Department of Economics
Working Paper No. 205

Who Creates Jobs? Econometric Modeling and Evidence for Austrian Firm Level Data

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September 2015

WIRTSCHAFTS UNIVERSITÄT WIEN VIENNA UNIVERSITY OF ECONOMICS AND BUSINESS

Who Creates Jobs?
Econometric Modeling and Evidence for Austrian Firm Level Data[⋆]

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Abstract

This paper offers an empirical analysis of net job creation patterns at the firm level for the Austrian economy between 1993 and 2013 focusing on the impact of firm size and age. We propose a new estimation strategy based on a two-part model. This allows to identify the structural parameters of interest and to decompose behavioral differences between exiting and surviving firms. Our findings suggest that conditional on survival, young Austrian firms experience the largest net job creation rates. Differences in firm size are not able to explain variation in net job creation rates among the group of continuing enterprises. Job destruction induced by market exit, however, is largest among the young and small firms with this effect being even more pronounced during the times of the Great Recession. In order to formulate sensible policy recommendations, a separate treatment of continuing versus exiting firms as proposed by the new two-part model estimation approach seems crucial.

Keywords: Net job creation; firm size; firm age; one-part versus two-part models; Austrian economy, Great Recession.

JEL: C18; C53; D22; E24; L25; L26; M13.

[⋆]We are grateful to Eric Leeper, an associated editor, three anonymous referees, John Haltiwanger, Ron Jarmin and Javier Miranda for their excellent comments on earlier versions of this paper and valuable discussions. We would also like to thank participants of various conferences and research seminars for their comments and suggestions. Previous versions of this paper circulated under the title: "Who creates Jobs? Estimating Job Creation Rates at the Firm level". Financial support from the 'Oesterreichische Nationalbank' (OeNB, grant numbers 13370 and 14383) is gratefully acknowledged.

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1 Introduction

From a public policy point of view, the question on which firms are the most important net job creators often attracts a lot of interest. The legacy of US presidents *inter alia* depends on their administrations' ability to create new jobs. The relevance of this issue is also documented on a wikipedia page reporting net job creation numbers by presidential terms since 1925 based on data gathered from the Federal Reserve Economic Data (FRED) database.[1] Accordingly a large number of policy programs including the US 2010 "Hiring Incentives to Restore Employment" (HIRE) Act, the European Commission's "Small Business Act for Europe" or the Austrian SME promotion act ("KMU-Förderungsgesetz") are designed to support overall net job creation. These programs frequently provide special support to SMEs. They thus share the belief that SMEs are pivotal for creating and sustaining the largest bulk of jobs in an economy.[2]

This view has also triggered heated discussions in the academic community. Starting with the early insights provided by Birch (1979) and spurred by the aim of researchers to advise policy makers, a large number of studies has analyzed the contribution of different types of firms to net job creation. A final conclusion on this issue has, however, not been reached. For instance, a recent study on the US by Neumark, Wall and Zhang (2011) reinforces the crucial role of small firms for net job creation, while Haltiwanger, Jarmin and Miranda (2013a) argue that young firms contribute most to net job creation.

At least in part, this debate and also its' different findings are driven by methodological issues. A careful empirical analysis of net job creation across different types of firms (small, large, young and old), which is able to inform policy makers, has to take into account several sources of net job creation. By definition, newly founded firms create jobs while exiting firms destroy them. Additionally, continuing firms adjust their firm size and may thus either increase or decrease their workforce. An analysis of the determinants of net job creation, therefore, has to simultaneously examine firm entry, exit, contractions and growth to address the issue accurately (see, e.g., Spletzer 2000). In their seminal contributions, Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996) proposed a measure of net job creation that normalizes the net job creation rate of exiting (entering) firms to -2 (2), while continuing firms exhibit net job creation rates in the open interval between -2 and 2. This allows for an integrated treatment of firm entry and exit as well as employment changes in surviving firms and provides a convenient way to describe the contribution of firm entry and exit to net job creation aggregates. In further

[1] See `https://en.wikipedia.org/wiki/Jobs_created_during_U.S._presidential_terms`

[2] The HIRE Act (see `http://hireact.org/`), for example, provided specific tax incentives for SMEs while the "Small Business Act for Europe" (see `http://ec.europa.eu/growth/smes/index_en.htm`) only targets this group of firms. The European Commission justifies this market intervention by the assumed key role of SMEs in supporting economic growth, innovation, job creation, and social integration within the European Union. The Austrian SME promotion act also exclusively provides support measures for SMEs. (see `https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=10007820` for German language legislative texts.)

consequence, many contributions in the literature calculated average job creation rates at, for instance, age-size-industry-year cells and used the respective cell-means as observational unit in a regression framework estimated via (weighted) OLS (e.g., Dunne, Roberts and Samuelson 1989; Baldwin, Dunne and Haltiwanger 1998; Faberman 2003; Stiglbauer, Stahl, Winter-Ebmer and Zweimüller 2003 and Armington and Acs 2004 and more recently Moscarini and Postel-Vinay 2012 as well as Ma, Qiao and Xu 2015).

With the increasing availability of individual firm level data, recent research has adopted a micro-econometric framework for studying this question. This approach predominantly applies employment-weighted OLS estimation to one- and two-way model specifications for firm size and age dummies (e.g., Burgess, Lane, Stevens 2000; Haltiwanger and Vodopivec 2003; Voulgaris, Papadogonas and Agiomirgianakis 2005) and additionally includes interaction terms of these dummies (see, e.g., Haltiwanger *et al.* 2013a; Decker, Haltiwanger, Jarmin and Miranda 2014; Geurts and Van Biesebroeck 2014). Some recent contributions extend this by including firm size and age as continuous variables (Lawless 2014) and/or augmenting the model with further explanatory variables such as initial firm size, GDP growth, domestic versus foreign ownership, productivity and profitability (Lawless 2014; Rijkers, Arouri, Freund and Nucifora 2014).

This paper contributes to both the methodological and empirical micro-econometric literature on net job creation at the firm level. Methodologically, we show that using employment-weighted OLS estimation procedures will accurately describe the contribution of different types of firms to net job creation only if a fully-saturated model is estimated. Further, these procedures are unable to uncover the structural parameters governing the (true) underlying relationship between net job creation and its' explanatory variables which are most relevant for giving policy advice. Therefore, we propose an alternative approach based on an employment-weighted two-part model. This approach yields unbiased estimates for the structural parameters of interest and allows to identify a firm group's relative contribution to net job creation without the need to specify very large and fully-saturated models. This approach also permits the estimation of unbiased effects for continuous variables included in the model. Further, it converts to the weighted OLS model in case of a fully-saturated model specification. The two-part procedure also has the additional advantage to allow for an explicit decomposition of the contributions of surviving and exiting firms to net job creation. This would not be feasible when applying employment-weighted one-part OLS estimation.

Empirically, we compare the two approaches using a data set capturing the universe of Austrian firms observed from 1993 to 2013. By doing this, we provide a comprehensive analysis of the effects of firm size and age on net job creation at the aggregate and individual firm level. In the analysis we also study how the patterns of net job creation are affected by the severe economic downturn induced by the Great Recession experienced in the Austrian economy between 2008 and 2010.

We find that during the time period from 1993 to 2013 and unconditional on survival, net job creation rates of continuing and exiting firms were largest for the youngest firms. Furthermore, the results from our decomposition exercise indicate that the low net job creation rates among small firms are primarily due to higher exit probabilities, while conditional on survival large and small firms show rather similar net job creation patterns. During the the Great Recession, by contrast, firms between 6 and 10 years of age have been most resilient. Again the decomposition results indicate this is primarily driven by a higher survival probability for these firms. Taken together, this evidence suggests that a separate analysis of firm exit allowed for by the proposed employment-weighted two-part model provides important and substantial additional insights. Finally, we document the impact of model choice for the identification of structural parameters governing the relationship between firm size, age and net job creation in the Austrian economy. Accordingly, when applying the employment-weighted one-part OLS estimation procedure, one underestimates net job creation rates for small firms (especially when they are also young).

2 The econometrics of net job creation rates

2.1 Concepts

As a starting point for our discussion we consider entry, employment changes in continuing firms and exit as three different sources of net job creation at the firm-level. Formally, in each year the population of firms can be partitioned into these three groups (see Horrace and Oaxaca 2006, for a similar approach in the context of the linear probability model)

$$
\begin{aligned}
G_{t,x} &= \{i | y_{it-1} \neq 0 \text{ and } y_{it} = 0\} \text{ (exiting firms)} \\
G_{t,c} &= \{i | y_{i,t-1} \neq 0 \text{ and } y_{it} \neq 0\} \text{ (continuing firms)} \\
G_{t,n} &= \{i | y_{i,t-1} = 0 \text{ and } y_{it} \neq 0\} \text{ (entrants)},
\end{aligned}
$$

where y_{it} denotes the number of employees of firm i at time t and $\pi_{i,k} = P(i \in G_{t,k}), k = x, c, n$ with $\pi_{i,x}+\pi_{i,c}+\pi_{i,n} = 1$ refer to a firm's state probabilities. These probabilities may be firm- and time-specific and can in principle be specified as functions of exogenous explanatory variables.

Following the net job creation literature and in line with Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996), firm i's net job creation rate during the period from $t-1$ to t is measured by

$$
g_{it} = 2\frac{y_{it} - y_{i,t-1}}{y_{it} + y_{i,t-1}} = \begin{cases} -2 & \text{if } i \in G_{t,x} \\ 2\frac{y_{it}/y_{i,t-1}-1}{y_{it}/y_{i,t-1}+1} & \text{if } i \in G_{t,c} \\ 2 & \text{if } i \in G_{t,n}. \end{cases}
$$

The main advantage of this measure is that it is defined for *all* observations, i.e., also for entrants ($y_{i,t-1} = 0$) and exiting firms ($y_{it} = 0$) and it can easily be aggregated into firm size or age groups. This convenience, however, comes at the cost of spikes of the distribution of g_{it} at -2 and 2 in the presence of positive entry and exit rates (probabilities) and causes an obviously non-normal distribution of net job creation rates. Further, in a list of 10 alternative measures surveyed by Tornqvist, Vartia and Vartia(1985), the net job creation rate g_{it} (denoted there as H_3) is shown to be a useful measure for relative changes, but to be non-additive in the time dimension.[3]

2.2 Employment-weighted OLS estimation

In the previous micro-econometric literature on net job creation, one-part models for net job creation rates at the firm level typically pool over entering, exiting and continuing firms and use a linear regression framework of the form

$$g_{it} = \mathbf{x}_{it}'\beta + \varepsilon_{it}, \tag{1}$$

where the set of exogenous covariates is collected in a $(K \times 1)$ vector $\mathbf{x}_{it}$ with the corresponding parameter vector β. ε_{it} denotes the *iid* disturbances and the pooling assumption over entering, exiting and continuing firms restricts the parameters β to have an equal impact on each of these types of firms.

This model formulation might be viewed as restrictive. Theoretical models analyzing entry, exit and firm dynamics within industries question the view that parameters are equal for continuing and exiting firms. This literature rather strongly argues for structural differences in their underlying characteristics and performance (see, e.g., Jovanovic 1982; Hopenhayn 1992; Arkolakis 2015; Clementi, Khan, Palazzo and Thomas 2015). Similarly, the evidence provided by the empirical industrial organization (IO) literature on the determinants of market exit suggests that that the poolability of exiting and surviving firms assumption lacks empirical support (see, e.g., Dunne *et al.* 1988, 1989; Sutton 1997; Caves 1998).

In addition under general assumptions this specification might not provide reasonable parameter and marginal effect estimates, as it can be shown that applying weighted OLS to equation (1) generally yields biased slope parameter estimates $\widehat{\beta}$ (see Appendix A). This bias results from pooling of exiting, entering and continuing firms in a single model and the lack of variation in the disturbances of exiting and entering firms. The model implies non-stochastic errors given by $\varepsilon_{it} = -2 - \mathbf{x}_{it}'\beta$ for exits and $\varepsilon_{it} = 2 - \mathbf{x}_{it}'\beta$ for entries, respectively. As a consequence

[3] The log difference $\ln(y_{it}/y_{i,t-1})$ is found to be preferable as it is the only measure of relative change that is symmetric, additive and normed. The drawback of the log differences as a measure of relative change, however, is that it is not defined for exiting and entering firms with $y_{it} = 0$ and $y_{i,t-1} = 0$, respectively.

the mean independence assumption for the validity of employment-weighted OLS, namely that $E[\varepsilon_{it}|\mathbf{x}_{it}] = 0$, is violated (see Angrist and Pischke 2009, pp. 37 and 48-51).

To illustrate this bias, we define diagonal matrices for entry and exit probabilities as $\mathbf{\Pi}_n = diag[\pi_{i,n}]$ and $\mathbf{\Pi}_x = diag[\pi_{i,x}]$, respectively. In a weighted regression framework one multiplies all variables in the model by some non-stochastic weights $\sqrt{w_{it}}$ which are collected in the matrix $\mathbf{W} = diag[\mathbf{W}_x, \mathbf{W}_c, \mathbf{W}_n]$. $\mathbf{W}_k$, $k = x, c, n$ contains the weight of the respective observation in its main diagonal and zero off-diagonal elements measured in relative within-cell employment given by $w_{ih} = \frac{y_{ih}+y_{ih,-1}}{\sum_{k=1}^{n_h} y_{kh}+y_{kh,-1}}$, where h refers to a specific cell.[4] Denoting all weighted variables with stars, we derive a bias formula for the pooled one-part model in Appendix A which is given by

$$E[\widehat{\beta}^{OP} - \beta|\mathbf{X}^*] = \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1} \mathbf{X}^{*\prime} \left[(\mathbf{\Pi}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta) + \mathbf{\Pi}_n(2\mathbf{e}^* - \mathbf{X}^*\beta)\right],$$

where $\mathbf{e}$ denotes a vector of ones and $\widehat{\beta}^{OP}$ collects the estimated parameters from the one-part model displayed in equation (1).

The bias does not disappear if a dummy for entering firms (with firm age amounting to zero) is included.[5] The predicted net job creation rates given by $\widehat{\mathbf{g}}^* = \mathbf{X}^*\widehat{\beta}^{OP}$ are also biased for most thinkable model specifications with its analytical expression reading as (see Appendix A for details)

$$E[\mathbf{W}(\widehat{\mathbf{g}}^{OP} - \mathbf{g})|\mathbf{X}^*] = (\mathbf{I} - \mathbf{P}_{\mathbf{X}^*}) \left[(\mathbf{\Pi}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta) + \mathbf{\Pi}_n(2\mathbf{e}^* - \mathbf{X}^*\beta)\right]. \tag{2}$$

From this equation it becomes obvious that the aggregated firm-specific bias resulting from the one-part model $E[\mathbf{W}(\widehat{\mathbf{g}}^{OP} - \mathbf{g})|\mathbf{X}^*]$ consists of three components. $\mathbf{\Pi}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta)$ captures the true non-stochastic residuals from exit for all firms multiplied by the individual exit probability. Analogously, $\mathbf{\Pi}_n(2\mathbf{e} - \mathbf{X}^*\beta)$ comprises the non-stochastic residuals for entry multiplied by the entry probability as elements. Finally, $\mathbf{I} - \mathbf{P}_{\mathbf{X}^*}$ is the residual projection matrix obtained from the one-part model.

Equation 2, however, also implies that in the specific case of a fully-saturated dummy variable model which includes all possible interaction terms (also of higher order) of all covariates included (e.g., also for time-, industry- and region-fixed effects) the expected net job creation rates predicted by a one-part model and its population counterpart coincide in expectation, and the parameter estimates are numerically equivalent (see also Wooldridge 2012, Problem 15.1 for a similar result for linear probability models). In order to illustrate this issue further, we exclude entering firms and consider a model, where the expected exit probabilities are group specific

[4] The weighting scheme induces heteroskedastic disturbances so that calculation of robust standard errors is called for.

[5] Applying the Frisch, Waugh and Lovell theorem (see, e.g., Davidson and Mackinnon 1993) allows to see that the inclusion of a dummy for entrants may, however, substantially reduce the bias. The same holds true, if one additionally includes a dummy variable for exiting firms. For such an approach one would need to assume that exit is exogenously determined which is at odds with the available evidence on the determinants of market exit.

and dummies for these groups denoted by $h = 1, .., H$ are the only explanatory variables (e.g. as with age and size groups) of the model. In this case, the model for net job creation reverts to

$$\pi_{ith,x} = P(d_{ith,x} = 1) = P(\gamma_h + \eta_{it} > 0), \quad g_{ith}|(d_{ith,x} = 0) = \mu_h + \varepsilon_{it},$$

where μ_h denotes a (e.g., size and age) group specific cell-parameter, γ_h the parameter of the cell specific exit probability and η_{it} is *iid* (normal). In this case $\mathbf{X}^*$ exclusively comprises the corresponding (weighted) cell specific dummy variables and it holds true that $\mathbf{\Pi}_x\mathbf{X}^* \in \mathbf{C}(\mathbf{X}^*)$ and $\mathbf{\Pi}_x\mathbf{e}^* \in \mathbf{C}(\mathbf{X}^*)$, with $\mathbf{C}(\mathbf{X}^*)$ being the column space of $\mathbf{X}^*$. Therefore, the fully-saturated model implies that $(\mathbf{I} - \mathbf{P}_{\mathbf{X}^*})\,\mathbf{\Pi}_x\mathbf{X}^* = (\mathbf{I} - \mathbf{P}_{\mathbf{X}^*})\,\mathbf{\Pi}_x\mathbf{e}^* = \mathbf{0}$. When inserting this result into equation 2 it follows that $E[\mathbf{W}\left(\widehat{\mathbf{g}}^{OP} - \mathbf{g}\right)|\mathbf{X}^\star] = 0$. Thus, with a fully-saturated model the net job creation rates can be predicted without bias.

The estimated parameters $\widehat{\mu}_h^{OP}$, however, are not unbiased estimates for the structural parameters μ_h. Specifically, the one-part model predicts net job creation in cell h as

$$\widehat{g}_h^{OP} = \widehat{\mu}_h^{OP} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}\left((1 - d_{ih,x})g_{ith} - 2d_{ih,x}\right)}{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}}.$$

Since $E[g_{ith}|d_{ih,x} = 0] = \mu_h$, the law of iterated expectations implies

$$E[\widehat{g}_h^{OP}] = \mu_h - \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}\pi_{ih,x}(\mu_h + 2)}{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}} \neq \mu_h.$$

Under group-specific exit probabilities ($\pi_{ih,x} = \pi_{h,x}$), it follows that

$$E[\widehat{g}_h^{OP}] = \mu_h - \pi_{h,x}(\mu_h + 2).$$

More general model specifications, may include further explanatory variables in addition to the group specific dummies. In this case the bias in $\widehat{g}_h^{OP}$ will not disappear. These explanatory variables induce variation within groups and firm specific exit probabilities so that in general it holds that $\mathbf{\Pi}_x\mathbf{X}^* \notin \mathbf{C}(\mathbf{X}^*)$ and $\mathbf{\Pi}_x\mathbf{e}^* \notin \mathbf{C}(\mathbf{X}^*)$. In this case even the expectation of the predictions of the one-part model deviate from their population counterpart, despite including the cell-specific group dummies (e.g, firm size and age effects and the interactions thereof) within the set of explanatory variables.

Lastly, the one-part model is typically used for the calculation of average predicted net job creation rates for specific groups of firms. For this we define a dummy variable $\mathbf{d}_h$, whose elements take the value 1 if a firm belongs to group h and zero otherwise. The expectation of the deviation of the weighted predicted average net job creation rates under the one-part model from its population counterpart (i.e., average prediction bias in group h) is given as

$$E\left[\frac{1}{\mathbf{d}_h^{*\prime}\mathbf{d}_h^*}\mathbf{d}_h^{*\prime}\mathbf{W}\left(\widehat{\mathbf{g}}^{OP}-\mathbf{g}\right)|\mathbf{X}^*\right]=\frac{1}{\mathbf{d}_h^{*\prime}\mathbf{d}_h^*}\mathbf{d}_h^{*\prime}\left(\mathbf{I}-\mathbf{P}_{\mathbf{X}^*}\right)\mathbf{\Pi}_x\left(\mathbf{X}^*\beta+2\mathbf{e}^*\right),$$

where, $\mathbf{d}_h^{*\prime}\mathbf{d}_h^*$ yields the sum of the weights in each cell h. In case the one-part model includes $\mathbf{d}_h$ in the set of explanatory variables, it follows that the cell-specific means of a one-part model coincide in expectation with those of the population model. The reason is that variation within cells averages out as the normal equations imply that $\mathbf{d}_h^{*\prime}\left(\mathbf{I}-\mathbf{P}_{\mathbf{X}^*}\right)=\mathbf{0}$.

2.3 A two-part model

An employment-weighted one-part OLS model of net job creation rates at the firm level will generate unbiased estimates of the contribution of different types of firms to overall net job creation only if a fully-saturated model involving all thinkable interactions of the explanatory variables (including higher order ones) is specified. Such a modeling strategy may make it necessary to estimate very large models with many potentially multi-collinear variables and insignificant parameter estimates. An alternative and easy to implement estimation strategy, which allows to consistently estimate the parameters for net job creation rates without having to specify fully-saturated models is to estimate separate equations for the entering, exiting and continuing firms in a three-part model.

In such a model the contribution of entry rates has to be estimated in a separate aggregated model. This, however, is up against important conceptual problems as firm-specific pre-entry characteristics are not observable. The most practicable way to account for job creation by market entry is to add the employment-weighted net job creation rates for entering firms to the aggregate predictions of a two-part model for surviving and exiting firms. For the latter two groups individual firm characteristics are observable and can be utilized in an econometric framework. For this purpose, we assume that the error term ε_{it} is distributed as *iid* normal for continuing firms. As a consequence a consistent ML estimator can easily be derived.[6] Following Butler (2000) one may use the weighted log likelihood function referring to a two-part model for exiting and continuing firms in period t

[6] Other distributional assumptions are also possible. For instance one could use the asymmetric exponential power distribution as proposed by e.g., Komunjer (2007), Zhu and Zinde-Walsh (2009) and Bottazzi and Secchi (2011) to account for the non-(log-)normal and asymmetrically skewed distribution of firm growth rates among continuing firms. Zhu and Zinde-Walsh (2009) show that the asymptotic properties of an asymmetric exponential power distribution based maximum likelihood estimator are only valid when both tail parameters exceed 0.5. For the data at hand this requirement is not fulfilled and, therefore, the asymmetric exponential power distribution does not form a valuable alternative for our case. On potential reason for this might be that more than 40 percent of all observed net job creation rates exactly amount to 0.

$$\ln L(\gamma,\beta,\sigma) = \sum_{t=1}^{T}\sum_{i=1}^{n_t} w_{it}[d_{it,x}\ln\pi_{it,x}(\mathbf{x}'_{it}\gamma) + (1-d_{it,x})\ln(1-\pi_{it,x}((\mathbf{x}'_{it}\gamma))$$
$$+ (1-d_{it,x})\left(\ln\tfrac{1}{\sqrt{2\pi}\sigma} - \tfrac{1}{2}\tfrac{\left(g_{it}-\mathbf{x}'_{it}\beta\right)^2}{\sigma^2}\right)].$$

Under the assumption of a two-part model, the parameter vector of the model for the probability of exit $\pi_{it,x}$ can be estimated by a separate (weighted) Probit model. The parameters of the specification for the continuing firms, β and σ^2, can be estimated by maximizing the likelihood excluding the observations referring to entering and exiting firms. Moreover, it can easily be demonstrated that with a fully-saturated two-part model maximum likelihood estimation generates cell specific predictions (i.e., $\widehat{g}_{th}^{TP}$) which are numerically identical to the ones obtained from fully-saturated employment-weighted OLS or more formally $\widehat{g}_{th}^{TP} = \widehat{g}_{th}^{OP}$. This equivalence can be seen from the first order conditions of the ML-estimation of the two-part model which imply (replacing β_k by μ_h, see the Appendix B for more details)

$$\widehat{\pi}_{ith} = \Phi(\widehat{\gamma}_h^{TP}) = \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}d_{ith,x}}{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}}$$
$$\frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1-d_{ith,x})\widehat{\mu}_h^{TP}}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1-d_{ith,x})g_{ith}}{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}}.$$

In order to analyze cell-specific net job creation rates applying the two-part model approach, we have to aggregate individual net job creation rates within different groups of firms (indexed by h). Accordingly, aggregate net job creation rates for various groups of firms (e.g., industry, size and age classes) that are populated by n_{th} firms are calculated as (see also Haltiwanger *et al.* 2013b)

$$\begin{aligned} g_{th} &= \sum_{i=1} w_{ith}g_{ith} = \sum_{i=1}^{n_{th}} \frac{y_{ith}+y_{i,t-1,h}}{\sum_{k=1}^{n_{th}} y_{kth}+y_{k,t-1,h}} g_{ith} \\ &= \sum_{i\in\{G_c,G_x\}} \frac{y_{ith}+y_{i,t-1,h}}{\sum_{k=1}^{n_{th}} y_{kth}+y_{k,t-1,h}}\left[(1-d_{ith,x})g_{ith} - 2d_{ith,x}\right] \\ &+ \sum_{i\in\{G_n\}} \frac{y_{ith}+y_{i,t-1,h}}{\sum_{k=1}^{n_{th}} y_{kth}+y_{k,t-1,h}} 2d_{ith,n} := g_{th}^{TP} + g_{th,n}. \end{aligned} \tag{3}$$

As mentioned above, equation (3) illustrates that there is no need to estimate a pooled model. It is possible to recover the net job creation rates by calculating g_{th}^{TP} or it's predictions for the continuing and exiting firms and adding the corresponding (weighted) rates referring to the entering firms, respectively. In this way it is possible to explicitly allow for heterogeneous and firm specific marginal effects for surviving versus exiting firms.

With respect to the calculation of comparative statics, the one-part model pools over continuing and exiting firms, while entry is typically controlled for by the inclusion of an age dummy for zero aged firms (see, e.g., Haltiwanger *et al* 2013a; Rijkers *et al* 2014). Formally, the marginal effects and counterfactuals are calculated from the predictions

$$\Delta\widehat{g}_{it}^{OP} = \begin{cases} \Delta\mathbf{x}_{it}'\widehat{\beta} \text{ if } d_{it,n} = 0 \\ 0 \text{ if } d_{it,n} = 1. \end{cases}$$

Due to the inclusion of an entry dummy a fully-saturated one-part model predicts $\widehat{g}_{it}^{OP} = 2$ for entering firms both under the base and any counterfactual scenario. Entry dynamics are thus held constant implicitly.

In the alternative two-part setting, model predictions are based on estimated exit probabilities from the Probit model and the equation for continuing firms using

$$\widehat{g}_{it}^{TP} = (1 - \widehat{\pi}_{it,x})\widehat{g}_{it,c}^{TP} - 2\widehat{\pi}_{it,x}, \tag{4}$$

where $\widehat{g}_{it,c}^{TP} = \mathbf{x}_{it}'\widehat{\beta}^{TP}$ are the predict outcomes from the second part of the model but are calculated for all firms, including the exiting ones. This approach can be viewed as predicting out of sample (counterfactual) net job creation rates for exiting firms as if these firms would have survived. The estimation of average marginal effects under the two-part model is based on exiting an surviving firms and uses

$$\begin{aligned} \Delta\widehat{p}_{it,x}^{TP} &= \widehat{p}_{it,x}^{TP}(\widehat{\gamma}; x_{it}) - \widehat{p}_{it,x}^{TP}(\widehat{\gamma}; x_{it}^c) \\ \Delta\widehat{g}_{it}^{TP} &= \widehat{g}_{it,c}^{TP}(\widehat{\beta}; x_{it}) - \widehat{g}_{it,c}^{TP}(\widehat{\beta}; x_{it}^c), \end{aligned}$$

where superscript c indicates the counterfactual and in x_{it}^c each column referring to a specific size or age class dummy is separately and counterfactually set to zero. Marginal effects can then be derived as

$$\Delta\widehat{g}_{it}^{TP} = (1 - \widehat{p}_{it,x}^{c,TP})\Delta\widehat{g}_{it,c}^{TP} - \Delta\widehat{p}_{it,x}^{TP}(\widehat{g}_{it,c}^{TP} + 2).$$

As entering firms are not included in the estimation of the two-part model for these firms $\Delta\widehat{g}_{it}^{TP} = 0$ holds as well.[7] The main advantage of the two-part model lies in its ability to explicitly isolate the differential impact of (exogenous) changes in explanatory variables on exiting and continuing firms. Using the result from above the marginal effects can be decomposed by using

$$\Delta\widehat{g}_{it}^{TP} = (1 - \widehat{p}_{it,x}^{TP})\underbrace{\Delta\widehat{g}_{it,c}^{TP}}_{\text{(a)}} - \underbrace{\Delta\widehat{p}_{it,x}^{TP}}_{\text{(b)}}\left(\widehat{g}_{it,c}^{TP} + 2\right).$$

The first component (a) refers to the predicted change in the net job creation rate under survival

[7] $\Delta\widehat{g}_{it,c}^{TP}$ can not be directly derived by the employed two-part estimation procedure. However, it can be calculated based on aggregate cell predictions $\widehat{g}_{it}^{TP}$ using $\Delta\widehat{g}_{it,c}^{TP} = \frac{\widehat{g}_{it}^{TP}+2}{1-\widehat{p}_{it,x}^{TP}} - \frac{\widehat{g}_{it}^{TP,c}+2}{1-\widehat{p}_{it,x}^{cTP}}$. To see this note that $\widehat{g}_{it}^{TP} = (1 - \widehat{p}_{it,x}^{TP})\widehat{g}_{it,c}^{TP} + 2(1 - \widehat{p}_{it,x}^{TP}) - 2 = (1 - \widehat{p}_{it,x}^{TP})\left(\widehat{g}_{it,c}^{TP} + 2\right) - 2 \rightarrow \widehat{g}_{it,c}^{TP} + 2 = \frac{\widehat{g}_{it}^{TP}+2}{1-\widehat{p}_{it,x}^{TP}}$.

holding the probability of exit constant, while the second component (b) comprises the contribution of a change in the exit probability. Applying instead a pooled one-part model would render such a decomposition impossible. Even in a fully-saturated model the comparison of cell means does not allow to uncover the differential impacts of firm characteristics on exiting and continuing firms.

3 Who creates jobs in Austria?

3.1 Data and descriptive statistics

To empirically investigate net job creation patterns by firm size and age groups for the Austrian economy, we apply the proposed employment-weighted two part model and compare its results to those obtained from the routinely applied employment-weighted one part model. The data for this comparison is gathered from the Austrian Social Security Database (ASSD).[8] This is an administrative data set that includes a daily calender of employment relationships between individuals and firms and allows to calculate the (overall) number of employees in a respective firm at each point in time.[9] For our purpose, we calculate firm-specific annual employment levels in the non-farm business sectors over the time period from 1993 to 2013, taking June 7th as the reference day. This leaves us with almost 3.7 million firm-year net job creation rate observations.

Studying net job creation in the Austrian economy is interesting for various reasons: The structure of the Austrian economy is characterized by a large number of very small firms. During our sample period 82.5 percent of all firms employ less than 10 employees while only 0.5 percent of firms in the overall population employ more than 250 workers. This dominance of micro firms makes the understanding of their role for net job creation inevitable for designing proper policy measures in Austria. Further, Austria constitutes a small open economy (with export and import to GDP ratios regularly exceeding 0.5, respectively) and was harshly hit by the economic crisis induced by the Great Recession. According to Eurostat, Austria's GDP declined by 3.8 percent in 2009 (Eurostat 2015). This severe downturn in economic activity provides a suitable framework for studying the impact of recessions on net job creation/destruction patterns over the firm size and age distribution. In contrast to the US, for which some evidence on net job creation effects of business cycles is already available (see e.g., Moscarini and Postel-Vinay 2012 and Fort, Haltiwanger, Jarmin and Miranda 2013), the Austrian labor market is also highly regulated. This might be a point of further interest as it may affect the behavioral response of

[8] This data source has already been used in other related applications in the field of empirical IO. Huber and Pfaffermayr (2010), for example, propose Wald tests for conditional convergence in the firm size distribution and apply these to firm level data constructed from the ASSD. Huber, Oberhofer and Pfaffermayr (2014) formulate an econometric structural model for initial firm size, survival and growth in order to estimate firm-specific transition probabilities between size classes of the Austrian firm size distribution.

[9] Fink *et al.* 2010 provide a comprehensive discussion on how to extract firm level information from the ASSD.

firms to economic recessions.

Table 1 provides some descriptive evidence on employment-weighted net job creation rates over firm size and age groups exclusively focussing on exiting and surviving firms. Following, Haltiwanger, Jarmin and Miranda (2013a, 2013b) and the theoretical work of van de Stadt and Wansbeek (1990), firm size groups are based on their average firm size over two consecutive years. The upper part of the table shows the results for the full sample period from 1993 to 2013. In the lower part the sample captures the Great Recession period which is restricted to the years from 2008 to 2010.

The left panel reports findings when pooling across exiting and entering firms. As a consequence the values in the cells of Table 1 correspond to the coefficients obtained from a fully-saturated employment-weighted OLS regression including four firm size and three age class dummies and their interactions. The right hand side panel distinguishes between continuing and exiting firms. The results reported there are equivalent to the parameter estimates from an employment-weighted fully-saturated two-part model specification. The cell-means reported in the left hand side panel can be recovered from the right hand side panel by inserting net job creation rates of surviving firms and the exit probabilities into equation 4. For example, the employment-weighted average net job creation rate of -11.22 percent for the youngest and smallest firms can be constructed by $\widehat{g}_{it}^{OP} = \widehat{g}_{it}^{TP} = (1 - \frac{8.42}{100}) * 6.13 - 2 * 100 * \frac{8.42}{100} = -11.22$.

Table 1: Employment-weighted net job creation rates and exit probabilities by size and age groups for continuing and exiting firms, in percent

	Pooled data: One-part model				Continuing versus exiting firms: Two-part model							
					Net job creation conditional on survival				Exit probability			
Size \ Age	1-5	6-10	>10	Total	1-5	6-10	>10	Total	1-5	6-10	>10	Total
	Full sample: 1993-2013											
1-10	-11.22	-9.70	-9.98	-10.32	6.13	-0.09	-2.19	0.78	8.42	4.81	3.94	5.53
11-50	-0.21	-1.44	-3.17	-2.40	6.60	1.86	-0.95	0.76	3.30	1.64	1.12	1.57
51-250	0.15	0.10	-2.21	-1.64	4.27	2.20	-0.69	0.27	2.02	1.04	0.76	0.95
>250	-0.31	1.45	-0.62	-0.41	0.67	2.01	-0.14	0.12	0.49	0.28	0.24	0.27
Total	-4.30	-2.78	-2.95	-3.15	4.92	1.45	-0.76	0.44	4.50	2.10	1.10	1.79
	Great Recession: 2008-2010											
1-10	-10.98	-9.59	-10.53	-10.48	6.33	-0.17	-2.09	0.96	8.39	4.72	4.27	5.70
11-50	-1.27	-2.00	-3.32	-2.77	5.61	1.70	-1.01	0.51	3.35	1.83	1.16	1.64
51-250	-5.40	-1.05	-3.05	-3.15	0.76	0.56	-1.30	-0.78	3.07	0.81	0.88	1.19
>250	-5.53	2.76	-1.99	-2.16	-4.52	3.27	-1.23	-1.38	0.52	0.25	0.38	0.39
Total	-6.33	-3.15	-3.71	-4.12	2.23	1.18	-1.30	-0.34	4.23	2.15	1.21	1.90

Notes: Employment-weighted net job creation rates by firm entry are excluded. The cell-means reported for the pooled data can be recovered from the two-part model results by inserting the conditional growth rates for surviving firms and the exit probabilities into equation 4.

Focusing first on the pooled results reported at the left hand side of Table 1, the entries suggests that net job creation rates of existing firms are negative for all firm size and age groups. Overall

3.15 percent of the jobs are lost by continuing and exiting firms between 1993 and 2013. However, when adding the overall annual job creation rate of entering firms which amounts to 3.59 percent (not reported in Table 1), the overall annual average net job creation rate in the Austrian economy results in 0.49 percent. Accordingly, net job creation by firm entry is able to compensate for the job losses in existing firms and the number of jobs in the Austrian economy increased by approximately 0.5 percent annually during the time period considered.

The job destruction tendencies among continuing and exiting firms are most pronounced among small firms (with an aggregated net job creation rate of -10.32 percent) and 1 to 5 year old firms (with an average job destruction of 4.3 percent). The effects in both of these groups are mainly driven by very young (with less than 6 years of age) and, at the same time, very small firms (with below 11 employees). For this group the average annual net job creation rate amounts to -11.22 percent.

Turning to the separate treatment of exiting and surviving firms, we are able to identify substantial heterogeneity across these alternative groups of firms. The youngest and smallest continuing firms (i.e., firms with less than 51 employees and a firm age below 6 years) exhibit the largest average employment weighted net job creation rates with 6.13 and 6.60 percent, respectively. At the same, these two firm groups are responsible for a large part of job destruction due to firm exit. This is indicated by their employment-weighted exit probabilities of 8.42 and 3.30 percent, respectively. By contrast, firms with more than 10 years of age and of any size destroy jobs due to negative net job creation rates conditional on survival (with -0.76 percent in aggregate) as well as due to market exit (with an employment-weighted exit probability of 1.10 percent).

It turns out that net job creation rates of small existing Austrian firms remained relatively stable during the Great Recession, when comparing the overall sample results with the ones for 2008 to 2010. Large firms with more than 50 employees, however, experience a significant reduction in their net job creation rates. The average net job creation rate of firms with more than 250 workers amounts to -0.41 percent over the 1993 to 2013 period, but during the Great Recession shrinks to -2.16 percent. Thus, large Austrian firms are particularly strongly affected by the crises. Focusing on firm age, net job creation rates are lowered for all age groups, with this effect being most pronounced for very young firms with less than 5 years of age.

Once more these findings are due to rather heterogeneous developments across exiting and continuing firms (see the right hand side of the lower panel in Table 1). During the crisis, large firms are responsible for job destruction due to market exit and also experience the strongest decline in net job creation rates conditional on survival. In particular, conditional on survival for less than 5 year old firms with more than 250 employees the net job creation rate dropped substantially from an average of 0.67 percent during the whole sample period to -4.52 percent from 2008 to 2010. The oldest and largest firms also experience a strong increase in their net job destruction rate conditional on survival from -0.14 to -1.23 percent. As a consequence, conditional on survival, the overall net job creation rate for large firms decreases from 0.12 to -1.38 percent. This finding might be driven by the sharp decline in Austria's export activity induced by the Great Recession, as this has mainly affected larger Austrian producers. In addition less than five year old continuing firms are disproportionately affected by the crisis. Among this group of firms employment-weighted average net job creation rates more than halved from 4.92 to 2.23 percent during the Great Recession.

Market exit dynamics, by contrast, are only mildly affected by the Great recession. Although job destruction due to market exit also slightly increases during the Great Recession, employment-weighted exit probabilities have moved by much less than net job creation rates among surviving firms of different size and age groups. For the youngest firms of all sizes, for example, the employment-weighted exit hazard even decreases slightly from 4.5 to 4.23 percent.

3.2 Estimation results

We use a more fine-grained classification of firm size and age groups, when estimating the econometric one-part and two-part models, respectively. These groups are again based on the current average firm size classification. Specifically, we construct eight dummy variables for firm size and firm age, respectively and include a full set of interactions thereof. Further, we include time-, (3-digit) industry and regional fixed effects and interactions of (2-digit) industry and time effects, in order to compare the employment-weighted one-part and two-part models when they are (almost) fully-saturated.[10] For the full-sample, this specification requires to estimate about 1,679 parameters. For the sake of brevity, we only report the conditional firm size and age group effects for net job creation in the following.[11]

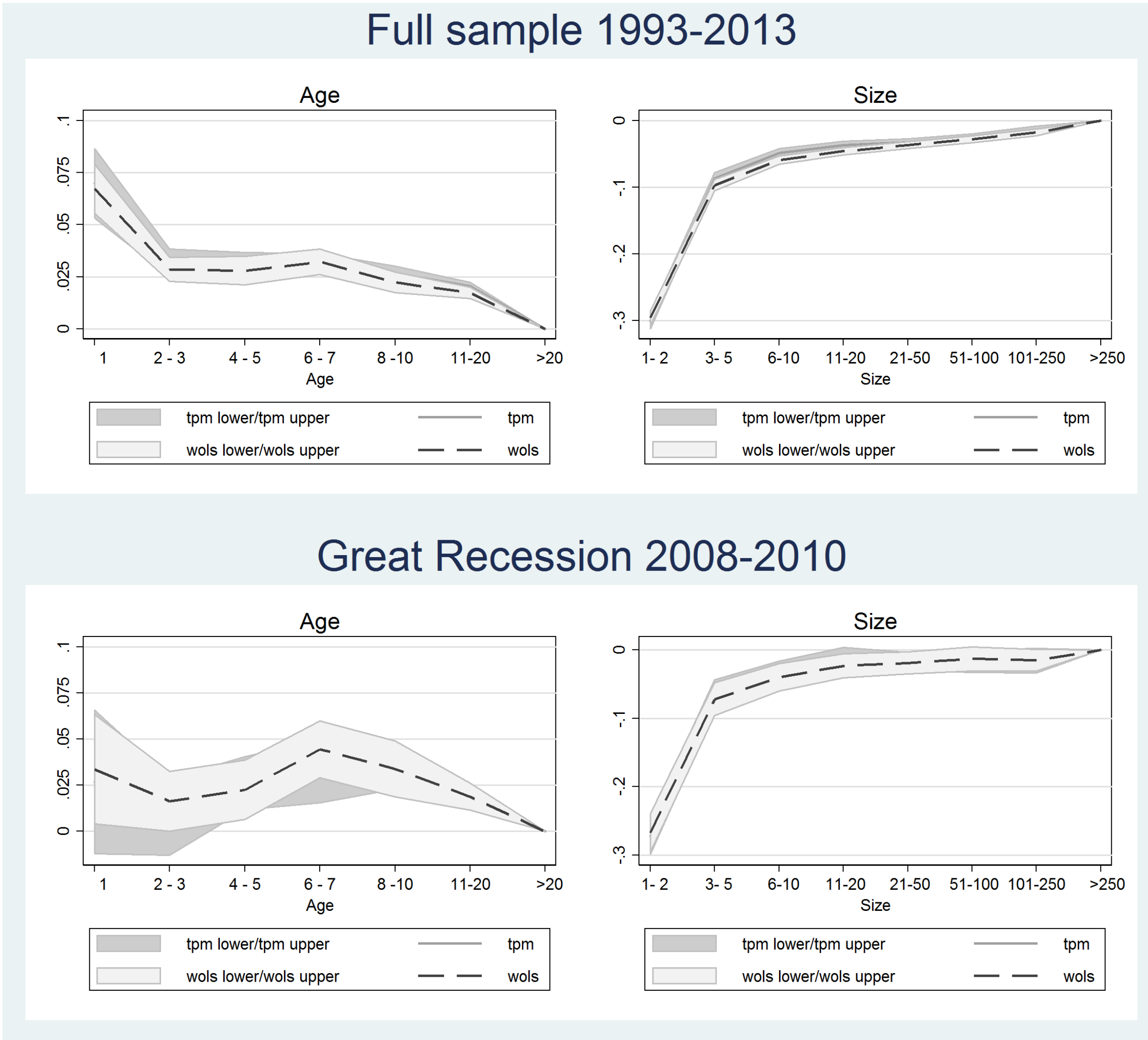
Figure 1 displays the estimated employment-weighted cell averages for firm age and firm size groups based on the two alternative models. The reported effects can be interpreted as aggregated marginal effects at the group-level. The largest firms with more than 250 employees and with more than 20 years of age form the reference group. Their marginal effects are normalized to zero. For the construction of conditional firm age (size) effects we hold the firm size (firm age) composition constant within each cell when calculating marginal age (size) effects (see, e.g., Haltiwanger *et al.* 2013a). Further, Figure 1 reports 95 percent confidence intervals for all estimates.[12]

[10] In our case, a fully-saturated specification would imply the necessity to estimate individual parameters for all size-age-time-industry-region groups requiring to include interactions of all covariates (including also higher order ones). As mentioned, this would require to estimate a large number of (potentially multi-collinear and likely insignificant) variables. We experimented with alternative approximations to the fully-saturated specification. The chosen one seems to be a reasonable approximation to a fully-saturated model.

[11] Detailed regression outputs for all estimated parameters are available upon request.

[12] To calculate these for the two-part model, Stata's *TPM* command has been adjusted to capture the bounded nature of the net job creation rate. The modified TPM-package is available from the authors upon request. Further details on using TPM and it's successor *twopm* for calculating marginal effects and confidence intervals

Figure 1: Estimated employment-weighted cell means for firm age and firm size groups



As expected, the two alternative employment-weighted models yield similar results. As mentioned, this is due to our specification being very close to a fully saturated model which would yield numerically perfectly identical results. Both models suggest that in Austria and over the full sample time period the aggregate net job creation rate of continuing and exiting firms is a decreasing (increasing) function of firm age (size) (see the upper two-graphs in Figure 1). Accordingly, the net job creation rate of one year old firms exceeds that of 20 year old ones by approximately 7.5 percentage points. Firms with one or two employees exhibit net job creation rates which are more than 30 percentage points lower than for firms with more than 250 worker. Similarly, the conditional net job creation rate of firms with 3 to 5 employees is 10 percentage points below the one of the largest firms in the sample. The time period from 1993 to 2013

are provided by Belotti, Deb, Manning and Norton (2015).

unambiguously illustrates the key importance of very young and very large firms for net job creation between 1993 and 2013.

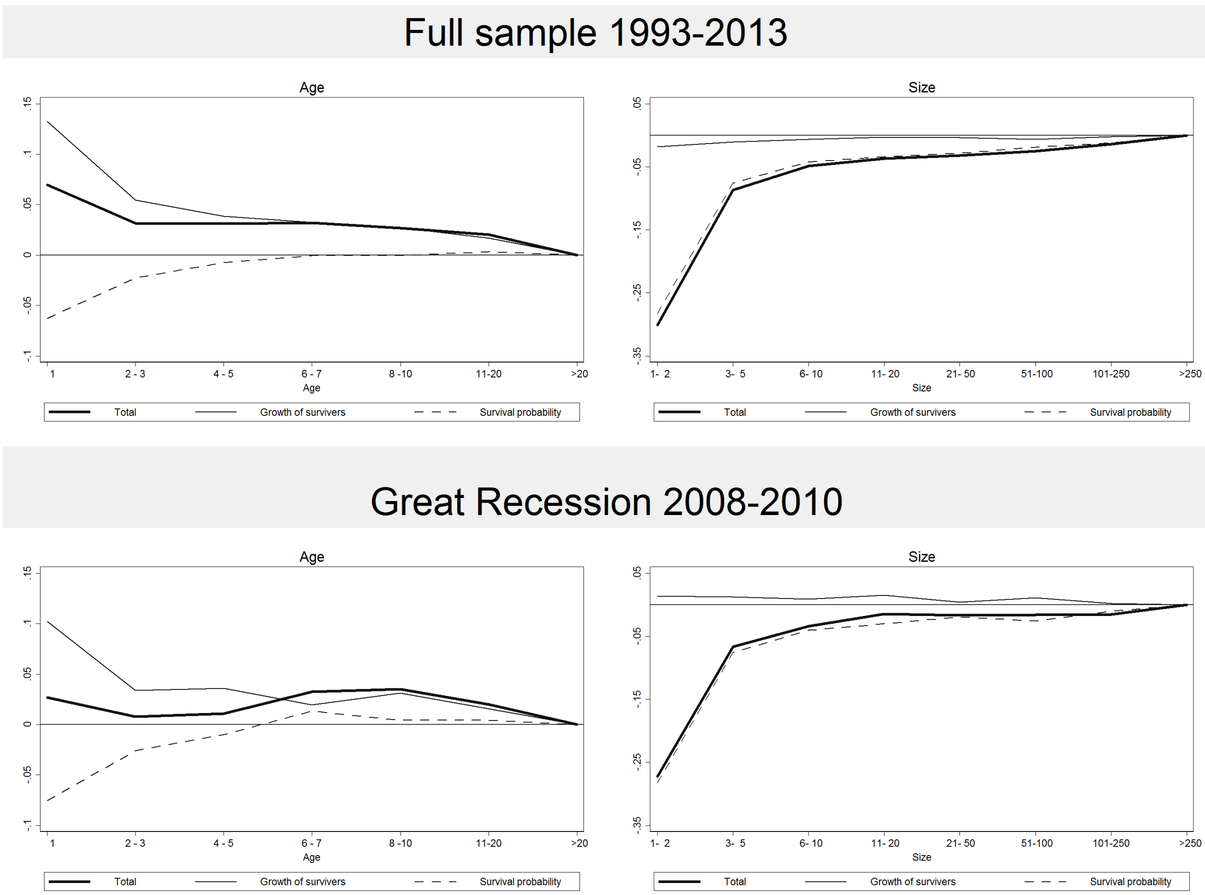
A comparison of these results to the ones for the Great Recession period from 2008 to 2010 (reported in the bottom panel of Figure 1) reveals some structural changes in relative net job creation rates across age groups. The weighted OLS one-part model (as indicated by the dotted line) identifies the 6 to 7 year old firms as most important contributors to net job creation during the crisis. The grey line which plots the conditional expectation derived from the two-part model suggests that firms aged between 8 and 10 years experience the largest relative net job creation rates. In addition the estimates obtained from both alternative models now are estimated with less precision as indicated by much larger confidence intervals. Some estimates from the two-part model suggest lower net job creation rates for one year old firms in comparison the reference group containing at least 20 year old firms. For firm size a Asimilar pattern becomes evident. Again the estimated standard errors of the predictions become larger during the crisis period, although net job creation is still an increasing function of firm size with similar magnitudes as obtained from the full sample. This is another indication for heterogeneous response to the harsh economic shocks induced by the Great Recession.

3.3 Decomposition Results

As discussed in Section 2, another advantage of the employment weighted two-part model is its ability to decompose the overall conditional marginal effects into effects arising from net job creation conditional on survival and from changes in survival probabilities. Figure 2 displays the results of this decomposition formally defined in equation (4) for both the full-sample period (in the top panel) and the Great Recession (in the bottom panel). The bold line represents the total marginal effect which is equivalent to the conditional expectation from the two-part model reported in Figure 1. The gray line represents the relative net job creation rates conditional on survival, while the dotted line displays the estimated relative survival probabilities.

Again focusing on the full-sample results first, this decomposition suggests that the relatively large net job creation rates for the one year old firms discussed above are due to two opposing effects: The first and dominating one arises because these firms possess of the largest net job creation rates conditional on survival. The second effect which is not identifiable in the employment weighted one-part model suggests that these firms also destroy the largest share of jobs due to market exit. In the Austrian economy the higher exit probability of one year old firms induces a relative net job creation rate of approximately -6 percent, while conditional on survival their net job creation rate exceeds the one of the largest firms by 13 percent annually. Taking these two opposing effects together the yearly estimated overall relative net job creation rate is 7 percent. More generally, relative net job creation conditional on survival (the survival probability decreases (increases) with firm age. Thus the overall declining relative net job cre-

Figure 2: Decomposition of the average marginal effects



ation rate with respect to age is due to the netting out of these two opposing effects. Similarly, the smaller relative net job creation rate of micro firms can be almost entirely attributed to their higher exit hazards. Conditional on survival firms of all sizes grow nearly at the same rate. Differences in the relative overall net job creation rate across firm size groups are thus almost entirely due to differences in exit probabilities.

When restricting the analysis to the Great Recession period, 6 to 10 year old firms contribute most positively to overall net job creation. This is due to a substantial increase in their survival probability relative to firms of all other ages and noticeable net job creation rates conditional an survival. For the youngest firms the survival probability and the net job creation rates conditional on survival both decrease during the Great Recession, thus reducing their importance for overall net job creation. With respect to the resilience of small firms the opposite applies. During the crisis their relative net job creation rates conditional on survival increased. The findings from the decomposition exercise suggest that during the Great Recession structural changes in exit hazards have been pivotal for changing overall net job creation patterns in the Austrian economy. This finding is at odds with the results from the simple descriptive statistics reported in Table 1 highlighting the need for systematic and econometric analyses of net job creation patterns.

3.4 Structural Parameters

The findings reported and discussed so far are only descriptive as they focus on employment-weighted firm size and age cell averages. This is suitable for providing a broad overview on net job creation patterns across different groups of firms. For informing policy makers structural parameters which describe how individual firms (rather than firm groups) of different sizes and ages contribute to net job creation are relevant. These structural parameters for continuing firms can be estimated via the proposed two-part approach. As discussed in Section 2.2, a pooled linear model for net job creation rates would not allow to uncover unbiased estimates for these underlying parameters governing the individual relationship between firm size, age and net job creation. The proposed two part model, by contrast, conditional on the correct specification of the data generating process, delivers such unbiased estimates of the structural parameters.

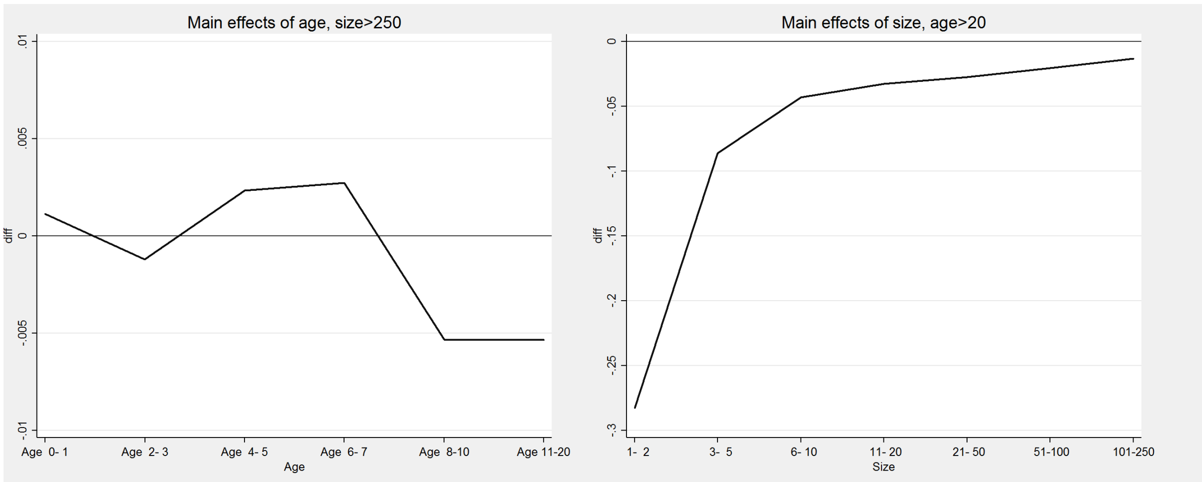
Figure 3 shows the differences between the structural parameters obtained from the one-part and the two-part model alternatives for the (a) main effects and (b) interaction terms specified in both models.[13] It thus allows to determinate for which firm groups the bias from the pooled one-part model is most severe. Regarding firm age the left panel indicates that some effects are overestimated while others would be larger when specifying the alternative two-part model. In particular, for the one year old firms and firms between 4 and 7 years of age, the estimates of the structural parameters in the one-part model exceed the ones obtained from the alternative two-part model. For the remaining age groups and especially for very old firms the one-part model underestimates their true role for overall net job creation.

The estimates for the main firm size effects, by contrast, reveal that the one-part model would (substantially) underestimate the effect of firm size for net job creation of surviving firms. In particular, for the smallest firms with up to two employees the one-part model estimates marginal net job creation effects of approximately 30 percent less than the alternative two-part model. The bias in the firm size estimates, however, decreases with firm size. Finally, turning briefly to the results for the interaction terms, the bottom panel of Figure 3 reveals even more strongly underestimated firm size effects for very young firms. By contrast, for older firms above 6 years of age the estimates from the one-part model exceed the unbiased two-part model estimates.

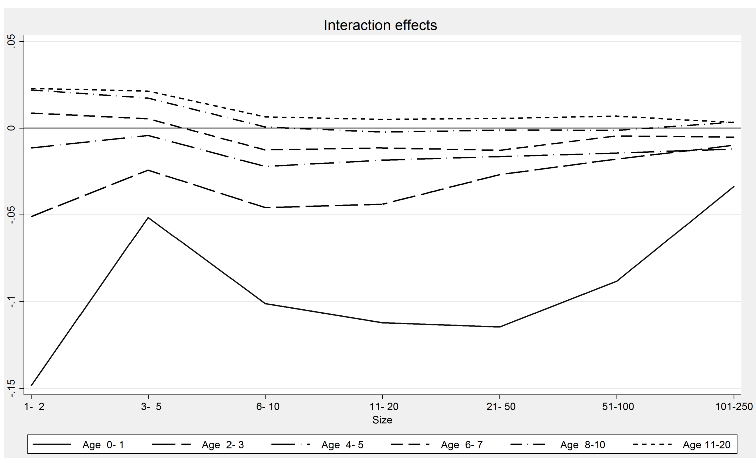
[13] Since the two models are not nested, we are not able to provide standard errors for the differences in parameters.

Figure 3: Differences in structural parameters: One-part vs. two-part model,
(a) main effects, (b) interaction effects

(a)



(b)



4 Conclusions

This papers provides a systematic analysis of net job creation at the firm level for the Austrian economy spanning the time horizon from 1993 to 2013. The economic downturn in Austria from 2008 to 2010 induced by the Great Recession provides a suitable framework for studying how net job creation patterns are affected by this event. The paper also proposes a new estimation strategy for identifying structural parameters that underlie the aggregated patterns observed in the data.

The results of our investigation reveal the necessity to separately treat continuing and exiting firms in order to obtain reliable results on the firm size and age effects for net job creation when analyzing individual firm level data. This is confirmed by a decomposition exercise based on the proposed two-part model for both the full sample period and the time span capturing the Great Recession. Accordingly, conditional on survival younger firms are more important job creators while firm size effects for surviving firms do not provide a clear-cut picture. Firm exit, however, decreases the relevance of both young and small firms for overall net job creation substantially. This finding is even more pronounced during times of economic turmoil. Furthermore, in the Austrian data and especially for small firms the routinely applied pooled employment-weighted OLS approach would severely underestimate the structural parameters underlying net job creation.

To provide policy recommendations on effective policies to foster overall net job creation in the economy, a better understanding of firm exit and entry is needed. While our results suggest that reducing exit of small and young firms could substantially increase net job creation, such policy measures could well be highly inefficient if they support uncompetitive firms which in any case will exit (at least) in the long-run. In order to provide additional insights into the exit processes, it seems warranted to conduct systematic micro-econometric studies aiming to understand to what extent exit is due to market failures and to identify the group of unviable enterprises which are exiting.

With respect to market entry the conceptional issues are even more difficult as entering firms are not observable prior to their entry. The recent theoretical and empirical contributions studying entry- and exit dynamics at the industry-level may thus be specifically relevant for providing policy advice with regard to measures aiming to increase market entry and foster entrepreneurial activities. Alternatively the insights of the (international economics) literature investigating the driving forces for new foreign market entry by already existing firms may be of relevance in this context. A recent contribution by Berthou and Vicard (2015) studies this question and highlights the usefulness of the net job creation rate also in this field of empirical examination. The econometric two-part approach suggested in this paper could easily be extended to a three-part model in order to decompose the heterogeneous effects of firm size and age for the different sources of firms' export dynamics including foreign market entry and exit.

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Appendix

A The bias of weighte OLS estimation in a one-part model for net job creation rates

In order to derive the bias of the weighted OLS estimator for a linear net job creation model that uses all observations, we partition the data into three groups of firms. Index x labels exiting firms (with $y_{it} = 0$ and $y_{i,t-1} \neq 0$) and index c refers to the continuing firms (with $y_{it} \neq 0$ and $y_{i,t-1} \neq 0$). The third set of observations with index n denotes entering firms (with $y_{it} \neq 0$ and $y_{i,t-1} = 0$). Applying the definition of net job creation rate and assuming a standard data generating process the model can be written as

$$g_{ith} = \begin{cases} -2 & \text{if } i \in G_{h,x}, P\left(i \in G_{h,x}\right) = P(\mathbf{x}'_{ih,x}\gamma \geq \mathbf{0}) = \pi_{ih,x} \\ \mathbf{x}'_{it,c}\beta + \varepsilon_{ih} & \text{if } i \in G_{h,c},\ \varepsilon_{ih}|d_{ih,c} \sim iid(0,\sigma^2) \\ 2 & \text{if } i \in G_{h,n}, P\left(i \in G_{h,n}\right) = P(d_{ih,n} = 1) = \pi_{ih,n} \end{cases}$$

We collect the indicators for exiting, continuing and entering firms in diagonal matrices $\mathbf{D}_x$,$\mathbf{D}_c$ and $\mathbf{D}_n$, respectively. A one-part model for weighted OLS estimation is then given by (again a star indicates weighted variables)

$$\mathbf{W}\mathbf{g} = \mathbf{X}^*\beta + \mathbf{D}_n\left(2\mathbf{e}^* - \mathbf{X}^*\beta\right) + \mathbf{D}_x\left(-2\mathbf{e}^* - \mathbf{X}^*\beta\right) + \mathbf{D}_c\varepsilon^*.$$

Denoting the corresponding weighted OLS-estimate of this one-part model by superscript OP, we obtain

$$\begin{aligned}\widehat{\beta}^{OP} &= \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1}\mathbf{X}^{*\prime}\mathbf{g}^* \\ &= \beta + \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1}\mathbf{X}^{*\prime}\left[\mathbf{D}_x\left(-2\mathbf{e}^* - \mathbf{X}^*\beta\right) + \mathbf{D}_n\left(2\mathbf{e}^* - \mathbf{X}^*\beta\right) + \mathbf{D}_c\varepsilon^*\right]\end{aligned}$$

and

$$E[\widehat{\beta}^{OP} - \beta|\mathbf{X}^\star, \mathbf{D}_n, \mathbf{D}_c, \mathbf{D}_x] = \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1}\mathbf{X}^{*\prime}\left[(\mathbf{D}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta) + \mathbf{D}_n(2\mathbf{e}^* - \mathbf{X}^*\beta)\right].$$

Using $E[\mathbf{D}_c\varepsilon|\mathbf{X}^*] = 0$, $E[\mathbf{D}_x|\mathbf{X}^*] = \mathbf{\Pi}_x$ and applying the law of iterated expectations with $E[\mathbf{D}_x|\mathbf{X}^*] = \mathbf{\Pi}_x$ and $E[\mathbf{D}_n|\mathbf{X}^*] = \mathbf{\Pi}_n$ gives

$$E[\widehat{\beta} - \beta|\mathbf{X}^\star] = \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1}\mathbf{X}^{*\prime}\left[(\mathbf{\Pi}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta) + \mathbf{\Pi}_n(2\mathbf{e}^* - \mathbf{X}^*\beta)\right].$$

Defining the projection matrix $\mathbf{P}_{\mathbf{X}^*} = \mathbf{X}^* \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1} \mathbf{X}^{*\prime}$ and inserting the population model, the predicted net job creation rate is given as

$$\begin{aligned}\mathbf{W}\widehat{\mathbf{g}}^{OP} &= \mathbf{X}^*\widehat{\beta}^{OP} = \mathbf{X}^* \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1} \mathbf{X}^{*\prime} \left((\mathbf{I} - \mathbf{D}_n - \mathbf{D}_x)\mathbf{X}^*\beta + 2(\mathbf{D}_n - \mathbf{D}_x\mathbf{e}^*) + (\mathbf{I} - \mathbf{D}_x - \mathbf{D}_n)\varepsilon^*\right) \\ &= \mathbf{X}^* \left(\mathbf{X}^{*\prime}\mathbf{X}^*\right)^{-1} \mathbf{X}^{*\prime} \left((\mathbf{I} - \mathbf{D}_n - \mathbf{D}_x)\mathbf{X}^*\beta + 2(\mathbf{D}_n - \mathbf{D}_x\mathbf{e}^*) + (\mathbf{I} - \mathbf{D}_x - \mathbf{D}_n)\varepsilon^*\right) \\ &\left(\mathbf{I} - \mathbf{P}_{\mathbf{X}^*}(\mathbf{D}_x + \mathbf{D}_x)\right)\mathbf{X}^*\beta + 2\mathbf{P}_{\mathbf{X}^*}(\mathbf{D}_n - \mathbf{D}_x)\mathbf{e}^* + \mathbf{P}_{\mathbf{X}^*}(\mathbf{I} - \mathbf{D}_x - \mathbf{D}_n)\varepsilon^*,\end{aligned}$$

while the population (true model) based prediction reads as

$$\mathbf{W}\mathbf{g} = \left(\mathbf{I} - (\mathbf{D}_n + \mathbf{D}_x)\right)\mathbf{X}^*\beta + 2(\mathbf{D}_n - \mathbf{D}_x)\mathbf{e}^* + (\mathbf{I} - \mathbf{D}_x - \mathbf{D}_n)\varepsilon^*.$$

Applying again the law of iterated expectations, the difference of the conditional expectation of $\mathbf{W}(\widehat{\mathbf{g}}^{OP} - \mathbf{g})|\mathbf{X}$ can be derived as

$$E[\mathbf{W}(\widehat{\mathbf{g}}^{OP} - \mathbf{g})|\mathbf{X}^*] = \left(\mathbf{I} - \mathbf{P}_{\mathbf{X}^*}\right)\left[(\mathbf{\Pi}_x(-2\mathbf{e}^* - \mathbf{X}^*\beta) + \mathbf{\Pi}_n(2\mathbf{e}^* - \mathbf{X}^*\beta)\right].$$

B The Two-part model

Under homoskedasticity and normality of $\varepsilon_{ih}|d_{ih,c}$ for a two-part model the following weighted log likelihood is maximized

$$\begin{aligned}\ln L(\gamma, \beta, \sigma) = \sum_{t=1}^{T}\sum_{i=1}^{n_t} & w_{it}[d_{it,x}\ln \pi_{it,x}(\mathbf{x}_{it}'\gamma) + (1 - d_{it,x})\ln(1 - \pi_{it,x}((\mathbf{x}_{it}'\gamma)) \\ & + (1 - d_{it,x})\left(\ln \tfrac{1}{\sqrt{2\pi\sigma}} - \tfrac{1}{2}\tfrac{\left(g_{it} - \mathbf{x}_{it}'\beta\right)^2}{\sigma^2}\right)].\end{aligned}$$

The estimation of the general model is straight forward. In a fully-saturated model where $\mathbf{x}_{it}$ includes group dummies only (using μ instead of β)), the score reads as

$$\begin{aligned}\frac{\ln L(\gamma, \mu, \sigma)}{\gamma_h} &= \sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}\left(\frac{d_{ih,x} - \pi_{ih,x}(\gamma_h)}{\pi_{ih,x}(\gamma_h)\left(1 - \pi_{ih,x}(\gamma_h)\right)}\right)\frac{\partial \pi_{ih,x}(\gamma_h)}{\partial \gamma_h} \\ &= \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}\left(d_{ih,x} - \pi_{ih,x}(\gamma_h)\right)}{\pi_{ih,x}(\gamma_h)\left(1 - \pi_{ih,x}(\gamma_h)\right)}\frac{\partial \pi_{ih,x}(\gamma_h)}{\partial \gamma_h} \\ \frac{\ln L(\gamma, \mu, \sigma)}{\mu_h} &= \sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1 - d_{it,x})(g_{ih} - \mu_h)\tfrac{1}{\sigma^2},\end{aligned}$$

where $\pi_{ih,x}(\gamma_h) = \Phi(\gamma_h)$ and $\frac{\partial \pi_{ih,x}(\gamma_h)}{\partial \gamma_h} = \phi(\gamma_h)$. This shows that for the special case of a fully-saturated model specification the predictions from the one-part and two-part models perfectly coincide, since

$$\begin{aligned}
\Phi(\widehat{\gamma}_h^{TP}) &= \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith} d_{ith,x}}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} \\
\frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1-d_{it,x})g_{ih}}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} &= \frac{\widehat{\mu}_h \sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1-d_{ih,x})}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} = \widehat{\mu}_h(1-\Phi(\widehat{\gamma}_h^{TP})) \\
\widehat{g}_h^{TP} &= \widehat{\mu}_h(1-\Phi(\widehat{\gamma}_h^{TP})) - 2\Phi(\widehat{\gamma}_h^{TP}) \\
&= \frac{\sum_{t=1}^{T}\sum_{i=1}^{n_{th}} w_{ith}(1-d_{it,x})g_{ih}}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} - 2\frac{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith} d_{ith,x}}{\sum_{t=1}^{T}\sum_{i=1}^{n_h} w_{ith}} = \widehat{g}_h^{OP}
\end{aligned}$$

where $\pi_{ih,x}(\gamma_h) = \Phi(\gamma_h)$ and $\frac{\partial \pi_{ih,x}(\gamma_h)}{\partial \gamma_h} = \phi(\gamma_h)$.