Competition and Gender Prejudice: Are Discriminatory Employers Doomed to Fail?*

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January 15, 2010

Abstract

According to Becker's (1957) famous theory on discrimination, entrepreneurs with a strong prejudice against female workers forgo profits by submitting to their tastes. In a competitive market their firms lack efficiency and are therefore forced to leave. We present new empirical evidence for this prediction by studying the survival of startup firms in a large longitudinal matched employer-employee data set from Austria. Our results show that firms with strong preferences for discrimination, i.e. a low share of female employees relatively to the industry average, have significantly shorter survival rates. This is especially relevant for firms starting out with female shares in the lower tail of the distribution. They exit about 18 months earlier than firms with a median share of females. We see no differences in survival between firms at the top of the female share distribution and at the median, though. We further document that highly discriminatory firms that manage to survive submit to market powers and increase their female workforce over time.

Keywords: Firm survival, profitability, female employment, discrimination, market test, matched employer-employee data
JEL classification: J16, J71, L25

*We thank David Card, Dennis C. Mueller and Philipp Schmidt-Dengler as well as seminar participants at Norwegian School of Economics and Business Bergen, University of California at Berkeley, Copenhagen Business School, University Linz, University Mannheim, University Munich, Purdue University, Oesterreichische Nationalbank, University St. Gallen and University Vienna for helpful suggestions and discussions. Martina Fink and Esther Kalkbrenner provided excellent assistance with data processing. Christine Zulehner gratefully acknowledges financial support from the Berkeley-Austrian-Exchange Program. Both authors thank the Center for Labor Economics at the Economics Department at the University of California, Berkeley where the paper was partly written for its hospitality and generous support. This project received funding from the Austrian Science Fund (NRN Labor Economics and the Welfare State). All errors and opinions are the authors' sole responsibility.

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1 Introduction

Becker (1957)'s classical theory - fundament of the formal economic analysis of labor market discrimination - supposes that the source of discrimination is personal prejudice. Gender biased employers prefer hiring male workers even if their market wages exceed those of equally productive females. This behavior gives rise to a gender wage gap and to segregation of female workers towards less prejudiced employers. However, discrimination does not pay and prejudiced employers have to give up profits in order to indulge their prejudices. Competitive market mechanisms should thus ensure that discriminatory employers are replaced by less prejudiced firms. In this paper, we investigate empirically whether discrimination is indeed driven out of the market by studying the survival of new market entrants. The motivation for our analysis is based on Stigler (1958)'s survivor principle which postulates that competition between different types of firms sifts out the more efficient enterprizes.

Previous empirical research about the relationship between discrimination and market competition has pursued two main approaches. The focus of studies at the industry level is whether in sectors sheltered by regulation employers hire relatively more male workers (Ashenfelter and Hannan, 1986), or favor male over female workers in terms of wages and promotion aspects (Black and Brainerd, 2004; Black and Strahan, 2001). More recently, studies at the firm level have tested for cross-sectional correlation between female employment and profitability among firms with varying degree of product market power (Hellerstein et al., 2002; Kawaguchi, 2007). The findings in both literatures unanimously support the hypothesis that discrimination is less evident in more competitive environments.[1] However, the existing empirical evidence is primarily based on correlations, while the underlying causal mechanisms remain largely uninvestigated. Our main contribution, achieved by exploiting information at the linked firm-worker level, is to shed light on the process by which market competition punishes discriminatory behavior. Specifically, we ask the following two questions: Can discriminatory market entrants survive? Do surviving firms submit to market pressure and give

[1] In a meta analysis, Weichselbaumer and Winter-Ebmer (2007) find that countries adopting equal opportunity legislation have smaller gender wage gaps while countries with institutions that protecting women from dangerous and strenuous work tend to have higher wage gaps.

up their discriminatory attributes over time?

To motivate our empirical analysis, we first develop a dynamic model of employer discrimination in a market with firm entry and incomplete information. We consider a framework where firms enter each period from a pool of potential firms with a constant distribution of discriminatory preferences. Because they are ignorant about the true effects of discrimination on profitability, entering firms choose their workers according to Becker's (1957) decision strategy, i.e. firms with low prejudices hire mainly females with lower wages while firms with a high level of prejudice hire male workers. Over time, firms learn about their true profitability, as in Jovanovic (1982), and decide whether to remain in the market or drop out based on expected future profits. This model predicts, on the one hand, a long-run persistence of the gender wage gap and segregation of female workers towards the least discriminatory employers, because of the constant entry of all types of prejudiced employers. On the other hand, the model also predicts that firms with strong prejudices against females are more likely to leave the market. This second prediction is the focus of our empirical analysis.

We test the model empirically using a sample of newly entering firms from administrative matched employer-employee data in Austria over the period 1978-2006. Specifically, we relate the first year's share of female employees relative to the industry average to firm survival. The data provide a rich array of workforce characteristics which allow us to control for heterogeneity in productivity and input costs. After establishing the basic result of a negative relationship between the share of female employees and exit hazards we perform a series of robustness checks, motivated by the model and the data, with the aim of ruling out alternative explanations for our finding. First, according to the model primarily employers with the strongest discriminatory preferences are driven out of the market, which implies a non-linear relationship. We thus test for non-linearity in the effect of the workforce gender composition on firm survival and investigate the functional form of the relationship. Second, the share of female employees is an imperfect proxy for the employer's prejudicial tastes, if firms sample from a limited pool of applicants. Thus even a firm unaware of its workers' gender faces a positive probability of hiring a segregated workforce, and especially if it is a small firm. We therefore test whether the relationship between female shares and exit rates is stronger for larger firms.[2] Third, we exploit variation in the gender composition of the pool of potential applicants to test for a correlation of the gender workforce composition with unobserved firm characteristics. From the overall fraction of females hired per industry and time period we construct instrumental variables capturing a supply-push in the female share at the firm level.

To anticipate our main results the average share of female workers relative to the industry average by quarter after firm entry is shown in Figure 1. The black line represents the development of female shares of all firms in our sample, while the lines with dots and diamonds represent restricted samples of firms surviving at least 5 or 10 years, respectively. We notice two important features in the graph. First, short lived firms start out with a significantly lower share of females than those surviving for at least 5 or even 10 years. Second, while the share of female rises slightly during the first 5 years for all firms, those who started out with lower female shares see the largest increases. The first impression is confirmed by our estimation results. We find a strong negative relationship between the share of female workers and exit probabilities. This effect is mainly concentrated at the bottom of the distribution: firms with relative female shares in the bottom quartile exit about 18 months earlier than firms with a median share of females, while there is no difference in survival between the median and the top of the female share distribution. We further document that highly discriminatory firms that manage to survive submit to market powers and increase their female workforce over time.

In addition to the papers discussed above, our study contributes to two other strands of the literature. First, we add to recent work investigating the influence of demand side factors on the high rates of gross job flows at the micro level (Davis and Haltiwanger, 1999; Foster et al., 2008b). Our results show that business failures caused by incorrect perceptions of profitability due to discrimination significantly contribute to job turnover. Second, in the field of industrial organization the implications of firm heterogeneity on firm turnover have received a lot of empirical attention (Caves, 1998; Geroski, 1998), while the effects of selection and turnover on productivity growth have been studied in theoretical models

[2] The relationship between firm size and gender or racial composition of the workforce has been used as an indicator for discrimination in litigation cases in the US (Leonard, 1989).

(Asplund and Nocke, 2005; Jovanovic, 1982; Klette and Kortum, 2004). Our analysis relates detailed workforce characteristics to the survival of individual firms and presents evidence on the impact of several factors not generally available in representative firm surveys.

The paper proceeds as follows. In the next section we set up a stylized model of firm entry and incomplete information with regard to the effects of gender discrimination on profitability. Section 3 describes the data, defines the sample of entering firms, and introduces the key variables. Section 4 introduces the empirical strategy and presents the results along with a discussion of alternative interpretations of our findings. The final section 5 concludes.

2 Gender Discrimination in a Model with Firm Entry

To explain labor market discrimination, Becker (1957) introduces agents who are not acting in response to economic fundamentals but who also take their personal tastes or distastes into account. The degree to which discriminatory employers behave as if the wage for female workers were higher than the actual market wage depends on their prejudicial preference which is assumed to vary continuously among firms. Consequently, employers with a small dislike for female workers prefer hiring women if female wages are lower, while employers with a strong dislike hire male workers even if there is a wage differential. Market clearing in the short run ensures that the differential between male and female wages is positive and determined by the discriminatory taste of the marginal employer.[3] Prejudicial preferences are satisfied at the expense of profits, however, and competitive pressure will therefore force discriminatory employers out of the market. In consequence, Arrow (1973) argues that in a perfectly competitive environment only the least discriminatory employers can ultimately survive and discrimination is eliminated in the long run. This fundamental critique on the discrimination model has spurred efforts to investigate whether market imperfections block anti-discriminatory market responses. Recent work shows how prejudicial tastes leads to dis-

[3]Charles and Guryan (2008) provides clear tests of and evidence for the main predictions in Becker's model concerning the relationships between relative wages of black workers, prejudicial tastes among whites, and preferences of employer at the margin of hiring blacks. We are therefore confident to use the gender composition as a proxy for discriminatory taste.

crimination in setups characterized by imperfect competition (Becker, 1957; Manning, 2003), incomplete information such as search frictions (Black, 1995; Rosen, 2003), or adjustment costs (Lang et al., 2005).

In the spirit of this literature we propose a dynamic model which shows how the entry of firms with imperfect knowledge about the consequences of decisions influenced by prejudicial tastes leads to persistence of market discrimination. At the same time the model incorporates competitive forces which lead to a selection process by which employers with strong discriminatory tastes are weeded out. Our model combines the basic ideas of employer discrimination in Becker (1957) with the theory of selection with incomplete information in Jovanovic (1982). The main intuition is the following: Members from a pool of potential firms with a constant distribution of prejudicial tastes enter the market. At entry these firms are unaware of the effects of discrimination on their profitability. After entry they receive noisy signals about the true profits. While firms with low discriminatory tastes receive positive signals and thus grow and survive, those with strong desire to discriminate receive negative signals, shrink, and eventually exit.

For the formal description of the model we follow a setup similar to Jovanovic (1982). The setting is a small industry with equally productive workers who only differ by gender. Labor is the only input in production and firm's profits in each period t depend on the output produced minus labor costs

$$\pi_t = f(L_f + L_m) - w_f L_f - w_m L_m + \epsilon_t \tag{1}$$

where L_f and L_m are the numbers of female and male workers, w_f and w_m are the wages of each group of workers. The ϵ_t are firm specific shocks, which are independently distributed over time and across firms with $\epsilon_t \sim N(0, \sigma_\epsilon^2)$.

Firms differ in the taste for discrimination, which affects their perception of worker productivity. Specifically, firms do not choose L_m and L_f to maximize profits π_t, but they maximize perceived profits given by

$$\pi_t^d = f(L_f + L_m) - (w_f + d)L_f - (w_m - d)L_m + c_t \tag{2}$$

The desire for discrimination is expressed by the discrimination coefficient $d \geq 0$, which varies continuously across firms. Employers with $d > 0$ overestimate the cost of female employees and underestimate the costs of male workers at the same time. Firms do not know the true costs of production with certainty and neither do they know the relationship between discrimination and production costs. In the perceived profit equation the firm's uncertainty about costs is captured by the term $c_t = c + \epsilon_t$, which consists of a firm specific component c and the independent shocks. Potential firms assume that c is a random draw from a prior distribution F with mean zero. Once a firm enters the market it observes the actual profit π_t at the end of each period t and updates c. Here, we assume that d is an inherent characteristic and firms do not update d. We later discuss the implications of relaxing this assumptions.

For market entrants the intuition for the hiring decision and the process of updating are shown in Figure 2. The upper Graph A plots expected costs per worker according to π_t^d and implied hiring decisions for different levels of d. Starting from the left, firms with low levels of d such that $d < \frac{w_m - w_f}{2}$ expect that costs for females are lower than costs for male employees and thus decide to hire females. Because of their increasing dislike of female workers the expected costs are rising. A firm with $d = \frac{w_m - w_f}{2}$ is indifferent between hiring males or females, because expected costs are equal. Firms with higher values of d expect hiring costs for males are lower than those for females, with increasing levels of d the overestimation of male productivity leads them to expect even lower costs per worker.

At the end of the first period in the market firms observe the true level of profits π_t which they compare to the expectations π_t^d to update c. The updating mechanism in absence of the random shocks is shown schematically in Graph B in Figure 2. Firms that do not discriminate against women with $d = 0$ have no reason to update, because their cost expectations are equal to the actual labor costs. Firms with low values of d who still hire women find out that they were overly pessimistic about the true costs and will revise expected profits upwards in the next period. Firms with values of d exceeding $\frac{w_m - w_f}{2}$, on the other hand, are negatively surprised by the actual profits, because they underestimated the cost of their male employees. They will thus revise profits downwards in the next period.

After observing actual profits at the end of each period the firm decides whether to continue operation for a further period or to exit the market. We assume that each firm has a fixed outside option of value W to which it compares the discounted stream of expected future profits $V(d, c, \tau, t)$ from staying in the market for one more period and behaving optimally afterwards. The available information in each period is given by the discrimination coefficient d, the updated expectation of c, and the time the firm is already in the market τ.

$$V(d, c, \tau, t) = \pi_t^d + \beta \int \max[W, V(d, z, \tau + 1, t + 1)] P(dz|c, \tau, t). \tag{3}$$

Entering firms have to bear a fixed cost of entry k. The entry decision is thus based on $V(d, c, 0, t) - k \geq W$. This condition assures that each period firms with a whole range of discrimination coefficients enter the market, although $V(d, c, 0, t)$ is not the same for all entering firms. According to Graph A in Figure 2 firms with very low and very high values of d have the highest expectation of future profits, while firms with intermediate values of d have a lower $V(d, c, 0, t)$. At the end of the first period firms compare actual profits to their expectations and update. As we have seen in Graph B in Figure 2 firms with low values of d are confirmed in their decision or even positively surprised. They will thus grow and continue operation. Firms with the highest values of d are faced with negative revisions of their prior expectations and see a need to shrink or exit. The existence of the random shocks ϵ_t prevents firms from realizing their true costs immediately at the end of the first period. Thus even firms with high values of d will stay in the market for some time.[4]

Without providing a formal model solution, we regard the intuition above as sufficient to outline a number model predictions. First, because of constant entry of firms of all d-types and their ignorance about the true cost of labor, market clearing requires a positive wage differential between male and female workers. The exact magnitude of the differential is determined by the distribution of d among potential firms, the distribution among incumbent firms, and the relative supply of female workers. Second, the wage gap determines the firm's

[4]Our formulation of the expected profits deviates from Becker's original model in that we assume that discriminators do not only underestimate female productivity with $(w_f + d)$ but also overestimate males $(w_m - d)$. We include this feature to make sure that firms with different levels of d face similar incentives of entering the market. If d only implies an underestimation of the productivity of female workers expected profits of high d firms, hiring male workers, would be systematically lower than those of firms hiring females.

hiring strategy in dependence of d. While high d firms still seek to hire male workers, firms with small levels of prejudice have an incentive to hire females. Third, the selection mechanism in the model predicts that firms with high values of d receive negative productivity signals and eventually leave the market.

The first two predictions set the stage for our empirical analysis, by establishing the existence of a wage gap and the hiring strategy. The correlation between d and the gender workforce composition implies that a firm reveals its taste for discrimination by the share of female workers it hires, which provides us with an observable proxy for discriminatory tastes. Prediction three, explains the role of selection in driving discriminators out of the market and is the main focus of our empirical analysis, which tests if discriminatory firms can survive in the market. As shown in Graph B in Figure 2 the effect of d on the survival rate affects especially firms with the strongest discriminatory tastes should be forced out of the market.

So far we have assumed that firms are completely unaware of the effects of discrimination on profits. When realizing actual profits at the end of each period they only update the idiosyncratic cost component, but do not change the hiring strategy. An alternative updating strategy could also incorporate firms learning over time about the true productivity of their male or female workers. Under this scenario firms with a strong taste for discrimination would realize that their male employees are less productive than previously assumed and thus adapt the gender composition of their workforce. Due to the change in the hiring strategy we should see an increase in the share of female workers among the surviving firms and especially for those firms with high d who started out with a very low share of female workers.

3 Data and Institutional Background

Austria offers a promising environment to study the relationship between competition and discrimination, first, because of the availability of excellent micro data and second, because the Austrian society is rather conservative and holds very traditional views about the role women. The institutional environment reflects the potential for prejudices against females. In Austria anti-discrimination legislation was first introduced in 1979 and until then different contractual agreements for men and women in the collective bargaining institutions were common practice even if women and men worked on the same jobs. Further, women were banned from work under conditions involving hardship such as night-shifts or work under extreme temperatures before Austria joined the European Union in 1995. But the legal environment loosening the restrictions was not implemented until 2002, so the bans were actually in place for much longer. In Austria there is no law restricting hiring practices of private sector employers with respect to gender or minority status of employees. Our understanding of the institutional environment is that there were no major reforms that would have triggered sudden changes in the labor market situation of women, such the Equal Pay Act in the UK which had an immediate impact on the male/female wage differential (Manning, 1996). Instead, laws reinforcing gender equality have probably induced slow moving processes and changed prejudices in the society.

Unlike other central European countries which experienced a convergence of the male/female wage differential, the gender wage gap in Austria is rather large and has been more or less stable for decades. For the years 2003-2005, Gruenberger and Zulehner 2009 report wage differences of about 22 percent for full-time employees. After controlling for human capital, horizontal, and vertical segregation the wage gap reduced to 12 percent.[5]

Our empirical analysis is based on the Austrian Social Security Database (ASSD), which covers the universe of private sector workers in Austria over the years 1972-2006 (Zweimüller et al., 2009). Each individual employment spell in the universe is linked to an employer identifier. We exploit this matched employer-employee structure of the ASSD to construct our firm sample. As a starting point we organize the data in a quarterly panel based on the sample dates February 10, May 10, August 10, and November 10. Panel observations on firm size are counts of the number of blue collar and white collar employees per employer id and sample date. In terms of time invariant employer characteristics the ASSD provides regional

[5] Geisberger (2007) find that the gender wage gap in 2002 was of about 26 percent and accounting for individual characteristics like education and experience and occupational segregation it is about 19 percent. Böheim, Hofer and Zulehner (2007) find that the gender wage gap in Austria hardly changed between 1997 and 1983. In 1983, women earned on average a quarter less than men did. If differences in education, job position, and the like, are taken into account, womens' earnings are on average about 17 percent lower than mens'. In 1997, the mean raw wage gap dropped to 23.3 percent of men's wages. Controlling for observable differences, the unexplained average difference in wages between men and women was 14 per cent. At the beginning of the 1980s the gender wage gap was about 37 percent in the private sector, and about 12 percent in the public sector (Zweimüller and Winter-Ebmer 1994).

and industry indicators, at the postal code and 4 digit NACE levels, respectively.

The employer identification number in the ASSD is a number assigned for administrative purposes, which means that this concept does not allow us to a-priori distinguish between firms or establishments. As the majority of the identifiers corresponds to small units one might be inclined to argue that they are more likely establishments. However, as is demonstrated in Fink et al. (2009) by comparing the firm demographics implied from the ASSD in the year 2005 with the respective numbers from Statistik Austria (2009), these units are actually firms. The life span of a firm can be measured by the time between appearance and disappearance of an employer id in the data. To be precise, it is defined as the time between the quarter date after the entry of the first employee and the quarter date preceding the exit of the last one. Because of the administrative nature of the employer identifiers it is unclear, however, whether a new appearance (or disappearance) corresponds to a firm entry (or exit) or if the firm was just assigned a new identifier. We thus analyze worker flows to identify true entries and exits. Our strategy is to drop observations from the sample where a a new identifier appears, but a significant fraction (more than 50%) of the workforce in the first year transited jointly from the same previous employer. We apply an analogous definition to identify exits or firm closures. If a significant fraction of the workers in the last year before disappearance of the identifier jointly move to the same new employer the event does not correspond to a closure. In this case we mark the firm's survival time as censored. For an exact definition of the entry and exit types we can identify in the ASSD and descriptives of Austrian firm dynamics see Fink et al. (2009).[6]

Starting from the initial sample of 303,030 firms who have at least 5 employees at one quarter date between 1972 and 2006 we apply a series of restrictions to arrive at our primary analysis sample. The restrictions are summarized in Table 1. We exclude firms operating in the public administration, construction, or tourism sectors. Employment in the Austrian construction and tourism industry is highly seasonal and many firms temporarily close down all activity during the off-season which makes it difficult to identify entries and exits. To rule out left censored spells and because of inconsistencies in recording in the early 1970's,

[6] Our strategy is similar to the one used by Benedetto et al. (2007) to analyze firm dynamics in the US.

we only use firms entering after 1977. Likewise, we restrict the sample to firms entering before 2004 to be able to follow each firm for at least 2 years after entry. We drop firms that have long periods with zero employees (four consecutive quarter dates) or which have zero employees repeatedly (more than 8 quarters). This is to eliminate firms with seasonal employment patterns in sectors other than construction or tourism.[7] To avoid bias in the survival size relationship, we restrict the sample to firms with 5 or more employees on at least one quarter date in the first year. We only consider firms which we can observe for at least one year after entering the records. From the resulting sample of 51,695 entering firms we finally drop those which can not be identified as true entries using our worker flow definition. We are left with an analysis sample of 29,935 new firms.

As shown in Table 2 the median survival time among new firms, censored and uncensored, is 6.25 years. A fraction of 74% of survival times is right censored, the major part of the censoring (47%) occurs at the end of the observation period, while the rest is due to exits that are not identified as closures.

Our proxy of discriminatory taste at the firm level is given by the share of female employees relative to the industry and time average defined by $\tilde{r}_{ijt} = \frac{r_{ijt} - \bar{r}_{jt} + 1}{2}$. Here r_{ijt} is the share of females employed in new firm i, industry j and time period t, and $\bar{r}_{jt}$ is the share of female employees in industry j and time period t. We obtain $\tilde{r}_{ijt}$ by taking the residual from a regression of the share of female employees at the firm level on industry, year, and quarter dummy variables. The resulting measure is normalized to lie between zero and one. As industry classification, we use a mixture of the 3-digit and 4-digit code; 4-digit industries with only very few firms are aggregated to the 3-digit level, otherwise we use the 4-digit level. Histograms in figure 3 compare the distributions of the raw female shares at the firm level with the female shares relative to the industry means. The variation in female shares with a significant mass of firms with fully segregated workforce is reduced considerably once we take the industry averages into account.

Other workforce characteristics calculated at the quarterly level are the mean age of

[7]Note also that identifiers of exiting firms may have been reassigned to new businesses after a period of 2 years.

workers, the share of white collar workers, and the median monthly wage. In addition to stocks at the quarter dates, we also observe flows of entries and exits of workers between quarter dates. In the analysis of new firms we focus especially on worker entries or "hires" during the first year of firm existence. We calculate the turnover rate during the first year by the number of hires over the number of workers still employed by the end of the first year. Further information on the type of hires can be constructed from the longitudinal structure of each worker's employment career. We divide the overall number of hires into the fraction hired from employment, unemployment, or out of the labor force. Likewise, we compare previous wages of hires with their wages in the new firm and calculate the share of hires who experienced a wage gain (more than 5% increase), wage loss, or no change in wages. Using the previous employer id of new hires we can identify teams of workers, which used to share a workplace in the past. A variable expressing shared experiences in the workforce is thus given by the share of this largest team in total hires.

Summary statistics of the variables used in the analysis of new firms are presented in Table 3. Quarterly stocks are measured at the 4th quarter date after entry. We can see that the average size of new firms is moderate with 11 employees. The female share among employees is 46%; note that this is a sample of firms excluding the male dominated construction sector. The majority of workers is hired directly from their last job, without intervening unemployment spell. A high fraction of 36% of hires also experienced a significant wage gain with the job transition. Table 3 also shows that firm entry varies over the calender year, with a higher fraction (39%) entering in the first quarter. The workforce of firms surviving for 5 years grows by 31% on average from year 1 to year 5.

We would like to stress that the major advantage of our data, beside the large sample size and long observation period, is that it allows the construction of a wealth of very detailed workforce characteristics, which are not usually available in micro-level longitudinal firm surveys. We will use those as determinants of firm survival in the empirical analysis. Apart from the workforce and payroll, however, there is no information on profits, other measures of output, prices, or technology.

4 Empirical Analysis

The theoretical model in section 2 predicts that new market entrants with a strong prejudice against females reveal their preference by hiring a share of male workers above the market average. Because this behavior diminishes profits they face difficulties in sustaining competitive market pressure and leave the market in favor of their competitors. We test this fundamental prediction on the impact of competition on firms with strong taste for discrimination, by relating the relative share of females in the workforce r_{ijt}, measured in the fourth quarter after firm entry, to firm survival using a Cox proportional hazard model. An alternative reaction to market pressure involves learning about market fundamentals. Thereby discriminatory employers should increase the relative share of females over time. We test this in a regression analysis examining the relationship between the initial relative female share and the growth rate in the relative female share over the first five years for surviving firms.

Before presenting the estimation results we discuss two strategies that allow us to assess the robustness of our results.

Sampling Bias in the Proxy for Employer Prejudice

In the previous section we have motivated the use of the share of females in the workforce as a proxy for discriminatory employer tastes. The quality of the approximation is, however, subject to sampling bias that is negatively correlated with firm size. To see this, imagine a small firm with 5 employees entering the market. Even if the employer is perfectly gender-neutral he/she is faced with the choice of hiring 2 or 3 female workers or a corresponding female share of 40% or 60%, respectively. In this case the variation in the female share is related to the chance that the last worker hired happens to be a man or a woman rather than to differences in discriminatory tastes. For a larger firm, on the other hand, the variation in the female share should be more revealing about the employer's preferences. More generally, the argument is that even a gender-neutral employer, hiring workers by randomly drawing from a pool of applicants regardless of their gender, faces a positive probability of ending up with a segregated workforce. Of course, the probability decreases in the total number of hires.

If the relationship between the share of female hires and firm survival is due to discriminatory behavior we would thus expect to find less attenuation by sampling bias in the estimates and stronger effects for larger entrants.

Exogenous Variation in the Supply of Female Workers

To get an idea whether the relationship between the share of female workers and firm survival is driven by unobserved factors rather than a causal connection we exploit the variation in supply shift factors. The idea here is to model the pool of potential applicants for each new firm and to examine whether variation in the gender composition of applicants determines the female share at the firm level using an instrumental variables strategy. So the question we are asking is: What happens to firm survival if a gender-neutral employer is driven to hire relatively more male workers, because of the dominance of male applicants in the market? If firm survival is unaffected by variation in the female share that is due to exogenous supply shifts this would be evidence that unobservable factors such as technology are driving the relationship between survival and the gender workforce composition.

Our strategy is to model the pool of potential applicants by the total set of hires in new and established firms occurring in the corresponding quarter at the industry and region level. We argue that the gender composition in the hires is likely driven by supply shift factors releasing either more women or more men to the market. Specifically, we experiment with two sets of instruments for the relative female share. The first set is given by the ratio of female hires to all hires per region and industry in the quarter of firm entry and in the subsequent three quarters. There is a tradeoff between the number of industry region cells and the amount of variation provided by the instruments. If we use too small cells the number of hires will be determined by the entering firms only. Therefore, we define industries at the 2-digit NACE level, for regions we use the 2-digit NUTS definition.[8] This instrumental variable strategy captures symmetric responses to positive and negative supply shocks of female workers and disregards the possibility of different reactions for smaller and larger firms.

[8] 48 industries * 9 regions = 432 cells per quarter

Our second approach attempts to model hiring behavior given the gender composition in the pool of applicants and firm size more closely. We construct sets of instruments based on the predicted probabilities that a firm selects a low share or a high share of females given the share of females in total hires in each of the first four quarters as well as firm size at the end of year one. Thereby we assume that the firm is gender-neutral and samples workers from the pool of potential applicants in independent random draws. The probabilities that firm i in period t ends up with a low (high) female share r_{ijst} - that is a female share in the bottom (top) quartile $r_{(25)js}$ ($r_{(75)js}$) of the long-run distribution of industry j and region s - are given by the binomial distribution

$$Prob\left[r_{ijst} \leq r_{(25)js}\right] = \sum_{k=0}^{n_{(25)it}} \begin{pmatrix} n_{(25)it} \\ k \end{pmatrix} p_{jst}^{k}(1-p_{jst})^{n_{(25)it}-k} \tag{4}$$

$$Prob\left[r_{ijst} \geq r_{(75)js}\right] = 1 - \sum_{k=0}^{n_{(75)it}} \begin{pmatrix} n_{(75)it} \\ k \end{pmatrix} p_{jst}^{k}(1-p_{jst})^{n_{(75)it}-k} \tag{5}$$

where p_{jst} is the female share in total hires and $n_{(25)it} = size_{ijst} * r_{(25)js}$ and $n_{(75)it} = size_{ijst} * r_{(75)js}$ with $size_{ijst}$ being the size of firm i in period t. The expression in equation (4) is particularly sensitive to a variation in the female share in market hires at the bottom of the distribution, while equation (5) is more sensitive to variation at the top. In addition, the variation in the sensitive areas is always higher for larger firms than for small firms. This allows us to concentrate on variation in exogenous supply conditions of larger firms. As before, we calculate the instruments for each of the first four quarters of a firm's existence and classify industry and region at the 2-digit NACE and NUTS levels.

4.1 Estimation Results

The presentation of estimation results starts with hazard models of firm survival, which examine the basic relationship between the relative female share of workers and firm survival as well as the non-linearity the relationship in table 4. Then we proceed to the instrumental variables strategy using a control function approach in table 5 and present findings about the determinants of the growth in the relative female share in table 6.

4.1.1 Firm Survival

Table 4 presents results from Cox regressions. We start with a simple specification in column (1), which relates the exit hazard to the relative share of female employees and some firm characteristics. All models also control for industry, region, year, and quarter effects using a rich set of dummy variables.[9] The share of female workers has a strong negative effect on exit rates. The coefficient estimate implies that a 10 percentage point increase in the share of females hired reduces the exit hazard by about 50%. The effects of the remaining variables are also of interest. The share of white collar workers and the median wage, both possibly related to the qualification level of the workforce, have a positive effects on the survival probability. Firms starting with a larger workforce survive longer as well. Foster et al. (2008a) argue that the initial size of a firm may reflect idiosyncratic demand conditions; the higher the initial demand the higher is the probability to survive. The effect of the average worker's age is negative.

In the next two columns we add further variables to the initial model. We do this to find out whether the relative female share is correlated with other firm characteristics that are relevant for productivity. Adding characteristics derived from the workers' employment careers, however, does not lead to a major change in the coefficient on the relative share of female workers. Its magnitude is slightly reduced but the main effect appears to be robust. The share of workers hired from previous jobs has a strongly positive effect on firm survival, while hiring for wages that differ from their last wage increases the exit probability. The effect is bigger for hires with a wage loss, though, which reflects workers who have been possibly overpaid in their last jobs. A high turnover rate of workers in the first year appears to be detrimental for firm survival. Firms who succeed in hiring teams workers who used to work

[9] We do not use the market concentration or the Hirsch-Herfindahl-Index as measures of the competitive environment in an industry. As Austria is a small open economy, these measures do not necessarily reflect the competitive environment. For example, the figures for market concentration might be equal for a local industry and a market with the same number of firms but facing international competition. Therefore, we think that dummy variables for industries are more appropriate. To account for changes in the competitive environment over time, we estimated our empirical model for five year periods. The estimated effects do not change.

together in the past face a large increase in the probability to survive. Overall, these results confirm that the female share is not strongly correlated with other observable determinants of survival.

In column (4) we investigate the functional form of the relationship between the relative female share and firm survival by adding quadratic term. The result strongly confirm the hypothesis supported by theory that the effect should be a non-linear. To visualize the functional form, we plot the the implied parabola along with results form a more flexible specification using dummy variables for deciles of the relative female share distribution in left graph in figure 4. The result is striking: predominantly firms with the lowest shares of female workers are driven out of the market. The effect from increasing the female share for firms above the third tertile of the distribution is zero. To the magnitude of the effect on firms with strong prejudice is also considerable. For firms with very low female share (lowest quartile relative to the industry average) we estimate an increase in the exit rate of 20 percentage points relative to firms with a median relative share of females. Given a median survival time of 6.25 years, this corresponds to a reduction of the time the firms stays in the market by 18 months.

Columns five and six in table 4 show the effects for samples of larger firms. We restrict the sample to firms with at least ten employees and in column (5) and to firms with at least 15 employees in column (6). At small levels of the relative female share the negative slope in the effect on the exit rate increases when we move to samples with increasing average firm size. This is also visualized in the right graph in figure 4, which is based on results from the sample in column (5). This finding confirms our prediction that the effect of discrimination is stronger for larger firms, resembling the quality of the approximation of discriminatory prejudice by the relative female share.

4.1.2 Instrumental Variable Analysis

The most straightforward way to account for endogeneity in a nonlinear model, like our survival equation, is via a control function approach, which introduces residuals from the reduced form for the regressors as covariates in the structural model (Blundell and Powell, 2003). We thus use a a two-step estimation procedure: in the first step we estimate a reduced form equation regressing the relative female share on the instruments and the additional exogenous variables. The second stage model includes flexible functions of the reduced form residuals in the Cox regression model of firm survival. In table 5, we present estimation results for linear and the quadratic models. For comparison, columns (1) and (4) are copied from table 4 and refer to the results without adjustment for endogeneity of the relative female share. In columns (2) and (5) we use the first set of instruments derived from the share of female hires at the industry and regional level, while columns (3) and (6) are using the second set of instruments based on the probabilities of observing a low or a high female share given firm size, and industry, region share of female hires.

In the first stage equations both sets of instruments have significant impacts on the relative female share at the firm level. A lower share of female applicants at the market level also lowers the share of female workers in new firms or increases the probability that new firms end up with a low relative female share. Values of the F-test for joint significance of the coefficients are 23.85 and 15.01 for the first and second set of instruments, respectively.[10] If we look at the point estimates in the second stage results in table 5 all coefficients imply a negative impact of the relative share of female workers on exit rates. The magnitudes of the coefficient estimates are in line with the unadjusted models. But standard errors are large, especially in the linear models. In the quadratic models, the instrumental variables estimates yield significant effects on the relative share of female workers and the point estimates hardly differ from the unadjusted model in the case of the second set of instruments based on the probabilities of hiring low or high female shares. The control function terms are insignificant, however, which could imply that relative female share is not endogenous with respect to firms survival. Or in other words, unobserved heterogeneity doesn't play a major role when it comes to the relationship between the share of female workers and survival prospects of the firm. Even a gender-neutral firm hiring a large number of male workers, because there is a lack of supply from females, faces a higher exit probability.

[10]The results for the first stage regressions for both sets of instruments can be found in Appendix table A.1.

4.1.3 Growth of the Relative Female Share

Table 6 presents results from linear regressions with the growth rate in the share of female employees from year 1 to year 5 as the dependent variable for the set of firms surviving at least 5 years. Following Davis and Haltiwanger (1999) we calculate the growth rate in the female share as the difference in female share between year 1 and year 5 over the average female share during that period $gr_{it} = \frac{\tilde{r}_{i(t+4)} - \tilde{r}_{it}}{0.5(\tilde{r}_{it} + \tilde{r}_{i(t+4)})}$ to obtain a value in $[-2, 2]$.

The results show that firms starting out with a low relative female share in the first year experience a stronger growth than firms starting with high female shares. This effect appears to be non-linear as well, implying that firms starting out with the lowest female share take an extra effort to pick up to the industry average. We take this as evidence for a learning effect. If a discriminatory employer, hiring few female workers initially, manages to survive, he will adapt his hiring strategies and increase the female share over the first 5 years.

4.2 Discussion: Alternative Explanations

On the whole, the results presented above are strongly supportive of the theoretical prediction that competitive pressure drives discriminatory employers out of the market. But are they strong enough to provide evidence for a causal relationship between discrimination and employer success? Obviously also other interpretations are compatible with our results. Here we discuss alternative explanations of our findings in turn and argue why we think that taking all pieces of evidence together our interpretation is more convincing.

Technology as a Source of Unobserved Heterogeneity Our empirical research design is based on the hypothesis that competition sifts out more productive firms. Variables that determine firm survival should therefore also be related to profitability. The interpretation of the negative effect of the relative female share on exit rates is that it proxies for discriminatory prejudices which bear a higher cost on the firm. However, the female share could be correlated with other productivity relevant factors as well. We included a rich set of controls in the regressions to test for correlation of the female share with observable firm characteristics. The results show that even after controlling for all observable factors, the effect of the female share on survival is still substantial. This leaves unobserved productivity related variables, like technology, as sources of potential bias. It could be that firms using more advanced technologies hire more women, because their production processes require less of the menial work mostly done by males. The instrumental variables strategy based on the supply-push argument is designed to confront this argument by exploiting variation in female shares at the market level. Estimates from the control function models reinforce the main result and provide evidence against omitted variables bias.

Further evidence against the concern that our results might be driven by unobserved heterogeneity comes from the strong non-linearity in the effect. Although we lack information on several measures of profitability that might be correlated with the gender distribution of the workforce, it hard to imagine why their effects would be concentrated at the lowest levels of the female share.

Females Hired in Part-Time Work One shortcoming of the data is that it does not provide information on working hours and we thus cannot identify whether an employee is working part-time or full-time. This is a disadvantage as part-time work is especially prominent among females and there is evidence that part of the gender wage gap is due to women working in part-time jobs (Manning and Petrongolo, 2008). Hiring cheap part-time workers might not only be a cost effective option but also allows for flexible reactions to demand shocks. To deal with this argument we use the observation that part-time work is highly concentrated in certain occupations. Controlling for industry indicators at a narrow level, allows us to capture some of the occupational effects. In addition, we estimated models for a restricted sample of industries with a low share of part-time employment. Results are shown in Appendix table A.2. Although the effect of the female share on firm survival is somewhat smaller among the selected industries, the relationship is still significantly negative. Therefore we conclude that the basic result is not driven by firm heterogeneity in the use of part-time work.

Higher Risk Aversion Among Females A growing literature demonstrates systematic gender differences in risk aversion and competitiveness (Croson and Gneezy, 2009; Niederle and Vesterlund, 2007). If women are less willing to take the risk of job loss they might select into firms that are offering more stability. The difference in gender workforce composition between failing and surviving firms might thus be the result from selection by employees rather than the employer's preferences. However, it is probably much harder to make a prediction about future job stability for new firms than for established firms with a well-known record. While there may be a significant difference in worker preferences for new versus established firms between genders[11], it is less plausible that workers are able to predict the risk of failure of newly entering firms. In addition, we find stronger effects for larger firms which typically offer more stable jobs. This allows us to rule out employee selection by firm size.

Managerial Ability and Social Interactions Another crucial factor for the success of a new firm, which is unobservable in the data, is the manager's ability. It seems plausible that managerial ability is negatively correlated with discriminatory prejudice, which would imply that managers who realize that discrimination is detrimental for profits, are also better at taking decisions in other areas that are crucial for success. In this case the effect from a low female share on firm survival would capture the negative impact of bad management practices in general with discrimination being one of them.

In the theoretical model the competitive advantage of firms with low levels of prejudice is due to lower wage costs and the correct perception of female versus male productivity that determines the expected flow of profits. Additional factors relevant for the success of non-discriminatory firms, could be due to an improvement of social interactions among workers in a less male-dominated environment. Experimental evidence highlights substantial productivity gains from social interaction among coworkers or between managers and subordinates (Bandiera et al., 2005, 2009).[12]

[11] The effects of starting a new job in a new firm as opposed to starting a job in and established firm on individual careers is the subject of future research.

[12] In related research we examine whether the female share is correlated with the gender of high wage workers hired in the first month of firm existence (Weber and Zulehner, 2010).

5 Summary and Policy Implications

In this paper we have examined whether market competition contributes to the reduction of discrimination against females. Our empirical analysis is based on a dynamic model of employer discrimination in a market with firm entry and incomplete information. As there is constant entry of all types of prejudiced employers, we predict a persistent wage gap and a segregation of female workers towards the least discriminatory employer. The other prediction of the theoretical model that firms with the strongest prejudices against females are more likely to leave the market is the focus of our empirical analysis.

In the presence of a gender wage gap discriminatory employers should reveal their preferences by hiring relatively more male workers than the average firm. Our strategy is thus to relate the share of female workers relative to the industry average to firm survival, the ultimate measure of its economic success. The empirical analysis is set in Austria where labor market institutions have historically promoted differential treatment of female and male workers. The Austrian Social Security database provides excellent micro-data on the life spans of large sample newly entering firms plus a number of workforce characteristics based on individual employment careers.

We find strong indication for a negative effect of relative female share on exit rates, which is not diminished by the inclusion of a rich set of other productivity relevant variables in the regression model. This effect is mainly concentrated at the bottom of the distribution: firms with relative female shares in the bottom quartile exit about 18 months earlier than firms with a median share of females, while there is no difference in survival between the median and the top of the female share distribution. We regard this as strong evidence for the competitive pressure which drives discriminatory employers out of the market.

We also perform robustness checks to rule out alternative explanations for our finding. As firms draw from a limited pool of applicants, small firms unaware of the workers' gender may still end up with a segregated workforce. We find that the relationship between female shares and exit rates is stronger for larger firms providing confirmation for the share of female workers to be a valid proxy for the employer's prejudicial tastes. As the female share may also be correlated with unobserved managerial talent, we use instruments constructed from the overall fraction of females hired by industry and time period capturing a supply-push in the female share at the firm level and find that unobserved heterogeneity does not play a major role. Our result is also not driven by industries prone to part time work or other particular industries.

We further analyze the growth in the relative female share for firms that survive for at least 5 years. The initial share of female workers has a significant effect on the growth of the female share over the first five years. We find that highly discriminatory firms that manage to survive submit to market powers and increase their female workforce over time.

Our results show that firms that discriminate give up profits and are driven out of the market by competitive pressures. Market forces are a strong force against discrimination. But, do these results imply that competition makes anti-discrimination legislation obsolete? We would not agree to this statement. The theoretical analysis shows that although discriminatory firms do not survive in the market, a constant entry of all types of prejudiced employers may still lead to wage gaps and segregation. And although our empirical results show that competitive pressure eliminates businesses with discriminatory preferences above the equilibrium level, policy effort may still be required to change the equilibrium level.

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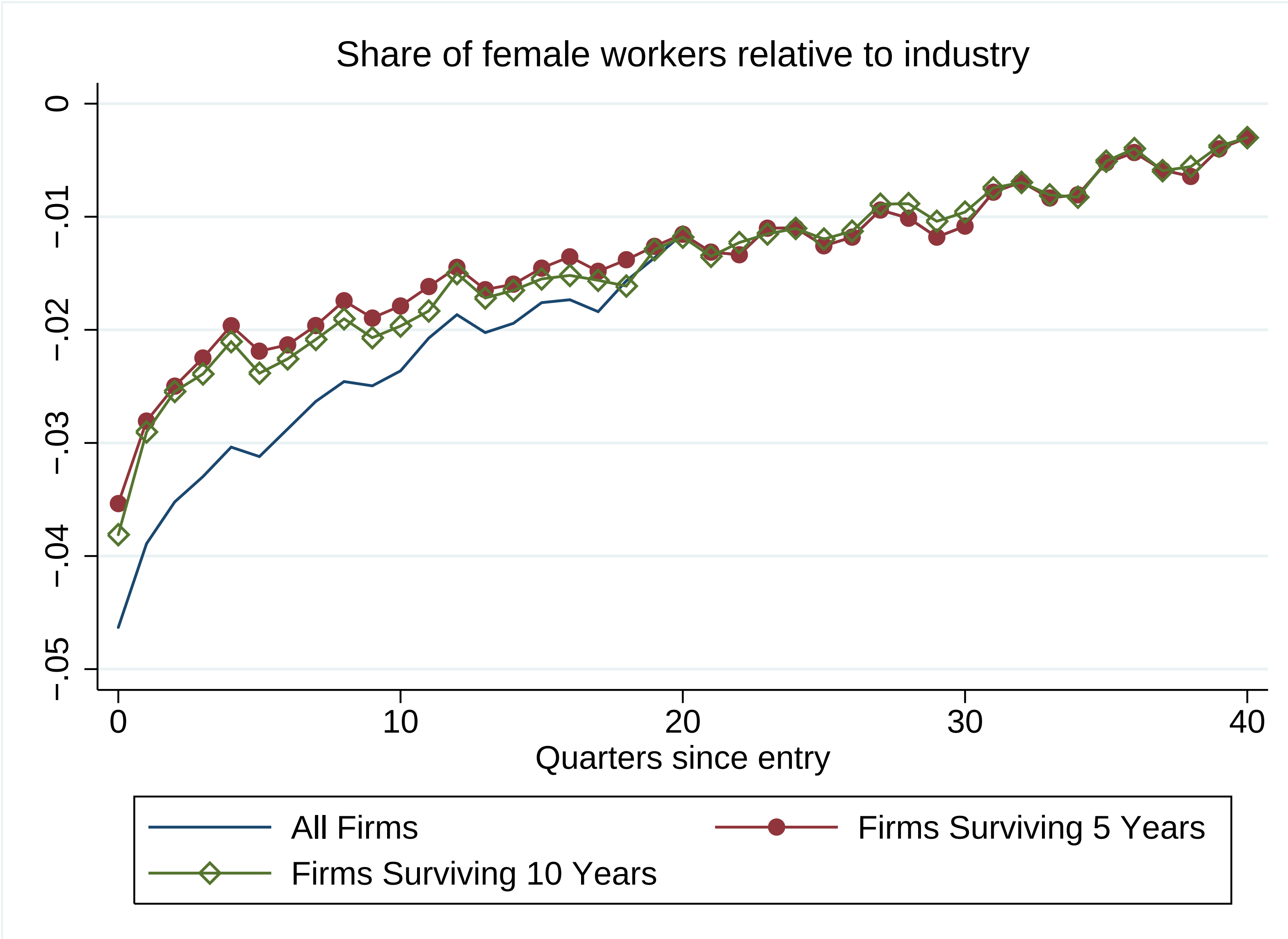
Figure 1: Survival Groups - Share of Female Workers



Notes: Firms correspond to firm identifiers in the Austrian Social Security Database.

Figure 2: The effect of the level of discrimination on expected and actual costs per worker

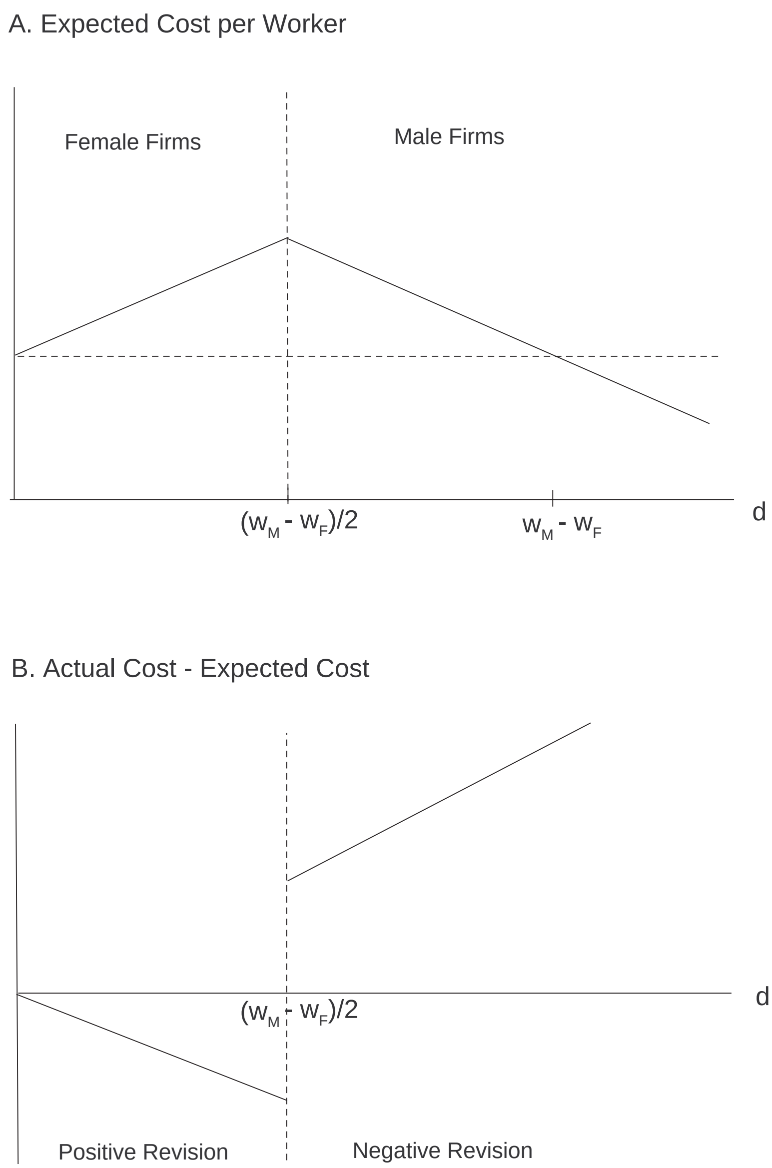
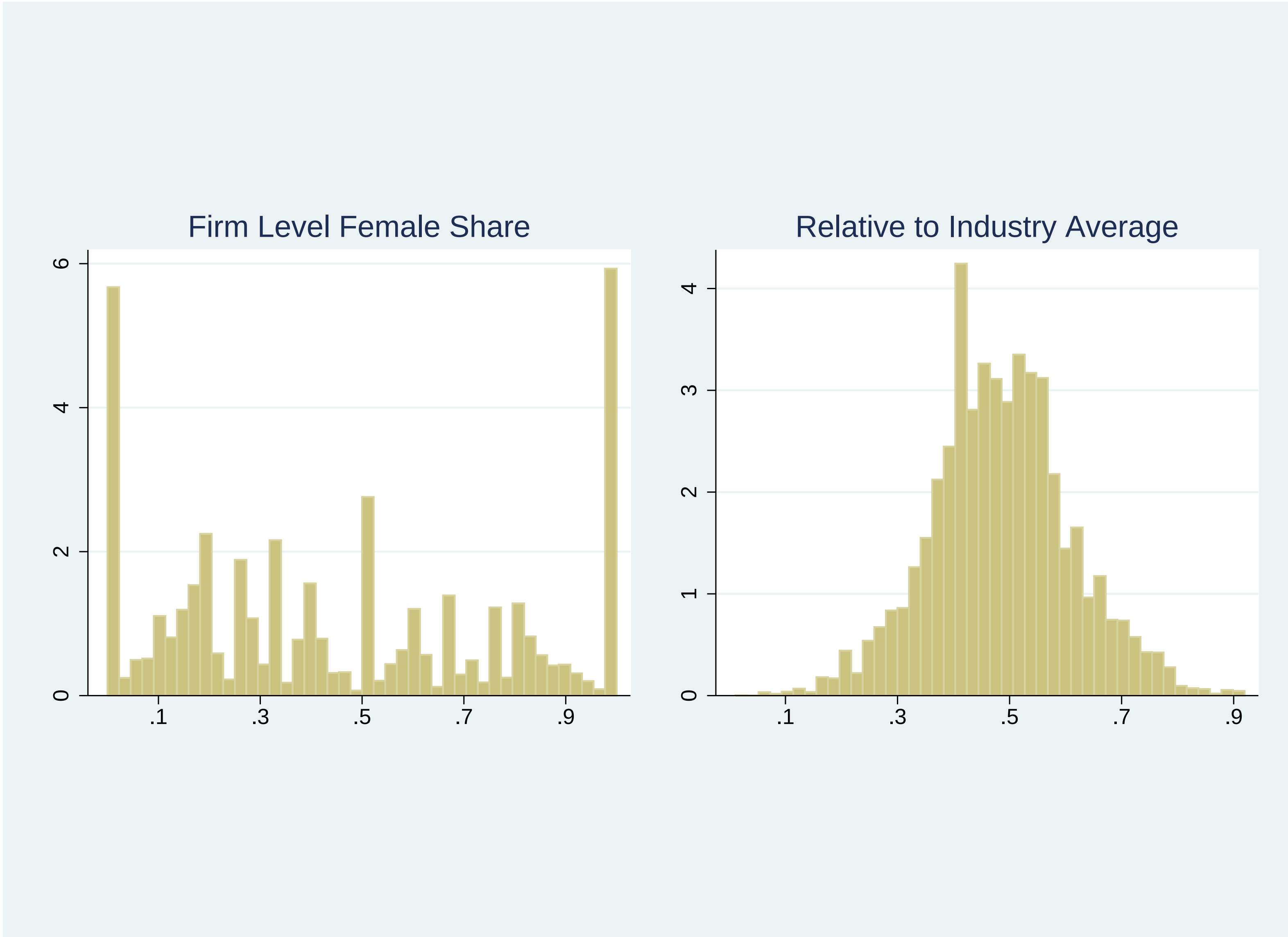
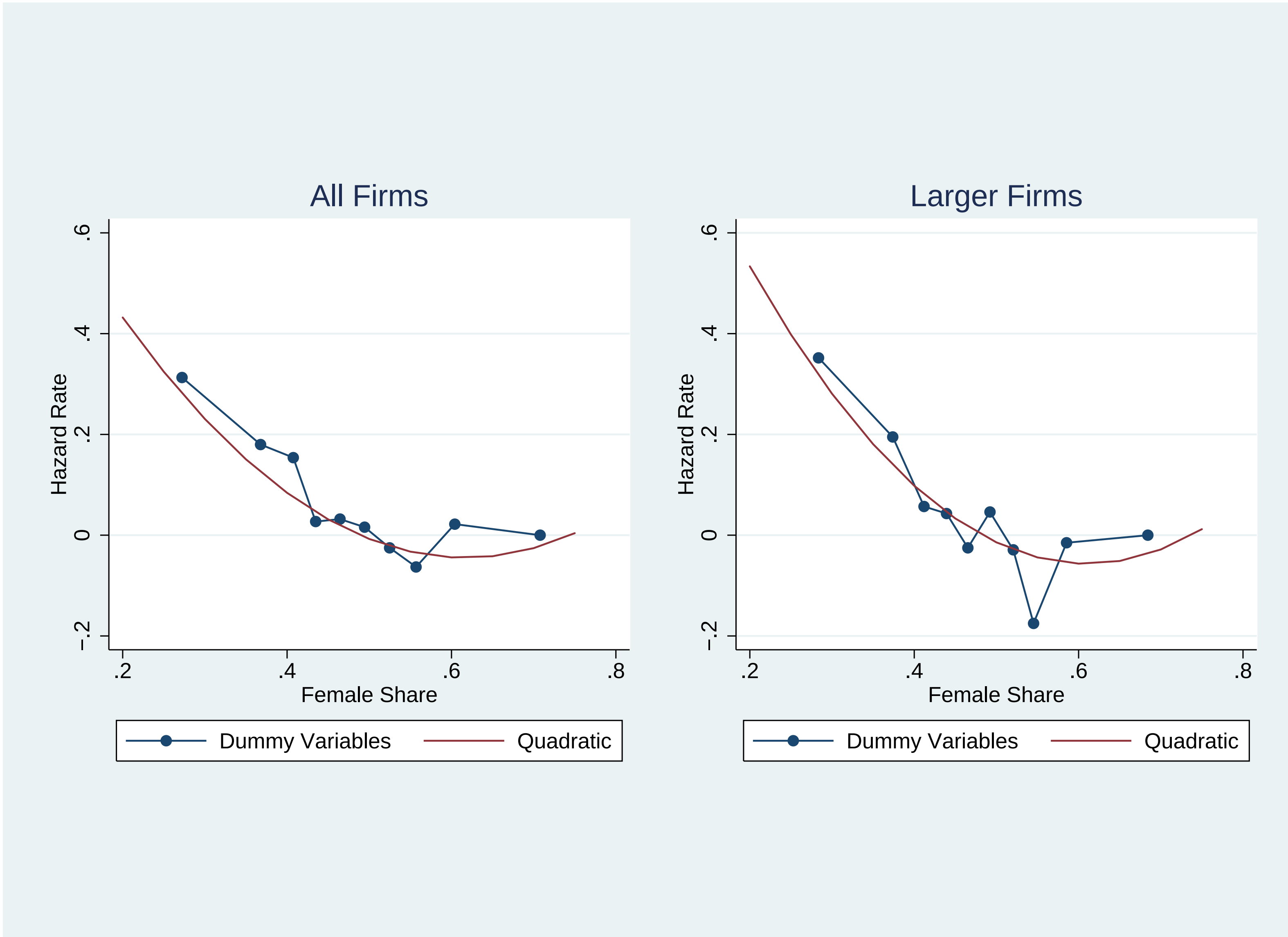


Figure 3: Histograms - Share of Female Workers and Share of Female Workers Relative to Industry Mean



Notes: Firms correspond to firm identifiers in the Austrian Social Security Database.

Figure 4: Effect of Discrimination



Notes: Firms correspond to firm identifiers in the Austrian Social Security Database. Larger firms include at least 10 employees.

Table 1: Sample of Startup Firms

	Number of Firms	Percentage
Selection of Firms		
Firms operating 1972-2006 with at least 5 workers	303,030	
Excl. construction, tourism and public administration	174,988	-42%
Firms entering 1978 and later	119,567	-32%
Firms entering before 2003	104,000	-13%
No periods with zero employees longer than one year	96,698	-7%
No periods with zero employees more often than 8 times	95,805	-1%
At least 5 workers employed in the first year	56,218	-41%
Firms surviving one year	51,695	-8%
Classification of Startup Firms		
Change firm identifier	7,783	15%
Spinoff firms	13,977	27%
New firms	29,935	58%

Notes: Firms correspond to firm identifiers in the Austrian Social Security Database. Change of firm identifier defined by at least 70% of workers switching together from one firm identifier to the next, both firms of similar size, and previous firm identifier vanishes from the data. Spinoffs are defined as firms where at least 50% of workers switch together. All remaining firms are new firms.

Table 2: Survival Times of New Firms

	New Firms
Median survival time (in years)	6.25
Mean survival time	8.67
Censored observations	73.8%
Observations censored in 2006	46.9%
Number of firms	29,935

Notes: Observations are considered as censored if the firm identifier vanishes from the data but the event cannot be identified as plant closure or at the end of the observation period in the last quarter of 2006. Firms correspond to firm identifiers in the Austrian Social Security Database.

Table 3: Firm Characteristics in the Fourth Quarter after Entry

Variable	New Firms Mean	Std.dev
Number of workers	10.82	15.34
Female workers	4.76	8.75
White collar workers	6.08	10.75
Average worker age	33.79	5.57
Share of female workers	0.46	0.33
Share of females relative to industry average	-0.03	0.25
Median monthly wage	1255.0	591.0
Median wage males	1469.0	668.3
Median wage females	1050.1	520.7
Ratio female to male median wage	0.87	0.24
Turnover rate	1.83	0.64
Share hired from employment	0.53	0.23
Share hired from unemployment	0.23	0.20
Share without wage change	0.21	0.17
Share with negative wage change	0.23	0.17
Share with positive wage change	0.36	0.19
Share from largest team	0.32	0.19
Entry in first quarter	0.39	0.49
Entry in second quarter	0.21	0.41
Entry in third quarter	0.20	0.40
Entry in forth quarter	0.20	0.40
Growth rates year 1 to 5 Employment growth	0.061	0.942
Employment growth cond. on survival	0.310	0.878
Growth in Female Share cond. on survival	0.005	0.199
Number of observations	29,935	

Notes: Firms entering between 1978 and 2003. Turnover rate is defined as the number of employees hired during the first year over the number employed in the fourth quarter. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Share hired from employment, unemployment etc. refers to all workers hired in the first year. Firms correspond to employer identifiers in the Austrian Social Security Database.

Table 4: Determinants of Firm Survival - Basic Specifications

	All Firms				Larger Firms	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of Female Employees	-0.930	-0.753	-0.749	-3.626	-5.246	-6.207
Rel. to Industry Average	(0.106)	(0.105)	(0.103)	(0.468)	(0.783)	(1.258)
Share of Female Employees				2.963	4.470	5.324
Rel. to Industry Average Squared				(0.470)	(0.798)	(1.290)
Share from Employment		-1.180	-0.689	-0.653	-0.705	-1.029
		(0.073)	(0.089)	(0.089)	(0.139)	(0.218)
Share from Unemployment		-0.157	-0.115	-0.099	-0.217	-0.460
		(0.085)	(0.088)	(0.088)	(0.139)	(0.226)
Share with Wage Gain		0.436	0.373	0.365	0.469	0.317
		(0.075)	(0.077)	(0.077)	(0.119)	(0.196)
Share with Wage Loss		0.653	0.587	0.573	0.839	1.001
		(0.081)	(0.084)	(0.084)	(0.133)	(0.216)
Turnover Rate			0.370	0.357	0.322	0.218
			(0.020)	(0.020)	(0.032)	(0.051)
Share from Largest Team			-0.651	-0.651	-0.663	-0.598
			(0.092)	(0.092)	(0.142)	(0.221)
Share of White Collar Workers	-0.256	-0.158	-0.038	-0.032	0.089	-0.071
Rel. to Industry Average	(0.094)	(0.093)	(0.092)	(0.091)	(0.148)	(0.228)
Firm Size	-0.715	-0.728	-0.626	-0.584	-0.555	-0.325
	(0.134)	(0.131)	(0.127)	(0.125)	(0.161)	(0.159)
Median Wage	-0.468	-0.314	-0.236	-0.221	-0.081	0.039
	(0.033)	(0.035)	(0.035)	(0.035)	(0.054)	(0.084)
Average Worker Age	0.008	0.013	0.017	0.016	0.020	0.029
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)
Observations	29879	29879	29879	29879	14964	7484
log-likelihood	-74679	-74441	-74212	-74190	-31721	-13601

Notes: Estimation results from Cox regressions. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 5 includes firms with at least 10 employees; column 6 includes firms with at least 15 employees. All regressions also control for 22 year effects, 3 quarter effects, 160 industry effects, and 35 region specific effects.

Table 5: Determinants of Firm Survival - Instrumental Variable Results

	Linear Models			Quadratic Models		
		IV1	IV2		IV1	IV2
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of Female Employees	-0.749	-1.406	-1.112	-3.626	-4.259	-3.815
	(0.103)	(1.137)	(1.115)	(0.468)	(1.366)	(1.346)
Share of Female Employees Squared				2.963	2.893	2.921
				(0.470)	(0.803)	(0.806)
Residual from the first stage		0.654	0.362		0.701	0.228
		(1.140)	(1.119)		(1.140)	(1.117)
Residual from the first stage squared					0.085	0.033
					(0.919)	(0.925)
Share from Employment	-0.689	-0.658	-0.672	-0.653	-0.619	-0.642
	(0.089)	(0.103)	(0.101)	(0.089)	(0.103)	(0.101)
Share from Unemployment	-0.115	-0.093	-0.101	-0.099	-0.075	-0.088
	(0.088)	(0.093)	(0.092)	(0.088)	(0.093)	(0.092)
Share with Wage Gain	0.373	0.362	0.366	0.367	0.355	0.361
	(0.077)	(0.078)	(0.078)	(0.077)	(0.078)	(0.078)
Share with Wage Loss	0.587	0.519	0.558	0.548	0.500	0.548
	(0.084)	(0.142)	(0.138)	(0.084)	(0.141)	(0.139)
Turnover Rate	0.370	0.370	0.370	0.357	0.357	0.357
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Share from Largest Team	-0.651	-0.660	-0.656	-0.651	-0.660	-0.653
	(0.092)	(0.094)	(0.093)	(0.092)	(0.093)	(0.093)
Share of White Collar Workers	-0.038	0.125	0.027	0.052	0.142	0.026
Rel. to Industry Average	(0.092)	(0.295)	(0.289)	(0.091)	(0.295)	(0.228)
Firm Size	-0.626	-0.609	-0.615	-0.584	-0.566	-0.577
	(0.127)	(0.129)	(0.129)	(0.125)	(0.127)	(0.127)
Median Wage	-0.236	-0.302	-0.272	-0.221	-0.291	-0.244
	(0.035)	(0.117)	(0.115)	(0.035)	(0.117)	(0.115)
Average Worker Age	0.017	0.017	0.017	0.017	0.017	0.016
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of observations	29879	29829	29829	29879	29829	29829
log Likelihood	-74212	-74083	-74104	-74190	-74063	-74083

Notes: Estimation results from Cox regressions. Dependent variable is the survival time in quarters. Standard errors in parenthesis. In columns (2) and (5) we use the share of female hires in the first four quarters of entry at the 2-digit industry and nuts2 regional levels as an instruments for the share of female workers; in columns (3) and (6) we use the probabilities to hire a female share in the top or bottom quartiles of the long run female share distribution determined by aggregate hires in the first four quarters and firm size as instruments for the share of female workers. All regressions also control for 22 year effects, 3 quarter effects, 160 industry effects, and 35 region specific effects.

Table 6: Determinants of the Growth Rate in the Share of Female Employees for Surviving Fimrs

Variable	Linear Model (1)	Quadratic model (2)
Share of Female Employees Rel. to Industry Average	-0.545	-1.449
	(0.017)	(0.122)
Share of Female Employees Rel. to Industry Average Squared		0.911
		(0.114)
Share from Employment	0.002	0.009
	(0.012)	(0.012)
Share from Unemployment	-0.007	-0.005
	(0.013)	(0.013)
Share with Wage Gain	-0.020	-0.021
	(0.009)	(0.009)
Share with Wage Loss	-0.017	-0.020
	(0.011)	(0.011)
Turnover Rate	0.007	0.004
	(0.003)	(0.003)
Share from Largest Group	-0.018	-0.019
	(0.011)	(0.010)
Share of White Collar Workers Rel. to Industry Average	0.030	0.034
	(0.013)	(0.013)
Firm Size	0.002	0.009
	(0.005)	(0.005)
Median Wage	-0.013	-0.012
	(0.005)	(0.004)
Average Worker Age	-0.000	-0.000
	(0.000)	(0.000)
Number of observations	19048	19048
R-squared adjusted	0.10	0.11

Notes: Estimation results from OLS regressions. Dependent variable is the growth rate from year one to year five in the share of female employees conditional on survival. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the largest group of workers who worked together in the same previous firm. All regressions also control for 22 year effects, 3 quarter effects, 160 industry effects, and 35 region specific effects.

A Appendix Tables

Table A.1: First Stage: Determinants of the Relative Female Share

Variable	(1)	(2)
Aggregate Hires Quarter 1	0.152 (0.018)	
Aggregate Hires Quarter 2	-0.03 (0.015)	
Aggregate Hires Quarter 3	-0.005 (0.015)	
Aggregate Hires Quarter 4	0.001 (0.015)	
Prob low female share given aggr. hires Quarter1		-0.047 (0.012)
Prob low female share given aggr. hires Quarter2		0.038 (0.011)
Prob low female share given aggr. hires Quarter3		-0.013 (0.012)
Prob low female share given aggr. hires Quarter4		-0.01 (0.010)
Prob high female share given aggr. hires Quarter1		0.025 (0.011)
Prob high female share given aggr. hires Quarter 2		0.034 (0.013)
Prob high female share given aggr. hires Quarter 3		-0.009 (0.012)
Prob high female share given aggr. hires Quarter 4		-0.006 (0.010)
Share of White Collar Workers	0.246 (0.012)	0.247 (0.012)
Share from Employment	0.043 (0.009)	0.045 (0.009)
Share from Unemployment	0.025 (0.007)	0.027 (0.007)
Share with Wage Gain	-0.009 (0.005)	-0.01 (0.005)
Share with Wage Loss	-0.098 (0.006)	-0.099 (0.007)
Turnover Rate	0.001 (0.002)	0.001 (0.002)
Share from Largest Team	-0.011 (0.006)	-0.012 (0.006)
Firm Size	0.021 (0.004)	0.023 (0.004)
Median Wage	-0.097 (0.006)	-0.098 (0.006)
Average Worker Age	0.000 (0.000)	0.000 (0.000)
Number of observations	29834	29834
log Likelihood	22881	22893
F-test	23.85	15.01

Notes: Estimation results from OLS regressions. Dependent variable is the the share of female employees relative to 3-digit industry average. Standard errors in parenthesis. Aggregate hires measured at the 2-digit industry and nuts2 regional level. Quarters refer to quarters since firm entry. Largest group is the largest group of workers who worked together in the same previous firm. All regressions also control for 22 year effects, 3 quarter effects, 160 industry effects, and 35 region specific effects. F-test for joint significance of the instrumental variables; degrees of freedom (4,321) and (8,321). Standard errors clustered at the 2-digit industry and nuts2 regional level.

Table A.2: Determinants of Firm Survival - Excluding industries with a high share of part-time work

		All Firms			Larger Firms	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of Female Employees	-0.668	-0.521	-0.541	-2.829	-4.711	-5.224
Rel. to Industry Average	(0.135)	(0.134)	(0.130)	(0.648)	(1.184)	(1.963)
Share of Female Employees				2.255	3.913	3.999
Rel. to Industry Average Squared				(0.626)	(1.152)	(1.930)
Share from Employment		-1.167	-0.667	-0.653	-0.649	-0.968
		(0.090)	(0.107)	(0.107)	(0.173)	(0.286)
Share from Unemployment		-0.196	-0.182	-0.183	-0.086	-0.093
		(0.105)	(0.109)	(0.109)	(0.175)	(0.292)
Share with Wage Gain		0.502	0.425	0.421	0.495	0.188
		(0.091)	(0.094)	(0.094)	(0.147)	(0.254)
Share with Wage Loss		0.755	0.673	0.667	0.684	0.711
		(0.100)	(0.103)	(0.103)	(0.168)	(0.281)
Turnover Rate			0.416	0.406	0.392	0.274
			(0.025)	(0.025)	(0.041)	(0.067)
Share from Largest Group			-0.702	-0.695	-0.706	-0.441
			(0.111)	(0.111)	(0.173)	(0.286)
Share of White Collar Workers	-0.258	-0.151	-0.015	-0.015	0.137	0.062
Rel. to Industry Average	(0.116)	(0.115)	(0.112)	(0.111)	(0.187)	(0.305)
Firm Size	-0.773	-0.767	-0.602	-0.573	-0.652	-0.519
	(0.163)	(0.158)	(0.149)	(0.146)	(0.190)	(0.219)
Median Wage	-0.517	-0.360	-0.258	-0.247	-0.132	-0.096
	(0.040)	(0.042)	(0.042)	(0.042)	(0.066)	(0.107)
Average Worker Age	0.009	0.015	0.019	0.018	0.019	0.023
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.008)
Observations	19114	19114	19114	19114	9385	4301
log-likelihood	-46368	-46210	-46024	-46018	-19581	-7772

Notes: Estimation results from Cox regressions excluding industries with high share of part-time work. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 5 includes firms with at least 10 employees; column 6 includes firms with at least 15 employees. All regressions also control for year effects, quarter effects, industry effects, and region specific effects. Excluded industries: Retail Sales, Services related to tourism, education, health, security, market research, janitorial services, temp work firms, unspecified other services

Table A.3: Determinants of Firm Survival - Manufacturing

Variable	All Firms (1)	(2)	(3)	(4)	Larger Firms (5)	(6)
Share of Female Employees	-0.977	-0.863	-0.894	-3.005	-7.266	-3.574
Rel. to Industry Average	(0.235)	(0.230)	(0.226)	(0.992)	(2.650)	(4.956)
Share of Female Employees				2.130	5.377	1.442
Rel. to Industry Average Squared				(0.980)	(2.634)	(4.829)
Share of White Collar Workers	-0.076	0.091	0.121	0.112	-0.077	0.048
Rel. to Industry Average	(0.204)	(0.202)	(0.198)	(0.197)	(0.460)	(0.872)
Firm Size	-0.195	-0.198	-0.065	-0.062	-0.237	-0.389
	(0.171)	(0.166)	(0.159)	(0.157)	(0.217)	(0.279)
Median Wage	-0.691	-0.505	-0.429	-0.405	-0.591	-0.437
	(0.085)	(0.089)	(0.090)	(0.089)	(0.193)	(0.333)
Average Worker Age	0.017	0.024	0.029	0.028	0.049	0.060
	(0.005)	(0.005)	(0.005)	(0.005)	(0.011)	(0.021)
Share from Employment		-1.437	-0.907	-0.892	-0.820	-1.341
		(0.160)	(0.197)	(0.196)	(0.453)	(0.721)
Share from Unemployment		-0.432	-0.360	-0.353	-0.353	-0.091
		(0.179)	(0.184)	(0.183)	(0.412)	(0.703)
Share with Wage Gain		0.716	0.599	0.597	0.746	-0.015
		(0.164)	(0.170)	(0.170)	(0.338)	(0.663)
Share with Wage Loss		0.979	0.794	0.789	0.882	0.168
		(0.178)	(0.185)	(0.185)	(0.408)	(0.761)
Turnover Rate			0.399	0.389	0.464	0.513
			(0.042)	(0.042)	(0.090)	(0.183)
Share from Largest Group			-0.714	-0.699	-1.273	-1.063
			(0.192)	(0.192)	(0.388)	(0.658)
Observations	5550	5550	5550	5550	1665	686
log-likelihood	-13766	-13694	-13637	-13634	-3583	-1370

Notes: Estimation results from Cox regressions for manufacturing industries. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 5 includes firms with at least 10 employees; column 6 includes firms with at least 15 employees. All regressions also control for year effects, quarter effects, industry effects, and region specific effects.

Table A.4: Determinants of Firm Survival - Non-Manufacturing

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Firms				Larger Firms	
Share of Female Employees	-0.954	-0.769	-0.764	-3.826	-5.096	-6.749
Rel. to Industry Average	(0.118)	(0.118)	(0.116)	(0.536)	(0.826)	(1.326)
Share of Female Employees				3.166	4.402	5.978
Rel. to Industry Average Squared				(0.541)	(0.841)	(1.367)
Share of White Collar Workers	-0.299	-0.215	-0.070	-0.057	0.064	-0.182
Rel. to Industry Average	(0.107)	(0.106)	(0.105)	(0.104)	(0.160)	(0.243)
Firm Size	-0.957	-0.966	-0.874	-0.820	-0.733	-0.305
	(0.177)	(0.174)	(0.171)	(0.168)	(0.219)	(0.199)
Median Wage	-0.434	-0.289	-0.213	-0.200	-0.051	0.084
	(0.036)	(0.038)	(0.038)	(0.038)	(0.056)	(0.088)
Average Worker Age	0.005	0.010	0.014	0.013	0.016	0.023
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
Share from Employment		-1.124	-0.647	-0.605	-0.695	-0.987
		(0.083)	(0.100)	(0.100)	(0.148)	(0.231)
Share from Unemployment		-0.100	-0.073	-0.057	-0.207	-0.561
		(0.098)	(0.101)	(0.101)	(0.151)	(0.250)
Share with Wage Gain		0.378	0.332	0.323	0.456	0.313
		(0.085)	(0.087)	(0.087)	(0.129)	(0.213)
Share with Wage Loss		0.572	0.534	0.518	0.837	1.097
		(0.092)	(0.095)	(0.095)	(0.142)	(0.231)
Turnover Rate			0.363	0.351	0.308	0.189
			(0.023)	(0.023)	(0.035)	(0.055)
Share from Largest Group			-0.631	-0.637	-0.554	-0.570
			(0.105)	(0.105)	(0.154)	(0.240)
Observations	24329	24329	24329	24329	13299	6798
log-likelihood	-56729	-56559	-56389	-56370	-26555	-11485

Notes: Estimation results from Cox regressions for non-manufacturing industries. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 5 includes firms with at least 10 employees; column 6 includes firms with at least 15 employees. All regressions also control for year effects, quarter effects, industry effects, and region specific effects.

Table A.5: Determinants of Firm Survival - Five year periods, linear specification

Variable	1979-2004 (1)	1979-1983 (2)	1984-1988 (3)	1989-1993 (4)	1994-1998 (5)	1999-2004 (6)
Share of Female Employees	-0.749	-0.627	-0.416	-1.092	-0.764	-0.597
Rel. to Industry Average	(0.103)	(0.314)	(0.299)	(0.222)	(0.208)	(0.213)
Share of White Collar Workers	-0.038	-0.432	-0.101	0.488	0.148	-0.346
Rel. to Industry Average	(0.092)	(0.284)	(0.259)	(0.203)	(0.181)	(0.181)
Share from Employment	-0.689	-0.490	-0.895	-0.535	-0.520	-1.040
	(0.089)	(0.232)	(0.234)	(0.198)	(0.188)	(0.188)
Share from Unemployment	-0.115	-0.114	-0.003	0.023	0.007	-0.525
	(0.088)	(0.319)	(0.239)	(0.184)	(0.179)	(0.181)
Share with Wage Gain	0.373	0.331	0.730	0.160	0.324	0.631
	(0.077)	(0.212)	(0.213)	(0.155)	(0.163)	(0.166)
Share with Wage Loss	0.587	0.841	0.627	0.292	0.369	0.883
	(0.084)	(0.251)	(0.230)	(0.183)	(0.173)	(0.175)
Turnover Rate	0.370	0.242	0.258	0.355	0.384	0.508
	(0.020)	(0.057)	(0.054)	(0.044)	(0.041)	(0.040)
Share from Largest Group	-0.651	-0.447	-0.448	-0.502	-0.827	-0.728
	(0.092)	(0.238)	(0.242)	(0.196)	(0.192)	(0.203)
Firm Size	-0.626	-0.994	-0.449	-0.658	-0.891	-0.215
	(0.127)	(0.303)	(0.374)	(0.285)	(0.231)	(0.212)
Median Wage	-0.236	-0.283	-0.227	-0.347	-0.271	-0.142
	(0.035)	(0.180)	(0.139)	(0.086)	(0.063)	(0.057)
Average Worker Age	0.017	0.009	0.030	0.006	0.020	0.024
	(0.002)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
Observations	29879	3254	3430	5839	6772	10584
log-likelihood	-74212	-8257	-8556	-14857	-15427	-16027

Notes: Estimation results from Cox regressions. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 1 uses all observations; the other columns use observations from five year periods. All regressions also control for year effects, quarter effects, industry effects, and region specific effects.

Table A.6: Determinants of Firm Survival - Five year periods, quadratic specification

	1979-2004	1979-1983	1984-1988	1989-1993	1994-1998	1999-2004
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of Female Employees	-3.626	-5.835	-3.951	-1.885	-3.524	-4.699
Rel. to Industry Average	(0.468)	(1.404)	(1.227)	(1.030)	(0.933)	(0.945)
Share of Female Employees	2.963	5.230	3.631	0.831	2.865	4.147
Rel. to Industry Average Squared	(0.470)	(1.355)	(1.210)	(1.042)	(0.945)	(0.935)
Share of White Collar Workers	-0.032	-0.400	-0.089	0.483	0.153	-0.320
Rel. to Industry Average	(0.091)	(0.278)	(0.257)	(0.203)	(0.179)	(0.176)
Share from Employment	-0.653	-0.439	-0.817	-0.525	-0.489	-0.986
	(0.089)	(0.232)	(0.234)	(0.198)	(0.188)	(0.188)
Share from Unemployment	-0.099	-0.091	0.053	0.029	0.012	-0.490
	(0.088)	(0.317)	(0.239)	(0.184)	(0.178)	(0.181)
Share with Wage Gain	0.365	0.309	0.721	0.161	0.297	0.636
	(0.077)	(0.209)	(0.212)	(0.155)	(0.163)	(0.166)
Share with Wage Loss	0.573	0.779	0.583	0.294	0.343	0.876
	(0.084)	(0.250)	(0.229)	(0.183)	(0.173)	(0.175)
Turnover Rate	0.357	0.237	0.238	0.350	0.369	0.493
	(0.020)	(0.057)	(0.055)	(0.045)	(0.041)	(0.040)
Share from Largest Group	-0.651	-0.424	-0.457	-0.500	-0.841	-0.719
	(0.092)	(0.237)	(0.241)	(0.196)	(0.192)	(0.203)
Firm Size	-0.584	-0.887	-0.415	-0.645	-0.857	-0.167
	(0.125)	(0.291)	(0.361)	(0.284)	(0.228)	(0.206)
Median Wage	-0.221	-0.295	-0.207	-0.339	-0.257	-0.129
	(0.035)	(0.178)	(0.139)	(0.086)	(0.063)	(0.057)
Average Worker Age	0.016	0.008	0.028	0.006	0.019	0.022
	(0.002)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
Observations	29879	3254	3430	5839	6772	10584
log-likelihood	-74190	-8249	-8551	-14857	-15423	-16017

Notes: Estimation results from Cox regressions. Dependent variable is the survival time in quarters. Standard errors in parenthesis. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to 3-digit industry average. Largest group is the share of the largest group of workers who worked together in the same previous firm. Column 1 uses all observations; the other columns use observations from five year periods. All regressions also control for year effects, quarter effects, industry effects, and region specific effects.