confirms for each specification that the coefficient associated with women's lagged wages is statistically different from the one associated with men's wages. The relationship between transitions to better firms and the share of women in such companies is positive in both men and women samples, although in the latter case the parameter is substantially higher. Furthermore, the parameters on the share of women in the current firms are generally larger and more precisely estimated than those on the share of women in the sending firm. As a consequence, it seems that better firms present on average a greater number of female employees. Network effects looks slightly more significant and stable in the sample of men.

The discrepancies between men and women in assortativity are confirmed in subsamples referring to age, occupation and education (Table 6), civic status and other family characteristics (Table 7). As earlier, men do not generally show any significant and consistent sorting pattern. Women instead present a PAM that is increasing with age, occupational and educational levels. This assortativity is also stronger when women are not married and don't have a child in very young age, suggesting that PAM is at play especially when job transitions are not driven by a child birth. Furthermore the fact that the assortativity coefficient is not significant for women with family network, allows us to dismiss the surmise that women have a stronger assortativity because of stronger familiar ties in the labour market.

Looking at the nature of the transitions (Tables 8, 9 and 10), we find that the result of stronger PAM holds true for women that move to similar but not better job positions. The assortativity parameter is also larger for transitions to female oriented firms, i.e. companies characterized by a share of women in white-collar positions which is higher than the industrial mean, and to firms which do business in a different industry compared to the sending firm. Gender differences in assortativity do not qualitatively change with respect to the main results, if we only consider transitions without job-to-job unemployment periods. Not surprisingly, women's PAM is greater when movements are associated with wage increases or with no changes in place of residence, as this kind of movements are probably more likely to capture seeking career transitions rather than job changes because of family reasons. Conversely, reduction in labor supply represented by shifts from full- to part-time employment is not associated with positive and significant assortativity, as changes in hours worked are very likely to be triggered by family considerations. There is no evidence of PAM either for transitions from a firm closure, as this mobility patterns may not completely reflect employees voluntary choices and career concerns. The fact that PAM holds especially for career oriented women and voluntary transitions is further supported by findings on transitions 2 years before a firm closure or from surviving firms, as the assortativity coefficients are statistically different across genders and are estimated to be larger compared to the baseline results reported in Table 5. Finally, differences in PAM are stronger when women move to smaller firms and in manufacturing and financial and business services.

All in all, our empirical evidence generally suggests that women have a higher degree of positive assortativity compared to men. This result, though, does not hold for all type of transitions and women, as their degree of assortativity may be severely affected by childcare, reduction in their labor supply, their partner's residential mobility and marriage because of household responsibilities. Looking more closely at the other mobility patterns will help us clarifying the reasons and the mechanisms behind this gender heterogeneity in assortativity.

5.2 Promotion patterns

The main findings on sorting in job positions within firms are finally reported in Table 11. Not surprisingly, we find a general positive relationship between a stayer's lagged wage and his probability to be promoted. The size of the elasticity parameter is about three times lower if we only consider promotions to managerial jobs. Being a woman reduces the conditional probability of promotion and the parameter on the interaction between past wages and the female dummy is also significantly negative. This finding on gender differences is confirmed when we separately investigate sorting in promotion for the sample of men and women. Interestingly, a greater share of women is associated with an average higher conditional probability for both men and women, but for the former the estimate is larger. This suggests that the share of female workers *per se* is not an indication of unbiased promotion policies. Not surprisingly, native status, higher education and network are positively associated with the conditional likelihood of being promoted, too.

Looking at results by age group in Table 12, we find that the discrepancy in the sorting parameter enlarges as individuals get older. It looks consistent with the fact that women tend to climb the carrier ladder at slow pace, cumulating an increasing gap with men and therefore lowering their probability to reach top position levels at a given age. Differences in our key parameters do not decrease when we focus on samples composed of singles or individuals without children, even though the coefficient of past wage earned is typically higher for both men and women (Table 13). Furthermore, focusing on the subsample of female oriented and non-discriminating firms[13] provides us with an additional interesting result. For this group of female friendly companies, we find in fact evidence that almost negligible differences arise in the sorting parameter between men and women. These firms are by construction more profitable in our empirical strategy, but we have explicitly tested the correlation between profitability and female-friendliness as well by estimating a productivity equation with fixed effects on the non-discriminating dummy, and we found a positive and significant coefficient.[14]

[13]Female oriented firms are those with a share of white collar women higher than the industrial mean. Non discriminating firms only include the destination firms of the job to job transitions model whose share of white collar women is higher than the industrial mean.

[14]These results are available upon request.

Together with the job-to-job transitions results, this evidence on gender differences in promotion suggest that women, who cannot climb the occupational latter within a firm because subject to discriminating promotion policies, try to overcome these gender barriers by searching for a better job offered by fairer firms.

To complete the description of mechanisms driving the positive assortativity results, we proceed by examining the gender differences in transitions to unemployment and self-employment.

5.3 Job-to-unemployment and job-to-self-employment transitions

Results referring to transitions from employment to unemployment are reported in Table 14. Not surprisingly, the association between last earned wages and propensity to become unemployed is significantly negative and it is estimated to be about -0.005. Women seem to be more exposed to open unemployment than men and, as indicated by the coefficient on the interaction term, this applies even for higher wages. The likelihood of falling in open unemployment increases with age, having at least a child, and being foreigner. Instead, longer tenure, better education, higher shares of women in sending firms, having a parent with managerial experiences, and being married generally lower the probability to enter unemployment. By splitting the full sample in gender-specific sub-samples (columns 2 and 3, Table 14), we find that both women and men with a higher past wages experience a lower likelihood of unemployment than otherwise comparable individuals. However the coefficients estimated in the male subsample is higher and statistically different from the female equivalent, as also revealed by the hypothesis testing reported at the bottom of the table. Tables 15 and 16 generally confirm these gender heterogeneity in the association between wages and the risk of open unemployment, in favor of men. However no statistically significant differences across genders emerge for, alternatively, individuals with at least tertiary education, a child in age 0-3, or previously employed in female oriented firms.

Tables 17, 18 and 19 include results for the sorting patterns in transitions from employment to self-employment. As in job-to-unemployment transitions, the past wages seems to be generally negatively and significantly associated to the likelihood of self-employment. Gender interaction reveals that this is especially true for men. Results reported for alternative sub-samples confirm this gender differences, with the magnitude of the association between wages and of self-employment being higher for men.

Thus, the analysis of job-to-unemployment and job-to-self-employment transitions provide evidence of significant differences between men and women in the propensity to become self-employed or to experience open unemployment in favor of women, revealing a general lower employer's willingness to retain women compared to men. Combining these results with those reported in the previous sub-sections, it seems that the higher female PAM in job-to-job transitions may be partly explained by women experiencing a lower probability to stay within the same employer compared to men and a higher probability to move to firms where females do not face glass ceilings.

6 Conclusions

In this paper, we measured sorting in different labor market transitions for female and male workers using Danish matched employer-employee matched data to assess the reasons behind gender gaps in labor market outcomes. In particular, we studied the relationship between workers' ability, measured by one's position in the wage hierarchy of the firm (s)he works for, and the probability to move to a better firm–in the sense that it generates more profits/value added,–the probability to get promoted and the probability to enter self-employment or unemployment.

The detailed account of gender differences that emerged provided support to the hypothesis that there are some firms where female workers face glass ceilings. This leads good female workers to look for firms where their talents are rewarded in a fairer way. As a result, good female workers are more mobile than male workers towards better firms, while it is easier for good male workers to get promoted by the firms they work for. Furthermore, good female workers are less prone than men to enter unemployment and self-employment, revealing a lower willingness of firms to retain female than male workers.

Since positive sorting is stronger is stronger for older and more experienced workers, we find some support for the theory that asymmetric information is more severe for female workers, but the fact that this phenomenon does not happen in the firms where good female workers get employed suggests that this effect is of second order with respect to the glass ceilings in explaining gender gaps. Quite interestingly, these female friendly firms are highly profitable. Since labor diversity does not seem to increase firm performance *per se* (see Parrotta, Pozzoli and Pytlikova, 2011), our evidence suggests that the positive effect of good female workers on profits is due to their lower market opportunities resulting from the glass ceilings they face in discriminating firms.

Overall, our findings imply that there is scope for policy intervention in order to prevent this glass ceilings effects, since the benefits from reallocating the labor force in an efficient way can be substantial.

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Table 1: Main descriptive statistics

Variables	**Sample of switchers**				**Sample of stayers**			
	Women		**Men**		**Women**		**Men**	
	Mean	*S.d.*	*Mean*	*S.d.*	*Mean*	*S.d.*	*Mean*	*S.d.*
log(wage_sending)	12.055	0.661	12.304	0.647	12.261	0.454	12.510	0.447
age	34.161	9.711	35.367	10.150	39.403	10.470	40.554	11.048
tenure	2.800	2.993	2.898	3.104	6.090	5.154	6.693	5.450
labour market experience	11.137	8.101	13.883	9.107	15.052	8.698	18.464	9.997
manager	0.018	0.133	0.042	0.177	0.015	0.121	0.033	0.200
middle manager	0.256	0.436	0.220	0.414	0.269	0.443	0.230	0.421
blue collar	0.726	0.446	0.748	0.434	0.716	0.451	0.728	0.445
with at least a child (0-3)	0.145	0.352	0.140	0.347	0.112	0.315	0.104	0.305
primary (1, if with primary education)	0.374	0.484	0.305	0.460	0.415	0.493	0.331	0.470
secondary (1, if with secondary and post-secondary education)	0.559	0.497	0.648	0.478	0.534	0.499	0.624	0.484
tertiary (1, if with tertiary education)	0.067	0.250	0.047	0.212	0.051	0.220	0.045	0.207
foreigner	0.056	0.230	0.048	0.214	0.053	0.223	0.049	0.217
network (1, if father or mother is manager)	0.042	0.215	0.039	0.193	0.033	0.179	0.029	0.168
married or cohabitating	0.681	0.466	0.662	0.473	0.763	0.425	0.726	0.446
share of women in the sending firm	0.472	0.203	0.260	0.183	-	-	-	-
share of women in the current firm	0.470	0.208	0.251	0.184	0.470	0.211	0.257	0.179
sending firm size less than 50 employees	0.741	0.438	0.667	0.471	-	-	-	-
sending firm size between 51 and 100 employees	0.137	0.344	0.186	0.389	-	-	-	-
sending firm size more than 100 employees	0.122	0.327	0.148	0.355	-	-	-	-
current firm size less than 50 employees	0.706	0.456	0.630	0.483	0.740	0.438	0.642	0.480
current firm size between 51 and 100 employees	0.162	0.369	0.214	0.410	0.143	0.350	0.207	0.405
current firm size more than 100 employees	0.132	0.339	0.156	0.363	0.116	0.321	0.152	0.359
sending firm profit per worker	81.856	357.505	74.273	263.465	-	-	-	-
current firm profit per worker	102.114	483.849	98.450	439.194	107.777	356.815	110.623	298.070
obs	112387		267449		829071		1620834	
number of individuals	35096		89865		100240		203790	
number of firms	8535				9117			

Notes: All variables are averages from 1995 to 2005.

Table 2: Mean of all the dependent variables

	Sample of switchers	
Variables	**Women**	**Men**
prob(profits current firm>profits previous firm)	0.494	0.498
prob(profits current firm>profits previous firm by 10%)	0.360	0.366
prob(va current firm>va previous firm)	0.481	0.472
prob(va current firm>va previous firm by 10%)	0.438	0.441
prob(profits current firm per worker>profits previous firm per worker)	0.552	0.543
prob(profits current firm per worker>profits previous firm per worker by 10%)	0.414	0.408
prob(va per worker current firm>va per worker previous firm)	0.558	0.554
prob(va per worker current firm>va per worker previous firm by 10%)	0.489	0.469
prob(average profits current firm>average profits previous firm)	0.504	0.501
prob(average profits current firm>average profits previous firm by 10%)	0.400	0.394
prob(average profits current firm per worker> average profits previous firm per worker)	0.561	0.556
prob(average profits current firm per worker> average profits previous firm per worker by 10%)	0.446	0.441
prob(past profits current firm> past profits previous firm)	0.499	0.503
prob(past profits current firm> past profits previous firm by 10%)	0.395	0.397
prob(past profits current firm per worker> past profits previous firm per worker)	0.544	0.543
prob(past profits current firm per worker> past profits previous firm per worker by 10%)	0.434	0.432
Obs	112387	267449
	All sample without observations with switching	
promotion	0.011	0.020
promotion to a managerial position	0.001	0.004
unemployment (0, stayers)	0.024	0.019
self-employment (0, stayers)	0.002	0.004
Obs	1464451	3050674

Notes: All the dependent variables are expressed as time averages from 1995 to 2005.

Table 3: Sorting models results, main results

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**	**Model9**
log(wage_lag)	0.005***	0.005***	0.012***	0.005***	0.010***	0.005***	0.006***	0.004**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
female	-0.003*	-0.003*	-0.002	-0.005**	-0.004**	-0.004**	-0.004**	-0.002*	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
log(wage_lag)*female	-	0.007**	0.005*	0.005*	0.008**	0.005*	0.007**	0.006**	0.006**
	-	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
age	0.001	0.001	0.002***	0.001*	0.002***	0.001*	0.003***	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2/1000	-0.021**	-0.022**	-0.046***	-0.027***	-0.047***	-0.026**	-0.051***	-0.016**	-0.010
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)
tenure	0.001	0.001	0.003***	0.001*	0.003***	0.000	0.002***	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
tenure2/1000	-0.080**	-0.080**	-0.172***	-0.073**	-0.156***	-0.046	-0.132***	0.026	0.053*
	(0.032)	(0.032)	(0.035)	(0.028)	(0.032)	(0.035)	(0.040)	(0.029)	(0.029)
share of women in the sending firm	-0.008*	-0.008*	-0.109***	0.021***	-0.116***	0.005	-0.106***	-0.035***	-0.026***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
share of women in the current firm	0.161***	0.160***	0.055*	0.078***	0.087***	0.030	0.022	0.018	0.082***
	(0.026)	(0.026)	(0.028)	(0.023)	(0.025)	(0.025)	(0.028)	(0.022)	(0.023)
child	0.001	0.002	-0.002	0.002	-0.002	0.000	0.003	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
secondary	0.001	0.001	0.005**	0.004**	0.001	-0.000	-0.001	0.004**	0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
tertiary	0.031***	0.031***	0.042***	0.032***	0.037***	0.020***	0.026***	0.031***	0.029***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
married	0.005***	0.006***	0.008***	0.007***	0.010***	0.006***	0.006***	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
foreigner	-0.009**	-0.009**	-0.012***	-0.013***	-0.013***	-0.010**	-0.009**	-0.013***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
network	0.003	0.003	0.005	0.001	0.004	-0.001	0.001	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
N	379836	379836	379836	379836	379836	379836	379836	379836	379836
R-sq	0.120	0.120	0.009	0.152	0.008	0.111	0.004	0.284	0.283

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1 and 2); ii) higher profits per worker (model 3); iii) higher average profits (model 4); iv) higher average profits per worker (model 5); v) higher past profits (model 6); vi) higher past profits per worker (model 7); vii) higher value added (model 8); viii) vi) higher value added per worker (model 9). All specifications include experience and experience squared, previous firm fixed effects, size dummies of the receiving and previous firm, year and occupational dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 4: Sorting models results, estimations with alternative definitions of the dependent and the ranking variable

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**	**Model9**	**Model10**	**Model11**
log(wage_lag)	-	-	0.002**	0.003**	0.011***	0.006***	0.011***	0.006***	0.008***	0.017***	0.015***
	-	-	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
female	-0.004**	-0.004**	-0.006***	-0.005**	-0.003	-0.006***	-0.003**	-0.001	-0.002	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(wage_lag)*female	-	-	-	0.007**	0.005*	0.003	0.007**	0.003	0.009**	0.010***	0.006**
	-	-	-	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fixed effects from a wage equation	0.016***	0.016***	-	-	-	-	-	-	-	-	-
	(0.002)	(0.002)	-	-	-	-	-	-	-	-	-
(Fixed effects from a wage equation)* female	-	0.007**	-	-	-	-	-	-	-	-	-
	-	(0.003)	-	-	-	-	-	-	-	-	-
age	0.002**	0.002**	0.001	0.001	0.003***	0.001**	0.002***	0.001	0.003***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2/1000	-0.033***	-0.034***	-0.020**	-0.021**	-0.049***	-0.029***	-0.047***	-0.019**	-0.053***	-0.082***	-0.087***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
tenure	0.000	0.000	-0.001	-0.001	0.002**	-0.000	0.003***	-0.000	0.002**	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tenure2/1000	-0.067**	-0.067**	-0.029	-0.030	-0.100**	-0.022	-0.134***	-0.005	-0.092**	-0.077**	-0.088**
	(0.032)	(0.032)	(0.030)	(0.030)	(0.034)	(0.028)	(0.032)	(0.034)	(0.040)	(0.034)	(0.034)
share of women in the sending firm	-0.007*	-0.007	-0.001	-0.001	-0.055**	-0.018	-0.126***	-0.015	-0.078**	-0.142***	-0.156***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.028)	(0.023)	(0.025)	(0.025)	(0.027)	(0.028)	(0.028)
share of women in the current firm	0.160***	0.160***	0.051**	0.051**	0.099***	0.009**	0.112***	0.005	0.103***	0.332***	0.300***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
child	0.001	0.001	0.002	0.003	-0.000	0.001	-0.001	0.000	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
secondary	0.006***	0.006***	0.001	0.001	0.003**	0.001	-0.000	-0.001	-0.002	0.008***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
tertiary	0.036***	0.036***	0.026***	0.026***	0.034***	0.031***	0.034***	0.022***	0.023***	0.064***	0.067***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
married	0.005**	0.005***	0.004**	0.004**	0.006***	0.004**	0.008***	0.004**	0.004**	0.007***	0.007***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
foreigner	-0.009**	-0.009**	-0.008**	-0.008**	-0.012***	-0.008**	-0.011***	-0.009**	-0.007**	-0.017***	-0.021***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
network	0.003	0.003	-0.000	-0.000	0.003	-0.001	0.002	-0.002	0.002	0.008**	0.011**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
N	379836	379836	379836	379836	379836	379836	379836	379836	379836	379836	379836
R-sq	0.120	0.120	0.125	0.125	0.005	0.154	0.007	0.113	0.004	0.028	0.025

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1, 2); ii) higher profits by 10% (model 3, 4); iii) higher profits per worker by 10% (model 5); iv) higher average profits by 10% (model 6); v) higher average profits per worker by 10% (model 7); vi) higher past profits by 10% (model 8); vi) higher past profits per worker by 10% (model 9); vii) higher value added by 10% (model 10); viii) vi) higher value added per worker by 10% (model11). All specifications include experience and experience squared, previous firm fixed effects, size dummies of the receiving and previous firm, year and occupational dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 5: Sorting models estimated separately for men and women: main results

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Women								
log(wage_sending)	0.011***	0.011***	0.004**	0.017***	0.010***	0.007***	-	-
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	-	-
Fixed effects from a wage equation	-	-	-	-	-	-	0.019***	0.015***
	-	-	-	-	-	-	(0.003)	(0.003)
age	0.003**	0.004**	-0.003**	0.004***	-0.000	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2/1000	-0.050***	-0.064***	0.026**	-0.070***	-0.005	-0.010	-0.022	-0.024*
	(0.015)	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
tenure	0.002**	0.002**	-0.001	-0.001	-0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tenure2/1000	-0.098	-0.147**	0.032	0.071	-0.053	-0.047	-0.047	-0.041
	(0.062)	(0.063)	(0.056)	(0.060)	(0.060)	(0.057)	(0.060)	(0.057)
share of women in the sending firm	-0.065	0.058	0.225***	0.173***	-0.160***	0.139**	-0.157***	0.141***
	(0.046)	(0.045)	(0.037)	(0.046)	(0.042)	(0.042)	(0.042)	(0.042)
share of women in the current firm	0.215***	0.213***	0.139***	0.404***	0.133***	0.124***	0.132***	0.123***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
child	-0.004	-0.004	-0.001	0.000	0.001	0.002	0.000	0.002
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
secondary	0.005*	0.004	0.003	0.011***	0.002	0.001	0.000	0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
tertiary	0.039***	0.040***	0.030***	0.064***	0.032***	0.030***	0.008**	0.006**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)
married	0.010***	0.008**	0.001	0.007**	0.009***	0.008**	0.009***	0.008**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
foreigner	-0.016**	-0.016**	-0.018***	-0.023***	-0.010*	-0.011**	-0.010*	-0.012**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
network	-0.004	-0.003	-0.008	-0.002	0.001	0.002	0.038***	0.035***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
N	112387	112387	112387	112387	112387	112387	112387	112387
R-sq	0.110	0.110	0.017	0.014	0.248	0.042	0.110	0.110
Men								
log(wage_sending)	-	-	0.003	0.003	0.002	0.013***	0.003**	0.000
	-	-	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Fixed effects from a wage equation	0.010***	0.006**	-	-	-	-	-	-
	(0.002)	(0.002)	-	-	-	-	-	-
age	0.002**	0.001	0.002**	0.002**	0.001*	0.006***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2/1000	-0.033**	-0.023**	-0.043***	-0.043***	-0.022**	-0.091***	-0.024**	-0.019*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.009)	(0.011)	(0.010)	(0.010)
tenure	0.001	-0.000	0.003***	0.002**	-0.001**	0.002**	0.001*	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
tenure2/1000	-0.081**	-0.021	-0.204***	-0.099**	0.027	-0.152***	-0.097**	-0.033
	(0.038)	(0.036)	(0.041)	(0.041)	(0.033)	(0.041)	(0.038)	(0.036)
share of women in the sending firm	-0.153***	-0.017	-0.042	0.034	-0.045*	0.169***	-0.153***	-0.017
	(0.033)	(0.033)	(0.036)	(0.035)	(0.028)	(0.035)	(0.033)	(0.033)
share of women in the current firm	0.069***	0.070***	0.043***	0.034***	0.035***	0.288***	0.069***	0.069***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
child	0.002	0.002	-0.002	0.000	0.002	0.004	0.002	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
secondary	0.004	-0.002	0.004**	0.003	0.004**	0.008***	0.001	-0.000
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tertiary	0.004**	0.002	0.042***	0.030***	0.028***	0.068***	0.029***	0.022***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
married	0.003	0.001	0.007***	0.004**	0.000	0.007***	0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
foreigner	-0.008**	-0.006*	-0.010**	-0.011**	-0.012***	-0.016***	-0.008**	-0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
network	0.032***	0.023***	0.009**	0.004	0.006*	0.015***	0.004	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	267449	267449	267449	267449	267449	267449	267449	267449
R-sq	0.127	0.132	0.007	0.004	0.298	0.024	0.126	0.132
Hypothesis tests [Chi2; p-value]:								
log(wage_sending) women=log(wage_sending) men	953.69; 0.000	1045.69; 0.000	119.16; 0.000	118.14; 0.000	225.77; 0.000	57.87; 0.000	1091.35; 0.000	1954.55; 0.000

Notes: The dependent variable is a dummy that takes the value of 1, if the worker switches to a firm with: i) higher profits (model 1 and 7); ii) higher profits by 10% (model 2 and 8); i) higher profits per worker (model 3); ii) higher profits per worker by 10% (model 4); i) higher value added (model 5); ii) higher value added by 10% (model 6). All specifications include experience and experience squared, firm fixed effects, size dummies of the receiving and previous firm a full set of industry, year and occupational dummies. In columns 7 and 8, the estimated fixed effects from a standard wage equation à la Abowd et al. (1999) are included as a measure of the workers' ranking, instead of the log of wages. Standard errors clustered at the individual level are reported in parentheses. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 6: Sorting models estimated separately for men and women: results by age, occupation and education

	Less than 35 years		**Between 35 and 50 years**		**More than 50 years**	
			Women			
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.010***	0.007**	0.010**	0.008*	0.020**	0.015*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.009)	(0.009)
N	68275	68275	35140	35140	8972	8972
R-sq	0.115	0.113	0.104	0.107	0.089	0.092
			Men			
log(wage_sending)	0.002	-0.002	0.005*	0.004*	0.004	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)
N	149689	149689	89724	89724	28036	28036
R-sq	0.133	0.137	0.123	0.128	0.102	0.116
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	19049.14; 0.000	1266.50; 0.000	37.01; 0.000	218.22; 0.000	882.29; 0.000	136.61; 0.000
	Blue collar		**Middle manager**		**Middle manager**	
			Women			
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.008**	0.005**	0.014**	0.015**	0.033	0.036*
	(0.003)	(0.003)	(0.005)	(0.005)	(0.023)	(0.023)
N	81639	81639	28728	28728	2020	2020
R-sq	0.112	0.113	0.106	0.104	0.111	0.099
			Men			
log(wage_sending)	0.003*	0.001	0.009**	0.002	-0.017*	-0.004
	(0.002)	(0.002)	(0.004)	(0.004)	(0.010)	(0.010)
N	200024	200024	58730	58730	8695	8695
R-sq	0.136	0.144	0.101	0.100	0.097	0.094
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	203.84; 0.000	76.56; 0.000	1095.94; 0.000	91.99; 0.000	387.61; 0.000	207.38; 0.000
	Primary education		**Secondary education**		**Tertiary education**	
			Women			
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.008**	0.005	0.011***	0.010**	0.016**	0.008**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.008)	(0.004)
N	42072	42072	62800	62800	7515	7515
R-sq	0.110	0.114	0.108	0.108	0.119	0.104
			Men			
log(wage_sending)	-0.001	-0.003	0.006**	0.002	0.008	0.004
	(0.003)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)
N	81559	81559	173227	173227	12663	12663
R-sq	0.138	0.141	0.123	0.131	0.107	0.103
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	4621.08; 0.000	207.49; 0.000	103.09; 0.000	144.47; 0.000	205.63; 0.000	184.27; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1), ii) higher profits by 10% (model 2). All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, sending firm fixed effects, share of women and size dummies of the receiving and sending firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 7: Sorting models estimated separately for men and women: results by relevant individual characteristics

	Married or cohabiting		**Single**		**With family network**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.008**	0.007**	0.013**	0.008**	0.009	0.017*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.010)	(0.010)
N	76576	76576	35811	35811	5457	5457
R-sq	0.110	0.111	0.109	0.107	0.123	0.113
	Men					
log(wage_sending)	0.002	-0.000	0.005**	0.001	-0.006	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)
N	177124	177124	90325	90325	10373	10373
R-sq	0.124	0.130	0.132	0.137	0.117	0.123
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	80576.84; 0.000	542.02; 0.000	159.08; 0.000	36.83; 0.000	228.98; 0.000	53.79; 0.000
	Without family network		**With child (0-3 years)**		**Without child (0-3 years)**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.010***	0.007**	0.008	0.005	0.010***	0.008**
	(0.002)	(0.002)	(0.006)	(0.005)	(0.003)	(0.002)
N	106930	106930	16274	16274	96113	96113
R-sq	0.109	0.110	0.118	0.115	0.108	0.109
	Men					
log(wage_sending)	0.004**	0.001	0.007	0.003	0.004**	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
N	257076	257076	37415	37415	257076	257076
R-sq	0.127	0.133	0.126	0.130	0.127	0.133
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	1188.70; 0.000	12460.19; 0.000	1.95; 0.163	3.90; 0.07	519.64; 0.000	906.37; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1), ii) higher profits by 10% (model 2). All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, sending firm fixed effects, share of women and size dummies of the receiving and sending firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 8: Sorting models estimated separately for men and women: results by type of transitions

	Transition to a better occupational level		**Transition to the same occupational level**		**Transition to female oriented firms**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.000	0.006	0.012***	0.008**	0.015***	0.011**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
N	18948	18948	76728	76728	47252	47252
R-sq	0.122	0.119	0.105	0.106	0.129	0.130
	Men					
log(wage_sending)	0.003	0.001	0.003	-0.000	0.004*	0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
N	40474	40474	191832	191832	129372	129372
R-sq	0.123	0.125	0.128	0.134	0.145	0.153
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men:	1.15; 0.31	20.89; 0.000	4132.64; 0.000	1051.20; 0.000	1341.97; 0.000	913.93; 0.000
	Transition not to female oriented firms		**Transition within the same industry**		**Transition to a different industry**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.010***	0.007**	0.006***	0.006***	0.011***	0.008**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
N	64913	64913	45254	45254	67133	67133
R-sq	0.089	0.090	0.101	0.106	0.117	0.114
	Men					
log(wage_sending)	0.003	-0.002	0.003*	0.000	0.004*	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	136379	136379	230034	230034	152588	152588
R-sq	0.107	0.111	0.127	0.133	0.137	0.140
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	8782.68; 0.000	403.98; 0.000	263.47; 0.000	1165.32	621.20; 0.000	322.66; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1), ii) higher profits by 10% (model 2). All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, sending firm fixed effects, share of women and size dummies of the receiving and sending firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. Female oriented firms are those with a share of white collar women is higher than the industrial mean. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 9: Sorting models estimated separately for men and women: results by other relevant types of transitions

	Transition without unemployment		Transition from a firm exit		Transition 2 years before a firm exit		Transition from a surviving firm	
	Women							
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.009**	0.010**	0.001	0.001	0.013*	0.018*	0.011***	0.008**
	(0.004)	(0.003)	(0.007)	(0.007)	(0.007)	(0.010)	(0.002)	(0.002)
N	62348	62348	10846	10846	3481	3481	101541	101541
R-sq	0.101	0.101	0.085	0.094	0.107	0.103	0.112	0.111
	Men							
log(wage_sending)	0.005**	0.002	0.001	-0.000	0.006	0.007	0.003**	0.000
	(0.002)	(0.002)	(0.005)	(0.005)	(0.008)	(0.008)	(0.002)	(0.002)
N	171178	171178	22368	22368	9042	9042	245081	245081
R-sq	0.122	0.125	0.082	0.096	0.125	0.116	0.130	0.135
Hypothesis tests [Chi2; p-value]**:**								
log(wage_sending) women=log(wage_sending) men	17848.64; 0.000	3043.78; 0.000	0.923; 0.540	0.810; 0.561	5.34; 0.03	7.89; 0.000	1672.47; 0.000	1554.55; 0.000

	Transition without change in residence		From full to part-time		Transition with a wage improvement	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.013***	0.011**	-0.002	-0.004	0.016***	0.012***
	(0.004)	(0.004)	(0.012)	(0.010)	(0.003)	(0.003)
N	47926	47926	11556	11556	37129	37129
R-sq	0.100	0.103	0.09	0.11	0.107	0.104
	Men					
log(wage_sending)	0.003	-0.001	-0.003	-0.003	0.001	-0.001
	(0.003)	(0.003)	(0.008)	(0.007)	(0.002)	(0.002)
N	112680	112680	14566	14566	77592	77592
R-sq	0.124	0.133	0.098	0.124	0.123	0.126
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	49952.48; 0.000	5476.98; 0.000	2.38; 0.17	2.71; 0.16	4183.49; 0.000	4382.01; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1), ii) higher profits by 10% (model 2). All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, sending firm fixed effects, share of women and size dummies of the receiving and sending firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 10: Sorting models estimated separately for men and women: results by size of sending firm and industry of current firm

	Firm size: 20-49 employees		**Firm size: 50-99 employees**		**Firm size: more than 99 employees**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.016**	0.017***	0.007**	0.006	0.009**	0.007**
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
N	18237	18237	14856	14856	79294	79294
R-sq	0.017	0.007	0.016	0.007	0.011	0.008
	Men					
log(wage_sending)	0.007**	0.004	0.003	0.001	0.002	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)
N	57297	57297	41762	41762	168390	168390
R-sq	0.008	0.003	0.007	0.004	0.008	0.006
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	254.88; 0.000	7202.17; 0.000	43.28; 0.000	2958.82; 0.000	3168.19; 0.000	3410.62; 0.000
	Manufacturing		**Construction**		**Whole sale trade**	
	Women					
	Model1	**Model2**	**Model1**	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.006**	0.009***	0.008	0.006	0.003	0.001
	(0.003)	(0.003)	(0.014)	(0.014)	(0.004)	(0.004)
N	47395	47395	3075	3075	35443	35443
R-sq	0.135	0.127	0.125	0.151	0.099	0.100
	Men					
log(wage_sending)	0.000	-0.004*	0.008	0.005*	0.001	0.002
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.003)
N	121997	121997	49753	49753	52080	52080
R-sq	0.145	0.145	0.136	0.152	0.106	0.111
Hypothesis tests [Chi2; p-value]**:**						
log(wage_sending) women=log(wage_sending) men	392.72; 0.000	110.79; 0.000	0.991; 0.653	1.765; 0.235	1.899; 0.245	0.651; 0.420

	Transport		**Business and financial**	
	Women			
	Model1	**Model2**	**Model1**	**Model2**
log(wage_sending)	0.006	0.007	0.019***	0.013**
	(0.012)	(0.011)	(0.005)	(0.005)
N	5304	5304	21115	21115
R-sq	0.094	0.097	0.087	0.089
	Men			
log(wage_sending)	-0.002	-0.001	0.007	0.005
	(0.006)	(0.006)	(0.005)	(0.004)
N	15121	15121	27932	27932
R-sq	0.141	0.154	0.081	0.075
Hypothesis tests [Chi2; p-value]**:**				
log(wage_sending) women=log(wage_sending) men	10.059; 0.000	98.01; 0.000	225.22; 0.000	93.32; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker switches to a firm with: i) higher profits (model 1), ii) higher profits by 10% (model 2). All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, sending firm fixed effects, share of women and size dummies of the receiving and sending firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 11: Promotion models estimated for all sample and separately for men and women: main results

	Model1		Model2		Model1		Model2	
	All sample				Women	Men	Women	Men
log(wage_sending)	0.015***	0.014***	0.005***	0.005***	0.009***	0.016***	0.002***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female	-0.008***	-0.008***	-0.002***	-0.002***	-	-	-	-
	(0.000)	(0.000)	(0.000)	(0.000)	-	-	-	-
female*log(wage_sending)	-	-0.005***	-	-0.003***	-	-	-	-
	-	(0.000)	-	(0.000)	-	-	-	-
age	0.002***	0.002***	0.001*	-0.000**	0.001***	0.003***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age2/1000	-0.029***	-0.029***	-0.020***	0.002***	-0.015***	-0.035***	0.001	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
tenure	-0.002***	-0.002***	-0.001***	-0.000***	-0.001***	-0.002***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure2/1000	0.057***	0.056***	0.008***	0.008***	0.039***	0.064***	0.005***	0.010***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
share of women in the current firm	0.016***	0.015***	0.002***	0.002***	0.002***	0.026**	0.001***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
child	0.001**	0.001**	0.000	0.000	0.000	0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
married	0.004***	0.003***	0.001***	0.001***	-0.001**	0.006***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
secondary	0.007***	0.006***	0.001***	0.001***	0.004***	0.007***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tertiary	0.034***	0.035***	0.007***	0.007***	0.033***	0.034***	0.004***	0.008***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
foreigner	-0.008***	-0.008***	-0.001***	-0.001***	-0.003***	-0.011***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
network	0.009***	0.009***	0.001***	0.001***	0.006***	0.010***	0.000	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
N	4657199	4656516	4657199	4656516	1518826	3138373	1518826	3138373
R-sq	0.016	0.017	0.017	0.017	0.011	0.019	0.007	0.021
Hypothesis tests [Chi2; p-value]**:**								
log(wage_sending) women=log(wage_sending) men	-	-	-	-	21.55; 0.000		7.89; 0.000	

Notes: The dependent variable is a dummy that takes the value of one, if the worker is, within the same firm, promoted to: i) a better occupational level (model 1); ii) a managerial position (model2). All specifications include experience and experience squared, firm and occupation specific fixed effects, size dummies of the receiving firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 12: Promotion models estimated separately for men and women: results by age and education

	Less than 35 years	**Between 35 and 50 years**	**More than 50 years**
		Women	
log(wage_sending)	0.002***	0.018***	0.016***
	(0.000)	(0.001)	(0.001)
N	615559	634702	235016
R-sq	0.006	0.013	0.009
		Men	
log(wage_sending)	0.002***	0.027***	0.037***
	(0.000)	(0.001)	(0.001)
N	1165410	1298495	598292
R-sq	0.010	0.022	0.025
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	5.33; 0.02	11.60; 0.000	8.14; 0.000
	Primary education	**Secondary education**	**Tertiary education**
		Women	
log(wage_sending)	0.001***	0.014***	0.003***
	(0.000)	(0.000)	(0.001)
N	605965	816780	96081
R-sq	0.004	0.007	0.009
		Men	
log(wage_sending)	0.003***	0.022***	0.004***
	(0.000)	(0.000)	(0.001)
N	1009583	1961845	166945
R-sq	0.013	0.016	0.040
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	14.33; 0.000	11.40; 0.000	1.331; 0.242

Notes: The dependent variable is a dummy that takes the value of one, if the worker is, within the same firm, promoted to a better occupational level. All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, occupation-firm fixed effects, current firm share of women and size and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 13: Promotion models estimated separately for men and women: results by other relevant subgroups

	Married or cohabiting	**Single**	**Without child (0-3 years)**
		Women	
log(wage_sending)	0.004***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)
N	1142086	376740	181302
R-sq	0.012	0.011	0.011
		Men	
log(wage_sending)	0.006***	0.016***	0.017***
	(0.000)	(0.000)	(0.001)
N	2244977	893396	364886
R-sq	0.021	0.014	0.019
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	18.21; 0.000	23.67; 0.000	19.60; 0.000
	Female oriented firms	**Not Female oriented firms**	**Non discriminating firms**
		Women	
log(wage_sending)	0.008***	0.006***	0.006***
	(0.001)	(0.000)	(0.001)
N	527579	991320	447471
R-sq	0.013	0.009	0.014
		Men	
log(wage_sending)	0.009***	0.017***	0.007***
	(0.001)	(0.000)	(0.001)
N	650983	2486938	504269
R-sq	0.017	0.019	0.018
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	4.93; 0.030	11.83; 0.000	3.97; 0.082

Notes: The dependent variable is a dummy that takes the value of one, if the worker is, within the same firm, promoted to a better occupational level. All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, occupation-firm fixed effects, current firm share of women and size and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. Female oriented firms are those with a share of white collar women higher than the industrial mean. Non discriminating firms only include the destination firms of the job to job transitions model whose share of white collar women is higher than the industrial mean. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 14: Unemployment probability estimated for all sample and separately for men and women: main results

	All sample		**Women**	**Men**
log(wage_sending)	-0.005***	-0.005***	-0.002***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
female	0.005***	0.005***	-	-
	(0.000)	(0.000)	-	-
female*log(wage_sending)	-	0.004***	-	-
	-	(0.000)	-	-
age	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
age2/1000	-0.062***	-0.063***	-0.064***	-0.059***
	(0.001)	(0.001)	(0.002)	(0.001)
tenure	-0.010***	-0.010***	-0.011***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
tenure2/1000	0.360***	0.360***	0.421***	0.330***
	(0.002)	(0.002)	(0.004)	(0.002)
share of women in the sending firm	-0.007***	-0.007***	0.001	-0.013***
	(0.000)	(0.000)	(0.001)	(0.001)
child	0.006***	0.006***	0.014***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
married	-0.011***	-0.011***	-0.003***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
secondary	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
tertiary	-0.013***	-0.013***	-0.015***	-0.012***
	(0.000)	(0.000)	(0.001)	(0.000)
foreigner	0.007***	0.007***	0.002**	0.011***
	(0.000)	(0.000)	(0.001)	(0.001)
network	-0.005***	-0.005***	-0.007***	-0.004***
	(0.000)	(0.000)	(0.001)	(0.000)
N	5595917	5595917	1948925	3646992
R-sq	0.024	0.024	0.022	0.026
Hypothesis tests [Chi2; p-value]**:**				
log(wage_sending) women=log(wage_sending) men	-	-	6.53; 0.010	

Notes: The dependent variable is a dummy that takes the value of one, if the worker is unemployed. All specifications include experience and experience squared, previous firm fixed effects, size dummies of the previous firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 15: Unemployment probability estimated separately for men and women: results by age and education

	Less than 35 years	Between 35 and 50 years	More than 50 years
		Women	
log(wage_sending)	0.000	-0.019***	-0.013***
	(0.000)	(0.001)	(0.001)
N	859650	731470	357805
R-sq	0.027	0.028	0.014
		Men	
log(wage_sending)	-0.005***	-0.024***	-0.020***
	(0.000)	(0.000)	(0.001)
N	1449266	1406579	791147
R-sq	0.029	0.035	0.020
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	4.59; 0.0322	3.21; 0.0730	10.16; 0.001
	Primary education	**Secondary education**	**Tertiary education**
		Women	
log(wage_sending)	-0.0001***	-0.019***	-0.013***
	(0.000)	(0.000)	(0.001)
N	887656	953566	107703
R-sq	0.024	0.025	0.018
		Men	
log(wage_sending)	-0.003***	-0.023***	-0.012***
	(0.000)	(0.000)	(0.001)
N	1311176	2157782	178034
R-sq	0.030	0.028	0.018
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	8.18; 0.004	6.96; 0.007	0.84; 0.358

Notes: The dependent variable is a dummy that takes the value of one, if the worker is unemployed. All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, previous firm fixed effects, previous firm share of women and size and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 16: Unemployment probability estimated separately for men and women: results by other relevant subgroups

	Married or cohabiting	Single	With child (0-3 years)
		Women	
log(wage_sending)	-0.012***	-0.001**	-0.019***
	(0.000)	(0.000)	(0.001)
N	1354806	594119	202354
R-sq	0.022	0.025	0.034
		Men	
log(wage_sending)	-0.018***	-0.006***	-0.019***
	(0.000)	(0.000)	(0.001)
N	2471976	1175016	390681
R-sq	0.023	0.032	0.032
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	4.71; 0.031	10.58; 0.001	0.01; 0.932

	Female oriented firms	Not Female oriented firms
	Women	
log(wage_sending)	-0.005***	-0.001**
	(0.000)	(0.000)
N	1106363	842497
R-sq	0.019	0.025
	Men	
log(wage_sending)	-0.008***	-0.009***
	(0.000)	(0.000)
N	1620291	2026734
R-sq	0.021	0.028
Hypothesis tests [Chi2; p-value]**:**		
log(wage_sending) women=log(wage_sending) men	2.34; 0.126	11.24; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker is unemployed. All specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, previous firm fixed effects, previous firm share of women and size and a full set of industry and year dummies. Female oriented firms are those with a share of white collar women higher than the industrial mean. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 17: Self-employment probability estimated for all sample and separately for men and women: main results

	All sample		**Women**	**Men**
log(wage_sending)	-0.001***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
female	-0.004***	-0.004***	-	-
	(0.000)	(0.000)	-	-
female*log(wage_sending)	-	0.001***	-	-
	-	(0.000)	-	-
age	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
age2/1000	-0.012***	-0.012***	-0.010***	-0.014***
	(0.000)	(0.000)	(0.001)	(0.001)
tenure	-0.001***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
tenure2/1000	0.051***	0.051***	0.029***	0.062***
	(0.001)	(0.001)	(0.001)	(0.001)
share of women in the current firm	0.002***	0.002***	0.001***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
child	0.001***	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
married	0.001***	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
secondary	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
tertiary	-0.001***	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
foreigner	0.001**	0.001**	-0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
network	0.002***	0.002***	0.001**	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
N	5702811	5702811	1995164	3707647
R-sq	0.003	0.003	0.002	0.004
Hypothesis tests [Chi2; p-value]**:**				
log(wage_sending) women=log(wage_sending) men	-	-	3.55; 0.06	

Notes: The dependent variable is a dummy that takes the value of one, if the worker is self-employed. All specifications include experience and experience squared, previous firm fixed effects, size dummies of the previous firm and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 18: Self-employment probability estimated separately for men and women: results by age and education

	Less than 35 years	**Between 35 and 50 years**	**More than 50 years**
		Women	
log(wage_sending)	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
N	898005	739293	357866
R-sq	0.002	0.002	0.002
		Men	
log(wage_sending)	-0.001***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)
N	1500106	1416311	791230
R-sq	0.005	0.004	0.004
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	6.75; 0.009	3.27; 0.070	4.65; 0.031
	Primary education	**Secondary education**	**Tertiary education**
		Women	
log(wage_sending)	-0.001***	-0.002***	-0.001**
	(0.000)	(0.000)	(0.001)
N	915013	966758	113393
R-sq	0.002	0.002	0.003
		Men	
log(wage_sending)	-0.001***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.001)
N	1344753	2176755	186139
R-sq	0.004	0.004	0.004
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	0.33; 0.563	7.52; 0.000	27.81; 0.000

Notes: The dependent variable is a dummy that takes the value of one, if the worker is self-employed. ll specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, previous firm fixed effects, previous firm share of women and size and a full set of industry and year dummies. Standard errors are reported in parentheses and are clustered at the individual level. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table 19: Self-employment probability estimated separately for men and women: results by other relevant subgroups

	Married or cohabiting	Single	With child (0-3 years)
		Women	
log(wage_sending)	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N	1374296	620868	207643
R-sq	0.002	0.002	0.002
		Men	
log(wage_sending)	-0.003***	-0.001**	-0.004***
	(0.000)	(0.000)	(0.000)
N	2494438	1213209	396983
R-sq	0.004	0.004	0.005
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	5.56; 0.012	0.93; 0.331	5.145; 0.023
	Female oriented firms	**Not Female oriented firms**	
		Women	
log(wage_sending)	-0.001***	-0.001***	
	(0.000)	(0.000)	
N	1131726	863092	
R-sq	0.002	0.002	
		Men	
log(wage_sending)	-0.001***	-0.002***	
	(0.000)	(0.000)	
N	1645943	2060672	
R-sq	0.002	0.005	
Hypothesis tests [Chi2; p-value]**:**			
log(wage_sending) women=log(wage_sending) men	0.27; 0.608	4.67; 0.041	

Notes: The dependent variable is a dummy that takes the value of one, if the worker is self-employed. ll specifications include age, age squared, tenure, tenure squared, work experience, work experience squared, foreigner status, marital status, parental status, education, occupation, a network dummy, previous firm fixed effects, previous firm share of women and size and a full set of industry and year dummies. Female oriented firms are those with a share of white collar women higher than the industrial mean. *Statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.