The sustainability of increased female representation in management positions*

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Abstract

Women are heavily underrepresented in management positions. This paper investigates if there is state dependence in the share of female manager hires in German plants to assess if increased female representation in management positions is sustainable. Using administrative data from the Integrated Employment Biographies of the IAB, we apply dynamic tobit models and dynamic linear models taking unobserved heterogeneity and the endogeneity of lagged dependent variables into account. We find that there is state dependence in the female share of manager hires. Dynamic linear models for the number of female manager hires also point to the sustainability of female manager hires showing that there is state dependence in the number of female manager hires. However, there is no state dependence in the number of male manager hires.

Keywords: female managers; gender discrimination; state dependence; dynamic panel data models

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1 Introduction

Women are heavily underrepresented in management positions. Across Europe, for example, 45 percent of the labor force is female, whereas only 11.9 percent of the boards of directors consists of women (Pande and Ford, 2011). In Germany, the share of women in management positions is still about 27 percent lower than in non-management jobs.[1,2]

The literature on promotion rates offers a number of possible explanations for the often observed gender gap in promotions to top positions of firms (see Blau and deVaro (2007) as well as Smith et al. (2015) for surveys). The classical argument is that female applicants face lower chances because of taste-based discrimination. Females may be discriminated on the labor market simply because employers, customers or colleagues dislike to engage with females (Becker, 1957). Apart from taste-based discrimination, there are a number of theoretical models that predict different promotion rates for men and women based on rational behavior. Lazear and Rosen (1990), for instance, assume that the female part of the workforce has the same distribution of labor market ability but a higher ability for household activities than men (Lazear and Rosen, 1973). It follows that women have a larger probability of leaving the workforce. Given that the output of career jobs is initially (due to human-capital investments) lower than the output of non-career jobs, women have a lower probability than men of taking up career jobs and hence of being promoted — even if they have the same ability.

Booth et al. (2003) provide a theoretical framework which is consistent with that by Lazear and Rosen (1990) but also with sticky floor models, i. e. with models which predict a similar promotion rate for both sexes but lower wages for women after

[1]Own calculations based on the Integrated Employment Biographies.

[2] Against this background, in March 2015 the German government passed a new law on gender quotas . By 2016, supervisory boards of stock market listed companies with more than 2,000 employees must comprise of at least 30 % females. Moreover, other companies with co-determination duty have to impose quotas on themselves for supervisory boards, the boards of directors and the medium and upper management levels. One goal of this policy is to enhance the chances of females to obtain management positions.

promotion. In the sticky floor model, gender differences result from higher duties of women in household production. Women get less job offers which they are willing to accept because they are less flexible with respect to certain job characteristicts like the distance from home. The current employer takes the lower outside options of females into account and pays lower wages. Their model, however, results in promotion rates which are similar to the ones of males. The model leads to the same results when assuming that gender differences come from taste-based discrimination.

Schein (1973) and Schein and Mueller (1992) argue that employers, colleagues and possible applicants may have stereotype views about characteristics and attitudes of successfull middle managers. Empirically, Schein (1973) find that in the UK, the US and in Germany, males tend to have such views on mangers. In Germany, even women perceive that they need characteristics which are usually more ascribed to men. They argue that these stereotype views build barriers which hinder women to access management positions.

Bjerk (2008) provides a model of statistical discrimination which results in lower promotion rates of females to top positions because men still form the majority in management positions. Gender differences like differences in communication styles or separated networks for men and women lead to a higher ability of men to assess the skills of male applicants than those of female applicants.[3] As males still provide more human capital on average (due to more working hours and more further education) and because of assymetric information concerning the skill of applicants, employers prefer male applicants over females with equal skills.

There are further possible reasons why women might have a lower access to management positions. For instance, labor supply to top positions is probably lower since women have more often career breaks (as emphasized by the model of Lazear and Rosen 1990) and because they are less likely to work overtime (Zapf, 2015). Labor supply to management positions may also be lower because women are observed to be less inclined to perform in competitions (Niederle and

[3] Empirical evidence for gender segregation in social networks on the labor market is found by Saygin et al. (2014).

Vesterlund, 2007). This may be even more pronounced in the presence of a glass ceiling, i. e. when the share of women in top positions of a firm is low. Then women might perceive the effort required to achieve a top position as too high and not apply for such a job.

This paper investigates if there is genuine state dependence in the *share* of female manager hires in German plants.[4] Using administrative data from the Integrated Employment Biographies of the IAB (1979–2010), we apply dynamic tobit models and dynamic linear models taking unobserved heterogeneity and the endogeneity of lagged dependent variables into account. We analyze (at the establishment-level) whether an increase in the current share of females within the newly hired managers leads to an increase in the future share of females among the hired managers. In additional specifications, we analyze if there is state dependence in the *number* of female manager hires and in the *number* of male manager hires.

Considering the literature mentioned above, there are several reasons why there might be state dependence in female manager hires. Taste-based discrimination (Becker 1957; Booth et al. 2003) or gender stereotype views (Schein and Mueller 1992) could be reduced once women enter management positions. Similarly, firms with a high share of female managers might be more attractive for female applicants increasing the female labor supply to to these firms' managerial positions. Furthermore, female networks could become more important for the hiring process and enhance the ability in the firm to assess skills of females reducing statistical discrimination (Bjerk, 2008).

The paper proceeds as follows: Section 2 discusses the existing literature; Section 3 presents the empirical specification. Section 4 describes the dataset and Section 5 presents the state dependence estimates. Section 6 concludes.

[4]Genuine state dependence (GSD) refers to the fact that the current value of a variable is causally related to the value of the variable in the past, i.e. controlling for associations arising from heterogeneity, observed or unobserved. The greater the GSD in the case of female manager hires, the more favorable the introduction of female quotas. Conversely, spurious state dependence favors measures related to individual or firm characteristics (Heckman, 1981).

2 Review of empirical literature

hile there has been so far, to the best of our knowledge, no study investigating state dependence in manager hires, there are, however, considerable studies examining related topics like the gender gap in promotion rates and the effect of female representation in firms on chances of female promotion.

The empirical literature on the gender gap in promotion rates yields mixed results. Booth, Francesconi and Frank (2003) show evidence from the BHPS which is consistent with the theoretical framework by Lazear and Rosen (1990) and with sticky floor models. On the one hand, women leave the labor force more often than men. On the other hand, the probability of promotion is similar when staying in the labor force. However, wage increases after promotion are higher for men.

Blau and deVaro (2007) use the Multi-City Study of Urban Inequality (MCSUI) employer survey for the US and come to different results. Women have lower promotion rates than men but the same wage growth after promotion. Smith et al. (2015) use a linked employer-employee dataset of all Danish companies to investigate gender differences in promotion rates to CEO positions. They find that after controlling for a wide number of variables there remains a considerable gap. However, an important part of the gap in promotion rates can be explained by sorting of women into HR, R&D, and IT departments where the chances for promotion are lower.

Other studies investigate the link between the existing representation of women in a firm (or sector) on the share of women hired for leading positions. Farrell and Hersch (2005) investigate the number of women added to the corporate board of firms in the US listed in the Fortune 500 and Service 500 lists. They find that the existing percentage of women on the board is negatively associated with the probability that the next manager added to the board is female. Parrotta and Smith (2013) use a panel on all Danish companies and fixed effects methods to investigate the share of women on the board of directors. Firms with a female chairman have significantly fewer female members on the board. Interestingly, when the share of females in a given sector is high, the share of women on the board increases, pointing to the importance of sector-specific female labor supply. Kunze and Miller (2014) use a panel dataset of 4000 private firms in Norway. Overall, there is a considerable gender gap in promotions even after controlling for a large number of variables on employers and employees and fixed effects. Higher shares of female workers at the next highest rank are associated with a significantly smaller gap. However, a larger number of females at the same rank leads to a smaller share of females getting promoted.

Another strand of the literature deals with the impact of females in leading positions on firm and worker outcomes. For instance, Bertrand et al. (2014) find that the 30% quota for the board of directors in Norway (2006) had no significant spill-over effects on wages and career opportunities of women. Matsa and Miller (2013) establish that firms affected by the Norwegian quota undertook fewer workforce reductions and experienced increasing labor costs and employment levels as well as a reduction of the short-run corporate profitability. The results by Ahern and Dittmar (2012) point to negative effects of the Norwegian quota. The announcement of the law caused a significant drop in the stock price of firms. Finally, Hirsch (2013) shows that an increasing female share in lower level management in Germany decreases the gender wage gap.

3 Empirical Specification

3.1 Share of female manager hires

Linear models

We specify a dynamic linear model for y_{it}, the female share of hired managers of plant i in period t:

$$y_{it} = \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \mathbf{x}_{it}\boldsymbol{\beta} + a_i + e_{it} \qquad (i = 1, \dots, N; t = 3, \dots, T). \tag{1}$$

We assume that the current share of females is affected by the share of females in periods $t-1$ and $t-2$. γ_1 and γ_2 measure the effect of the share of females in past manager hires, i.e. true state dependence. $\mathbf{x}$ is a vector of control variables.[5] a_i capture unobserved individual-specific effects and e_{it} time-varying unobserved effects.[6]

When estimating Equation (1) by OLS, i. e. not controlling for a_i, the correlation of a_i and y_{it-1}, y_{it-2} leads to overestimation of state dependence (assuming positive state dependence). The a_i can be swept out by taking first differences of Equation (1). However, correlation of Δy_{it-1} and Δe_{it} leads to a downward bias in the estimates of γ_1. Relatedly, elements of $\Delta\mathbf{x}$ which are not strictly exogenous are correlated with Δe_{it}. Therefore, we instrument Δy_{it-1} with y_{it-2}, y_{it-3} and $\Delta\mathbf{x}_{it}$ with $\mathbf{x}_{it-1}, \mathbf{x}_{it-2}$ in a GMM framework.[7],[8] Assuming that $E[y_{it-s}\Delta e_{it}] = 0$ for $s \geq 2$ and $E[x_{it-s}\Delta e_{it}] = 0$ for $s \geq 1$, estimates of γ_1 and γ_2 are consistent. Hence, e_{it} is assumed not to be autocorrelated, which can be tested.[9]

Nonlinear models

The linear model outlined above does not take into account that the female share in manager hires lies in the interval (0,1) and that the share has corner solutions at both ends of the interval. As a consequence the coefficients of the linear models may poorly approximate partial effects. For panel data with fractional dependent

[5] $\mathbf{x}$ includes a constant, the female share among non-managers, the share of managers, the share of highly-qualified employees as well as dummy groups for the number of employees, for sectoral affiliation, for region (Bundesland) and for urbanisation.

[6] For ease of exposition, we ignore unbalancedness of the data in this section.

[7] Further instruments are available by using further lagged values back to y_{i1} and $\mathbf{x}_{i1}$. However, as discussed by Andersen and Sørensen (1996) and Roodman (2009), the coefficients of dynamic linear models as well as the tests of overidentifying restrictions may be sensitive to the number of instruments used. Therefore, we restrict the set of instruments to y_{it-2}, y_{it-3} and $\mathbf{x}_{it-1}, \mathbf{x}_{it-2}$. Specifications with more instruments led partly to unsatisfactory Hansen test-statistics, while the coefficient estimate of the lagged dependent variable remained largely unchanged.

[8] Note that we can use y_{it-2}, y_{it-3} as instruments despite the fact that the difference of the two level variables (Δy_{it-2}) is already included in the regression model (see as an example Arrellano and Bond 1993, page 290).

[9] Blundell and Bond (1998), proposed to use additionally moment conditions where equations in levels are instrumented by lagged differences assuming that $E[\Delta y_{i1} a_i] = 0$. In our case, y_{it-2} would also be instrumented with $\Delta y_{it-2}, \ldots, \Delta y_{i2}$ because it is correlated with a_i. If these moment conditions hold, the efficiency is greatly improved compared to the estimator by Arrellano and Bond (1993). However, ...

variables, Papke and Wooldridge (2008) propose to estimate a pooled fractional probit model. However, the presence of lagged dependent variables requires to specify the distribution of unobserved effects in a maximum likelihood framework which leads to inconsistent results in the fractional probit model (Papke and Wooldridge 2008, Wooldridge 2010, p. 629). We therefore follow Loudermilk (2007) and apply dynamic two-limit tobit models with random effects which are estimated with maximum likelihood.

For the two-limit tobit model we specify the latent dependent variable y^* for firm i in period t as follows:

$$y^*_{it} = \omega_1 y_{it-1} + \omega_2 y_{it-2} + \mathbf{x}_{it}\boldsymbol{\eta} + \nu_i + \varepsilon_{it} \qquad (i = 1, \ldots, N; t = 3, \ldots, T). \tag{2}$$

The lagged values of the dependent variable in Equation (2) are necessarily correlated with the random effects ν_i. While the correlation of the endogenous variables $y_{i3}, \ldots, y_{iT}$ with ν_i is explicitly modelled when estimating Equation (2), correlation of y_{i1} and y_{i2} with ν_i is not controlled for which leads to the initial conditions problem (Heckman 1981).[10] Heckman (1981) suggests to approximate the distribution of the initial values conditional on $\mathbf{x}$ and $\boldsymbol{\nu}$ with an additional equation and hence to model the correlation of the initial values and the random effects. A solution which is easier to implement is proposed by Wooldridge (2005). Here, the correlation of the initial values and the random effects is modelled by specifying the distribution of $\boldsymbol{\nu}$ conditional on $\mathbf{x}$ and the initial values y_{it-1}, y_{it-2}:

$$\nu_i = \kappa_0 + \kappa_1 y_{i1} + \kappa_2 y_{i2} + \bar{\mathbf{x}}_i\boldsymbol{\tau} + \xi_i, \tag{3}$$

where $\bar{\mathbf{x}}_i = \frac{1}{T-2}\sum_{t=3}^{T} \mathbf{x}_{it}$.[11] Hence, we can now substitute Equation (3) into Equation (2). $y_{it-1}, y_{it-2}, \bar{\mathbf{x}}_i$ are simply added to the vector of explanatory variables.

[10] We can only model the joint distribution of $y_{i3}, \ldots, y_{iT}$ because the explanatory variables y_{it-1}, y_{it-2} are not observed prior to $t = 3$.

[11] Wooldridge (2005) proposes to include $x_{i3}, \ldots, x_{iT}$ instead of $\bar{\mathbf{x}}_i$. However, Rabe-Hesketh and Skrondal (2013) show in a simulation study that including the mean values of $\mathbf{x}$ produces similar results. This procedure is attractive because it can also be applied on unbalanced datasets.

We assume that ε_{it} is strictly exogenous and follows a normal distribution with mean 0 and variance σ_{ϵ}^{2}.[12] The resulting likelihood function for the dynamic two-limit Tobit model has the following form:

$$L = \sum_{n=1}^{N} \int \Phi\left\{\frac{-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_{\varepsilon}}\right\}^{(1[y_{it}=0])} \Phi\left\{\frac{y_{it}-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_{\varepsilon}}\right\}^{(1[0<y_{it}<1])} \Phi\left\{\frac{\mathbf{z}_{it}\boldsymbol{\iota}-1}{\sigma_{\varepsilon}}\right\}^{(1[y_{it}=1])} \frac{1}{\xi}\phi\left\{\frac{\xi}{\sigma_{\xi}}\right\} d\xi, \tag{4}$$

where $\mathbf{z}_{it}\boldsymbol{\iota} = \mathbf{x}_{it}\boldsymbol{\eta} + y_{it-1}\omega_1 + y_{it-2}\omega_2 + \xi_i + \boldsymbol{\tau}\bar{x}_i + \kappa_1 y_{i1} + \kappa_2 y_{i2}$; Φ and ϕ denote the cdf and pdf of the standard normal distribution, respectively.

The APE of explanatory variables y_{it-s} with $(s = 1, 2)$ for the two-limit tobit model are calculated as follows:

$$\omega_s \frac{1}{N}\sum_{n=1}^{N}\left\{\frac{(1-\sigma_\alpha)}{\sigma_\alpha}\phi_2 - \frac{(1-\sigma_\alpha)}{\sigma_\alpha}\mathbf{z}_{it}\boldsymbol{\iota}(\phi_2-\phi_1) + (\Phi_2-\Phi_1)\right\}, \tag{5}$$

where $\sigma_\alpha = \sigma_\xi + \sigma_\varepsilon$ and $\phi_1 = \phi\left\{\frac{-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_\alpha}\right\}$, $\phi_2 = \phi\left\{\frac{1-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_\alpha}\right\}$, $\Phi_1 = \Phi\left\{\frac{-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_\alpha}\right\}$, $\Phi_2 = \Phi\left\{\frac{1-\mathbf{z}_{it}\boldsymbol{\iota}}{\sigma_\alpha}\right\}$.

3.2 Number of female manager hires

In additional specifications, we are interested in the *number* of female hired managers. Therefore, we estimate dynamic linear models for f_{it}, the number of female hired managers in plant i in period t:

$$f_{it} = \lambda_1 f_{it-1} + \lambda_2 m_{it-1} + \mathbf{x}_{it}\boldsymbol{\chi} + c_i + v_{it} \qquad (i = 1, \ldots, N; t = 2, \ldots, T). \tag{6}$$

m_{it-1} denotes the total number of hired managers period $t-1$. It is important to control for the (lagged) total number of managers in order to assure that measured state dependence in f_{it} (captured by λ_1) is related to the theoretical channels

[12] Modelling unobserved heterogeneity as the sum of time-constant random effects $\boldsymbol{\xi}$ and strictly exogenous contemporary time shocks $\boldsymbol{\varepsilon}$ rules out firm specific time trends in manager hires. Prowse (2013) estimates a dynamic multinomial logit model with random effects and relaxes the assumption of time-constant individual effects by modelling autocorrelation in the time shocks. However, the underlying assumptions of this model are quite restrictive concerning the structure of autocorrelation. Moreover, the female share of hires for management positions should be less affected by time trends than the share of females in the stock of management positions.

discussed in the introduction and not to gender-neutral state dependence in the number of hired managers (which would be captured by λ_2). [13] $\mathbf{x}$ is a vector of control variables similar to Equation (1) except that we exclude the share of managers because it is highly related to both m_{it-1} and plant size.[14] c_i are time-constant and v_{it} time-varying unobserved characteristics. As with the dynamic linear models for the female share of hired managers, we use first differencing and internal instruments to get rid of endogeneity problems (Arrellano and Bond, 1993).[15]

4 Data Construction and Descriptive Statistics

4.1 Data construction

Our analysis is based on the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). It is the major administrative data source for employment information in Germany, which is retrieved from mandatory employment reports to the federal employment agency for each regular employee in Germany since 1975. Each employer located in Germany is required to report detailed information about each employee at least once a year. This information is of high precision as it is the basis for social security contributions and benefit eligibility. The data includes each employment spell with a start date and an date. It covers information on wages and occupations, but also some demographic characteristics such as gender, which is the focus of this paper. The data has been used in well-published studies in labor economics including Card et al. (2013) and Schmieder et al. (2012). A more comprehensive description of the Integrated Employment Biographies can be found in Oberschachtsiek et al. (2009).

We started by selecting all employees in the IEB who are employed on June

[13] We do not include lags for $t-2$ because for our regression sample v_{it} did not seem to be autocorrelated (which was the case, however, when Equation (1) included only one lag of the dependent variable.)

[14] We should note, however, that the results discussed in Section 5.2 remained unchanged when we added the share of managers to the vector of control variables.

[15] We use f_{it-2}, f_{it-3} as instruments for Δf_{it-1}, m_{it-2}, m_{it-3} for Δm_{it-1} – note that in $t=3$ one can only use f_{it-2} and m_{it-2} as instruments – and x_{it-1}, x_{it-2} for Δx_{it}.

30th of a respective year. We then restricted the sample to establishments with a median employment of at least 50 in order to reduce attrition due to zero manager hires (see below).[16] The data includes unique individual as well as establishment identifiers which allow tracking both individuals and establishments over time. By the combination of both we can distinguish between newly hired individuals and incumbent workers.[17] Also vital for our research question, managers can be identified from a 3-digit occupational code. According to an aggregation proposed by Blossfeld (1987), the following occupations were categorized as managers: entrepreneurs, managing directors, divisional managers; management consultants, organisors; chartered accountants, tax advisers; association leaders, officials.

Next, we aggregated the individual information concerning the number of employees, the number of managers, and the number of manager hires – each differentiated by gender – as well as the total number of hires and the number of high qualified employees to the establishment level, which is the unit of observation for our analysis. Since most of the establishments do not replace their management year-by-year, for these plants we do not observe manager hires each year. We therefore aggregated the establishment-level observations into 4-year periods, which is approximately equal to the median tenure of a manager in the observed sample (4.02 years). This leads to an establishment panel dataset with eight waves: $t_1 = 1979-1982, t_2 = 1983-1986, \ldots, t_8 = 2007-2010$. [18] The number of manager hires is cumulated over such 4-year periods. All other variables including establishment size, the share of high qualified employees, and the share of females in non-managerial occupations is retrieved from the first year of these 4-year periods. This ensures that co-variates are rather pre-determined and are not endogenously determined within these 4-year time horizons.

[16] The restriction according to the median (instead of the current employment) ensures that all establishments in our sample are tracked from the very beginning of their appearance until they disappear from the data.

[17] We also categorize employees as new hires as soon as they left the respective establishment for more than 30 days.

[18] We did not include $1975 - 1978$ since without information in 1974 we could not calculate the number of hires between 30th of June 1975 and 30th of June 1974.

We restricted our regression sample to establishments located in western Germany allowing us to construct a time-series starting prior to the German reunification. Furthermore, this leads to a more homogeneous sample; in 2013, for example, the labor market participation of women has still been 5 percentage points higher in eastern than in western Germany (Schnabel, 2015). Further, after constructing a time-persistent industry identifier using the procedure by Eberle et al. (2011) we excluded the public sector. We also dropped all establishments for which we do not observe any managers (which are in most cases small single-unit establishments). Finally, we excluded all establishments in which the fraction of managers exceeds 50 percent of the work force, most of which were operating in consulting.

In our regression analysis, we investigate state dependence in the share of female manager hires and, alternatively, state dependence in the number of females among all manager hires. The sample size differs for these two outcome variables. As the share of female manager hires cannot be calculated for establishments which did not hire any manager in the respective period, this outcome is analysed using a sample comprising of observations with a positive number of manager hires (*Regression Sample 1*). In addition, each plant has to be observed in at least four consecutive time periods which is (according to Equation (1) with two lagged dependent variables in first differences) the minimal requirement to be included in the Arellano-Bond specification. Regression Sample 1 contains 62,021 observations from 24,405 plants, pooled over the six periods $t_3 = 1987 - 1990, \ldots, t_8 = 2007 - 2010$.[19]

By contrast, the number of females among all manager hires takes on a value of *zero* if no female manager is hired, irrespective of whether or not a manager is hired in the respective time period. However, we still exclude non-managed workplaces. This leads to our *Regression Sample 2*, which includes plants which are observed in at least three consecutive time periods which is (according to Equation (6) with one lagged dependent variable in first differences) the minimal requirement to be included in the

[19]The first two periods are not counted because they are used to construct y_{it-1} and y_{it-2}.

Arellano-Bond specification. Regression Sample 2 contains 181,566 observations from 50,927 plants, pooled over the seven periods $t_2 = 1983-1986, \ldots, t_8 = 2007-2010$.[20]

4.2 Descriptive statistics

Table 1 presents variable means for *Regression Sample 1*, i.e. the sample with the female share of manager hires as the dependent variable. For 56 percent of all plant-observations, the female share of manager hires in period t is equal to 0, for 38 percent the share of female manager hires is between 0 and 1, while about 6 percent of all plant-observations are observed to hire only women. As is displayed in the first row of the table, the overall average of the female share of manager hires is 19 percent, while the average share for those plants which hire some, but not only managers who are female is 33.8 percent. The lagged values of the female share of hired managers are in favor of the state dependence hypothesis. For establishments with a share of female manager hires equal to 0 in t, the average share has only been equal to 9.3 percent $t-1$, while for establishments with a share between 0 and 1, the respective figure has been 23.1 percent in $t-1$. Finally, the lagged value is highest (40.1 percent) for those establishments which have a female share in manager hires of 100 percent in t. The values referring to the shares in $t-2$ and in the initial periods also point to the existence of state dependence. Whether these aggregate statistics stem from true or spurious state dependence will be investigated in Section 5.1.

As expected, those observations with an observed female share of hired managers of 0 in t are also those which employ the fewest female managers (on average 0.4). However, the respective number in establishments which hire only female managers in t amounts also to only 1.7 and is thus lower than the overall sample average (2.3). This is clearly an establishment size effect. The average establishment size in the sample is 408 employees, which is smallest (216.2) for those which hire only women. The average number of managers is 14.7, whereas the average number of female managers is only 2.3. On average, plants in Regression Sample 1 hiree 220.5

[20]The first period is not counted because it is used to construct f_{it-1} and m_{it-1}.

employees (within four years), of which 8.5 were managers.

The female share among non-managers is on avereage 38.6 percent and thus considerably higher than the share of females within managers (15.6 percent) supporting the view that women are heavily under-represented in management positions. The female share among non-managers is also relatively high for those observations which do no hire any female managers (34.2 percent) but – not suprisingly – larger for those who hire solely female managers (50.7 percent). Most of the plants in our sample belong to metropolitan areas (41 percent) and metropolitan surroundings (43 percent). There is no clear pattern concerning the relationship between urbanization and the female share of hired managers. For example, an establishment is more likely to be located in a rural area if it either hires only female managers or no female managers, but this is probably driven by establishment size. The mean values of the period dummy variables imply that in our unbalanced sample we observe slightly more observations in recent time periods (where the highest share corresponds to the period 1999-2002).

Table 2 reports variable means for *Regression Sample 2*, i.e. the sample with the number of female hired managers as the dependent variable. The average number of employees is 269.5 (compared to 408 for Regression Sample 1). Correspondingly, averages of other count variables are also lower for Regression Sample 2, i.e. the number of managers (7.7 vs. 14.7) and the number of hires (149.9 vs. 220.5). Variables referring to the composition of employees have by and large comparable means in both samples, though the female share of managers is somewhat lower for Regression Sample 2 (12.7 percent vs.15.6 percent).

According to the last but one row of Table 2, for the majority of all plant-year observations in Regression Sample 2 (namele 77.4 percent) we do not observe non-zero hires of female managers.[21] 34,951 observations (about 19.2 percent) hire 1-4 female managers and the highest category (more than 50 female hired managers) contains only of 0.1 percent of observations.

[21]Note that this could be due to zero manager hires or due to the fact that only male managers are hired.

For Regression Sample 2, the female share of hired managers in t is 16.4 percent. However, for plants with at least 1 female hired manager in t, this share is considerably larger (37.9 percent - 46.9 percent). Yet, for plants with at least 1 female hired manager, there seems to be no relationship between the female share of managers and the number of female hired managers.

5 Results

5.1 Female share of manager hires

Linear models for the female share of manager hires

Table 3 shows the results from linear models for the female share in manager hires as the dependent variable. Specification 1 is a simple OLS model including the first two lags of the dependent variable and time dummies. The coefficient of the first lag of the dependent variable shows that an increase of the share of female manager hires by 10 percentage points is on average associated with an increase of the share in the next period by 3.2 percentage points. The second lag of the dependent variable points to an additional direct effect on the next but one period by 2.2 percentage points (not controlling for observed and unobserved variables).

The coefficients of model 1 point to a strong relationship between the past and the current share of female manager hires. For example, consider two plants where plant A hires a female manager in period $t-1$ and plant B hires a male manager. If both hire one manager again in period 2, A has (due to state dependence) a 32 percentage points larger probability to hire a female manager than B.

In model 2 we include various control variables: the share of females among non-managers, the share of managers, the share of highly skilled employees, the year of foundation of the plant and dummy categories for plants size, regions and sectors. Adding the control variables only leads to a slight increase of the R-squared from 0.203 to 0.234. Similarly, the coefficients of the lagged dependent variables remain by and large unchanged.

Nevertheless, the coefficients of the control variables are significant. For instance, a higher female share among non-managers is associated with a higher female share in manager hires. One explanation is that plants with a high share of female employees belong to sectors with a high female labor supply (which may not be completely captured by the sector dummies in our model).[22] Similarly, the share of managers in a plant and the share of highly qualified employees may capture heterogeneity across plants which is not controlled for by the sector dummies and which might be associated with the labor supply of women to manager positions. Note that by controlling for the share of managers, we take into account that plants without managers are not included in our sample. Plants with more than 1000 employees have a significantly higher female share in manager hires than smaller plants. This is consistent with Adams and Ferreira (2003) who argue that larger companies may have a larger preference for diversity since they are more in the public focus and therefore face a stronger obligation for diversity.

Model 3 estimates the dynamic linear model without control variables in first differences and uses y_{it-2} and y_{it-3} as instruments for Δy_{it-1}. The coefficients of the lagged dependent variables are significantly reduced by taking into account time-constant unobserved heterogeneity. However, the model still points to a significant state dependence. An increase of the share of female manager hires by 10 percentage points is associated with an increase of the share in the next period by about 1.2 percentage points and by about 0.5 percentage points in the next but one period.

Model 4 adds time-varying control variables to the model estimated by first differences. For those variables in $\mathbf{x}_{it}$ which are assumed to be predetermined, $\mathbf{x}_{it-1}$ and $\mathbf{x}_{it-2}$ can be used as instruments for $\Delta\mathbf{x}_{it}$. The statistic of the Hansen test for the preferred preferred model shows that the null-hypothesis that the instruments are exogenous is not rejected.[23] The Arellano-Bond test shows that there is no

[22] See Hirsch (2013) and Ludsteck (2014) for studies on employment seggregation and the gender wage gap in Germany.

[23] In the reported specification, plant size dummies and the share of managers were not included as instruments, i.e. in $\mathbf{x}_{it-1}$ and $\mathbf{x}_{it-2}$, because if they were included the Hansen test indicated that some instruments might be endogenous. Nevertheless, whether we used these variables as instruments or not had no effect on the coefficient estimates of the lagged dependent variables.

second-order autocorrelation in the error term which is crucial for the identification of true state dependence. Note that estimating model 4 including only one lag of the dependent variable instead of two goes along with second-order autocorrelation (results are available upon request).

Controlling for observed and unobserved characteristics, the coefficients of the control variables become insignificant, apart from the coefficients for the female share among non-managers which is negative and significant at the 10 percent level.[24]

While most coefficients of the control variables are not significantly different from zero in model 4, the coefficients measuring state dependence are still of considerable size and significant. The coefficient for the first lag of 0.119 implies that a plant hiring one female manager in t has a probability of hiring a female manager in $t + 1$ which is about 12 percentage points higher than a plant hiring a male manager in t — given that the number of manager hires is one in both periods. In period $t + 2$ the probability is still 4.5 percentage points higher.

Non-linear models for the female share of manager hires

Table 4 shows average partial effects of dynamic tobit models. These models take into account that the dependent variable cannot be smaller than zero and larger than one and do not rely on the unrealistic assumption of constant partial effects. Disadvantages of the dynamic tobit models compared to the dynamic linear models lie in the assumption that the error terms follow a normal distribution and in the assumption of strict exogeneity of control variables.

Model 5 is a simple dynamic pooled tobit model excluding control variables and not controlling for time-constant random effects. Compared to the dynamic linear model without controls (model 1) the partial effects of the lagged dependent variables have slightly decreased. The average partial effect of the female share in manager

[24] A negative effect of the female share among non-managers may be explained by the fact that our dependent variable measures the female share in manager hires from outside the plant. That is, if the share of female employees among non-managers increases the number of internal promotions of female non-managers to manager positions may increase and the number of female manager hires from outside the plant may decrease.

hires in $t-1$ is 0.265 and the average partial effect of the second lag is 0.174.

Model 6 adds control variables to the dynamic pooled tobit model. The average partial effects of the lagged dependent variables are again slightly reduced, but remain economically and statistically significant. The signs of the control variables are similar to those of model 2. However, the size of the average partial effects rises in some cases. In particular, the average partial effects of the variable "Share of managers" and of the plant size dummies.

Model 7 is a dynamic tobit model with random effects including the first two initial values of the dependent variable to take into account the initial conditions problem. The average partial effects of both initial values are positive and highly significant — implying that the initial values are correlated with time-constant unobserved variables and that not controlling for the initial conditions leads to an upward bias of the coefficients of the lagged dependent variables. Consequently, the average partial effects are considerably reduced compared to the average partial effects of the models 5 and 6. The average partial effect of the first lag of the dependent variable is 0.043 and the one of the second lag is almost 0. σ_ξ is also significant meaning that not controlling for time-constant random effects would lead to biased estimates (Wooldridge, 2010).

Model 8 includes time-constant and time-varying control variables as well as plant-averages of the time-varying variables. The average partial effects of the control variables do not change qualitatively compared to those estimated in model 6 although average partial effects of same variables like "Female share among non-managers" and "Share of managers" are reduced in size. The main variables of interest, namely the lagged variables of the female share in hired managers are highly significant. According to model 8, an increase of the female share of hired managers by 10 percentage points in period t leads to an increase in the share in $t+1$ by 0.62 percentage points. The share in period $t+2$ is increased by 0.16 percentage points. These estimates are smaller than the ones obtained with the dynamic linear specification of model 4. However, they still point to true state dependence in the female share of hired managers.

The tobit model is particularly sensitive with respect to violations of distributional assumptions (e. g. Cameron and Trivedi 2005, p. 538). To test the robustness of our results, we estimate a dynamic ordered probit model with random effects where the dependent variable represents six categories for the female share of hired managers: $y = 0$, $0 < y < .25$, $.25 \leq y < .5$, $.5 \leq y < .75$, $.75 \leq y < 1$, $y = 1$. Also for the dynamic ordered probit model, the problem of initial conditions is addressed by applying the method of Wooldridge (2005). In this case, initial values of the six categories (again, both for $t = 1$ and $t = 2$) are included. We find that state dependence is present for the whole distribution of the lagged dependent variables. Moreover, the ordered probit model yield the same effects as a dynamic tobit model where y_{t-1} and y_{t-2} are both split into the six categories listed above.[25] This is in favor of the validity of the assumptions of normality and homoskedasticity.[26]

5.2 Linear Models for the number of female manager hires

We now turn to the dynamic linear models estimating state dependence in the number of female managers in a plant. The number of plants is considerably increased for these specifications to 50,927 because plants with zero manager hires are now included into the sample.[27] Model 9 in Table 5 is a simple dynamic linear model controlling for the first lag of the number of female managers and for the number of hired managers in total. Control variables are excluded (apart from time dummies). We did not control for the second lag of the dependent variable because model 12 which uses first differences and internal instruments did not point to second-order autocorrelation (in contrast to the dynamic linear models for the female share in manager hires).

[25] Results for both models, the dynamic ordered probit and the dynamic tobit with the lagged dependent variable split into categorie are available upon request.

[26] We refer to Ruud (1984) who points out that under normality and homoskedasticity the tobit and the probit model should yield similar results for $P(y > 0)$ while results should differ when the distributional assumptions are violated.

[27] The results (available upon request) obtained for the smaller sub-sample without plants with zero managers (i.e. for Regression Sample 1) are qualitatively similar to those reported in this subsection.

The first lag of the number of female manager hires is almost equal to one and highly significant whereas the lagged number of managers in total is insignificant. That is the number of female manager hires is only sensitive to the number of female manager hires, but not to the number of male manager hires in the past.[28] The results are consistent with the results from the models for the female share in hired managers. Consider a plant A which hires 1 female manager in period t and 0 male managers whereas plant B only hires 1 male manager in period t. In period $t+1$ plant A would hire 1 female manager again whereas plant B would not hire female managers at all (due to state dependence).

Model 10 adds control variables to the dynamic linear model for the number of female manager hires. The coefficients show that the number of female manager hires rises significantly when the share of highly qualified workers increases. As expected, larger plants hire on average more female managers than small plants. The coefficient for the lagged dependent variable remains almost unchanged after adding control variables. Relatedly, the coefficient for the lagged (total) number of hired managers is still very small and insignificant.

Model 7 is a dynamic linear model using first differences and f_{it-2}, f_{it-3} as instruments for Δf_{it-1} as well as m_{it-2}, m_{it-3} for Δm_{it-1} (where f denotes the number of female hired managers and m denotes the number of total hired managers). Not using control variables other than time dummies, the coefficients for the lagged number of female hired managers is reduced to 0.732. The coefficient for the lagged total number of hired managers remains small and insignificant.

Adding control variables to the Arellano-Bond specification (model 12) leads to a further decrease of the coefficient for the lagged number of female hired managers to 0.583. However, this coefficient is still quite large and significant. An increase of the number of female hired managers in t by 10 leads to an increase of female hired managers in $t+1$ by about 6. Again, there is no effect of the total number of hired managers. The Hansen test-statistic for model 12 suggests to the validity of the used

[28]The effect of male hire managers is given by the coefficient for the variable (total) manager hires.

instruments. Also, the Arellano-Bond test is satisfactory since there is evidence for negative autocorrelation of first order and of no autocorrelation of second order.

As robustness checks, we estimated the dynamic linear models from Table 5 using spline regressions to investigate if the effect of the lagged number of female manager hires is linear and to rule out that the effect is only driven by some plants, for instance only by plants with a high number of female manager hires in the past.[29] Since the parameter estimates for specifications (13)–(16) in Table 6 are qualitatively the same, we immediately turn to the Arellano-Bond specification including control variables (model 16). For the reference category ($10 - 14$ female hired managers in $t-1$), the effect of a one-unit-increase of female hired managers in $t-1$ on the current number of female manager hires is 0.555 and therefore almost identical to the number obtained in model (12) for the overall sample.[30] Furthermore, the coefficients for most splines are insignificant implying that the effect is mainly linear.[31] Only for a small number of female manager hires in $t-1$ (1-4 hires), the effect is significantly reduced to about 0.236. Model 16 confirms the result of Table 5 that the total number of hired managers in $t-1$ has no effect on the current number of female hired managers.

Unfortunately, the Hansen test-statistic of model 16 rejects the null hypothesis that the instruments are uncorrelated with the error term. However, model 15 excluding control variables gives mainly similar results as those of model 16 and does not reject the null hypothesis of the Hansen test. Furthermore, both models show insignificant autocorrelation of second-order.

Table 7 shows analogous regressions, but now with the number of male hired managers as the dependent variable. For model 18 which specifies a dynamic linear model including control variables, suggests also state dependence in the number of male manager hires. The estimates imply that increasing the number of male

[29]The spline variables are constructed as follows: For instance, the variable "Spline: 1-4" is an interaction of "Number of female hired managers, $t-1$" with a dummy-variable which is one if the number of female hired managers is between one and four and zero otherwise.

[30]Note that plants where the number of female hired managers is zero are captured by the constant, but not by the spline reference category.

[31]Splines 15-19, ..., 50 + are jointly insignificant with a p-value of 0.22.

manager hires in $t-1$ by 10 and holding the number of total manager hires constant increases the number of male manager hires in t by about 5. However, when controlling for unobserved heterogeneity by using first differences and internal instruments (model 20) the coefficient becomes negative and insignificant thus ruling out true state dependence. The model passes both the Hansen test for overidentifying restrictions and the Arellano-Bond test for autocorrelation of second order.

In conclusion, the models for the number of female manager hires show that there is true state dependence, i. e. increasing the number of female manager hires in present leads to more female manager hires in the future (for instantce because increasing the number of female managers corrects wrong believes about female managers). In sharp contrast, there is no true state dependence in the number of male hired managers.

5.3 Further robustness Checks

One might speculate that the parameter estimates for the lagged female shares of hired managers (models 1 – 8) and for the lagged number of female hired managers (models 9 – 12) capture rather firm-specific time-trends in the female work-force than true state-dependence. Firstly, we argue that the female hires for management positions (i.e. our dependent variable) should be less affected by time trends than the actual number of females in the stock of management positions. Secondly, we offer indirect evidence on this issue by re-running our preferred specifications with interaction terms between time and industry dummies. The obtained coefficients for the lagged female shares of hired managers remain almost unaffected for model 4 (with coefficient estimates of 0.132 and 0.038) and model 8 (with coefficient estimates of 0.064 and 0.018). In model 12, the coefficient estimate for the the number of female hired managers reduces slightly from 0.583 to 0.430, but the difference is far from being statistically significant. These results indicate that our findings of state dependence in establishments' hiring behavior of female managers is not confounded by time trends in female manager hires, assuming that these do not differ within sectors.

We also investigated whether state dependence in the hiring of female managers changes over time. This is interesting *per se*. In addition, if there are establishment-specific trends in the hiring of females, we would expect to find a larger state dependence in the second half of the sample.[32]

6 Conclusions

This study analyzes genuine state dependence in female manager hires of German firms to investigate if an increase in female manager hires is sustainable. Using dynamic linear and nonlinear models controlling for unobserved heterogeneity and the endogeneity of lagged dependent variables and administrative data on all German establishments, we find that there is state dependence in the female share of manager hires. That is, an increase in the current *share* of female manager hires leads to an increase in the *share* of female manager hires in the future. The result is confirmed by dynamic linear models for the *number of female manager hires*. We also show that there is no state dependence in the number of male manager hires, which we take as evidence that our results are not a statistical artefact.

The results are very robust with respect to a number of different specifications. For instance, we find true state dependence in the share of female manager hires using dynamic linear and dynamic tobit models. We also used different sets of instrumental variables in the GMM-regressions which let the main results unchanged. Moreover, state dependence is still present after the inclusion of sector-specific time trends and when dividing the sample into two time-windows. This speaks against the conjecture that the lagged dependent variables measure firm-specific trends instead of true state dependence.

The results suggest that hiring managers is not gender neutral and that the

[32] The issue of increasing the share of women in leadership positions has become more prominent in Germany during the last 10 years. In 2010, for example, there was a first attempt for a law on gender quotas in supervisory boards. While it took until 2015 until the law finally passed, the discussion may have already encouraged firms to rise the share of women voluntarily.

chances of women to reach management positions are better if the firm has hired female managers in the past. Reasons might be that the importance of gender stereotypes or taste-based discrimination is reduced once the number of female managers in a firm is increased. Alternatively, a greater importance of female networks in an establishment could enhance chances of females to get management positions and make management positions more attractive for female applicants. Our finding of positive state dependence is (besides other pro/contra arguments) in favor of the introduction of female quotas.

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Table 1: Variable means by female share of hired managers; Regression Sample 1

	Female share of hired managers t[a]			
	$y = 0$	$0 < y < 1$	$y = 1$	All
Female share of hired managers in ...				
t	0.000	0.338	1.000	0.190
t - 1	0.093	0.231	0.401	0.164
t - 2	0.086	0.190	0.323	0.140
t = 1	0.074	0.141	0.259	0.111
t = 2	0.079	0.167	0.325	0.128
Female share of managers	0.061	0.242	0.492	0.156
Number of ...				
employees	285.1	618.9	216.2	408.3
managers	6.7	28.2	3.9	14.7
female managers	0.4	5.2	1.7	2.3
male managers	6.3	23.0	2.2	12.4
hires	152.2	332.1	145.8	220.5
hired managers	3.1	17.4	1.6	8.5
hired female managers	0.0	4.8	1.6	1.9
hired male managers	3.1	12.6	0.0	6.5
Female share of non-managers	0.342	0.431	0.507	0.386
Share of managers	0.039	0.070	0.036	0.051
Share of high qualified employees	0.077	0.137	0.090	0.101
Year of foundation	1981.3	1982.3	1983.2	1981.8
Urbanization:				
Metropolitan	0.364	0.480	0.414	0.411
Metropolitan surroundings	0.453	0.396	0.406	0.429
Urbanized	0.113	0.080	0.106	0.100
Rural	0.069	0.043	0.073	0.060
Panel periods:[b]				
1979-1982	0.000	0.000	0.000	0.000
1983-1986	0.000	0.000	0.000	0.000
1987-1990	0.189	0.101	0.082	0.149
1991-1994	0.177	0.133	0.100	0.156
1995-1998	0.184	0.163	0.132	0.173
1999-2002	0.166	0.204	0.178	0.181
2003-2006	0.153	0.187	0.256	0.172
2007-2010	0.131	0.211	0.252	0.169
Number of observations[c]	34,584	23,670	3,767	62,021
Number of plants	18,263	11,681	3,194	24,405

Data source: Integrated Employment Biographies.

[a] y denotes the female share of hired managers.

[b] There are no observations in the first two periods because estimations of the share of female manager hires contain two lags of the dependent variable.

[c] Note that the sum of the number of plants in the first three columns exceeds the number in the fourth column since plants may change through time between categories.

Table 2: Variable means by number of female hired managers,
Regression Sample 2

	Number of female hired managers in period t						
	0	1 – 4	5 – 9	10 – 19	20 – 49	50+	All
Female share of hired managers in ...							
t	0.000	0.469	0.441	0.443	0.431	0.379	0.164
t - 1	0.100	0.230	0.313	0.355	0.358	0.318	0.142
t - 2	0.097	0.190	0.263	0.291	0.300	0.276	0.129
t = 1	0.086	0.162	0.201	0.226	0.223	0.210	0.109
t = 2	0.064	0.254	0.260	0.270	0.268	0.226	0.123
Female share of managers	0.079	0.283	0.337	0.354	0.363	0.319	0.127
Number of ...							
employees	205.1	376.4	676.0	1222.3	2221.0	4489.9	269.5
managers	3.9	11.1	32.9	63.7	145.2	538.4	7.7
female managers	0.3	1.8	6.7	14.0	31.1	111.6	1.1
male managers	3.7	9.3	26.3	49.7	114.1	426.8	6.6
hires	112.9	214.4	394.5	673.9	1126.8	2526.9	149.9
hired managers	1.4	6.2	20.8	41.9	92.2	405.0	4.0
hired female managers	0.0	1.6	6.4	13.3	29.1	124.5	0.8
hired male managers	1.4	4.6	14.5	28.6	63.1	280.4	3.1
Female share of non-managers	0.353	0.438	0.479	0.494	0.507	0.458	0.374
Share of managers	0.031	0.051	0.099	0.134	0.177	0.211	0.038
Share of high qualified employees	0.059	0.106	0.177	0.221	0.251	0.351	0.072
Year of foundation	1981.6	1983.4	1984.8	1985.0	1984.8	1982.9	1982.0
Urbanization:							
Metropolitan	0.340	0.440	0.569	0.603	0.664	0.692	0.368
Metropolitan surroundings	0.449	0.405	0.360	0.338	0.302	0.282	0.437
Urbanized	0.127	0.096	0.047	0.046	0.030	0.023	0.119
Rural	0.083	0.059	0.024	0.012	0.005	0.004	0.076
Panel periods:[a]							
1979-1982	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1983-1986	0.175	0.081	0.040	0.024	0.023	0.038	0.152
1987-1990	0.167	0.102	0.061	0.053	0.050	0.060	0.151
1991-1994	0.158	0.132	0.105	0.104	0.103	0.068	0.151
1995-1998	0.138	0.150	0.149	0.120	0.145	0.120	0.141
1999-2002	0.130	0.183	0.221	0.221	0.208	0.218	0.143
2003-2006	0.122	0.173	0.189	0.201	0.191	0.203	0.134
2007-2010	0.110	0.179	0.235	0.277	0.280	0.293	0.128
Number of observations[b]	140,538	34,954	3,681	1,467	660	266	181,566
Number of plants	46,094	19,320	2,604	1,031	431	128	50,927

Data source: Integrated Employment Biographies.

[a] There are no observations in the first period because estimations of the number of female manager hires contain one lag of the dependent variable.

[b] Note that the sum of the number of plants in the first six columns exceeds the number in the fourth column since plants may change through time between categories.

Table 3: Dynamic linear models; dependent variable: **Female share of hired managers**

	OLS		Arrellano-Bond	
Explanatory variables	(1)[a]	(2)[a,b]	(3)[c]	(4)[c]
Female share of hired managers, $t-1$	0.321***	0.275***	0.113***	0.133***
	(0.006)	(0.006)	(0.021)	(0.024)
Female share of hired managers, $t-2$	0.217***	0.175***	0.047***	0.046***
	(0.006)	(0.006)	(0.013)	(0.016)
Female share among non-managers		0.175***		0.044
		(0.006)		(0.345)
Share of managers		0.057***		-2.594
		(0.018)		(1.829)
Share of highly qualified employees		0.043***		0.015
		(0.009)		(0.562)
Size dummies (ref. group: $1-19$ employees)	—	—	—	—
	—	—	—	—
$20-49$		0.008		-0.698
		(0.011)		(0.554)
$50-99$		-0.000		-0.063
		(0.009)		(0.423)
$100-199$		0.002		-0.074
		(0.009)		(0.401)
$200-499$		0.007		0.015
		(0.009)		(0.376)
$500-999$		0.013		-0.474
		(0.009)		(0.684)
$1000-4999$		0.028***		0.249
		(0.010)		(0.609)
5000 and more		0.035***		1.586
		(0.011)		(5.236)
Period dummies (ref. group: $1987-1990$)				
$1991-1994$	0.025***	0.025***	0.027***	0.032***
	(0.003)	(0.003)	(0.011)	(0.011)
$1995-1998$	0.034***	0.034***	0.040***	0.075***
	(0.003)	(0.003)	(0.010)	(0.022)
$1999-2002$	0.061***	0.061***	0.070***	0.113***
	(0.003)	(0.003)	(0.010)	(0.028)
$2003-2006$	0.079***	0.077***	0.089***	0.150***
	(0.004)	(0.004)	(0.010)	(0.037)
$2007-2010$	0.090***	0.086***	0.108***	0.183***
	(0.004)	(0.004)	(0.011)	(0.044)
Observations	62,021	62,021	37,616	37,616
Number of plants	24,405	24,405	15,199	15,199
R-squared	0.203	0.234	—	—
Hansen test χ^2 (degrees of freedom)	—	—	19.38 (7)	18.13 (17)
Prob $> \chi^2$	—	—	0.007	0.381
Z-value of Arellano-Bond test for AR(1)	—	—	-28.05	-6.44
Prob $> Z$	—	—	0.000	0.000
Z-value of Arellano-Bond test for AR(2)	—	—	0.04	-0.58
Prob $> Z$	—	—	0.965	0.562

Data source: Integrated Employment Biographies. *, **, *** denotes significance at the 10%, 5% and 1 % level.

[a] Standard errors of models (1) and (2) are clustered at the plant level.

[b] Model (2) additionally includes 9 region dummies (Bundesland), 7 sector dummies, 3 dummies for urbanisation type and the year of foundation of the plant.

[c] Standard errors of models (3) and (4) are calculated using the method of Windmejer (2005). $y_{it-2}, y_{it-3}, \mathbf{x}_{it-1}, \mathbf{x}_{it-2}$ are used as instruments (plant size dummies excluded).

Table 4: Dynamic tobit models; dependent variable: **Female share of hired managers**; average partial effects (APE)

	Dynamic pooled tobit models		Dynamic tobit models with random effects	
Explanatory variables	(5)	(6)[a]	(7)	(8)[a,b]
Female share of hired managers, $t-1$	0.265***	0.217***	0.043***	0.062***
	(0.004)	(0.004)	(0.006)	(0.006)
Female share of hired managers, $t-2$	0.174***	0.132***	0.006	0.016***
	(0.004)	(0.004)	(0.005)	(0.006)
Female share of hired managers, $t=0$	—	—	0.138***	0.094***
	—	—	(0.006)	(0.006)
Female share of hired managers, $t=1$	—	—	0.199***	0.142***
	—	—	(0.007)	(0.007)
Female share among non-managers	—	0.172***	—	0.074***
	—	(0.005)	—	(0.017)
Share of managers	—	0.277***	—	0.136***
	—	(0.016)	—	(0.031)
Share of highly qualified employees	—	0.087***	—	0.013
	—	(0.008)	—	(0.022)
Size dummies (ref. group: $1-19$ employees)	—	—	—	—
	—	—	—	—
$20-49$	—	0.018**	—	0.029***
	—	(0.007)	—	(0.011)
$50-99$	—	0.016**	—	0.016*
	—	(0.006)	—	(0.009)
$100-199$	—	0.034***	—	0.024***
	—	(0.006)	—	(0.009)
$200-499$	—	0.054***	—	0.034***
	—	(0.006)	—	(0.009)
$500-999$	—	0.078***	—	0.047***
	—	(0.007)	—	(0.010)
$1000-4999$	—	0.119***	—	0.077***
	—	(0.008)	—	(0.013)
5000 and more	—	0.191***	—	0.105***
	—	(0.016)	—	(0.030)
Period (ref. group: $1987-1990$)	—	—	—	—
	—	—	—	—
$1991-1994$	0.032***	0.031***	0.032***	0.031***
	(0.003)	(0.003)	(0.003)	(0.003)
$19995-1998$	0.043***	0.045***	0.048***	0.050***
	(0.003)	(0.003)	(0.003)	(0.003)
$1999-2002$	0.074***	0.074***	0.082***	0.083***
	(0.003)	(0.003)	(0.003)	(0.003)
$2003-2006$	0.083***	0.080***	0.099***	0.096***
	(0.004)	(0.004)	(0.003)	(0.003)
$2007-2010$	0.096***	0.088***	0.118***	0.112***
	(0.004)	(0.004)	(0.003)	(0.004)
Individual averages ($\bar{\boldsymbol{x}}_i$) :	—	—	—	—
Female share among non-managers	—	—	—	0.122***
	—	—	—	(0.018)
Share of managers	—	—	—	0.218***
	—	—	—	(0.039)
Share of highly qualified employees	—	—	—	0.087***
	—	—	—	(0.024)
σ_ε (coefficient)	0.544***	0.529***	0.454***	0.466***
	(0.003)	(0.003)	(0.003)	(0.003)
σ_ξ (coefficient)	—	—	0.355***	0.284***
	—	—	(0.006)	(0.007)
Observations	62,021	62,021	62,021	62,021
Number of plants	24,405	24,405	24,405	24,405
Wald-test-χ^2 (degrees of freedom)	1557.15 (7)	364.20 (37)	6183.75 (9)	9923.58 (28)
Prob > χ^2	0.000	0.000	0.000	0.000

Data source: Integrated Employment Biographies. *, **, *** denotes significance at the 10%, 5% and 1 % level. Average partial effects.

[a] Models (6) and (8) additionally include 9 region dummies (Bundesland), 7 sector dummies; 3 urbanisation type dummies, 5 period dummies and the year of foundation of the plant.

[b] Model (8) additionally includes the individual averages of the plant size dummies.

Table 5: Dynamic linear models; dependent variable: **Number of female hired managers**

Explanatory variables	OLS (9)	OLS (10)	Arrellano-Bond (11)	Arrellano-Bond (12)
Number of female hired managers, $t-1$	0.954***	0.967***	0.732***	0.583***
	(0.109)	(0.111)	(0.167)	(0.169)
Number of hired managers in total, $t-1$	0.020	0.011	-0.026	-0.018
	(0.016)	(0.017)	(0.021)	(0.027)
Female share among non-managers	—	0.092	—	-3.470
	—	(0.099)	—	(6.095)
Share of highly qualified employees	—	1.391***		-2.459
	—	(0.376)	—	(16.846)
Size dummies (ref. group: 1 – 19 employees)	—	—	—	—
	—	—	—	—
20 – 49	—	0.434***	—	4.223
	—	(0.063)	—	(17.296)
50 – 99	—	0.496***	—	6.325
	—	(0.063)	—	(16.157)
100 – 199	—	0.516***	—	6.241
	—	(0.070)	—	(16.328)
200 – 499	—	0.570***	—	2.128
	—	(0.088)	—	(16.045)
500 – 999	—	0.665***	—	1.924
	—	(0.140)	—	(16.815)
1000 – 4999	—	1.434***	—	-7.448
	—	(0.256)	—	(21.642)
5000 and more	—	5.920***	—	20.970
	—	(2.007)	—	(1.192)
Period (ref. group: 1983 – 1986)	—	—	—	—
	—	—	—	—
1987 – 1990	0.124***	0.103***	-0.043	0.160
	(0.013)	(0.014)	(0.297)	(0.226)
1991 – 1994	0.152***	0.122***	0.053	0.305
	(0.024)	(0.018)	(0.295)	(0.479)
1995 – 1998	0.143***	0.112***	0.041	0.250
	(0.042)	(0.034)	(0.301)	(0.594)
1999 – 2002	0.226***	0.200***	0.161	0.482
	(0.050)	(0.037)	(0.309)	(0.753)
2003 – 2006	-0.181**	-0.202***	-0.190	0.178
	(0.083)	(0.062)	(0.323)	(0.912)
2007 – 2010	0.238***	0.208***	0.080	0.550
	(0.083)	(0.061)	(0.325)	(1.192)
Observations	181,566	181,566	130,639	130,639
Number of plants	50,927	50,927	38,833	38,833
Hansen test χ^2 (degrees of freedom)	—	—	24.64 (19)	26.57(34)
Prob > χ^2	—	—	0.173	0.827
Z-value of AB test for AR(1)	—	—	-7.10	-3.16
Prob > Z	—	—	0.000	0.002
Z-value of AB test for AR(2)	—	—	-0.15	-0.03
Prob > Z	—	—	0.879	0.765

Data source: Integrated Employment Biographies. *, **, *** denotes significance at the 10%, 5% and 1 % level.

[a] Standard errors of models (9) and (10) are clustered at the plant level.

[b] Model (10) additionally includes 9 region dummies (Bundesland), 7 sector dummies, 3 dummies for the region type, 7 plant size dummies, 5 time dummies and the year of foundation of the plant.

[c] Standard errors of models (11) and (12) are calculated using the method of Windmejer (2005). $f_{it-2}, f_{it-3}, m_{it-2}, m_{it-3}, \mathbf{x}_{it-1}, \mathbf{x}_{it-2}$ are used as instruments (plant size dummies excluded).

[d] Model 12 additionally includes 7 plant size dummies and 5 time dummies.

Table 6: Dynamic linear models; dependent variable: **Number of female hired managers**; spline regressions

Explanatory variables	OLS (13)	(14)	Arrellano-Bond (15)	(16)
Number of female hired managers, $t-1$	0.829***	0.814***	0.502***	0.555***
	(0.062)	(0.063)	(0.145)	(0.153)
Spline: 1-4	-0.238***	-0.273***	-0.314***	-0.319***
	(0.044)	(0.043)	(0.099)	(0.117)
Spline: 5-9	-0.087*	-0.092**	-0.190**	-0.148
	(0.047)	(0.046)	(0.075)	(0.097)
Spline: 10-14 (reference)	—	—	—	—
	—	—	—	—
Spline: 15-19	-0.043	-0.041	-0.102	-0.121
	(0.075)	(0.073)	(0.088)	(0.111)
Spline: 20-29	0.161*	0.162**	0.042	0.123
	(0.083)	(0.082)	(0.104)	(0.123)
Spline: 30-39	0.051	0.052	0.085	0.185
	(0.112)	(0.111)	(0.174)	(0.185)
Spline: 40-49	-0.006	-0.000	0.171	0.196
	(0.078)	(0.077)	(0.134)	(0.144)
Spline: 50 +	0.153	0.187*	0.143	0.192
	(0.105)	(0.103)	(0.134)	(0.160)
Number of hired managers in total, $t-1$	0.050***	0.022*	-0.086	-0.035
	(0.009)	(0.012)	(0.096)	(0.029)
Spline: 1-4	-0.019**	-0.017**	-0.066	-0.016
	(0.008)	(0.008)	(0.159)	(0.026)
Spline: 5-9	0.001	-0.001	-0.019	-0.014
	(0.005)	(0.005)	(0.044)	(0.018)
Spline: 10-14 (reference)	—	—	—	—
	—	—	—	—
Spline: 15-19	0.000	0.002	0.003	-0.005
	(0.007)	(0.007)	(0.027)	(0.020)
Spline: 20-29	-0.012*	-0.007	-0.007	-0.019
	(0.007)	(0.007)	(0.042)	(0.023)
Spline: 30-39	-0.017*	-0.012	-0.009	-0.017
	(0.009)	(0.009)	(0.057)	(0.036)
Spline: 40-49	-0.007	-0.000	0.034	0.013
	(0.013)	(0.013)	(0.069)	(0.036)
Spline: 50 +	-0.033***	-0.014	-0.000	-0.026
	(0.011)	(0.010)	(0.088)	(0.037)
Observations	181,566	181,566	130,639	130,639
Number of plants	50,927	50,927	38,833	38,833
Hansen test χ^2 (degrees of freedom)	—	—	13.19 (15)	42.56 (30)
Prob > χ^2	—	—	0.588	0.064
Z-value of AB test for AR(1)	—	—	-1.42	-2.81
Prob > Z	—	—	0.156	0.005
Z-value of AB test for AR(2)	—	—	-0.51	-0.61
Prob > Z	—	—	0.611	0.544

Data source: Integrated Employment Biographies. *, **, *** denotes significance at the 10%, 5% and 1 % level.

[a] Standard errors of models (13) and (14) are clustered at the plant level.

[b] Control variables of (13), (14), (15) and (16) are the respective covariates of Models (9), (10), (11) and (12).

[c] Standard errors of models (15) and (16) are calculated using the method of Windmejer (2005). $f_{it-2}, f_{it-3}, m_{it-2}, m_{it-3}, \mathbf{x}_{it-1}, \mathbf{x}_{it-2}$ are used as instruments (plant size dummies excluded).

Table 7: Dynamic linear models; dependent variable: **Number of male hired managers**

	OLS		Arrellano-Bond	
Explanatory variables	(17)	(18)	(19)	(20)
Number of male hired managers, $t-1$	0.558**	0.466*	-0.333	-0.264
	(0.235)	(0.248)	(0.400)	(0.442)
Number of hired managers in total, $t-1$	0.212	0.254	0.514	0.434
	(0.170)	(0.178)	(0.359)	(0.393)
Female share among non-managers	—	-0.205	—	1.523
	—	(0.164)	—	(9.989)
Share of highly qualified employees	—	4.439***		30.234
	—	(1.300)	—	(36.466)
Size dummies (ref. group: $1-19$ employees)	—	—	—	—
	—	—	—	—
$20-49$	—	1.272***	—	16.642
	—	(0.161)	—	(25.463)
$50-99$	—	1.523***	—	11.059
	—	(0.161)	—	(23.026)
$100-199$	—	1.675***	—	13.732
	—	(0.175)	—	(23.278)
$200-499$	—	1.916***	—	-1.050
	—	(0.245)	—	(23.533)
$500-999$	—	2.447***	—	-6.248
	—	(0.433)	—	(27.016)
$1000-4999$	—	4.931***	—	14.879
	—	(0.981)	—	(41.102)
5000 and more	—	34.695***	—	100.439
	—	(8.084)	—	(157.842)
Period (ref. group: $1983-1986$)	—	—	—	—
	—	—	—	—
$1987-1990$	0.601***	0.532***	0.885	0.401
	(0.053)	(0.061)	(2.452)	(0.375)
$1991-1994$	0.445***	0.371***	0.872	0.471
	(0.085)	(0.065)	(2.451)	(0.786)
$1995-1998$	0.436***	0.409***	0.767	-0.349
	(0.090)	(0.098)	(2.407)	(1.120)
$1999-2002$	0.344***	0.390***	0.696	-0.354
	(0.099)	(0.115)	(2.362)	(1.386)
$2003-2006$	-0.757***	-0.634***	-0.393	-1.939
	(0.153)	(0.159)	(2.285)	(1.764)
$2007-2010$	0.183	0.317	-0.126	-1.913
	(0.139)	(0.206)	(2.272)	(2.282)
Observations	181,566	181,566	130,639	130,639
Number of plants	24,405	24,405	38,833	38,833
Hansen test χ^2 (degrees of freedom)	—	—	20.64 (19)	18.22(22)
Prob > χ^2	—	—	0.357	0.693
Z-value of AB test for AR(1)	—	—	3.10	-2.69
Prob > Z	—	—	0.002	0.009
Z-value of AB test for AR(2)	—	—	-0.06	-0.28
Prob > Z	—	—	0.952	0.779

Data source: Integrated Employment Biographies. *, **, *** denotes significance at the 10%, 5% and 1 % level.

[a] Standard errors of models (17) and (18) are clustered at the plant level.

[b] Model (18) additionally includes 9 region dummies (Bundesland), 7 sector dummies, 3 dummies for urbanisation type, 7 plant size dummies, 5 time dummies and the year of foundation of the plant.

[c] Standard errors of models (19) and (20) are calculated using the method of Windmejer (2005). $f_{it-2}, f_{it-3}, m_{it-2}, m_{it-3}, \mathbf{x}_{it-1}, \mathbf{x}_{it-2}$ are used as instruments (plant size dummies excluded).