COMPETITION AND GENDER PREJUDICE: ARE DISCRIMINATORY EMPLOYERS DOOMED TO FAIL?

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Abstract

According to Becker's famous theory on discrimination (Gary Becker, 1957, *The Economics of Discrimination*, University of Chicago Press), 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 start-up firms in longitudinal matched employer–employee data. We find that firms with strong preferences for discrimination approximated by a low share of female employees relative 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. Competition at the industry level additionally reduces firm survival and accelerates the rate at which prejudiced firms are weeded out. We also find evidence for employer learning as highly discriminatory start-up firms that manage to survive submit to market powers and increase their female workforce over time. (JEL: J16, J71, L25)

1. Introduction

The classical theory of Becker (1957)—foundation 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

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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 preferences. Competitive market mechanisms should thus ensure that discriminatory employers are replaced by less prejudiced firms. In this paper, we empirically investigate whether discrimination is indeed driven out of the market by studying the survival of start-up firms. The motivation for our analysis is based on Stigler's (1958) survivor principle which postulates that competition between different types of firms sifts out the more efficient enterprises.

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 (Black and Strahan, 2001; Black and Brainerd, 2004). 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, Neumark, and Troske, 2002; Kawaguchi, 2007; Heyman, Svaleryd, and Vlachos, 2011).[1]

The findings in the empirical literature unanimously support the hypothesis that discrimination is less evident in more competitive environments.[2] Our main contribution, achieved by exploiting information at the linked firm–worker level, is to shed more light on the process by which market competition punishes discriminatory behavior. Specifically, we ask the following two questions: Can discriminatory start-up firms survive? Do surviving firms submit to market pressure and give up their discriminatory attributes over time?

Our empirical analysis is based on a large sample of start-up firms from administrative matched employer–employee data in Austria over the period 1978–2006. The data provide a rich array of detailed workforce characteristics which allow us to investigate the determinants of the survival of start-up firms by controlling for heterogeneity in productivity and input costs. Our specific interest lies in the relationship between firm survival and the first year's share of female employees relative to the industry average which we take as a proxy for the employer's gender preference.

To anticipate our main results we plot the average share of female workers relative to the industry average by quarter after firm entry 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

1. An example in the experimental literature that assesses the impact of competition on discrimination is List (2004).

2. In a meta analysis, Weichselbaumer and Winter-Ebmer (2007) find that countries with a higher degree of product market competition and countries adopting equal-opportunity legislation have smaller gender wage gaps, while countries with institutions that protect women from dangerous and strenuous work tend to have higher wage gaps.

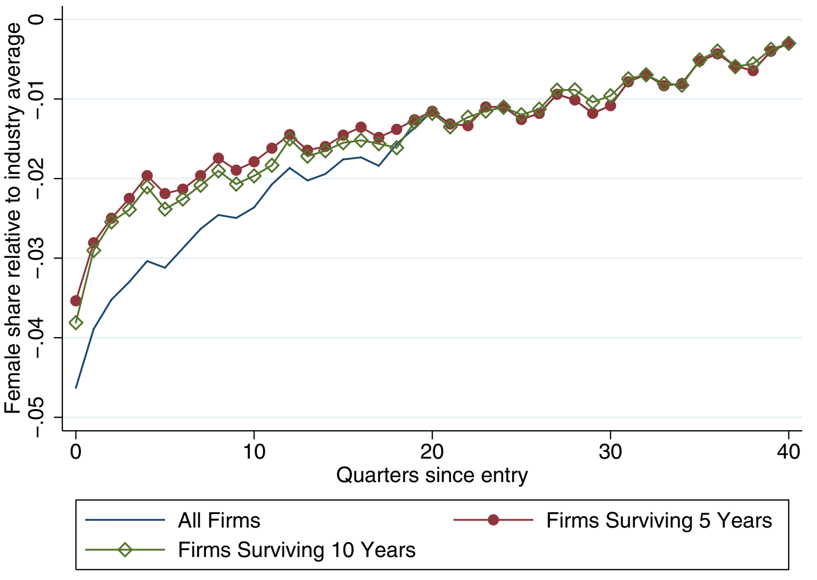

FIGURE 1. Survival groups—share of female workers relative to the industry average in start-up firms. Firms correspond to firm identifiers in the Austrian Social Security Database. Sample of start-up firms.

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 females rises slightly during the first 5 years for all firms, those who started out with lower female shares see the largest increases.

The advantage of our empirical setup is the clear time-line. We observe conditions at firm entry and can follow firms over time to see how the events play out. There are, however, also drawbacks. First, we do not observe discriminatory preferences directly, but take the share of female employees as a proxy. Second, our analysis is based on correlations as we lack a credible source of exogenous variation in the share of female workers at the firm level.

In order to confront these problems we provide four additional pieces of evidence that lend credibility to the interpretation of our results as market responses to discriminatory behavior. First, we investigate how the relationship between the female share and firm survival changes with market concentration at the industry level. If markets are highly competitive, discriminatory firms should be driven out at a higher rate, while discrimination is more likely to survive in concentrated markets. Second, we explore the idea that the quality of the female share as a proxy for employer tastes improves with firm size and thus the relationship should be stronger among larger firms. Third, to judge to what extent our results could be driven by unobserved heterogeneity, we directly investigate the extent of selection on observables. Finally, we experiment with alternative proxies of employer discrimination by analyzing the job and wage changes of workers leaving start-up firms.

The graphical impression in Figure 1 is confirmed by our estimation results. We find a strong negative relationship between the share of female workers and exit probabilities that is robust to the inclusion of different sets of controls. The effect is mainly concentrated at the bottom of the distribution: start-up firms with very low relative female shares exit about 18 months earlier than firms with a median share of females. Among start-ups that manage to survive the incentive to adapt the gender workforce composition is strongest among initially highly discriminatory firms. We further document that market competition not only reduces average survival times, but also accelerates the process by which discriminatory firms are driven out of the market.[3]

Besides the literature on labor market discrimination, our study contributes the literature in industrial organization, which empirically investigates the implications of firm heterogeneity on firm turnover (Caves, 1998; Geroski, 1995) and studies the effects of selection and turnover on productivity growth in theoretical models (Jovanovic, 1982; Asplund and Nocke, 2006; Klette and Kortum, 2004). By relating detailed workforce characteristics to the survival of individual firms, our analysis confirms theoretical predictions 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 discuss the model by Becker (1957) on employer discrimination in a market with firm entry, employer learning, and varying levels of market power. Section 3 describes the data, defines the sample of start-up firms, and introduces the key variables. Section 4 explains the empirical strategy and presents estimation results as well as robustness checks. Section 5 summarizes the results and provides a discussion of alternative interpretations of our findings. The final section concludes.

2. The Becker Model and its Empirical Tests

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. Besides positive utility from profits, discriminatory employers derive negative utility from interacting with female employees. Due to their preferences they behave as if the wage for female workers were higher than the actual market wage. If discriminatory tastes are heterogeneous in the population of employers, those 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.

In the short run, market clearing ensures that workers are segregated across workplaces and the differential between male and female wages is positive. Because market forces sort away females from the most discriminatory employers, the wage

3. In related research, we investigate the relationship between females among the high-wage workers hired in the first six months of firm existence and business success (Weber and Zulehner, 2010). The results show that firms with female first hires stay longer in the market, supporting the hypothesis that gender diversity in leading positions is an advantage for start-up firms.

difference is determined by the discriminatory taste of the "marginal" employer, who is indifferent between hiring male or female workers. Charles and Guryan (2008) derive a powerful empirical test from this prediction. Based on a measure of racial sentiment across regions in the United States, they demonstrate that racial wage gaps are not determined by the mean level of prejudice among employers in the market, but by the most-prejudiced employers with whom black workers interact. Because they are a small minority, and because of market sorting, only the prejudice in the left tail of the distribution matters for the racial wage gap. In related work addressing gender discrimination, Charles, Guryan, and Pan (2010) show that gender wage gaps and relative employment rates are related to the degree of sexist views held by the median male, but not with male sexism at the tails of the distribution. By uncovering the underlying mechanism of the Becker model, rather than just testing predictions about equilibrium outcomes, these studies provide impressive direct evidence in favor of the discrimination model.

In Becker's model 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 (1971) 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 antidiscriminatory market responses. Recent work shows how prejudicial tastes lead to discrimination in setups characterized by imperfect competition (Becker, 1957; Manning, 2003), incomplete information such as search frictions (Black, 1995; Rosen, 2003), or adjustment costs (Lang, Manove, and Dickens, 2005).

Several studies empirically examining Becker's predictions shed light on the relationship between profits, competition, and employer discrimination by investigating the effects of market regulation (Ashenfelter and Hannan, 1986; Black and Strahan, 2001), differences in competitiveness across industries (Hellerstein, Neumark, and Troske, 2002; Heyman, Svaleryd, and Vlachos, 2011), or the impact of globalization (Black and Brainerd, 2004). These studies focus on the cross-sectional relationship between market power and female labor market outcomes or exploit potentially endogenous variation over time, which makes it hard to pin down the causal mechanism. The advantage of a design based on firm entry and survival is that it enables us to exploit the timing of events and study the relationship between conditions at entry and outcomes occurring at a later point in time.

Next we discuss how firm entry can influence the discriminatory environment in a competitive market. We start with Jovanovic (1982), who introduces a dynamic model of firm entry and selection in a market with employer learning. In this model, firms that are not fully informed of their true production costs constantly enter the market. Over time they learn about their true profitability and decide whether to remain in the market or drop out depending on updates of their expected profits. This mechanism leads to a selection of the most efficient firms over time. In a discrimination setting, we could interpret the unobserved cost at entry as the disadvantage firms have from following their discriminatory tastes. If entering firms are ignorant about the true effects of discrimination on profitability and collect information about their true profitability only over time, as in Jovanovic (1982), we may observe a long-run persistence of the gender wage gap and segregation of female workers towards the least discriminatory employers. Firms decide whether to remain in the market or drop out based on expected future profits, and as in Becker (1957) firms with strong prejudices against females are more likely to leave the market.[4]

Asplund and Nocke (2006) introduce the concept of competition into Jovanovic (1982)'s theory and build a dynamic model of entering firms that differ in their efficiency levels and are subject to idiosyncratic shocks over time. The model predicts that in larger markets, where the level of competition is higher, the expected life span of entering firms is lower. In addition, stronger competition in larger markets weeds out less efficient firms and leads to a more efficient population of active firms.

Following these theoretical considerations, we propose several empirical tests. First, we investigate the relationship between discriminatory preferences proxied by the relative share of female employees and firm survival. If discriminatory market entrants find out about their disadvantage in terms of profitability over time, we should see higher exit rates among firms with a low share of female employees. Alternatively, discriminatory entrants could learn about the true productivity of their male and female workers over time. We will therefore test whether surviving firms increase their female share over time, especially the firms who started out with a very low share. Third, we test the influence of market power on firm survival and especially whether the effect of the female share on firm survival varies with the level of industry concentration.

3. Data and Institutional Background

Austria offers a promising environment to study the relationship between competition and discrimination, first, because the Austrian society is rather conservative and holds very traditional views about the role of women and second, because of the availability of excellent micro data.

A potential for prejudices against females is reflected in the Austrian institutional environment. In Austria, antidiscrimination legislation was first introduced in 1979. 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 extreme conditions such as night-shifts until 2002.[5] No Austrian law regulates the hiring in the private sector with respect to gender or minority status and applicants cannot sue their prospective employers for unfair treatment during the hiring process.[6] Looking at economic

4. For a more formal discussion of this theoretical framework see Weber and Zulehner (2009).

5. The bans became illegal with Austria's entry into the European Union in 1995, but due to delayed implementation into national law were effective much longer.

6. According to our understanding no major reforms that could have triggered sudden changes in the labor market situation of women, comparable for example to the Equal Pay Act in the United Kingdom (Manning, 1996), were implemented in Austria.

outcomes, we observe a rather large gender wage gap, which has been relatively stable for decades. Unlike many other European countries, Austria hardly experienced any convergence of the male/female wage differential between the early 1980s and the late 1990s; only over the last five to ten years have we see some movement in the gender wage gap (Böheim et al., 2013). The most recent numbers (for 2007) report a wage differential of about 18% for full-time workers, which reduces to 12% after controlling for observable characteristics (Böheim et al., 2013).

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). The matched employer–employee structure of the ASSD is defined by employer identifiers which are linked to individual employment spells. We organize the data in a quarterly panel, collapsing it along employer identifiers on the quarterly sample dates 10 February, 10 May, 10 August, and 10 November. Panel observations are thus constructed from workforce characteristics per employer identifier and sample date. In terms of time-invariant employer characteristics, the ASSD provides regional and industry indicators, at the postal code and four-digit NACE levels, respectively. For a detailed description of the ASSD Firm Panel we refer the reader to Fink et al. (2010). There we discuss how the administrative employer identifiers relate to actual firms and introduce an approach based on flows of workers between firms to identify start-ups and closures from other types of entry and exit like spin-offs and takeovers.[7]

We derive our *sample of start-up firms* by imposing a series of restrictions summarized in panel A of Table 1. From the initial sample of 303,030 firms with at least five employees at one quarter date between 1972 and 2006 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 eliminate left censoring and recording inconsistencies in the early 1970s, we only consider 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 eight quarters). This is to eliminate firms with seasonal employment patterns in sectors other than construction or tourism. Our initial sample restriction of firms with at least five employees at one point during their lifetime includes small firms only if they live long enough to reach the five-employee threshold. To avoid a bias in the relationship between firm size and survival, we further restrict the sample to firms with five or more employees on at least one quarter date in the first year of existence. We only consider firms which we can observe for at least one year after entering the records. From the

7. The main definition is that the appearance of a new identifier in the panel qualifies as start-up only if less than 50% of the workforce in the first year transited jointly from the same previous employer. Analogously, closures are restricted to the disappearance of an employer identifier where less than 50% of the last year's workforce jointly move to the same new employer. For a similar application of the worker flow approach to US data see Benedetto et al. (2007).

TABLE 1. Sample of start-up firms and their survival times.

Panel A. Sample of start-up firms

	No. of firms	Percentage
Selection of firms		
Firms operating 1972–2006 with at least five workers	303,030	
Excl. construction, tourism and public administration	174,988	–42%
Firms entering 1978 and later	119,567	–32%
Firms entering before 2004	104,000	–13%
No periods with zero employees longer than one year	96,698	–7%
No periods with zero employees more often than eight times	95,805	–1%
At least five workers employed in the first year	56,218	–41%
Firms surviving one year	51,695	–8%
Classification of entering firms		
Change firm identifier	7,783	15%
Spinoff firms	13,977	27%
Start-up firms	29,935	58%

Panel B. Survival times of start-up firms

	New firms	New larger firms
Median survival time (in years)	6.76	7.01
Mean survival time (in years)	8.69	8.85
Standard deviation survival time (in years)	6.49	6.28
Censored observations	73.8%	75.9%
Observations censored in 2006	46.9%	49.5%
No. of firms	29,935	14,969

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

resulting sample of 51,695 entering firms we drop those which cannot be identified as start-up entries based on the worker flow definition—that is, renames and spinoffs. The final analysis sample consists of 29,935 start-up firms.

The *survival time* is defined as the period between entry of the start-up and the disappearance of its identifier in the panel. If we cannot identify the exit event as closure, we mark the survival time as censored. As shown in Panel B of Table 1 the median survival time among start-up firms, censored and uncensored, is 6.25 years. 74% of survival times are 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. For comparison, the table also shows the respective numbers for firms with at least ten employees. The standard deviations of the survival times are most similar. If smaller firms were more risky, we should see a higher variance.

Our *proxy of discriminatory taste* at the firm level is given by the share of female employees relative to the industry and time average $\tilde{r}_{ijt}$. It is obtained by regressing r_{ijt}—that is, the share of females employed in start-up firm i, industry j and time period t—on industry, year, and quarter dummy variables. We then normalize the residuals from this regression to lie between zero and one. For the industry classification, we use a mixture of the three-digit and four-digit NACE codes, which give us a set of 160 industry identifiers.[8,9] Despite this level of detail, we cannot completely rule out that in some industries there are firms with a more male-specific occupational profile and others with a more female-specific profile.

The detailed longitudinal information at the individual level in the ASSD allows us to compute an array of additional characteristics of the workforce, which we use as control variables in the regressions. Workforce characteristics are calculated either at the quarter dates—we include values from the fourth quarter after entry—or from flows of worker entries or "hires" during the first year. At the fourth quarter we measure firm size, the shares of female workers and white-collar workers, as well as mean worker age and median worker wages.[10] From the flow of entries, we calculate the share of workers in three age groups and the share of workers in each wage tertile of the corresponding annual industry-specific wage distribution at the four-digit industry level. The turnover rate is defined as the number of hires during the first year over the number of workers still employed by the end of the first year. Further information is extracted from the longitudinal structure of each worker's employment career. We distinguish between hires from employment, unemployment, or out of the labor force. Likewise, we exploit wage changes between jobs and calculate the share of hires who experienced a wage gain (more than 5% increase), wage loss (more than 5% loss), or no change in wages (within $\pm 5\%$). Based on the previous employer identifier of new hires we can identify teams of workers, who used to share a workplace in their previous job. A measure of shared experiences in the workforce is given by the share of the largest team in total hires. We would like to stress that the major advantage of our data, beside the large sample size and long observation period, is the wealth of very detailed workforce characteristics, which are not usually available in micro-level longitudinal firm surveys. Apart from the workforce and payroll, however, there is no information on profits, other measures of output, prices, or technology.

Table 2 gives a first impression of the characteristics of start-up firms in our sample by presenting sample means of the most important variables in column 1. The average size of start-up firms is moderate with eleven employees by the end of the first year.

8. Specifically, four-digit industries with only very few firms are aggregated to the three-digit level, otherwise we use the four-digit level.

9. Histograms in Online Appendix Figure 1 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.

10. Individual wage measures in the ASSD are constructed from annual earnings per employer identifier and days employed by year. Thus they do not correspond to hourly wage rates.

TABLE 2. Firm characteristics in the fourth quarter after entry.

	All new firms		Mostly male firms[a]		Mostly female firms[b]		
Variable	Mean	SD	Mean	SD	Mean	SD	p-value[c]
No. of workers	10.82	15.34	10.29	13.18	10.27	14.74	0.933
Female workers	4.76	8.75	1.73	3.52	7.91	10.80	0.000
White-collar workers	6.08	10.75	5.11	8.30	6.39	10.58	0.000
Share of female workers	0.46	0.33	0.16	0.17	0.80	0.20	0.000
relative to industry average	0.48	0.12	0.33	0.07	0.64	0.07	0.000
Average worker age	33.79	5.57	34.06	5.96	33.78	5.94	0.004
Share of workers aged 15–30	0.48	0.22	0.47	0.23	0.48	0.23	0.105
Share of workers aged 30–45	0.38	0.19	0.39	0.19	0.38	0.19	0.039
Share of workers aged $\geq$45	0.14	0.14	0.14	0.15	0.14	0.14	0.670
Median monthly wage	1255	591	1398	648	1054	517	0.000
Share of wages in 1st tertile	0.35	0.27	0.28	0.26	0.44	0.27	0.000
Share of wages in 2nd tertile	0.32	0.22	0.34	0.24	0.30	0.21	0.000
Share of wages in 3rd tertile	0.32	0.26	0.39	0.30	0.26	0.23	0.000
Turnover rate	1.83	0.64	1.85	0.67	1.92	0.65	0.000
Share hired from employment	0.53	0.23	0.51	0.24	0.51	0.22	0.832
Share hired from unemployment	0.23	0.20	0.25	0.21	0.24	0.19	0.172
Share hired from OLF	0.23	0.18	0.24	0.19	0.25	0.17	0.262
Share with positive wage change	0.36	0.19	0.36	0.20	0.34	0.19	0.075
Share with negative wage change	0.23	0.17	0.24	0.18	0.22	0.16	0.002
Share without wage change	0.21	0.17	0.21	0.18	0.19	0.17	0.005
Share from largest team	0.32	0.19	0.31	0.18	0.31	0.19	0.849
HHI	319	629	329	615	352	667	0.023
C4 ratio	0.21	0.17	0.22	0.16	0.23	0.17	0.021
C8 ratio	0.29	0.20	0.31	0.19	0.31	0.20	0.040
Manufacturing	0.19	.39	0.17	0.38	0.16	0.37	0.432
Sales	0.32	0.47	0.35	0.48	0.38	0.49	0.000
Transportation	0.10	0.30	0.06	0.23	0.07	0.26	0.000
Services	0.39	0.49	0.43	0.50	0.38	0.49	0.000
Entry in first quarter	0.39	0.49	0.36	0.48	0.40	0.49	0.000
Entry in second quarter	0.21	0.41	0.22	0.42	0.20	0.40	0.000
Entry in third quarter	0.20	0.40	0.21	0.41	0.19	0.39	0.009
Entry in fourth quarter	0.20	0.40	0.21	0.41	0.21	0.41	0.612
Growth rates year 1 to year 5							
Employment growth	0.06	0.94	0.05	1.05	0.08	0.99	0.18
Conditional on survival							
Employment growth	0.31	0.88	0.39	1.00	0.33	0.93	0.005
Growth in female share	0.01	0.20	0.09	0.25	–0.06	0.17	0.000
No. of observations	29,921		7,475		7,498		

Notes: Firms entering between 1978 and 2003. Firms correspond to employer identifiers in the Austrian Social Security Database. Wage groups are defined as tertiles of the annual wage distribution at the industry level. 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 four-digit industry average. Share hired from employment, unemployment, and so forth, refers to all workers hired in the first year.

a. Firms with a female share (relative to the industry average) in the lowest quartile.

b. Firms with a female share (relative to the industry average) in the top quartile.

c. The p-value originates from a two-sided t-test or test of proportions testing the significance of the mean difference of the respective variable between mostly male and mostly female firms.

The average female share among employees is 46%.[11] An average start-up has a young workforce and the average age of workers in new firms is a few years below the average age of workers in the Austrian labor force. This is also reflected in the age distribution in start-up firms: 48% of the workers are aged between 15 and 30, 38% are aged between 30 and 45 and 14% are older than 45. Compared to the industry-wide wage distribution, wages in start-up firms are only slightly over-represented in the lowest wage tertile. Considering the origin of hires in the start-ups, the majority of workers are hired directly from their last job, without intervening unemployment spells. A high fraction (36% of hires) also experienced a significant wage gain with the job transition. We also notice that firm entries are distributed unevenly over the calendar year, with most entries occurring in the first quarter.

To see to what extent the gender composition of the workforce is related to other firm characteristics, we contrast all entering firms with the subsamples of firms with a mostly male or a mostly female workforce relative to the industry average, corresponding to firms in the lowest and highest quartiles of the distribution of female shares relative to the industry average in the remaining columns of Table 2. The final column reports p-values from tests of mean differences between the mostly female and mostly male firms. We observe that there are no substantial differences in firm size or the age composition of workers across the two groups of firms. In several other dimensions mostly female and mostly male firms are significantly different, however. An important component are differences related to wages. Mostly male firms have a disproportionally high share of workers in the top tertile of the industry wage distribution, while mostly female firms have the largest share of workers in the bottom tertile. From the raw summaries it is not clear whether the wage differences by gender composition of the workforce just reflect economy-wide gender wage gaps, or whether they result from differences in the fractions of part-time workers, or from different wage setting policies at the firm level—namely, that mostly male firms pay higher wages in general. We will investigate differences in individuals' starting wages between mostly female and mostly male firms in more detail in Section 4.3. Further, there are differences in the share of white-collar workers employed in mostly-female and mostly-male firms, which are related to occupational differences as only few females work in blue collar occupations. The turnover rate of workers hired in the first year is higher among mostly-male firms and the level of industry-wide concentration expressed by the Herfindahl–Hirschman index (HHI) is significantly higher among mostly-female firms. These differences in observables give rise to concerns about selection in the share of female workers based on the probability of firm success, which we address in Section 4.1.

4. Empirical Analysis

To establish baseline results for the relationship of firm characteristics with the survival of startups, we estimate proportional hazard models for the risk of exiting the market. These models include unrestricted quarterly baseline hazards, the proxy of

11. The relatively high average female share is explained by the exclusion of the male-dominated construction sector from the sample.

TABLE 3. Determinants of firm survival—basic specifications.

	All firms				
Variable	(1)	(2)	(3)	(4)	(5)
Share of female employees	−0.596	−0.436	−0.435	−0.514	−0.661
rel. to industry average	(0.102)**	(0.102)**	(0.100)**	(0.097)**	(0.103)**
Firm size		−0.839	−0.809	−0.626	−0.620
		(0.140)**	(0.135)**	(0.128)**	(0.127)**
Share of white-collar workers		−0.703	−0.409	−0.187	−0.098
rel. to industry average		(0.090)**	(0.090)**	(0.089)*	(0.092)
Share from employment			−1.242	−0.802	−0.708
			(0.071)**	(0.088)**	(0.090)**
Share from unemployment			−0.156	−0.181	−0.125
			(0.084)	(0.088)*	(0.089)
Share with wage gain			0.299	0.335	0.376
			(0.073)**	(0.077)**	(0.077)**
Share with wage loss			0.766	0.696	0.584
			(0.080)**	(0.082)**	(0.086)**
Share of workers aged 15–30				−0.532	−0.572
				(0.090)**	(0.091)**
Share of workers aged 30–45				−0.072	−0.079
				(0.102)	(0.102)
Turnover rate				0.419	0.412
				(0.020)**	(0.020)**
Share from largest group				−0.609	−0.654
				(0.091)**	(0.092)**
Share of workers with low wages					0.276
					(0.062)**
Share of workers with medium wages					0.101
					(0.066)
Observations	29,921	29,921	29,921	29,921	29,921
Log-likelihood	−75186	−75116	−74816	−74534	−74522

Notes: Estimation results from Cox regressions. Dependent variable is the exit hazard in quarters. Standard errors in parentheses. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to the four-digit industry average. "Largest group" is the share of the largest group of workers who worked together in the same previous firm. Wage groups are defined as tertiles of the annual wage distribution at the industry level. All regressions also control for 22 year effects, three quarter effects, 160 industry effects, and 35 region-specific effects.
** Significant at 99%; * significant at 95%.

discriminatory taste at the firm level (that is, the share of female employees relative to the industry and time average ($\tilde{r}$)), a varying sets of firm-level covariates (X), as well as an exhaustive set of industry, entry year, entry quarter, and region dummies (D). Specifically, we model the discrete hazard function $h(T|\tilde{r}, X, D)$ as the probability that firm i exits the market at quarter time T, given that it existed up to quarter $T-1$, as

$$h(T|\tilde{r}_i, X_i, D_i) = \lambda(T)\exp(\alpha\tilde{r}_i + \beta X_i + \gamma D_i), \qquad (1)$$

where the baseline function $\lambda(T)$ specifies the quarterly hazard rate when all covariates are set to zero and α, β, and γ are the vectors of coefficients to be estimated.

Table 3 presents the estimation results. To examine the uncontrolled correlation between the share of female workers and the exit rate, we start with a simple specification in column (1), where the only additional controls are the set of industry, region, year, and quarter dummies. The share of female workers is strongly negatively related to exit rates. The coefficient estimate implies that a ten percentage point increase in the share of females hired reduces the exit hazard by about 60%. In the next specification, column (2), we add firm size and the share of white-collar workers as additional controls. Starting with a larger workforce is strongly related to a longer survival of the firm. Foster, Haltiwanger, and Syverson (2012) argue that the initial size of a firm may reflect idiosyncratic demand conditions; the higher the initial demand, the higher is the probability of survival. The share of white-collar workers partly resembles the qualification level of the workforce and is thus positively related to the survival probability. In the previous section we have seen, however, that firms with a higher share of females also have higher shares of white-collar workers. Due to this correlation the coefficient on the female share drops in absolute value compared to the uncontrolled specification in column (1).

Columns (3) and (4) add further control variables, most of which seem to have significant impacts on firm survival. Past employment experience of new hires is important for firm survival. Exit rates are lower among new firms that hire workers from other jobs and lower if they hire workers who were not participating in the labor force. Hiring workers at lower wages than their previous job is related to high exit rates, however. We also find higher exit rates for firms that offer workers gains over their previous jobs, which might be indicative of competition in the labor market. The share of young employees in the workforce is positively related to firm success. A high turnover rate of workers in the first year appears to be detrimental for firm survival. Firms that succeed in hiring teams of workers with shared work experience have an increased probability of survival. Adding this last group of controls in column (4) appears to increase the absolute value of the coefficient on the share of female employees.

Column (5) we additionally control for the wage level of hires in the first year. Arguably, these are problematic controls in the sense that wages could be endogenous to the firm's level of prejudice if discriminatory firms pay lower waged to females. But other than the white-collar status we have no controls for qualification or skill levels in the workforce in our regressions. Thus we can also interpret the effects from the firm-specific wage level on the exit rate as a proxy for the effects of skills in the workforce. In line with this argument we find that wages (relative to industry wages) have a negative relationship to firm survival indicating that a higher-skilled workforce makes the firm more competitive. Especially, a large share of workers with wages at the bottom of the industry-specific wage distribution increases the exit rate.[12,13]

12. Online Appendix Table A.1 shows results using gender-specific age groups and gender-specific wages. Adding the more detailed age and wage variables to the model does not change the estimated effects of the female share on firm survival, however.

13. For Germany, Card, Heining, and Kline (2012) find a similar result. They report that high-wage establishments are more likely to survive than low-wage establishments.

4.1. Threats to Identification

Selection on Observables and Unobservables. In the baseline results in Table 3 we have seen that controlling for additional covariates only slightly changes the coefficient of our proxy for discriminatory taste. In the final specification including the full set of available controls, the estimated effect is even stronger than the uncontrolled correlation. But as our data do of course not include all potential determinants of firms success, we might be worried about unobserved confounders. Here we discuss what we can infer from observable selection based on the list of covariates on the potential selection on unobservables.

First, we examine the correlation structure between the observed covariates X and either the share of female employees or the survival time of start-up firms. Columns (1) and (2) in Table 4 report results from regressions of the female share and a Cox regression of the exit hazard, respectively. As noted before, most of the covariates are significantly related to either of the dependent variables. But if we examine the signs of the correlations, we notice that the first block of covariates indicate positive selection in the female share. The correlations with either outcome variable are oppositely signed; for example, larger firms typically have a higher female share and a lower exit rate. The variables in the second block of covariates indicate negative selection in the female share, as the correlations on both outcomes have equal signs. For example, firms with a higher share of young workers tend to have relatively fewer female workers and also lower exit rates, which indicates negative selection in the female share based on these covariates.

Next, we investigate whether positive selection dominates the negative selection in the correlation of the female share with firm survival or whether both cancel out using a strategy based on Altonji, Elder, and Taber (2005). We construct a composite covariate index from the predicted female share based on the model in column (1) and estimate a Cox model regressing the firm exit hazards on this index. The resulting coefficient in column (4) is positive, suggesting negative selection or a downward bias in our estimates of the effects of the female share on firm survival. It is very imprecisely estimated, however, with a high standard error. In column (3), we perform a similar exercise examining how much the female share loads on the same observable variables that predict firms' exit. We predict the survival time from the model in column (2) and regress the female share on the predicted survival time. In this regression, the coefficient is negative, close to zero and also insignificant.[14]

Taken together the evidence indicates that selection on unobservable variables is probably not an important concern. Selection on unobservable factors would have to

14. Our argument is based on the effects of "net" selection on observables and assumes that net selection on unobservables might be of the same magnitude. As one referee correctly points out, a more conservative strategy would be to consider "gross" selection on observables that is the sum of the absolute values of positive and negative selection. In our case this would lead to a much larger amount of selection on observables. In the light of this argument our results should still be interpreted with caution.

TABLE 4. Impact of female share on firm survival: robustness.

Dependent variable Variable	Female share (1)	Survival time (2)	Female share (3)	Survival time (4)
Predicted survival time			−0.003	
			(0.002)	
Predicted female share				0.285
				(0.267)
Covariates indicating positive selection in female share				
Firm size	0.021	−0.511		
	(0.005)∗∗	(0.091)∗∗		
Share of white-collar workers	0.228	−0.251		
rel. to industry average	(0.005)∗∗	(0.083)∗∗		
Share from employment	0.066	−0.657		
	(0.005)∗∗	(0.085)∗∗		
Share from unemployment	0.040	0.158		
	(0.005)∗∗	(0.077)∗		
Share with wage gain	−0.017	0.296		
	(0.004)∗∗	(0.070)∗∗		
Share with wage loss	−0.116	0.624		
	(0.005)∗∗	(0.080)∗∗		
Covariates indicating negative selection in female share				
Share of workers aged 15–30	−0.034	−0.575		
	(0.005)∗∗	(0.087)∗∗		
Share of workers aged 30–45	−0.020	0.010		
	(0.006)∗∗	(0.102)		
Turnover rate	0.010	0.430		
	(0.001)∗∗	(0.018)∗∗		
Share from largest group	−0.039	−0.743		
	(0.005)∗∗	(0.087)∗∗		
Share of workers with low wages	0.177	0.113		
	(0.003)∗∗	(0.054)∗		
Share of workers with medium wages	0.081	−0.001		
	(0.004)∗∗	(0.063)		
Observations	29,921	29,921	29,921	29,921
R-squared adjusted	0.14		0.03	
Log-likelihood		−74545		−75206

Notes: Estimation results from OLS and Cox regressions. In the first and third columns, the dependent variable is the female share. In the second and fourth columns, the dependent variable is the exit hazard in quarters. Standard errors in parentheses. The predicted female share is derived from the regression in column (1). The predicted survival time is derived from the regression in column (2). Share of female workers relative to industry average is measured by the ratio of female to all employees relative to four-digit industry average. "Largest group" is the share of the largest group of workers who worked together in the same previous firm. Wage groups are defined as tertiles of the annual wage distribution at the industry level. The regressions in columns (3) and (4) also control for 22 year effects, three quarter effects, 160 industry effects, and 35 region-specific effects.
∗∗ Significant at 99%; ∗ significant at 95%.

be considerably stronger than selection on observables. If we only include variables on which the female share is positively selected in the Cox regression model, as shown in column (3) of Table 3, the coefficient on the female share is still negative and highly significant.

Nonlinearity in the Effect of Discrimination. A concern with the interpretation of the baseline results as the effects from discrimination is due to the fact that we cannot directly measure discriminatory tastes but proxy them with the share of female employees. In addition, the quality of the approximation is subject to sampling bias. Here we investigate the functional form of the relationship between the female share and firm survival and then turn to exploring the fact that sampling bias should be negatively correlated with firm size.

Column (1) in Table 5 tests for nonlinearity in the functional form of the relationship between the relative female share and firm survival by adding its quadratic term to the baseline specification with the full set of controls. The result shows that the effect is indeed nonlinear. To visualize the relationship, we plot the implied parabola along with results from a more flexible specification using dummy variables for deciles of the relative female share distribution in the left panel of Figure 2. The graph shows that predominantly firms with the lowest shares of female workers are driven out of the market, while for firms starting out with a female share above the median, raising the female share has virtually no impact on survival. The magnitude of the effect on the survival rate of firms with strong prejudice is considerable. To facilitate comparisons across specifications, we report the implied slopes at the mean female share in the lowest quartile relative to the industry average, which is 0.33 according to Table 2. Compared to the linear specification, the quadratic model predicts more than double the exit rate for firms with lowest female shares. Using a different interpretation, for firms with a very low female share (lowest quartile relative to the industry average) the estimates imply 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.[15]

Sampling Bias in the Proxy for Employer Prejudice. The interpretation of our results takes 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 five employees entering the market. Even if the employer is perfectly gender-neutral, he/she is faced with the choice of hiring two or three 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 the variation in the female share should be more revealing about the employer's preferences, however. More generally, the argument is that even a gender-neutral employer, hiring workers by randomly drawing from a pool of applicants, faces a positive probability of ending up with a segregated workforce. But the probability decreases in the total number of

15. As a robustness check we also tested for nonlinearities in other explanatory variables of firm survival. The results do not indicate any major nonlinearities in other variables, though. Also the coefficients on the female share are unchanged in this regression.

TABLE 5. Determinants of firm survival—quadratic specifications.

	All firms	Larger firms		
Variable	(1)	(2)	(3)	(4)
Share of female employees	−3.713	−5.159	−6.161	−3.092
rel. to industry average	(0.469)**	(0.786)**	(1.265)**	(0.822)**
Share of female employees	3.131	4.394	5.296	2.415
rel. to industry average squared	(0.469)**	(0.800)**	(1.294)**	(0.827)**
Implied slope in bottom quartile	*−1.646*	*−2.258*	*−2.665*	*−2.160*
	*(0.178)***	*(0.289)***	*(0.459)***	*(0.412)***
Firm size	−0.578	−0.548	−0.318	−0.527
	(0.125)**	(0.159)**	(0.159)*	(0.130)**
Share of white-collar workers	−0.081	0.097	−0.030	0.012
rel. to industry average	(0.090)	(0.148)	(0.223)	(0.112)
Share from employment	−0.667	−0.713	−1.075	−0.692
	(0.090)**	(0.141)**	(0.222)**	(0.109)**
Share from unemployment	−0.110	−0.244	−0.541	−0.022
	(0.089)	(0.141)	(0.230)*	(0.109)
Share with wage gain	0.370	0.505	0.327	0.285
	(0.077)**	(0.119)**	(0.197)	(0.093)**
Share with wage loss	0.566	0.823	1.004	0.556
	(0.086)**	(0.137)**	(0.225)**	(0.107)**
Share of workers aged 15–30	−0.550	−0.731	−0.916	−0.559
	(0.091)**	(0.145)**	(0.240)**	(0.110)**
Share of workers aged 30–45	−0.085	−0.186	−0.204	−0.038
	(0.102)	(0.165)	(0.274)	(0.122)
Turnover rate	0.397	0.354	0.250	0.376
	(0.020)**	(0.033)**	(0.053)**	(0.025)**
Share from largest group	−0.656	−0.655	−0.553	−0.615
	(0.092)**	(0.142)**	(0.220)*	(0.110)**
Share of workers with low wages	0.266	0.169	−0.069	0.162
	(0.061)**	(0.097)	(0.149)	(0.076)*
Share of workers with medium wages	0.111	0.063	0.061	0.060
	(0.066)	(0.097)	(0.148)	(0.080)
Observations	29,921	14,969	7,486	22,078
Log-likelihood	−74499	−31759	−13614	−52015

Notes: Estimation results from Cox regressions. Dependent variable is the exit hazard in quarters. Standard errors in parentheses. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to the four-digit industry average. "Largest group" is the share of the largest group of workers who worked together in the same previous firm. Wage groups are defined as tertiles of the annual wage distribution at the industry level. Implied slope at the bottom quartile is the slope on the parabola in the relative share of female workers at 0.33. Column (1) includes all new firms, column (2) firms with at least ten employees, column (2) firms with at least 20 employees, and column (4) all new firms with both male and female workers. All regressions also control for 22 year effects, three quarter effects, 160 industry effects, and 35 region-specific effects.
** Significant at 99%; * significant at 95%.

hires.[16] 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.

16. 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 United States (Leonard, 1989).

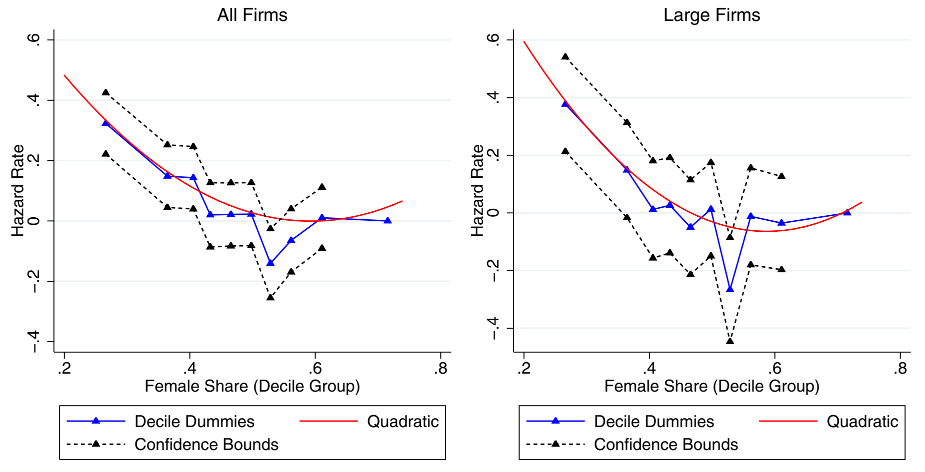

FIGURE 2. Effect of discrimination. Firms correspond to firm identifiers in the Austrian Social Security Database. Sample of start-up firms. Larger firms include at least 10 employees.

Columns (3) and (4) in Table 5 estimate the model for larger firms. We restrict the sample to firms with at least ten employees in column (3) and to firms with at least 15 employees in column (4). Relative to the full sample, the implied slopes on the relative female share at the lowest quartile increases for larger firms resulting in an even stronger effect on the exit rate of highly discriminatory firms. This is also visualized in the right-hand-side graph of Figure 2, which is based on results from the sample in column (3).[17] The last column adds estimation results from excluding all completely segregated firms with only female or only male employees from the sample. As the estimated coefficients are very similar to the overall results this model shows that our main results cannot be driven by the segregated firms.

4.2. *The Effect of Industry Concentration*

Our baseline specifications account for differences in the competitive environment at the industry level via a set of dummy variables. To see whether changes in competition over time affect firm survival and the speed at which discriminatory firms leave the market, we augment the Cox regressions with standard measures of competition and the interaction of these with the share of female workers. Specifically, we define quarterly

17. These results are consistent with measurement error. Let us assume that the noise to signal ratio is equal to 0.2—that is, a firm with four workers adding one worker may end up with the female share of 40% or 60%. The attenuation bias is $\rho = \delta(1 - \lambda/(1 - R^2))$, where ρ is the estimated coefficient using all firms, δ is the estimated coefficient using the large firms, $1 - \lambda$ the signal-to-noise ratio and R^2 is the R squared of a regression of the female share on all explanatory variables. With $\rho = -1.646$ (i.e. the implied slope in the bottom quartile, Table 5, column (1)) and the $R^2 = 0.14$ (Table 4, column (1)), we obtain an unbiased estimate δ of –2.145. Restricting the sample to larger firms gives an estimate of about –2.258 (Table 5, column (2)). The difference is rather small and we may contribute the whole difference to an attenuation bias.

measures of the HHI, the C4 ratio, and the C8 ratio at the four-digit NACE level.[18] Our definition implies that the product market is the four-digit NACE industry and the geographic market is Austria. Ideally, for some industries the product market as well as the geographic market should be defined at a narrower and for others at a broader level, thus our definition may introduce some measurement error and bias coefficients towards zero.

We do not find evidence that competition affects the level of discrimination at firm entry. Correlating the measures of industry competition with the female shares in start-up firms, we estimate a very precise correlation of 0.0006 (standard error 0.0001). But as the results from the Cox regressions in Table 6 show, market competition has a significant impact on firm survival. For all three measures we find that in industries with market power, start-up firms are less likely to exit the market. Upon entry, competition makes it more difficult to persist in a market. Moreover, the effect of the female share on the exit rate is more important in industries with high levels of competition. The higher the industry level of competition, the sooner discriminatory firms with a low share of females have to exit the market. These results are in line with Asplund and Nocke (2006), who predict that the expected life span of a firm becomes shorter when market size increases—that is, competition increases. The more-efficient firms are able to stay in the market and the less-efficient firms have to leave the market. The point estimates imply that with an increase in the HHI of 2.5 standard deviations, the effect of the female share is fully off-set. With the other two measures of competition, the C4 ratio and the C8 ratio, we obtain similar results.

4.3. Alternative Proxies for Employer Tastes

The main proxy for discriminatory employer behavior in our analysis is the share of females hired at firm entry. But discrimination against female workers could also manifest itself in other characteristics, such as salary. Following the literature exploring gender wage gaps at the firm level as indicators of discrimination, we examine wage changes of workers who leave the start-up firms and relate these changes to the share of female workers (Bayard et al., 2003; Cardoso and Winter-Ebmer, 2010). If highly discriminatory firms with a mostly male workforce also pay lower wages to their female employees, we should see higher exit rates of females from those firms and wage gains in their new jobs.[19] To investigate this issue further we follow the individual workers from start-up firms to their subsequent jobs. We study two outcomes, which we relate to the female share in the start-up firm: first, the determinants of job changes—that is, workers leaving the start-up firm for another job within one year—and second, the likelihood that they earn a higher wage in this new job.

Online Appendix Table A.7 presents a descriptive comparison of female and male workers in highly discriminatory, mostly male, and low discriminatory, mostly female,

18. The C4 (C8) ratio is the market share of the four (eight) largest firms. In the regressions we rescale the HHI to lie between zero and 100 and define the C4 ratio and C8 ratio in percent.

19. Note that we cannot distinguish between voluntary quits and layoffs in our data.

TABLE 6. The effect of industry concentration on firm survival.

Variable	(1)	(2)	(3)	(4)
Share of female employees	−0.661	−0.846	−1.170	−1.230
Rel. to Industry Average	(0.103)**	(0.115)**	(0.162)**	(0.180)**
Herfindahl–Hirschman index		−0.030		
(HHI × 10^{-2})		(0.008)**		
Female share × HHI		0.052		
		(0.014)**		
C4-ratio (in percent)			−0.013	
			(0.003)**	
Female share × C4-ratio			0.022	
			(0.005)**	
C8-ratio (in percent)				−0.011
				(0.002)**
Female share × C8-ratio				0.018
				(0.005)**
Firm size	−0.620	−0.616	−0.615	−0.612
	(0.127)**	(0.127)**	(0.127)**	(0.127)**
Share of white-collar workers	−0.098	−0.089	−0.083	−0.083
rel. to industry average	(0.092)	(0.092)	(0.092)	(0.092)
Share from employment	−0.708	−0.700	−0.700	−0.699
	(0.090)**	(0.090)**	(0.090)**	(0.090)**
Share from unemployment	−0.125	−0.121	−0.119	−0.119
	(0.089)	(0.089)	(0.089)	(0.089)
Share with wage gain	0.376	0.375	0.373	0.374
	(0.077)**	(0.077)**	(0.078)**	(0.078)**
Share with wage loss	0.584	0.575	0.575	0.576
	(0.086)**	(0.087)**	(0.087)**	(0.087)**
Share of workers aged 15–30	−0.572	−0.575	−0.577	−0.579
	(0.091)**	(0.091)**	(0.091)**	(0.091)**
Share of workers aged 30–45	−0.079	−0.081	−0.083	−0.083
	(0.102)	(0.102)	(0.102)	(0.102)
Turnover rate	0.412	0.411	0.412	0.411
	(0.020)**	(0.020)**	(0.020)**	(0.020)**
Share from largest group	−0.654	−0.662	−0.664	−0.667
	(0.092)**	(0.092)**	(0.092)**	(0.092)**
Share of workers with	0.276	0.282	0.280	0.283
low wages	(0.062)**	(0.062)**	(0.062)**	(0.062)**
Share of workers with	0.101	0.104	0.105	0.105
medium wages	(0.066)	(0.066)	(0.066)	(0.066)
Observations	29,921	29,921	29,921	29,921
Log-likelihood	−74522	−74514	−74511	−74511

Notes: Estimation results from Cox regressions. Dependent variable is the exit hazard in quarters. Standard errors in parentheses. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to the four-digit industry average. "Largest group" is the share of the largest group of workers who worked together in the same previous firm. Wage groups are defined as tertiles of the annual wage distribution at the industry level. The Herfindahl–Hirschman index (HHI), C4-ratio, and C8-ratio are calculated using the size of firms at the four-digit industry level. We rescale the HHI to lie between zero and 100 and define the C4 ratio and C8 ratio in percent. All regressions also control for 22 year effects, three quarter effects, 160 industry effects, and 35 region-specific effects.

** Significant at 99%; * significant at 95%.

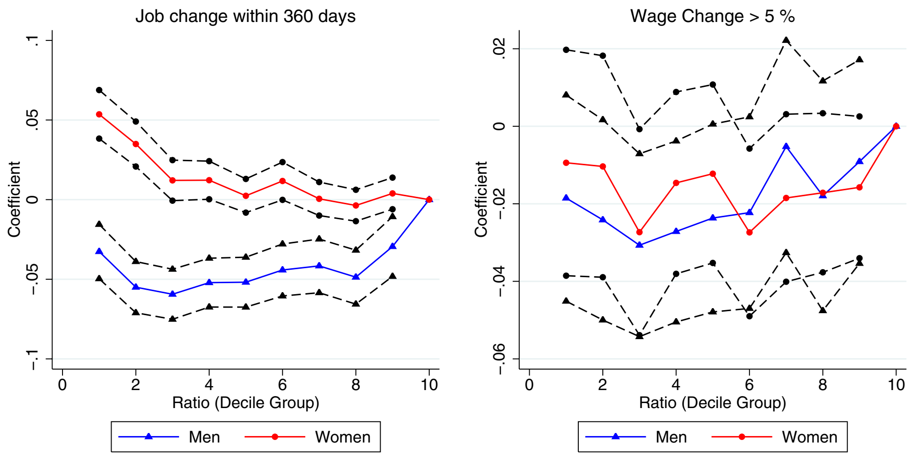

FIGURE 3. Probability of a job change. Firms correspond to firm identifiers in the Austrian Social Security Database. Sample of start-up firms.

start-up firms. We see that females earn higher starting wages in mostly-male firms than in mostly-female firms, while for male workers there is no such difference. Interestingly, the raw gender wage gap is larger in mostly female than in mostly male firms.[20] Nevertheless, female workers are more likely to leave mostly-male firms, while males are somewhat more likely to leave mostly-female firms. Changing a job is clearly related to wages—both men and women who leave their jobs within the first year, had below-average starting wages in the start-up firms. But surprisingly, females are slightly more likely to move to higher-paying jobs after leaving a mostly-female firm rather than a mostly-male firm. Again, for males there is no such difference.

The descriptive findings are confirmed by a regression analysis that controls for firm and worker characteristics and the usual set of industry, time, and region dummies. The left graph in Figure 3 plots the coefficient estimates from regressions of the job change indicator variable on a series of decile dummy variables in the share of female employees, separately for males and females. The results show that female workers are most likely to leave their jobs if they work for start-up firms in the bottom deciles with lowest relative shares of female workers. Males are more likely to either leave firms with either a high relative share of male workers or firms with a high relative share of female workers. The right graph in Figure 3 confirms that the discriminatory taste of the initial employer is not related to wage gains in the new jobs neither for women nor for men. It plots coefficients from regressions of the wage gain indicator for job movers on the same set of decile dummy variables in the relative share of female employees.[21] Table 7 presents the regression results underlying the graphs in Figure 3. While the

20. This finding is consistent with results from matched employer–employee data in other countries. See Card and de la Rica (2006) for evidence from Spain.

21. We also considered additional outcomes such as large wage gain of about 20%, wage losses, or specifications with linear wage changes, but we never found significant results.

TABLE 7. Probability to change jobs and probability of wage growth in new job.

	Job change in year 1		Job change in year 1		Wage growth > 5%	
Variable	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)
Share of female workers						
Quartile 1	0.034		0.034		−0.003	
	(0.005)**		(0.005)**		(0.009)	
Quartile 2	0.005	−0.005	0.005	−0.005	−0.010	−0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.006)
Quartile 3	0.001	0.004	0.001	0.004	−0.017	0.011
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)*	(0.007)
Quartile 4		0.024		0.024		0.011
		(0.005)**		(0.005)**		(0.008)
Herfindahl–Hirschman index (HHI)			−0.000	−0.028		
			(0.020)	(0.024)		
Firm size	0.000	0.000	0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of white-collar workers rel. to industry average	−0.018	−0.140	−0.018	−0.140	0.115	0.090
	(0.011)	(0.013)**	(0.011)	(0.013)**	(0.022)**	(0.019)**
Share from employment	0.082	0.171	0.082	0.172	0.020	0.088
	(0.010)**	(0.014)**	(0.010)**	(0.014)**	(0.026)	(0.025)**
Share from unemployment	0.110	0.134	0.110	0.134	0.038	0.102
	(0.011)**	(0.014)**	(0.011)**	(0.014)**	(0.024)	(0.021)**
Share with wage gain	0.084	0.115	0.084	0.115	−0.172	−0.224
	(0.009)**	(0.012)**	(0.009)**	(0.012)**	(0.020)**	(0.022)**
Share with wage loss	0.123	0.159	0.123	0.159	0.087	0.101
	(0.010)**	(0.012)**	(0.010)**	(0.012)**	(0.023)**	(0.020)**
Average worker age	0.001	0.002	0.001	0.002	−0.002	−0.002
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.000)**
Turnover rate	0.143	0.152	0.143	0.152	−0.017	−0.014
	(0.003)**	(0.003)**	(0.003)**	(0.003)**	(0.005)**	(0.004)**
Share from largest group	−0.095	−0.172	−0.095	−0.172	0.076	0.007
	(0.010)**	(0.011)**	(0.010)**	(0.011)**	(0.024)**	(0.020)
Median wage	0.025	0.051	0.025	0.051	0.029	0.055
	(0.004)**	(0.005)**	(0.004)**	(0.005)**	(0.009)**	(0.007)**
Individual characteristics						
Starting wage	−0.002	−0.080	−0.002	−0.080	−0.354	−0.300
	(0.005)	(0.006)**	(0.005)	(0.006)**	(0.017)**	(0.014)**
Starting wage squared	−0.002	0.006	−0.002	0.006	0.051	0.024
	(0.001)	(0.001)**	(0.001)	(0.001)**	(0.005)**	(0.003)**
Age	−0.009	0.003	−0.009	0.003	0.006	0.010
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.002)**	(0.001)**
Age squared	0.007	−0.010	0.007	−0.010	−0.011	−0.013
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.003)**	(0.002)**
Austrian	0.039	0.051	0.039	0.051	−0.004	−0.001
	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.006)	(0.005)
Observations	203,744	279,770	203,744	279,770	45,352	86,995
log-likelihood	−101449	−162631	−101449	−162628	−30679	−58292
R-squared adjusted	0.08	0.13	0.08	0.13	0.07	0.08

Notes: Sample of workers entering start-up firms during the first year. Results from linear regressions of an indicator equal to one if the individual changed jobs during the first year in columns (1) and (2), indicator equal to one if the job-changer's wage in new job is at least 5% higher than the wage in the start-up firm in columns (3) and (4). Standard errors are clustered at the firm level.

** Significant at 99%; * significant at 95%.

probability to receive a higher wage in the new job is unrelated to the share of female workers in the start-up firm, it is highly correlated with the individual starting wage, the median wage level at the start-up firm, or the share of workers who experienced a wage gain or a wage loss with respect to their previously held jobs. Industry-level competition, measured by the HHI, has no impact on either the decision to leave the start-up firm or on the probability of earning a higher wage in the new job.

Based on these results we reach two conclusions. First, the female-share proxy for discrimination does not predict wage differentials between males and females at the firm level. An explanation for this finding might be that male and female wages are relatively inflexible at the industry level. The Austrian wage-setting process is characterized by highly centralized collective bargaining at the industries. In general, the wage distribution in Austria is rather compressed, which together with the centralized wage setting leaves individual firms little room for maneuver. Further, we note that wages recorded in the ASSD are derived from annual earnings and thus also reflect differences in hours worked. This makes our measure of wages noisy, especially for women. As a second conclusion, the female share predicts whether workers leave the start-up firm. In particular, female workers employed in male-dominated firms are less likely to stay. A possible interpretation is that other non-wage related job characteristics might still differ across more and less discriminatory employers.

4.4. Firm Growth and Growth of the Relative Female Share

In this section we turn to employment growth and the change in the female share over the first five years in the sample of surviving firms. We investigate how firm growth and the change in the gender workforce composition are related to our set of workforce characteristics at entry.

Following Davis and Haltiwanger (1999), we calculate the employment growth rate and the growth rate in the relative female share as the difference in firm size (the relative female share) between year 1 and year 5 over the average firm size (relative female share) during that period—that is, $gr_{it} = (x_{i(t+4)} - x_{it})/(0.5(x_{it} + x_{i(t+4)}))$ with $x_{it} = size_{it}$ or $x_{it} = \tilde{r}_{it}$—to obtain a value in $[-2, 2]$. Descriptive results in the bottom part of Table 2 show that overall new firms grow only moderately between year 1 and year 5. But this is due to the high exit rate of start-up firms. Among survivors the yearly growth rate is about 8%. The average growth rate among survivors is slightly higher for mostly-male than for mostly-female firms.

Columns (1)–(3) of Table 8 present results from linear regressions of the growth rate in the number of workers in surviving firms, which seem to confirm the basic statistics. Conditional on surviving, the relative share of female workers in the first year is not significantly related to firm growth. More important determinants with positive impacts on growth are the share of workers hired from employment and the share of young and prime-aged workers. Firms who hired a large team of workers in the first year or who have a high fraction of workers with low wages tend to grow less than the average firm. Firms operating in concentrated markets, measured by the HHI, tend to grow faster (see column (3)).

TABLE 8. Determinants of firm growth conditional on survival and the growth rate in the female share for surviving firms.

	Firm Growth			Growth in Female Share		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share of female employees rel. to industry average	−0.021	−0.017	−0.014	−0.551	−0.546	−0.566
	(0.041)	(0.041)	(0.047)	(0.017)**	(0.016)**	(0.018)**
Share of female employees rel. to industry average squared		0.154			0.229	
		(0.058)**			(0.028)**	
Herfindahl–Hirschman index (HHI)			0.402			−0.213
			(0.335)			(0.123)
Female share × HHI			−0.212			0.398
			(0.621)			(0.221)
Firm size	−0.074	−0.069	−0.076	0.002	0.009	0.002
	(0.026)**	(0.026)**	(0.026)**	(0.005)	(0.005)	(0.005)
Share of white-collar workers rel. to industry average	0.096	0.100	0.093	0.031	0.037	0.032
	(0.037)**	(0.037)**	(0.037)*	(0.013)*	(0.013)**	(0.013)*
Share from employment	0.111	0.116	0.108	0.007	0.015	0.007
	(0.034)**	(0.034)**	(0.034)**	(0.012)	(0.012)	(0.012)
Share from unemployment	0.057	0.058	0.057	−0.002	−0.000	−0.002
	(0.037)	(0.037)	(0.037)	(0.013)	(0.013)	(0.013)
Share with wage gain	0.021	0.020	0.020	−0.020	−0.021	−0.020
	(0.026)	(0.026)	(0.026)	(0.009)*	(0.009)*	(0.009)*
Share with wage loss	−0.021	−0.023	−0.017	−0.026	−0.029	−0.026
	(0.033)	(0.033)	(0.033)	(0.011)*	(0.011)*	(0.011)*
Share of workers aged 15–30	0.275	0.278	0.275	0.007	0.010	0.007
	(0.033)**	(0.033)**	(0.033)**	(0.012)	(0.012)	(0.012)
Share of workers aged 30–45	0.247	0.247	0.245	0.019	0.018	0.019
	(0.036)**	(0.036)**	(0.036)**	(0.013)	(0.013)	(0.013)
Turnover rate	0.051	0.049	0.052	0.008	0.005	0.008
	(0.009)**	(0.009)**	(0.009)**	(0.003)*	(0.003)	(0.003)*
Share from largest group	−0.226	−0.227	−0.222	−0.020	−0.022	−0.020
	(0.032)**	(0.032)**	(0.031)**	(0.011)	(0.011)*	(0.011)
Share of workers with low wages	−0.138	−0.138	−0.144	0.036	0.035	0.036
	(0.023)**	(0.023)**	(0.023)**	(0.008)**	(0.008)**	(0.008)**
Share of workers with medium wages	−0.068	−0.065	−0.069	0.018	0.022	0.018
	(0.024)**	(0.024)**	(0.024)**	(0.008)*	(0.008)**	(0.008)*
Observations	19,075	19,075	19,075	19,057	19,057	19,057
R-squared adjusted	0.04	0.04	0.04	0.10	0.11	0.10

Notes: Estimation results from OLS regressions. In columns (1)–(3), the dependent variable is the growth rate from year one to year five in the number of workers conditional on survival. In columns (4)–(6), the dependent variable is the growth rate from year one to year five in the share of female employees conditional on survival. Standard errors in parentheses. Share of female workers relative to industry average is measured by the ratio of female to all employees relative to the four-digit industry average. "Largest group" is the largest group of workers who worked together in the same previous firm. The HHI, C4-ratio, and C8-ratio are calculated using the size of all firms at the four-digit industry level. We rescale the HHI to lie between zero and 100 and define the C4 ratio and C8 ratio in percent. All regressions also control for 22 year effects, three quarter effects, 160 industry effects, and 35 region-specific effects.
** Significant at 99%; * significant at 95%.

Next we turn to the change in the relative share of female employees. Descriptive evidence in Table 2 indicates large differences in the change over time between firms that started out with very low versus very high relative shares of female workers. Conditional on survival, mostly-male firms strongly increase their female workforce, while mostly-female firms lower theirs over the first five years. This is again confirmed by regressions results in columns (4)–(6) of Table 8, which show that firms starting out with a low relative female share in the first year experience a stronger growth than firms starting with a high female share. This effect is strongly nonlinear, implying that firms starting out with the lowest female share make an extra effort to pick up to the industry average. Compared with the initial gender workforce composition, other firm characteristics only have very small effects on the change in the relative female share over time. We interpret this result as a learning effect. If discriminatory employers, hiring relatively few female workers initially, manage to survive, they will adapt their hiring strategy and significantly increase the female share over the first 5 years.

5. Summary and Discussion of Alternative Explanations

Our empirical analysis leads to five main findings. First, we show a strong negative relationship between the relative share of female employees and the exit rate of new firms. The effect of the female share on firm survival is mainly concentrated at the lower tail 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.

Second, we document that average survival times of start-up firms vary with the level of market concentration. In highly concentrated markets entering firms survive longer. Moreover, the negative effect of a low female share on firm survival is accelerated in highly competitive markets, which is in line with the argument that in competitive markets the average surviving firm is more efficient.

Third, the effect of the female share on firm survival is very robust to the inclusion of a large set of other productivity-related covariates. If we conclude from the net bias with respect to observables on potential bias due to unobservables, there is not much reason for concern. Further, the effect is more pronounced in the subsample of larger firms, where measurement error due to random variation in the gender composition among applicants is smaller.

Fourth, our proxy of discriminatory employer tastes, the share of female workers, is not systematically related to gender wage gaps at the firm level, which are sometimes taken as proxies for discrimination. We find that male-dominated firms pay higher wages also to their female employees. Nevertheless, females are more likely to leave firms that with a mostly-male workforce even if they do not receive higher wages in their new jobs.

Fifth, the analysis of firm growth and the change in the female share among survivors shows that conditional on survival the relative share of female workers at entry has no effect on firm growth. But firms who started out with a comparatively low female share and manage to survive increase their female workforce over time.

On the whole, our results are strongly supportive of the theoretical prediction that competitive pressure drives discriminatory employers out of the market. But do they represent a causal relationship between discrimination and employer success? Obviously, other interpretations are also compatible with these results. Here we discuss alternative explanations of our findings and compare them to our preferred interpretation.

Technology as a Source of Unobserved Heterogeneity. We have discussed potential omitted variables bias based on selection on observables in Section 4.1. Differences in technology might be an unobservable component driving firm survival that is not very well captured by the list of observable workforce characteristics in our data. To the extent that firms with advanced technologies are more efficient and also employ relatively more women, our results could still be biased. Skill-biased technological advances might be proxied by higher firm-level wages.[22] We examine the relationship of within-firm wage distribution and survival in Online Appendix Table A.1. But including the additional regressors does not change the effect of the female share on survival.[23]

Females Hired in Part-Time Work. One shortcoming of the data is that there is no 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 it also allows for flexible reactions to demand shocks. To confront this argument we argue that part-time work is highly concentrated in certain occupations. Controlling for industry indicators at a narrow level captures some of the occupational effects. In addition, we estimate models for start-up firms in industries with a low share of part-time employment. Results, presented in Online Appendix Table A.6, show that the effect of the female share on the firms' exit hazard is smaller, but the relationship is still significantly negative.

Higher Risk Aversion Among Females. A growing literature discusses systematic gender differences in risk aversion and competitiveness (Croson and Gneezy, 2009; Niederle and Vesterlund, 2007; Bertrand, 2010). 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

22. Card, Heining, and Kline (2012) interpret their finding that jobs at high-wage establishments in Germany are more likely to survive with rent sharing. Establishments offering higher wages are more profitable and share some of the profits with workers.

23. In an earlier version of this paper we tried using the gender composition of potential applicants in the labor market as an instrument for the relative share of female workers (Weber and Zulehner, 2009). However, this instrument constructed from the female share in all new jobs at the region x time x industry level does not provide sufficient variation to obtain conclusive results.

thus be the result of selection by employees rather than the employer's preferences. We notice clear gender differences in the likelihood to start a job in an entering firm; women are under-represented in the workforce of start-up firms compared to established firms. However, it is probably difficult to make a prediction about future job stability in start-up firms. In contrast to established firms with a well-known record, there is no information from social networks like old colleagues or friends.

Managerial Ability and Organizational Changes. Another crucial, but unobservable, factor for the success of a start-up firm is the manager's ability. It is plausible that managerial ability is negatively correlated with discriminatory prejudice, which implies that managers who realize that discrimination is detrimental for profits, are also better at taking decisions in other areas that are crucial for success. If this is the case, the effect of a low female share on firm survival captures the negative impact of bad management practices in general with discrimination being one of them. Bloom and Van Reenen (2007) document a large dispersion in managerial efficiency across firms and countries. They emphasize that in terms of the effects of bad management practices on profitability the left tail of the distribution—that is, the very badly managed firms—matter. This is exactly what we find in the nonlinear specifications—firms at the bottom of the female share distribution are most likely to exit.

Social Interactions. According to our theoretical discussion, 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. Additional factors relevant for the success of nondiscriminatory firms could be social interactions among workers in a less male-dominated environment. Experimental evidence highlights substantial productivity gains from social interaction among co-workers or between managers and subordinates (Bandiera, Barankay, and Rasul, 2005, 2009). The results in Table 7, showing that female workers employed in male-dominated firms have a higher probability of leaving, indicate that social interactions might indeed matter. Further empirical evidence on the effect of gender diversity in top positions in start-up firms is provided by Weber and Zulehner (2010), where we find that early hires of high-wage female workers prolong firm survival and increase the overall female workforce in the firm.

6. Conclusions

In this paper we have examined whether market competition contributes to the reduction of discrimination against females. In our analysis we focus on start-up firms, for which we can measure various workforce-related characteristics at market entry. We proxy for discriminatory tastes by the share of females hired relative to the industry average and investigate how survival rates of start-up firms are related to discriminatory employer preferences. The empirical analysis is set in Austria where labor market institutions have historically promoted differential treatment of female and male workers. The ASSD firm panel provides excellent micro-data on the life spans of a large sample of start-up firms plus a number of workforce characteristics based on individual employment careers.

Our results indicate that market competition is a strong force against discrimination. We find that the female share is positively correlated with firm survival, and that this mechanism is reinforced in competitive industries. This result connects to three strands in the literature. First, it supports previous empirical tests of the Becker model which show that profitability and discrimination are negatively correlated (Hellerstein, Neumark, and Troske, 2002). Second, it links to the theoretical literature of firm entry and industry dynamics. We empirically confirm predictions by Asplund and Nocke (2006) that under increased competition the expected life span of firms is shorter and surviving firms are more efficient. Finally, if discrimination is an aspect of bad management practices, our findings are in line with results from the empirical literature on firms' productivity. Similarly to Bloom and Van Reenen (2007), we find that poor management practices are more prevalent when competition is weak.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Online Appendix. Competition and Gender Prejudice: Are Discriminatory Employers Doomed to Fail?