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DISCUSSION PAPER SERIES

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ABSTRACT

An Estimated Model of Employer and Non-employer Entrepreneurship*

What motivates individuals to become entrepreneurs and create jobs? We develop and estimate a dynamic structural microeconometric model that accounts for both employer and non-employer entrepreneurs. Individuals in each period choose to work as an employee, as one of the two entrepreneur types, or remain non-employed. Different work experiences may affect earnings in the three sectors differently. The estimated model replicates key data patterns. The results suggest that experience in employment provides positive returns in entrepreneurship, but entrepreneurial experience does not have positive returns in employment. The model is used to simulate how policy scenarios would affect individuals' entrepreneurial choices.

JEL Classification: J22, J23, L26, C61

Keywords: entrepreneurship, employer, dynamic structural model, life cycle

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1 Introduction

The interplay between the accumulation of work experience, returns in the form of labor earnings, and the corresponding incentives for labor supply over the life cycle has been studied intensively for wage and salary workers. However, we know little in this context about the roughly ten percent of the labor force who are entrepreneurs, although entrepreneurial activity is crucial for job creation, innovation, and growth. In particular, policymakers are eager to understand the individual decision to hire workers and to become an employer. Most entrepreneurs work on their own and never hire any workers (non-employers), so their impact on the economy is limited (Hurst and Pugsley, 2011). Governments around the world cite job creation as the justification for public programs aimed at promoting entrepreneurship, but the success depends on the small share of entrepreneurs who hire workers (employers) and thereby create jobs for people other than the entrepreneurs themselves (Cowling et al., 2004; Fairlie and Miranda, 2017). Therefore, it is important to better understand the distinct decisions to become an employer or a non-employer.

The values of work experience gained from being an employer, a non-employer, or a paid employee, may be different in each of these employment states. In this paper, we investigate how experience from the different employment states is valued in the same and other states. The structure of returns to experience within and across labor market activities will determine the dynamics of individual decisions to supply labor as employees, employers, and non-employers over the life cycle. Understanding how incentives drive these dynamics will not only advance the literature on labor supply and entrepreneurship, but also help policymakers to design policies that influence entrepreneurship and job creation, e.g., through tax policy, social insurance, or subsidies.

In this paper, we develop a dynamic structural microeconometric model of labor supply over the life cycle with the choice options of being a non-employer, an employer, an employee, or non-employed. Earnings in the different alternatives depend on the types of experience gained from the different employment forms. In our model, individuals' preferences and abilities may be different in both observable and unobservable ways. This approach allows us to take into account selection into different sectors due to observable and unobservable characteristics.

To estimate our dynamic structural model, we use a large household panel survey randomly drawn from the German resident population, the German Socio-Economic Panel Survey (SOEP), which includes annual information over a sufficiently long time period and distinguishes between employer and non-employer entrepreneurs. The estimated dynamic structural model fits key properties of the representative data well, such as the age-participation and age-earnings profiles of employees, non-employers, and employers. We use the estimated model to simulate the effects of hypothetical tax or subsidy policies on entrepreneurial activity.

Our main contribution to the literature is that we provide the first dynamic structural microeconometric model of labor supply that takes into account non-employer entrepreneurship and employer-entrepreneurship. Our results suggest that the transferability of experience between sectors is one way. In particular, returns to work experience accumulated as an entrepreneur are negligible or even negative for employees in Germany. However, experience accumulated as an employee substantially increases the earnings of an entrepreneur. Our policy simulations are examples of the wide range of applied research questions that our estimated model is suitable to address.

The literature on dynamic structural labor supply models (e.g., Keane and Wolpin, 1997; Baird, 2017; Haan and Prowse, 2014, using the SOEP) has tremendously improved our understanding of labor market dynamics and lays the methodological foundation for this paper. However, this literature mostly ignores entrepreneurship and usually excludes entrepreneurs from the estimation samples. It does not address the possibility of selection bias arising from dropping roughly ten percent of the working population who make this choice at each point in time.

Hincapié (2020) and working papers by Dillon and Stanton (2017) and Humphries (2024) are notable exceptions. These authors include self-employment in dynamic structural models using different data for different countries, but do not distinguish between non-employers and employers. Given the importance of job creation and growth orientation in the policy debate on entrepreneurship, this distinction is an important contribution we make. Hurst and Pugsley (2011) report that most self-employed individuals without employees have no intention to grow or to hire workers. Therefore, not distinguishing between the self-employed with and without employees can result in misleading policy conclusions for policymakers intending to promote entrepreneurship in order to stimulate economic growth and jobs.[1] In fact, in his conclusion, Hincapié (2020) calls for further research investigating which entrepreneurs hire workers to shed light on job creation. In this paper, we document that employers and non-employers are very different.

An emerging literature investigates the determinants of becoming an employer, without estimating dynamic structural models. Haltiwanger et al. (2013) identify firm age as a crucial determinant of the decision to hire workers. Consistent with this, Fairlie and Miranda (2017) document that many entrepreneurs start solo and decide to hire their first employee within the first three years after start-up. These findings underline the importance of dynamic choices in this context, which is an important motivation for our paper. Caliendo et al. (2022) test the effects of various individual characteristics on the choices to switch between non-employer and employer entrepreneurship, paid employment, and

[1]The extent papers partially distinguish between entrepreneurs with incorporated and unincorporated businesses. This approach of capturing heterogeneity among entrepreneurs has important limitations, as the decision to incorporate depends on the current legal context around liability issues and specific tax rules that differ across countries and US states and often change over time.

non-employment, in a reduced form approach using the SOEP. The results from this paper guide us to identify relevant variables for individual heterogeneity in our structural model. Åstebro and Tåg (2017) report that high-ability individuals are more likely to create jobs than low-ability individuals. This is in line with Caliendo et al. (2022), who find that higher education levels increase the probability of becoming an employer, and is consistent with our structural estimation results in this paper. In contrast to our structural model, the results from these reduced form estimations cannot be used for ex-ante simulations of the effects of hypothetical policies on entrepreneurship.

A related literature proposes static structural or semi-structural models of entrepreneurship (e.g., Rees and Shah, 1986; Fossen, 2009; Wen and Gordon, 2014; Hamilton et al., 2019). Some of these models include lifetime earnings as an input into a utility function, but the decision to be an entrepreneur is assumed to be a static decision in these papers. We argue that it is important to model entrepreneurship in a dynamic programming framework because we observe in the data that most entrepreneurs start working as paid employees and switch to entrepreneurship many years later. We also frequently observe transitions back to paid employment after working as an entrepreneur. The existing static models cannot capture any of these dynamics, whereas our model fits the observational patterns well and provides a rationale for them. This makes policy simulations based on our estimated dynamic model more plausible and reliable. None of the structural models provided in the literature distinguish between non-employer and employer entrepreneurs, whereas we include the dynamics of the important decisions to hire and to keep workers.

This paper proceeds as follows. Section 2 lays out the dynamic structural microeconometric model, and Section 3 introduces the data. Section 4 presents the estimation results, and Section 5 shows policy simulations. Section 6 concludes the analysis.

2 Dynamic Structural Model of Entrepreneurship

Our model focuses on four mutually exclusive and exhaustive choices for individuals. The four sectors to choose from are ($k = 1$) non-employer-entrepreneurship, ($k = 2$) employer-entrepreneurship, ($k = 3$) employed, and ($k = 4$) non-employed. Each individual's life span is finite, i.e., the individual optimization starts at age $t = 18$ and ends at age $t = T$. Individual i can choose any of the four options at any age t and will choose the option that maximizes the sum of the current and expected future utility until the end of the life span. Suppose $d_{itk} = 1$ if alternative k is chosen by individual i at current age t, where $k = 1, 2, 3, 4$. We take into account unobserved heterogeneity by modeling three discrete unobserved types; $j(i) = 1, 2, 3$ indicates the type of individual i. The current period alternative-specific utility function for each individual is given by

$$\mathrm{U}_{it}^{k}(\cdot) = \begin{cases} \dfrac{c_{itk}^{1-\rho_{j(i)}}}{1-\rho_{j(i)}}; & \text{if } k = 1, 2, 3;\ \rho > 0 \\ \beta_{4,j(i)} + \gamma q_i; & \text{if } k = 4, \end{cases} \tag{1}$$

where consumption $c_{itk} = \max(w_{itk} - \tau_{itk}, 0)$, and w_{itk} and τ_{itk} capture the annual earnings and the income tax liability of an individual, respectively. The coefficient of constant relative risk aversion, ρ, depends on unobserved types. In Germany, unemployed individuals receive full unemployment benefits for usually the first year of an unemployment spell, but only the lower unemployment assistance thereafter. Therefore, utility for the non-employed individuals depends on two components, fixed utility from non-employment depending on type, $\beta_{4,j(i)}$, which includes utility from leisure and from unemployment assistance, and one-time unemployment benefit, γ. The indicator q_i equals one at the beginning of an individual's unemployment spell and zero thereafter.

Individuals' earnings from labor ($k = 1, 2, 3$) are stochastic and given by Mincer-type earnings functions as follows:

$$\begin{aligned}\ln\left(w_{itk}\right) = & \beta_{k,j(i)} + \alpha_{1k} e_{1,i,t-1} + \alpha_{2k} e^2_{1,i,t-1} + \alpha_{3k} e_{2,i,t-1} + \alpha_{4k} e^2_{2,i,t-1} \\ & + \alpha_{5k} e_{3,i,t-1} + \alpha_{6k} e^2_{3,i,t-1} + \xi_k \mathbb{1}(k_{it} \neq k_{i,t-1}) + \alpha_{7k}(\text{University degree}_{itk}) + \\ & \alpha_{8k}(\text{Academic track}_{itk}) + \epsilon_{itk},\end{aligned} \tag{2}$$

where ϵ_{itk} is a vector of serially uncorrelated jointly normally distributed shocks with mean 0 and variance-covariance matrix Σ. Since some individuals report zero earnings, we add €100 per year to each individual's earnings before taking the logarithm. The indicator function, $\mathbb{1}$, takes the value 1 if the choice in the previous period and the current choice are not the same. The coefficient ξ_k is the one period transition cost incurred by an individual, which, for example, shows up as low profits in the first period in entrepreneurship. The two education dummies are one if an individual's highest educational attainment is a university degree or a high school leaving certificate that qualifies for university entry, respectively. A lower degree (vocational or no degree) is the omitted base category. The parameters $\alpha_{\nu k}$ represent the return to sector-specific experience and educational attainment.

An individual's experience vector, e_{kit}, evolves according to

$$e_{k,i,t} = e_{k,i,t-1} + d_{i,t,k}. \tag{3}$$

We approximate the German progressive personal income tax schedule and social security contributions by estimating a regression of individual tax liabilities[2] as a non-linear

[2]The SOEP survey asks respondents for before-tax and after-tax labor earnings in the month before the interview. We multiply by twelve to approximate annual labor earnings and calculate the tax liability as the difference.

function of before-tax annual earnings:

$$\tau_{itk} = \pi_{0k} + \pi_{1k} w_{itk} + \pi_{2k} w_{itk}^2 + \pi_{3k} w_{itk}^3 + \pi_{4k} age + \pi_{5k} w_{itk} age + \pi_{6k} w_{itk}^2 age + \pi_{7k} w_{itk}^3 age + \epsilon_{ik}. \tag{4}$$

We estimate this regression outside of the model; the estimated coefficients can be interpreted as tax parameters that capture the progressive tax schedule. The German personal income tax rules are mostly the same for income from different sources, in particular, from paid employment and self-employment, but social security contributions differ (the self-employed are exempt in most cases). We estimate separate tax regressions by employment state (employee, employer, non-employer) to allow for differences in effective taxation. This includes potentially better tax avoidance and evasion possibilities for the self-employed in comparison to employees (Kleven et al., 2011; Fossen et al., 2020). Although income taxes do not directly depend on age, the interaction terms with age capture individual circumstances that change with age on average, such as marital status, number of children, and health expenses. These circumstances affect taxes, but are not modeled explicitly here.

In our model, an individual maximizes the present value of remaining lifetime utility at any age. Suppose $\mathrm{V}_{it}(\Omega_{it}, t)$ is the value function of an individual with discount factor δ, set at 0.99. Ω_{it} represents the relevant components of the state space. The value function is given by

$$\mathrm{V}_{it}(\Omega_{it}, t) = \max_{d_{it}^k} \ \mathrm{E}\left[\sum_{s=t_0}^{T} \delta^{s-t_0} \sum_{k=1}^{4} \mathrm{U}_{is}^k(\cdot)\, d_{is}^k | \Omega_{it}\right]. \tag{5}$$

Then the Bellman equation is given by

$$\mathrm{V}_{it}(\Omega_{it}, t) = \begin{cases} \mathrm{U}_{it}^k(\Omega_{it}, t) + \delta \mathrm{EV}_{i,t+1}(\Omega_{i,t+1}, t+1 | d_{it}^k = 1, \Omega_{it}) & \text{for } t < T; \\ \mathrm{U}_{it}^k(\Omega_{it}, t); & \text{for } t = T. \end{cases} \tag{6}$$

We solve the Bellman equation by using backward recursion, beginning with the last period T. We use Monte Carlo integration to compute the multi-dimensional integrations necessary to calculate the expected value of the maximum of the alternative-specific value functions. We evaluate the value of the Emax function at every possible state point. The model is estimated by simulated maximum likelihood.[3]

Let O_{it} represent the choices (and earnings if individuals choose to work) of individual i at age t. Also, let I_i denote the set of initial conditions for that individual. Let $Pr(j(i) = 1|I_i)$ denote the type probability, which depends on initial conditions. The unobserved type is assumed to be known to the individual but not to the econometrician. The likelihood for individual i can be written as the product of the age-specific choice probabilities and the probability of observing the corresponding wage (if applicable), integrating over the unobserved type. Thus, the contribution to the likelihood of individual i is given by

$$\begin{aligned} L_i &= \sum_{j=1}^{3} \prod_{t=t_0}^{T_i} Pr\left(O_{it}|O_{i,t-1},...,O_{it_0}; j(i)=j, I_i\right) Pr\left(j(i)=j|I_i\right) \\ &= \sum_{j=1}^{3} \prod_{t=t_0}^{T_i} Pr\left(d_{it}^k|w_{it},\Omega_{it},I_i\right) f\left(w_{it}|\Omega_{it},I_i,j(i)=j\right) Pr\left(j(i)=j|I_i\right), \end{aligned} \tag{7}$$

where $f\left(w_{it}|\Omega_{it},I_i,j(i)=j\right)$ is the wage density. The overall likelihood for $i = 1,...,N$ individuals is the product of the individual likelihoods:

$$L = \prod_{i=1}^{N} L_i. \tag{8}$$

In our numerical implementation, we assume that there are three unobserved types, and that the type probabilities are multinomial logistic. In particular,

$$Pr(j(i) = 1|I_i) = \frac{e^{\eta I_i}}{1 + e^{\eta I_i} + e^{\zeta I_i}}, \tag{9}$$

[3] We only provide an outline of the solution and estimation methods since they have been described in detail elsewhere (Imai and Keane, 2004; Keane et al., 2011).

$$Pr(j(i) = 2|I_i) = \frac{e^{\zeta I_i}}{1 + e^{\eta I_i} + e^{\zeta I_i}}, \tag{10}$$

$$Pr(j(i) = 3|I_i) = 1 - Pr(j(i) = 1|I_i) - Pr(j(i) = 2|I_i). \tag{11}$$

The vector of initial conditions I_i consists of a constant, a dummy variable indicating whether the respondent's father was self-employed when the respondent was 15 years old, the respondent's general willingness to take risk, locus of control, a dummy indicating whether the respondent lives in eastern Germany, and migration background. The corresponding coefficients are $\eta = \{\eta_0, \eta_1, \eta_2, \eta_3, \eta_4, \eta_5\}$ and $\zeta = \{\zeta_0, \zeta_1, \zeta_2, \zeta_3, \zeta_4, \zeta_5\}$. We allow risk preference (ρ), the constants in the choice-specific wage functions (β_k), and the value of leisure to vary across the unobserved types.

The model parameters enter the likelihood function through the choice probabilities that are computed from the solution of the dynamic programming problem. We calculate the derivatives of the log likelihood function numerically. To calculate numerical derivatives, we use a step size equal to 1% of parameter estimates. The maximization of the likelihood function iterates between solving the dynamic program and calculating the likelihood.[4] We use a subroutine called HOPSPACK (Plantenga, 2009), a hybrid optimization parallel search package developed by Sandia National Laboratories. This subroutine uses a Generating Set Search (GSS) algorithm for optimization. To obtain the standard errors of the estimates, we invert the average of the product of the score matrices. This is known as the BHHH estimator (Berndt et al., 1974).

3 Panel Data

To estimate our dynamic structural model, we use the German Socio-Economic Panel Survey (SOEP). This large household panel survey is representative of Germany (Goebel

[4]We used 500 simulations for each individual to calculate the likelihood.

et al., 2019) and provides annual information on individuals, including non-employers and employers, over a sufficiently long time period. We use the waves from 2000 to 2016 (the survey was significantly enlarged in 2000). We focus on men at the prime working age between 18 and 57 years of age. This way, we can abstain from modeling non-participation of married mothers and early retirement decisions. Respondents who answer that their primary labor activity is self-employment are asked whether they have no employees (labeled as non-employer), or 1-9, or 10 or more (both labeled as employers). A non-employer could have one or more partners in a partnership business, who are not employees. While self-employment is typically used as a measurable proxy of entrepreneurship, in particular in labor economics, the literature has stressed the need to address heterogeneity in self-employment (Congregado et al., 2012). We address this call by distinguishing between non-employers and employers, the latter being more closely related to definitions of entrepreneurship that emphasize ambition and growth orientation. We do not distinguish between employers with less than 10 or 10 or more employees in our analysis because only 18% of the self-employed in our sample belong to the latter category, making it difficult to precisely estimate transitions into and out of this category.

In the SOEP, survey participants are asked how much they earned at work in the month before the interview, excluding special payments such as vacation pay. They are asked for the amounts both before and after taxes and social security contributions. In case of self-employment, they are asked to estimate what the monthly profits were before and after taxes. We exclude individuals from the sample who have less than three consecutive observations. After dropping individuals with missing values in our variables, we work with an unbalanced panel (minimum length 3 and maximum length 17 years) with 50,190 observations from 6,313 individuals.

Table 1 presents the descriptive statistics for the four employment states. In our data,

Table 1: Summary Statistics

Variable	Non-employer	Employer	Employed	Non-employed
Highest educ. degree				
Vocational	0.50 (0.50)	0.48 (0.50)	0.65 (0.48)	0.75 (0.43)
Academic track	0.33 (0.47)	0.23 (0.42)	0.22 (0.41)	0.17 (0.38)
University degree	0.17 (0.38)	0.29 (0.46)	0.13 (0.34)	0.08 (0.27)
Experience (years)				
Non-employer	5.57 (4.23)	2.30 (2.47)	0.17 (0.78)	0.56 (1.69)
Employer	2.47 (3.32)	8.01 (5.37)	0.14 (0.94)	0.35 (1.46)
Employed	11.36 (6.71)	10.67 (5.49)	18.40 (9.13)	12.57 (9.27)
Earnings	40.15 (35.06)	67.38 (63.07)	38.29 (22.69)	
Age	42.94 (8.09)	43.75 (7.50)	40.75 (8.98)	39.12 (10.56)
Father entrepreneur	0.10 (0.30)	0.18 (0.39)	0.07 (0.25)	0.07 (0.26)
Willingness to take risk	5.83 (2.17)	5.96 (2.08)	5.11 (2.12)	5.24 (2.32)
Locus of control	29.38 (5.96)	31.43 (5.72)	28.82 (5.70)	25.93 (6.42)
East Germany	0.25 (0.43)	0.19 (0.40)	0.22 (0.42)	0.33 (0.47)
Migration background	0.13 (0.34)	0.14 (0.34)	0.17 (0.37)	0.24 (0.43)
N	2396	3327	39204	5263

Notes: The table shows sample means (and standard deviations in parentheses) by sector choice group. Earnings (≥ 0) are annual in real €1000 in prices of 2005.

the average age varies from 39.12 for the non-employed to 43.75 years for employers. We group individuals into three categories according to their highest formal educational degree obtained: vocational school track (the higher secondary school degree "Abitur", which qualifies for entry into university in Germany, was not obtained), academic school track ("Abitur" obtained), and university degree. The table shows that employers on average have the highest level of formal education, and the non-employed have the lowest. About 29 percent of employers have a university degree compared to only 8 percent of the non-employed.

As discussed above, we distinguish between different types of experience. Individuals who are currently working as employees have, on average, 18.40 years of experience as employees, but little experience from entrepreneurship. In contrast, individuals who are working as non-employers have, on average, 5.57 years of experience as non-employers and

2.47 years as employers, but only 11.36 years of experience as an employee. Similarly, employers have, on average, 2.30 years of experience as non-employers, 8.01 years as employers, and 10.67 years as an employee.

Annual real earnings[5] before taxes and social security contributions are higher for non-employers (€40,150 on average) than for paid employees (€38,290) but highest by far for employers (€67,380). The earnings variance is also higher for both types of entrepreneurs than for employees, and highest for employers. Therefore, in sector choice, there is a trade-off between high expected earnings and high earnings risk. Thus, one would expect more risk-tolerant individuals to self-select into entrepreneurship, and the most risk-tolerant to upscale their business by hiring workers. The descriptive evidence supports this expectation: The self-reported general willingness to take risk on a Likert scale from 0 (completely unwilling) to 10 (completely willing) is highest for employers, followed by non-employers, whereas paid employees and the non-employed have lower levels of risk tolerance.[6]

Besides risk tolerance, in our model, we use a number of other characteristics that may affect individual labor market decisions to determine the unobserved type probabilities. These variables include a measure of locus of control. Individuals have an internal locus of control if they believe that outcomes are the consequences of their own actions rather than of luck or fate (Rotter, 1966).[7] Employers have the most internal locus of control, followed by non-employers, whereas employees have a more external and the non-employed have the most external locus of control. Furthermore, we include family and demographic background variables. Both types of entrepreneurs have a higher probability that the father

[5]We multiply monthly earnings by 12 to approximate annual earnings and deflate the amount to 2005 values.

[6]Dohmen et al. (2011) show that this survey measure of risk attitudes is a good predictor of actual risk taking behavior.

[7]In the survey, respondents are asked to state how much they agree with ten statements about themselves on a Likert scale from 1 to 7. This short inventory is used to calculate a score, with a high score indicating an internal locus of control.

was self-employed when the respondent was 15 years old than paid employees and the non-employed (in line with Dunn and Holtz-Eakin, 2000), and this probability is highest among employers. We further include whether a respondent has a migration background and is living in the area of former East Germany. Both these characteristics are more prevalent among non-employed individuals. The differences between the four groups support prior findings (Caliendo et al., 2022).

4 Estimation Results

In this section, we report the estimated parameters, assess how the estimated model fits the data, and present simulation results. Table 2 (Panel A) shows the estimates of the parameters of the earnings functions for non-employers, employers, and employed individuals. The returns to the higher secondary school degree "Abitur" (academic track) are comparable for employer entrepreneurs and employees, while the returns to a university degree are highest for employers. Transition cost is largest for non-employer entrepreneurs; the parameter is added to wages in Eq. 2 for individuals making a transition. Our estimate suggests that an individual who becomes a non-employer entrepreneur experiences a one-time cost amounting to 16 percent of the year's earnings. Panel B displays the estimated parameters in the utility function (Eq. 1). Estimates of the constant relative risk aversion parameter suggest that Type 1 individuals are less risk averse than Type 2 and Type 3 individuals.

Table 3 presents the estimates of the multinomial logit coefficients on the determinants of the type probabilities. The coefficient of the self-reported willingness to take risk (on a scale from 0 to 10) is positive and largest for Type 1. This is consistent with the smaller structural coefficient of relative risk aversion estimated for Type 1. Our finding that a larger stated willingness to take risks in the survey is associated with a lower coefficient

Table 2: Estimates of the Parameters of the Earnings and Utility Functions

Panel A: Earnings Functions				
Parameter	Description	Non-employers ($k=1$)	Employers ($k=2$)	Employed ($k=3$)
$\beta_{k,1}$	Constant type 1	0.7666 (2.9539)	0.5154 (4.6325)	0.8601 (0.3172)
$\beta_{k,2}$	Constant type 2	1.7466 (2.9988)	2.1483 (4.0983)	2.9217 (0.1787)
$\beta_{k,3}$	Constant type 3	1.3045 (2.9358)	1.1937 (4.6901)	2.3410 (0.2061)
α_{1k}	Exp. non-employer linear	0.2370 (0.1198)	0.0559 (0.1234)	-0.0711 (0.0231)
α_{2k}	Exp. non-employer squared	-0.0120 (0.0006)	-0.0065 (0.0009)	0.0035 (0.0003)
α_{3k}	Exp. employer linear	0.0814 (0.1437)	0.3240 (0.0837)	-0.0040 (0.0308)
α_{4k}	Exp. employer squared	-0.0037 (0.0011)	-0.0155 (0.0004)	0.0002 (0.0002)
α_{5k}	Exp. employee linear	0.0811 (0.1138)	0.0752 (0.1678)	0.0820 (0.0075)
α_{6k}	Exp. employee squared	-0.0042 (0.0003)	-0.0043 (0.0005)	-0.0019 (1.82e-5)
α_{7k}	Academic track	0.2571 (0.5725)	0.3323 (0.6371)	0.3495 (0.0214)
α_{8k}	University degree	0.4197 (0.8412)	0.7153 (0.6806)	0.6211 (0.0344)
ξ_k	Transition cost	-0.1623 (0.0792)	-0.0389 (0.0316)	-0.0455 (0.0037)
Panel B: Utility Functions				
Parameter	Description	Type 1 ($j=1$)	Type 2 ($j=2$)	Type 3 ($j=3$)
ρ_j	Constant Relative Risk Aversion coefficient	0.7604 (0.0066)	1.2528 (0.0030)	1.2616 (0.0007)
$\beta_{4,j}$	Constant utility of non-employed individuals	6.8225 (1.7138)	-2.0007 (0.4038)	-2.0006 (0.0937)
γ	One-period unemployment benefit (not type dependent)		0.0028 (0.0005)	

Notes: Panel A shows the estimated parameters of the earnings functions corresponding to the different choice alternatives ($k = 1, 2, 3$ represent non-employers, employers, and employed individuals, respectively). $\beta_{k,j}$ is the sector-specific constant in the Mincer-type earnings function, which depends on unobserved types ($j = 1, 2, 3$). The parameters $\alpha_{\nu k}$ represent the return to sector-specific experience and education categories relative to vocational degree. The parameters ξ_k represent one period search and transition cost.
Panel B shows the estimates of the parameters of the utility functions. The CRRA coefficient and the constant utility of non-employed individuals depend on the unobserved type, but the one-period unemployment benefit parameter does not.
Standard errors at 1% deviation are in parentheses.

of relative risk aversion, which is revealed from the sector choices in the structural model, increases confidence in the structural model and in the interpretation of our structural parameter ρ as risk aversion. The good alignment of stated and revealed preferences is similar to the results by Fossen and Glocker (2017) in the context of a static structural model of education choice.

Table 3: Estimates of the Parameters of the Type Probability Determinants

Column A	Column B:	Type 1	Column C:	Type 2
Variable	Parameter	Estimate	Parameter	Estimate
Constant	η_0	-0.8108 (497.6509)	ζ_0	-1.5485 (204.2140)
Father self-employed	η_1	0.6826 (235.0465)	ζ_1	0.3914 (94.9959)
Willingness to take risk	η_2	0.0552 (3.4634)	ζ_2	0.0484 (1.2958)
Internal locus of control	η_3	-0.0565 (0.5376)	ζ_3	0.0627 (0.1973)
East Germany	η_4	0.3050 (92.7071)	ζ_4	-1.9192 (54.6780)
Migration background	η_5	0.3838 (104.1125)	ζ_5	-0.5991 (36.9636)

Notes: Column A represents the names of the variables that determine the unobserved type of an individual. Column B represents the names of the parameters and corresponding estimates that determine the probability of being Type 1, and Column C those that determine the probability of being Type 2. Standard errors at 1% deviation are in parentheses.

It is important to model unobserved heterogeneity. As Table 4 shows, our estimates suggest that 7.6 percent of individuals in our sample are Type 1, 47.5 percent are Type 2, and 44.9 percent are Type 3. To compare and contrast the types, in this table we simulate the participation probabilities in the different sector choices that would occur if everybody in the sample was of one particular type. Type 1 individuals are substantially more likely to be non-employer entrepreneurs compared to the other types. They spend 11.0 percent of their time as non-employers, the respective share in the combined sample is only 2.4 percent. These sector choices correspond with expectations concerning the variables used to determine the type probabilities: According to Table 3, a higher stated willingness to take risk and a self-employed father increase the probability of being Type 1, and both characteristics are well-known individual determinants of entrepreneurship (Dunn and Holtz-Eakin, 2000; Caliendo et al., 2009). In addition, Type 1 individuals are more likely to spend more time in non-employment than the other types. Living in former East Germany and having a migration background increases the probability of being Type 1 (Table 3), which is consistent with the observation that these characteristics are disproportionately associated with non-employment in Germany (Table 1). An interesting insight from these results is

Table 4: Type Specific Participation - Simulated

	Type 1	Type 2	Type 3	All Types Combined
Non-employer	10.96	1.41	2.69	2.44
Employer	5.07	7.34	3.58	5.57
Employed	23.78	84.59	79.75	78.32
Non-employed	60.19	6.66	13.99	13.67
Share of type	7.64%	47.46%	44.90%	100%

Notes: Columns 2-4 show the simulated participation rates pretending that everybody was a specific type. For comparison, the rightmost column repeats the simulated participation rate considering unobserved heterogeneity as in Table 5. The last row shows the estimated shares of the specific types in the sample. The total number of observations is 50,190.

that non-employers and non-employed individuals often share some latent characteristics (Type 1), which is consistent with the interpretation that many non-employers are necessity entrepreneurs in the sense that they are likely to be either non-employers or unemployed (Fairlie and Fossen, 2019), but not paid employees, and that they do not tend to grow their businesses by hiring employees (Hurst and Pugsley, 2011). Type 2 individuals are likely to be either paid employees or employers, but not non-employers or non-employed. Since Type 2 is more risk averse than Type 1 (Table 3), high income risk for employers (the standard deviation of their earnings is largest in Table 1) might induce some Type 2 individuals from choosing to be an employee rather than an employer. Living in former East Germany also decreases the probability of being Type 2, which is again consistent with the higher unemployment rate in this part of Germany.

Further parameter estimates appear in the Appendix. Table A.1 shows the estimates of the variance co-variance matrix. Table A.2 displays the estimated regression coefficients of the individual tax liability function. The coefficients reflect the nonlinear schedules of personal income taxes and social security contributions in Germany, tax-relevant circumstances that on average change with age, and differences in effective taxation between employees and the self-employed. Evaluated at the average age, the differences between

Table 5: Participation Rates: Actual Versus Simulated

Sector Choice	Actual	Simulated
Non-employer	4.77	2.44
Employer	6.63	5.57
Employed	78.11	78.32
Non-employed	10.49	13.67

Note: The number of observations is 50,190.

the tax functions for the different groups are small.[8]

To assess how well the estimated model fits the data, we use it to simulate various moments and compare them with the sample statistics. Table 5 compares the actual with the simulated participation rates in the four different employment states, averaged over the whole life-cycle. To generate this table, we simulate[9] choices for all the individuals in our sample, starting with their initial conditions. Overall, the simulated model is able to replicate the sector choice pattern in the data, although the participation rate of non-employer entrepreneurs is smaller in our simulations than what we observe in the data, and the non-employment rate is somewhat larger.

Next, we compare the life cycle profiles of sector choices. We show the model fit in five-year age groups.[10] In Germany, the share of employees declines slightly from more than 80 percent in the early thirties to below 80 percent above 40 years of age, as shown in Figure 1. The model simulation replicates this decreasing pattern. In addition, Figure 2 shows that the percentage of individuals who are employers increases with age from about 2 percent among 25-29 year old men to about eight percent by their early forties and then remains stable. The simulated data replicates both the increase with age and then the leveling off.

[8] Plots are available from the authors on request.

[9] Each individual has been simulated 1000 times at each time point over the life span.

[10] We begin at age 25 since the number of entrepreneurs is small (less than one percent) in the early 20's and the focus of this paper is on entrepreneurship.

However, in the early part of the life-cycle, the predicted rate of employer-entrepreneurship is lower in the simulations than in the observed data.

Figure 1: Participation Fit By Five Years Age Band

Figure 2: Participation Fit By Five Years Age Band

Figure 3: Participation Fit By Five Years Age Band

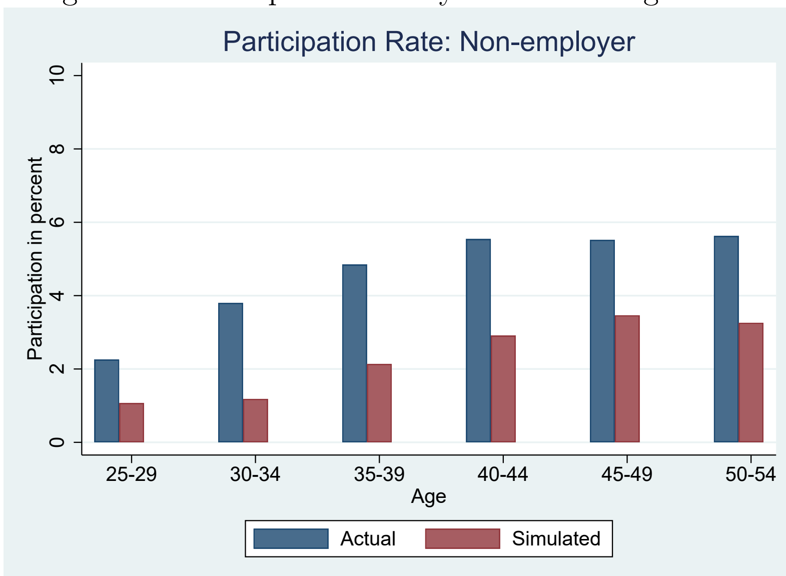
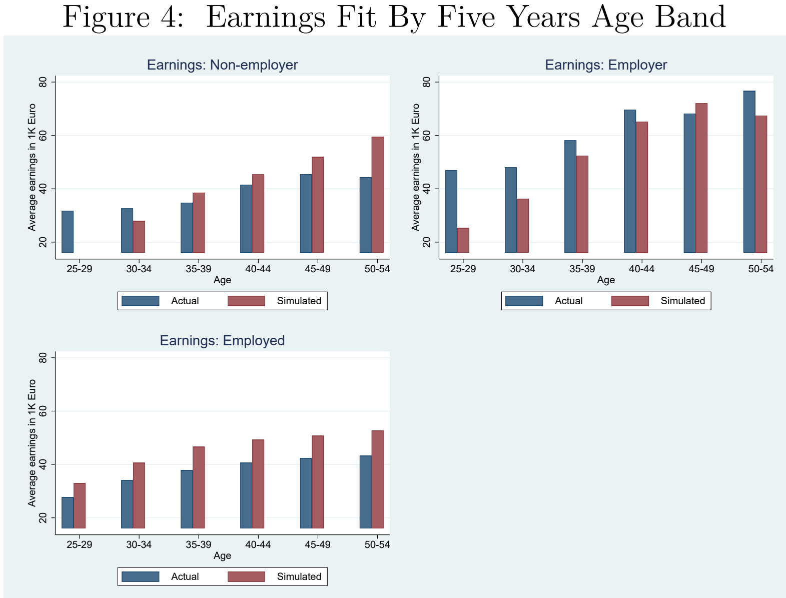


Figure 4: Earnings Fit By Five Years Age Band



Our model is less successful in replicating the percentage of men who choose non-employer entrepreneurship. In the data, the percentage of individuals who are non-employers increases with age from about two percent among 25-29 year old men to almost six percent above 40 years, when the participation rate levels off (Figure 3). Our simulated data replicates this pattern, but the percentage of individuals in non-employer entrepreneurship in the simulated data increases from about one percent to a little under four percent.

Our simulated model is able to replicate the employment dynamics observed in the data fairly well. Table 6 presents a one-year transition matrix – Panel A shows the actual data, and Panel B shows the simulated transition rates. The simulated rates replicate the overall pattern, although the persistence is lower than what we observe in the data, especially in non-employment. Interestingly, both in the actual and the simulated data, by far the most new employers (who had not been employers in the previous year) were non-employers before. Thus, being a non-employer is an important stepping stone toward becoming an employer.

Next, we assess the fit of individual labor earnings over the life-cycle. As shown in Figure 4, the simulated data from the estimated model replicates the growth in earnings in all three different sectors. In the data, the age-earnings profile of employers is the steepest, followed by non-employers, and the age-earnings profile of employees is the flattest. Our model produces the same pattern.

The age-earnings profiles mask substantial heterogeneity in the own and cross returns to experience. Table 7 shows how the earnings in each of the sectors change with own and cross experiences. In this table, we present the returns to own and cross experiences of an average individual in each of the three sectors. For example, in our sample, an average non-employer entrepreneur has 5.6 years of non-employer entrepreneur experience, 2.5 years of employer experience, and 11.4 years of experience as an employee (Table 1). Our estimates

Table 6: One Year Transition Matrix - Actual Versus Simulated

	Destination state (t)			
	Non-employers	Employers	Employed	Non-employed
Original state ($t-1$)				
Panel A: Actual				
Non-employers %	73.72	13.50	5.41	7.37
N	1540	282	113	154
Employers %	8.99	84.21	4.79	2.02
N	263	2463	140	59
Employed %	0.39	0.51	95.37	3.73
N	135	175	32756	1282
Non-employed %	4.28	1.54	28.12	66.06
N	192	69	1260	2960
Panel B: Simulated				
Non-employers %	62.66	15.89	9.88	11.57
Employers %	7.34	69.24	18.72	4.70
Employed %	0.48	2.16	77.38	19.99
Non-employed %	1.92	2.20	72.70	23.18

Note: Actual and simulated transition rates between the sectors from one year to the next in %. The numbers of observations in the sample making each transition are shown below the actual transition rates.

Table 7: Return From Average Years of Experience From Each Sector Choice

Variable	Non-employer	Employer	Employed
Return from exp. of non-employer	0.95	0.09	-0.01
Return from exp. of employer	0.18	1.60	0.00
Return from exp. of employed	0.37	0.31	0.87
Total	1.50	2.00	0.86

Note: Each number represents the return from average years of corresponding experience. Table 1 shows average years of experience from each sector choice.

Table 8: Return From Five Years of Experience From Each Sector Choice

Variable	Non-employer	Employer	Employed
Return from exp. of non-employer	0.89	0.12	-0.27
Return from exp. of employer	0.32	1.23	-0.01
Return from exp. of employed	0.30	0.27	0.36

Note: Each number represents the return from five years of corresponding experience.

suggest that a non-employer who has 5.6 years of experience in the same sector would earn 95 percent more than a non-employer who has no experience as a non-employer. Our estimates also indicate that a non-employer who has 2.5 years of experience as an employer would earn 18 percent more than a non-employer who has no experience as an employer. Finally, a non-employer who has 11.4 years of experience as an employee would earn 37 percent more than a non-employer who has no experience as an employee. The second column of Table 7 shows that for employers cross returns have a relatively small impact, but the experience as an employer increases earnings substantially. The third column suggests that for employees, work experience accumulated as an employee increases their earnings, but work experience accumulated as entrepreneurs has little or no effect on the earnings of employees. Taken together, these results suggest one-way transferability of skills across these three different types of sectors in Germany: Experience as an employee is valuable in all sectors, but experience as a non-employer or employer entrepreneur does not increase earnings in paid employment.

In interpreting the results of Table 7, one needs to take into account that the distribution of average years of own and cross experiences are different across sectors. To provide a different view, we also present Table 8, which shows the returns to five years of own and cross experience for each of the sectors. A few important differences across sectors become apparent. The returns to same-sector experience for entrepreneurs (both non-employers and employers) are substantially bigger than returns to same-sector experience among employees: Five years of same-sector experience increases earnings of non-employers by about 89 percent, employers by 123 percent, and employees by only 36 percent. However, these large percentage increases in earnings are coupled with relatively low starting wages for entrepreneurs. This suggests that entrepreneurs have to invest initially, and it takes some time to generate the returns from that investment.

The returns from other sectors inform about the transferability of skills across sectors. The returns to cross-experience is highest for non-employers. In other words, experience from other sectors increase earnings of non-employers most. For example, five years of experience as an employer (employee) increase the earnings of non-employers by about 32 (30) percent. However, experience as either a non-employer or an employer entrepreneur is not rewarded in terms of higher earnings as an employee. Somewhat surprisingly, experience as an employee is more valuable when working as an employer than experience gained as a non-employer.

Finally, to estimate the sensitivity of labor supply to earnings changes in each sector, we simulate the effects of a one percent increase in earnings in one of the sector alternatives (which can be thought of as an earnings subsidy, for example). Table 9 shows that the non-employers are the most sensitive to changes in earnings. Everything else equal, a one percent increase in the earnings of non-employers leads to a 6.1 percent increase in the share of individuals who are non-employers. This is coupled with a 0.83 percent drop in

Table 9: Simulated Elasticities of Participation Probabilities With Respect to Earnings

	Participation as...			
Earnings from...	Non-employers	Employers	Employees	Non-employed
Non-employers	6.05	-0.83	-0.12	-0.08
Employers	-0.91	2.77	-0.13	-0.20
Employed	-4.95	-1.50	0.87	-3.69

Notes: The table shows elasticities of participation probabilities in the sector choices listed in the columns with respect to changes in earnings in the sectors listed in the rows. Each elasticity has been calculated using 50,190 observations.

the number of employers and a 0.12 percent drop in the number of employees, with the rest coming from the ranks of the non-employed. The corresponding own-wage elasticity for employers (paid employees) is 2.77 (0.87).

5 Policy Simulations

In this section, we use the estimated structural model to simulate the effects of policies that are frequently discussed in the context of entrepreneurship. A policy that is very relevant in practice is differential tax treatment of business income versus labor income from paid employment. Many countries have policies that reduce effective tax rates for entrepreneurs. For example, variants of the Dual Income Tax, as seen in some Scandinavian countries, effectively reduce tax rates for entrepreneurs by dividing business earnings into labor and capital income and applying a lower tax rate to the capital income portion. In many countries, earnings retained in certain types of businesses are taxed at lower rates or taxation is deferred to the time when earnings are distributed, which results in lower effective tax rates. Moreover, it is often argued that it is easier for entrepreneurs to avoid or evade taxes because they self-report their earnings, whereas paid employees are subject to third-party reporting and face withholding taxes (Kleven et al., 2011; Fossen et al., 2020).

To simulate the idea of differential taxation in our model, we introduce hypothetical earnings subsidies of one, five, and ten percent of before-tax earnings, in one case for all entrepreneurs (both non-employers and employers), and in another set of simulations only for employers. This is equivalent to a lower effective tax rate for entrepreneurs (or employers, respectively). We do not model general equilibrium effects such as potentially changing wages and earnings of entrepreneurs. Such effects could be expected if a policy induced a large share of individuals to change sectors, which is why we choose to simulate policy interventions that are limited in scope.

The results from these policy simulations are shown in Table 10, with the baseline scenario in the top row and the two hypothetical policy scenarios below. The results suggest that a 5 percent subsidy for all entrepreneurs would increase the non-employer-entrepreneurship rate from 2.44 percent to 3.04 percent, i.e., by 0.6 percentage points or about 25 percent of the initial rate. A 10 percent subsidy for entrepreneurs would increase the non-employer-entrepreneurship rate by 1.15 percentage points and the employer-entrepreneurship rate by 1.18 percentage points. These increases would come at the expense of a 1.92 percentage points decrease in the share of paid employees. In contrast, the non-employment rate would decrease by only 0.41 percentage points. Thus, only about 18 percent of the simulated increase in entrepreneurship is due to individuals moving from non-employment to entrepreneurship. Most of the increase in entrepreneurship caused by the simulated incentive comes from individuals changing sector choice who would otherwise work as an employee.

Our simulations of the effects of a policy that increases only the earnings of employers, which appear in Panel B, show that a 10% subsidy of this type would increase the share of employers from 5.57 percent to 7.29 percent, or by about 31 percent. Thus, the more targeted policy would be more effective in encouraging individuals to become an employer.

Table 10: Partication Rates With Counterfactual Policy Scenarios

Subsidy	Non-employer	Employer	Employed	Non-employed
No subsidy	2.44	5.57	78.32	13.67
Panel A: Subsidy for all entrepreneurs				
1% earnings subsidy	2.57	5.67	78.13	13.63
5% earnings subsidy	3.04	6.12	77.37	13.47
10% earnings subsidy	3.59	6.75	76.40	13.26
Panel B: Subsidy for employers				
1% earnings subsidy	2.42	5.72	78.22	13.64
5% earnings subsidy	2.33	6.37	77.77	13.53
10% earnings subsidy	2.20	7.29	77.12	13.39

Notes: Using our estimated dynamic structural model, we simulate the effects of hypothetical policy scenarios on the participation rates in the different employment states. In Panel A, we simulate the effects of a subsidy of 1%, 5% and 10% of an individual's earnings paid if this individual chooses to be an entrepreneur (non-employer or employer). In Panel B, we simulate the effects of a subsidy of 1%, 5% and 10% of an individual's earnings paid if this individual chooses to be an employer. The first row repeats the baseline scenario without a subsidy for comparison. The number of observations in each simulation is 50,190.

6 Conclusion

In this paper, we develop and estimate a dynamic structural model of occupational sector choice with a focus on entrepreneurial careers. Within entrepreneurs, we distinguish between non-employers and employers, who hire other individuals as employees. In our microeconometric model, we distinguish between different types of experience (experience as an employee, as a non-employer, and as an employer). We solve the dynamic optimization problem by backward recursion and then estimate the model using the simulated maximum likelihood method.

Our results suggest that the transferability of experience between sectors is one way. In particular, returns to work experience accumulated as an entrepreneur are negligible or even negative for employees. However, experience accumulated as an employee substantially increases the earnings of an entrepreneur. This finding differs from results reported by Manso (2016) based on U.S. data, which may be due to different institutional structures and barriers to entrepreneurship in the U.S. in comparison to Germany or the relatively higher average age of our sample. Therefore, direct comparisons of different institutional settings are an important area for future research.

Our model is able to explain the major patterns observed in the data, which suggests that this model will provide valuable information about how policy changes may affect entrepreneurship. To that effect, we use the estimated structural model to simulate hypothetical policy scenarios, in particular, increases in the earnings of entrepreneurs, which can be interpreted as tax breaks or subsidies. Variants of such policies have been debated with the intention to promote entrepreneurship and to reduce unemployment. Our results suggest that subsidies to entrepreneurs increase the share of individuals who work as entrepreneurs, but most of these increases come from individuals who would otherwise work as employees, so the effectiveness of these policies with respect to reducing non-employment is limited.

One important avenue for future research would be to include capital accumulation in the model. This would greatly increase the state space and the required computing power, but—when the computer technology allows—the effort will eventually be worthwhile because the richer model would allow to simulate further relevant policies such as credit subsidies for entrepreneurs.

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Appendix

Table A.1: Estimates of the Variance-Covariance Matrix

Parameter	Variable	Estimate
σ_{11}	var(1,1)	0.8211 (0.4951)
σ_{21}	cov(2,1)	0.2275 (0.3896)
σ_{22}	var(2,2)	0.2872 (0.4829)
σ_{31}	cov(3,1)	0.6000 (1.46e-6)
σ_{32}	cov(3,2)	0.1651 (0.2061)
σ_{33}	var(3,3)	0.4491(0.1405)

Notes: The numbers 1, 2, and 3 represent the wage-shock vectors of non-employers, employers, and employees respectively. Standard errors at 1% deviation are in parentheses.

Table A.2: Estimated Coefficients of Tax Liability Functions by Employment State

Parameter	Variable	Non-employer ($k = 1$)	Employer ($k = 2$)	Employed ($k = 3$)
π_{0k}	Constant	-1.20 (1.76)	1.04 (4.25)	-4.93 (1.37)
π_{1k}	Earnings	0.27 (0.12)	0.26 (0.17)	0.58 (0.080)
π_{2k}	Earnings^2	0.0031 (0.0018)	0.0016 (0.0014)	-0.0015 (0.0011)
π_{3k}	Earnings^3	-1.00e-5 (4.2e-6)	-6.6e-7 (1.6e-6)	2.2e-6 (2.4e-6)
π_{4k}	Age	-0.0031 (0.044)	-0.091 (0.091)	0.051 (0.036)
π_{5k}	Earnings$\times$Age	0.0026 (0.0030)	0.0028 (0.0034)	-0.0036 (0.0021)
π_{6k}	Earnings$^2\times$Age	-6.6e-5 (4.1e-5)	-2.5e-5 (2.6e-5)	3.4e-5 (2.7e-5)
π_{7k}	Earnings$^3\times$Age	2.3e-7 (9.6e-8)	5.8e-9 (3.0e-8)	-5.0e-8 (6.4e-8)
N		1788	2406	35657
R^2		0.87	0.89	0.88

Notes: This table shows the estimated regression parameters (standard errors are in parentheses) of the tax liability function of gross income corresponding to the different choice alternatives ($k = 1, 2, 3$). The dependent variable is the real annual tax liability. The tax liability and annual earnings are in real €1000 in prices of 2005.