Wirtschaftsuniversität Wien

Vienna University of Economics and Business Administration

Working Papers Series:

Growth and Employment in Europe: Sustainability and Competitiveness

Working Paper No. 36

ENTRY AND EXIT DYNAMICS IN THE AUSTRIAN MANUFACTURING INDUSTRIES

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June ,2004

This working paper series presents research results of the WU-Research Focus:
Growth and Employment in Europe, Sustainability and Competitiveness
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Entry and Exit Dynamics in the Austrian Manufacturing Industries

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Abstract

This article investigates the determinants of entry and exit in the Austrian manufacturing sector based on 1981 to 1994 data. We study the response of entry, exit and other indicators of firm dynamics to changes in average plant size, size heterogeneity, concentration, incentives and vertical integration. By applying Bayesian simulation methods we estimate random coefficient models and study the symmetry of the determinants of entry and exit. Our empirical analysis shows that entry and exit rates are driven by the same determinants. The impacts of these determinants are nearly homogeneous for both, entry rates and exits rates, respectively. Moreover, we find (i) that changes in average plant size, size heterogeneity and concentration are not symmetric with respect to entry and exit, (ii) that changes in the growth of sales is weakly symmetric and (iii) that the growth rate of employment is strongly asymmetric across industries in Austrian manufacturing. Furthermore, we infer from the data that the turnover of firms influences the changes in the number of competitors. Low entry rates go hand in hand with low net entry rates and a low turnover.

Acknowledgements

We are grateful to participants of the 2004 conference of the Austrian Economic Association (NOEG 2004). Especially we thank Thomas Grandner and Alfred Stiassny for their helpful comments and discussions. All remaining errors and shortcomings are in our sole responsibility. Werner Hölzl acknowledges financial support from OeNB-Jubilaeumsfonds (Research contract Nr. 9800).

Keywords
Entry, Exit, Industry Turbulence, MCMC

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1 Introduction

Critical issues in Industrial Organization, such as competition, efficiency are studied by looking at the determinants of the inflow and the outflow of firms. The entry and exit of firms is an outcome of the markets' selection process. Entry and exit play a central role in industrial organization. Theories of limit pricing and the theory of contestable markets rely on the availability of a number of potential entrants to discipline incumbents. Models of Schumpeterian competition emphasize the role of new entrants as carriers of new ideas. The question what fosters and what hinders the entry of new firms into specific industries and the relationship between entry and exit is an important research question for industrial dynamics but figures also prominently in policy discussions in most industrial countries. Public programs to promote new entry are common practice in most countries of the European Union.

There are many papers which investigate the reasons behind entry and exit. This largely empirical literature has contributed to a better understanding of the determinants of the inflows and outflows of firms by establishing a number of stylized facts about entry and exit (see e.g. Geroski (1995), Caves (1998)). Entry and exit are quite volatile over time and highly correlated (see Cable and Schwalbach (1991), Geroski (1995)). It is sometimes argued that industries are more consistently characterized by turnover rates than by net entry rates (see Dunne *et al.* (1988)). We want to test this conjecture for Austrian manufacturing. This paper focuses on the short and medium run dynamics of entry and exit. The competing metaphors of the relationship between entry and exit are the metaphor of displacement, where new firms displace inefficient incumbents, replacement, where exit opens the room for new firms, and the revolving door metaphor, where there is considerable entry and exit but very little permanent penetration (see Audretsch (1995)). The third metaphor is also related to the hypothesis of symmetry, which states that the close relationship between entry and exit is due to fact that their determinants are actually the same. Which of the metaphors describes the relationship between entry and exit best is still an open question (see Shapiro and Khemani (1987), Fotopoulos and Spence (1998)). The need to understand the short-term dynamics of entry and exit and exit is motivated by important economic policy concerns about entry and exit.

In this article the data comprise industry based time series form 1981 to 1994, 17 manufacturing industries are within the data set. We apply Bayesian simulation methods in order to estimate random coefficient models. This methodology is that it provides an elegant method of model selection and allows thereby to obtain a parsimonious model which is capable to reflect the heterogeneity in the data in an appropriate way. To our knowledge our application is the first application of this methodology to study entry and exit dynamics. This methodology allows us to cluster industries (Bayesian clustering). I.e. we estimate groups of industries where similar behavior can be observed simultaneously with the model parameters. This analysis will show that the clustering is principally driven by the different growth rates of the different entry and exit time series. Our results suggest that at the industry level entry and exit are related in a dynamic way, at bottom of which demand and the nature industrial competition are responsible for the degree of turbulence observed. This paper shows that there is a close relationship between entry and exit rates across industries. Moreover, the turnover of firms influences the changes in the number of competitors, while low entry rates go hand in hand with low net entry rates and a low turnover. Furthermore, we test the symmetry hypothesis. For our data set we find out that the growth rates of the minimum efficient scale, of heterogeneity within industries and of industry concentration are not symmetric. The growth rate of sales is weakly symmetric while the growth rate of employment is asymmetric. The paper is organized as follows: Section 2 discusses current literature on entry and exit dynamics and presents the data. Section 3 illustrates the statistical framework used in this paper. A brief analysis on MCMC estimation of the latent class model is skipped to Appendix A. Section 4 presents and discusses the estimation results; section 5 concludes.

2 Market Entry and Market Exit

Entry is a response to perceived opportunities by new entrepreneurs, exit is induced by expected losses and provides a release of productive resources to alternative uses. Two sets of variables are central with respect to barriers and incentives when considering entry and exit (see Siegfried and Evans (1994), Geroski (1995), Caves (1998)). The literature on entry barriers emphasizes that there are market conditions that allow incumbents to raise prices above costs without attracting entry. Barriers to entry and barriers create an asymmetry between incumbents and potential new entrants. These barriers are often related to sunk costs. Incentives on the other hand refer to the expansion of the market and higher profitability which signal a potential disequilibrium. In this paper we focus on the relationship between entry and exit and changes in variables related to technology, market power, opportunity and incentives.
A second question we study is the relationship between entry and exit. It is a stylized fact that entry and exit are highly and positively correlated (see e.g. Cable and Schwalbach (1991), Geroski (1995)). This implies that entry and exit processes are dominated by within-industry replacement, while the transfer of firms from declining to expanding industries (between-industry replacement) is less important. The unconditional correlation between entry and exit is 0.512 and significant at the one percent level for Austrian Manufacturing. The high correlation can be due to the symmetry of entry and exit barriers or due replacement and displacement effects. We will study whether the variables we use are symmetric. Moreover, we will investigate conditional probabilities in order to answer the question whether a high entry rate implies a high exit rate (low net entry rate) and whether a high volatility of entry and exit implies high net entry rates.
In this paper we use data to from the membership statistics of the Austrian Chambers of Commerce (WKÖ) for the years 1980-1994. The data pertain to the two-digit level of industrial classification and are coded according to the code system by institutional aspects of the Austrian Chamber of Commerce.[1] To construct the independent variables we use the number of entries in year t, EN_t, the number of exits in year t, EX_t and the number of firms in year t, N_t. From these time series we construct the independent variables gross entry rate ($Entry$), gross exit rate ($Exit$), net

[1] The industries will be presented in Table 10.

Table 1: Dependent Variables

Variable	Name	Definition	Source
Gross Entry Rate	$Entry$	$\frac{EN_t}{N_{t-1}} * 100$	WKÖ
Gross Exit Rate	$Exit$	$\frac{EX_t}{N_{t-1}} * 100$	WKÖ
Net Entry Rate	Net	$\frac{N_t - N_{t-1}}{N_{t-1}} * 100$	WKÖ
Turnover Rate	$Turn$	$Entry + Exit$	WKÖ
Volatility Rate	Vol	$Turn - \|Entry - Exit\|$	WKÖ

Notes: EN_t is the number of entrants in year t, EX_t is the number of exits in year t, N_t is the number of firms in year t and WKÖ denotes the membership statistics of the Austrian Chambers of Commerce.

entry rate (Net), turnover rate ($Turn$) and the volatility rate (Vol). These series are stationary; cointegration relationships cannot be detected. Table 1 gives an overview over the variables. For more details on the construction and interpretation of the data the interested reader is referred to Hölzl (2003). Table 2 provides the summary statistics. Let $y_{i,t}$, $i = 1, \ldots, I$ $t = 1, \ldots, T$, represent the corresponding random variable: the column mean presents the sample average, the column StdDev shows the standard deviation, the columns Min and Max figure $\min(y_{i,t})$ and $\max(y_{i,t})$ respectively.

Beside the entry and exit rates we use net entry rates, turnover rates and also volatility rates as indicators of industrial dynamics. These variables are transformations of the variables $Entry$ and $Exit$. The net entry rate, Net, measures the change in number of firms; since $N_t = N_{t-1} + EN_t - EX_t$, the net entry rate is the difference between the entry and the exit rate, i.e. $Net = Enty - Exit$. It is primarily an indicator of the growth or decline of the number of active firms. However, net entry does not account for the turnover of the identities of firms. Therefore we use also the turnover and the volatility of firms. The turnover reflects entry and exit dynamics in terms of changes in the identities of firms in the industry. The turnover accounts for both changes in market size and replacement effects. Thereby it allows to investigate the symmetry hypothesis whether entry barriers are also exit barriers. The same holds for incentives. The volatility rate is a measure of the excess turnover, that is the turnover in identities which does not lead to changes in the stock of firms. Volatility is defined as the turnover minus the absolute value of the difference between entry and exit. Little algebra shows that $Vol = 2(\mathbf{1}_{(Net>0)}Exit + \mathbf{1}_{(Net\leq 0)}Entry) = 2(\mathbf{1}_{(Entry-Exit>0)}Exit + \mathbf{1}_{(Entry-Exit\leq 0)}Entry)$; $\mathbf{1}_{(.)}$ is an indicator function. Volatility is a measure of the turbulence within an industry. Industries with high volatility are those industries where large numbers of new firms displace a large number of incumbents, without affecting the total number of firms. By construction, volatility measures what triggers the replacement of incumbents by new firms.

In order to study the symmetry hypothesis we distinguish between weak and strong symmetry and weak and strong asymmetry. Symmetry is defined as independent variables having the same influence on entry and exit. We define weak symmetry as symmetry of the sign: $sign(parameter)|_{Entry} = sign(parameter)|_{Exit}$. Strong symmetry is related to the value of the parameters $\pm$ the estimated

Table 2: Summary statistics of dependent variables, values are expressed in percent.

Variable	Mean	StdDev	Min	Max
Entry rate	6.376	2.858	0.000	27.273
Exit rate	7.647	3.806	0.000	36.364
Net entry rate	-1.154	3.359	-15.789	8.475
Turnover rate	14.007	5.793	0.000	63.636
Volatility rate	15.160	7.431	-0.263	71.970

standard deviations. Strong symmetry can be observed by a parameter equal to zero in the net entry regression. Weak asymmetry is defined by $sign(parameter)|_{Entry} = -sign(parameter)|_{Exit}$. Strong asymmetry is related to the value of the parameters and can be observed by a parameter $\pm$ the estimated standard deviations equal to zero in the turnover regression.

Let us now turn to the independent variables. We aim at establishing whether there is a relationship between entry and exit dynamics and changes in average plant size, changes in concentration, and changes in the size heterogeneity within industries, as well as to changes in incentives and vertical integration. Table 3 provides an overview of the variables and their expected signs and Table 4 presents the descriptive statistics.

As measures of incentives we use the growth rates of deflated *industry sales* (GS) and the growth rate of *employment* (GE). Higher market growth should indicate opportunities for new entrants and reduce the selection pressure for incumbents. As the incentives are expected to be asymmetric for entry and exit, that is, positive for entry and negative for exit, we expect a strong positive association with net entry. When the effects have approximately the same size with regard to entry and exit (strong asymmetry) then the association with turnover should not be different from zero (see Table 3).

As measure of *complexity of operations* we use the measure of vertical integration proposed by Adelman (1955), value added over gross production values, which can be used as proxy for the complexity of operations (e.g. Pennings and Sleuwagen (2000)). Transaction cost theory predicts that the complexity of production is related to the complexity of contracts, therefore a higher complexity of production processes should be associated with a higher degree of vertical integration (see e.g. Williamson (1975), Masten (1984)). The degree of vertical integration within an industry changes when value added and gross production change. This measure is not only related to changes in vertical integration per se but also to changes in input prices and quality upgrading innovations, which increases the value added with respect to gross production. A high degree of vertical integration is expected to be both a barrier to entry and a barrier to exit due to the sunk cost effect. Higher vertical integration and quality improving innovations are likely to deter entry, as the set up costs rise in both cases. However, the effect on exit may be indeterminate as with this process weak incumbents may decide to abandon the industry, thereby increasing exit. On the other hand incumbents may be tempted to remain longer in the market due to the sunk cost effect. A-priori it is difficult to predict which of these effects dominates. We expect that a conservation effect prevails. Changes in vertical integration triggers a change in entry and exit behavior. When value added increases due to cheaper inputs, this suggests that there are opportunities to enter. Therefore during the adjustment process entry may increase. However, the effect on exit is again indeterminate.

The indicators for concentration, size heterogeneity within industries were derived using the indicator of minimum efficient plant size (MES) suggested by Pashigian (1969) in terms of employment. The MES is an weighted average measure of the form

$$MES = \sum (E_\iota / n_\iota)(E_\iota / E) \ ,$$

where E_ι is total employment in the ι-th size class, n_ι the number of firms in the size ι-th size class and $E = \sum E_\iota$ total industry employment (see Fotopoulos and Spence (1998)). As Davies (1980) suggests the ratio of MES to extent of the market is better interpreted as measure of the concentration within an industry. We follow this interpretation and use the growth rate of the MES to total employment, GCON, as measure of changing concentration. GCON depicts changes in the carrying capacity of the market (Carree and Thurik (1999)). Conventional wisdom suggests, that increasing concentration should deter entry and increase exit. GCON is expected to be related negatively with net entry and turnover.

Table 3: Independent Variables

Variable	Name	Definition: Growth of	Expected sign: Entry	Exit	Net	Turn	Vol
growth of sales	GS	Sales	(+)	(-)	(+)	(0)(+)	(-)
growth of employment	GE	Employment	(+)	(-)	(+)	(0)(+)	(-)
growth of plant size	GMES	MES	(-)	(+)	(-)	(-)	(+)
growth of concentration	GCON	$\frac{MES}{\text{Employment}}$	(-)	(+)	(-)	(-)	(+)
growth of heterogeneity	GSUB	$\frac{MES}{\text{Average plant size}}$	(+)	(-)	(+)	(0)(+)	(+)
growth of Vertical integration	GCPX	$\frac{\text{Value added}}{\text{Gross production value}}$	(-)	(+)(-)	(-)	(+)(-)	(+)(-)

The MES indicator is weighted measure of *plant size*. We use the growth rate of MES to proxy changes in plant size that is of economies of scale. Higher growth rate of minimum efficient plant size (GMES) indicates a that the average plant size increases. We expect a negative relationship between changes in minimum efficient plant size (GMES) and entry, and a positive relationship with the exit rate. Note however, that the effect of scale economies is not conclusive in the empirical literature (see Geroski (1995)), as there is abundant evidence that production functions in manufacturing industries are not homothetic (see Caves (1998)).

In order to account for this effect we use GSUB as indicator of *heterogeneity*. GSUB is defined as MES divided by average plant size. It can be thought as a measure of the sustainable importance

of the competitive fringe within an industry. MES is different from the average plant size when there is heterogeneity of plant sizes within an industry.[2] An increase in heterogeneity is expected to be correlated with higher entry and lower exit. The pressure to exit is lowered by higher heterogeneity, as higher heterogeneity allows for a number of market niches which can accommodate firms and weakens the competitive interaction (see Sutton (1998)). Therefore, we expect a negative relationship between GSUB and exit. GSUB should have a strong influence on net entry but be insignificant for the turnover when the effects are similar for entry and exit. The selection pressure in an heterogeneous industry is weaker than in a more homogeneous one, we expect a negative relationship between the entry and exit rate.
By definition, volatility is driven by the more important component making up the turnover of firms. For the period under consideration exit dominates entry in Austrian manufacturing. Therefore we expect that the parameters with volatility have the same signs as with the exit rate.

Table 4: Summary statistics of independent variables, values are expressed as growth rates in percent

Variable	Mean	StdDev	Min	Max
GE	6.169	12.537	-22.413	42.217
GS	-2.028	4.564	-21.798	13.730
GCON	0.946	7.035	-29.190	25.908
GSUB	-0.792	6.904	-30.135	25.670
GMES	-1.185	7.072	-42.632	18.726
GCPX	0.204	6.497	-28.887	34.223
|GCPX|	3.949	5.157	0.010	34.223

In addition to these variables we experimented with a number of other variables at the model selection stage. Most prominently we used the growth rate of price-cost margins, lagged employment growth, GDP growth, advertising intensity, export growth and a measure of capital intensity. However, these variable were skipped by the model selection procedure. Interestingly the growth rate of price cost margins is significant when GS is dropped form the regression. However, from a statistical perspective GS dominates the growth rate of price cost margins.[3]
In out dataset we detected two outliers. This was done as usual by looking at the residuals of the regression model. We checked whether these residuals are within the one times, two times, three times the standard deviation of the residuals. For our current application all except of two values fulfill this criterion. These two points result in residuals larger than five times the standard

[2]Average plant size is equal to MES if and only if all plants within the industry have the same employment.

[3]The growth rate of GDP is to the growth rate of sales. However sales is the better predictor. A three factor latent class model (see the following sections and Appendix A) provides us with means and standard deviations of the parameters α, β from the marginal posterior. The variable GS is the response, while the GGDP is the prediction variable. It turns out that $k = 3$. The following results are taken from 3000 MCMC steps with a burn-in of 1000 steps. GS is linked to GGDP. The elasticity is 2.5, but only 1/4th of the volatility of GS can be explain by GGDP.

deviation. Therefore we skip these observations in the further analysis. Both outliers are detected in the leather producing industries time series.

3 Econometric Model

In this paper we want to use a parsimonious model which is capable to reflect for heterogeneity in the data. From Section 2 we already know that our data consist of many relatively short time series. One opportunity to perform an econometric analysis is on an industry by industry basis. This approach suffers from the fact that a lot of parameters have to be estimated where these parameters are only based on a few data points. On the other had side we can try to aggregate the time series. However, this approach is not capable to reflect for heterogeneities in the data. Last but not least we can use panel data models, nevertheless this approach demands for much more parameters than the model used in this paper. This is the reason why we estimate latent class models and perform model selection within this class of models.

In the following sections we shall stick to the following notation: $y_{i,t}$ is a response variable of industry i, $i = 1, \dots, I$. Some prediction variables influence the repose variable in the same way via the regression parameter α; these variables are called *common variables* $Z_{i,t}$. On the other hand side we want to identify variables with a class specific impact. I.e. we consider class specific variables $W_{i,t}$ where the regression parameter β_j depends on a class index $j = 1, \dots, k$. This yields

$$y_{i,t} = Z_{i,t}\alpha + W_{i,t}\beta_j + \varepsilon_{i,t} \ , \tag{1}$$

where $\varepsilon_{i,t}$ are independent standard normally distributed error terms with variance σ^2, i.e. $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma^2)$. $\alpha = (\alpha_1, \dots, \alpha_{l_\alpha})'$ measures the homogenous effects while $\beta_j = (\beta_{1,j}, \dots, \beta_{l_\beta,j})'$, $j = 1, \dots, k$, are the random effects which are due to heterogeneity in the data. k is the number of classes.

Furthermore, let us define a group indicator S_i taking values in $\{1, \dots, k\}$; $S_i, S_{i'}$ are pair wise independent. The number of series i in class j can be observed by looking at S_i, it is given by $D_j = \#\{S_i = j\}$. The corresponding group probabilities $\mathbb{P}(S_i = j) =: \eta_j$, $j = 1, \dots, k$. The set $(S_1, \dots, S_i, \dots, S_I)$, $I = 17$, is abbreviated by S. The MCMC simulation of the group indicators will serve us with useful byproducts. E.g. we can perform inference whether industry i is most probably in state j, $j = 1, \dots, k$, (i.e. we perform clustering) and for sets of group indicators of different response variables, S_a and S_b respectively, we can analyze possible interdependences.

The set of unknown parameters, S and θ, will be denoted by Ψ in the further analysis. The goal of Markov Chain Monte Carlo methods is to draw samples from the posterior $\pi(\Psi|Y)$ given a prior

Common variables		Component specific variables		
GGDP	lag	$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	$\hat{\beta}_{c,3}$
2.5009	0.1481	-7.2460	0.6242	2.6363
(0.326)	(0.054)	(2.445)	(1.550)	(1.503)
R^2 =0.2350		R^2_C =0.2291		

distribution of these parameters $\pi(\Psi)$. Appendix A describes how $\pi(\Psi|Y)$ can be simulated by MCMC and how model selection will be performed.

4 Estimation Results

This section presents the parameter estimates for the entry and exit dynamics. The parameter estimates are sample means from MCMC output. The terms is parentheses are the corresponding standard deviations. The corresponding prediction variable is listed above the estimate of the corresponding parameter. $\hat{\beta}_{c,j}$ stands for the estimate of the constant term in class j. Whenever the variable lag is used, it denotes the lagged dependent variable. R^2 is the coefficient of determination, R^2_C is the adjusted R^2 while $\hat{\pi}(Y|\mathcal{M}_l)$ is the estimate of the marginal likelihood used to select amongst models in a Bayesian framework (see Appendix A); its standard deviation is the term in parentheses.[4] Moreover, we would like to comment on the fact that model selection prefers models also where for some variables the interval parameter estimate $\pm$ standard deviation covers zero. This is especially the case with the variable $GCPX$. Nevertheless, the reader should note that including these variables significantly improves the model likelihoods; in terms of R^2 this effect accounts for approximately 5 percentage points.

Table 5: Means and standard deviations of the parameters α, β from the marginal posterior for the variable $Entry_t$; $k = 3$; (3000 MCMC steps, 1000 burn-in steps).

Common variables					
GS	GE	GCON	GSUB	GMES	lag
0.0457	0.2252	-0.0908	0.2542	-0.2910	0.0819
(0.048)	(0.154)	(0.116)	(0.041)	(0.257)	(0.035)
Component specific variables					
GCPX_1	GCPX_2	GCPX_3	$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	$\hat{\beta}_{c,3}$
-0.0212	0.0285	0.0314	5.2868	5.8024	8.2406
(0.113)	(0.117)	(0.052)	(0.604)	(0.542)	(1.223)
R^2 =0.3973		R^2_C =0.3756			
$\hat{\pi}(Y|\mathcal{M}_l) = -530.4584$ (0.0484)					

Let us investigate the estimation results. In Table 3 we have listed the independent variables with their expected signs. The following paragraphs check these expectations against our estimation results. Before, we investigate the effects of the individual variables we want to note that the

[4]For example with Entry we get a model likelihood of -530.4584 (0.0484) for the model presented in Table 5; skipping the variable GCPX results in -541.6388 (0.1790) with $k = 3$, while using the predictors of Table 5 and $k = 2$ results in -534.0925 (0.139). E.g. for exits we derive -608.0214 (0.385), when skipping the variable $|GCPX|$; GCPX is component specific. For the same setting a two factor analysis results in -614.8413 (0.339). With Net the three factor model results in -617.5206 (0.0324). For Turn and Vol we derive -707.2449 (0.046) and -772.2268 (0.035) for $k = 2$ with equal prediction variables.

Table 6: Means and standard deviations of the parameters α, β from the marginal posterior for the variable $Exit_t$; $k = 3$; (3000 MCMC steps, 1000 burn-in steps).

Common variables					
GS	GE	GCON	GSUB	GMES	lag
0.0298	-0.2050	–	-0.1192	0.1491	-0.2318
(0.049)	(0.081)		(0.051)	(0.027)	(0.025)
Common variables			Component specific variables		
$\|GCPX\|$	GCPX		$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	$\hat{\beta}_{c,3}$
0.1227	-0.0337		7.4983	8.0249	9.8967
(0.052)	(0.029)		(0.547)	(0.570)	(0.6950)
R^2 =0.2326		R^2_C =0.2218			
$\hat{\pi}(Y\|\mathcal{M}_l) = -598.5181$ (0.0609)					

Table 7: Means and standard deviations of the parameters α, β from the marginal posterior for the variable Net_t; $k = 2$; (3000 MCMC steps, 1000 burn-in steps).

Common variables					
GS	GE	GCON	GSUB	GMES	lag
0.0354	0.2625	–	0.3103	-0.3402	-0.0289
(0.027)	(0.093)		(0.050)	(0.036)	(0.046)
Component specific variables					
GCPX_1	GCPX_2		$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	
0.1250	-0.0332		-2.2032	-0.3816	
(0.039)	(0.044)		(0.578)	(0.288)	
R^2 =0.3740		R^2_C =0.3582			
$\hat{\pi}(Y\|\mathcal{M}_l) = -598.2722$ (0.0033)					

estimates in Tables 5 to 9 are "consistent". From the definitions of Section 2, the variables Net, Turn and Vol are functions of Entry and Exit. E.g. we observe that the parameters of Net are approximately the parameters of Entry minus the parameters of Entry. This check is performed by looking at the parameter estimates of Table 5 ± the estimated standard deviations and the estimates of Table 6 ± the estimated standard deviations. If the Net parameters are in these intervals this kind of consistency criterion is fulfilled (see Table 7) ; for the variable GCPX this type of consistency can also be verified, this will be done during the discussion of GCPX. Similar checks have been performed for Turn and Vol.

Sales and Employment (incentives): First let us start with the growth of sales and employment. These variables are predictors of future profit and market growth, such that the term incentive variables can be used. We find that the response to the two indicators of market growth is different for entry and exit. First of all we observe that the variable GS turns out to be a common variable.

Table 8: Means and standard deviations of the parameters α, β from the marginal posterior for the variable $Turn_t$; $k = 3$; (3000 MCMC steps, 1000 burn-in steps).

Common variables					
GS	GE	GCON	GSUB	GMES	lag
0.0721	–	–	0.0664	-0.0748	-0.1336
(0.041)			(0.071)	(0.041)	(0.027)
Component specific variables					
$GCPX_1$	$GCPX_2$	$GCPX_3$	$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	$\hat{\beta}_{c,3}$
-0.1099	-0.0772	0.0707	13.9501	14.7697	17.2808
(0.179)	(0.175)	(0.107)	(0.936)	(0.825)	(1.303)
R^2 =0.2502		R_C^2 =0.2386			
$\hat{\pi}(Y\|\mathcal{M}_l) = -702.0179$ (0.0202)					

Table 9: Means and standard deviations of the parameters α, β from the marginal posterior for the variable Vol_t; $k = 3$; (3000 MCMC steps, 1000 burn-in steps).

Common variables					
GS	GE	GCON	GSUB	GMES	lag
0.0435	-0.4360	–	-0.3291	0.3796	-0.1700
(0.100)	(0.171)		(0.107)	(0.072)	(0.035)
Component specific variables					
$GCPX_1$	$GCPX_2$	$GCPX_3$	$\hat{\beta}_{c,1}$	$\hat{\beta}_{c,2}$	$\hat{\beta}_{c,3}$
-0.0123	-0.0646	-0.0470	14.841	15.903	17.7958
(0.246)	(0.202)	(0.245)	(1.169)	(1.033)	(1.625)
R^2 =0.2012		R_C^2 =0.1911			
$\hat{\pi}(Y\|\mathcal{M}_l) = -770.7551$ (0.7649)					

I.e. the effect of growth of sales on entry, exit, etc. is homogeneous across the industries concerned. The signs of the regression parameters in Tables 5, 7 and 8 meet our expectations (see Table 3), except for Exit. The positive sign in Table 9 shows that the effect from turnover is stronger than the effect from net entries. Note that the difference of the GS parameter estimate in Table 8 minus the estimate in Table 7 is approximately equal to the estimate in Table 9. Surprisingly the sign in Table 6 is positive which implies that higher sales growth increases exit. One explanation of this effect is that a growth in sales is accompanied by a displacement effect where newly entering firms drive small firms from the market (Carree and Thurik (1996)). The fact that the GS parameter in the turnover model dominates the GS parameter in the net entry model strengthens this claim. We conclude that unexpectedly GS is weakly symmetric. Next, let us investigate employment growth (GE). In contrast to GS the estimated parameter in Table 6 is negative an meets our expectations that an increase in employment reduces the pressure to exit. Interestingly model selection skips the variable GE in the turnover model. This shows that GE is asymmetric in strong form, as the GE parameter in the Net model is large and carries a low standard error. As already noted in Section 2, the strong asymmetry hypothesis corresponds to a coefficient of zero in the Turn model. We observe that GE is strongly asymmetric while GS is weakly symmetric. The strong symmetry of GE seems at first to contradict the findings of Carree and Thurik (1999) for retailing in the Netherlands and MacDonald (1986) for American Manufacturing, who find that the effect of industry growth on the entry rate is larger than on the exit rate. However, the symmetry of GS indicates that it is the growth without employment which drives these findings: While employment growth influences the entry and exit decisions in the same way, sales growth is different, as it drives firms into the industry but does not reduce the entry rate at all. Our finding of weak symmetry for an incentive variable is not without precedent. Dunne and Roberts (1991) are the first widely quoted study which found weak symmetry for the relationship of price-cost margins and entry and exit for US manufacturing industries. Fotopoulos and Spence (1998) found the same for Greek manufacturing. In our case entry is more elastic than exit, so that the sign of GS in the net entry equation is positive. Depending on entry barriers, entry may not be successful, leads to exit in the presence of higher sales growth, resulting in higher industry turbulence and volatility.

Growth of plant size: The variable GMES measures the change in the MES and therefore acts as a measure for the change in scale economies. Overall the estimation results show that the growth rate of weighted plant size (GMES) is not symmetric. It is as expected negative for entry, positive for exit. The influence on net entry is much stronger than its influence on the turnover. In both models the influence is negative. The growth rate of MES reduces both net entry and the turnover of firms. Therefore, climbing minimum weighted plant sizes increase the volatility. A higher MES reduces the carrying capacity of the industry and indicates the presence of scale economies. Contrary to the findings of Fotopoulos and Spence (1999) who report a negative relationship between scale economies and net entry for consumer and intermediate goods industries and a positive for net entry and capital goods industries for Greek manufacturing, we find that the relationship is negative for all industries. More formally, the variable GMES as a component specific variable has been rejected against GMES as a common variable by model selection.

Concentration: Concentration, measured by GCON, is primarily a barrier to entry. A higher concentration reduces entry. This is in line with the literature (Caves (1998)). However, the standard deviation of the estimator is high. Thus, model selection excludes the prediction variable GCON for Exit, Net, Turn and Vol. This result is not surprising given the generally thin evidence for a strong relationship between turnover and concentration. Baldwin (1995) finds for Canadian manufacturing that high turnover and stable concentration are compatible for industries at very different concentration levels. The evidence on the relationship running form concentration to mobility is similarly thin, for example Acs and Audretsch (1990) reported a positive influence of concentration on mobility in U.S. manufacturing.

Heterogeneity: As expected a higher heterogeneity - measured by the variable GSUB - increases entry, interestingly and in line with our expectations it decreases the exit rate. The effect on net entry is positive as is the effect on the turnover. We find that heterogeneity decreases volatility.

A more careful look at the parameter estimates of the variable GSUB shows that the estimate in Table 9 is the difference of the estimates in Table 8 and Table 7 . I.e. with respect to heterogeneity the effect of net entries is stronger than the turnover effect. Thus, despite of the fact of higher turnover (parameter estimate in Table 8 is positive), a higher GSUB creates some kind of room for new firms (see Audretsch (1995)). While the effect of GSUB on volatility is negative the effect on turnover is positive. The effect on net entries positive and stronger than on the turnover. This is a interesting finding, as this implies that a higher heterogeneity increases the successful survival of entering firms. GSUB is asymmetric which suggests that we are not capturing primarily a fringe effect. The fringe effect should be symmetric (see Dunne *et al.* (1988), Rosenbaum and Lamort (1992), Fotopoulos and Spence (1998)).

Growth in Vertical Integration, Complexity: The variable GCPX is the growth rate of the fraction of the net to the gross production value. GCPX can derive from vertical integration proper or from quality upgrading in production. Therefore, the signs in Table 3 are vague. The interesting fact from a statistical point of view has already been discussed at the beginning of this section. Only with the volatility the signs of the estimates are unique. A higher GCPX reduces volatility. For the other variables we observe positive and negative effects of GCPX. Moreover, let us comment on the exit rates (see Table 6), where the effect of GCPX is negative, but model selection demands the inclusion of the absolute value of GCPX. Including $GCPX$ and $|GCPX|$ implies nothing more than an asymmetry with respect to growing and falling vertical integration. If GCPX is positive the model predicts a rise in the exit rate of 0.0890, while a negative GCPX predicts a increase in the exit rate of 0.1564. This asymmetry may be due to non-rational effects, like every change - independent of the direction - creates an incentive for some firms to leave the market or due to threshold effects which are related to shocks. Model selection skips this variable $|GCPX|$ in all other setups. What remains to show is that the estimates of the variable $GCPX$ is "consistent" as discussed at the beginning of this section. Thus, the GCPX parameters in Table 5 minus the estimates in Table 6 have to approximately result in the GCPX parameters in Table 7. Using 0.0890 and 0.1564 with the corresponding standard deviations and the GCPX estimates of Table 5, we easily cover the estimates of Table 7. Overall we find that GCPX is weakly positively asymmetric for industries which have a low net entry state in the net entry equation (see Table 7). For the other industries nothing definitive can be said. The turnover equation (Table 8) is interesting. Here the intercept should capture primarily mobility barrier effects. Hölzl (2003) reports that CPX is a strong mobility barrier. We see that for high mobility barrier industries the effect of a higher GCPX is negative but for industries with low mobility barriers the association is positive. However, the standard errors are quite large. This suggests that changes in the complexity of operations have different effects on the turnover depending on the level mobility barriers. That the model selection did not call for the inclusion of the complexity variable (CPX) in levels can be interpreted in terms of the fixed effects captured by the switching intercept. It is well known that the relative time invariance of structural entry and exit barriers leads to the fact that industry dynamics regressions change dramatically when fixed effect regressions are used (Geroski (1995), Ilmakunnas and Topi (1999)). The fixed effects purge the variable of some of their between variation which is then already captured by the intercepts.[5]

Symmetry: The symmetry hypothesis states that entry barriers are also exit barriers. If this is correct the estimates in the Entry and the Exit model have to agree. Investigating our results this implies that the marginal posteriors do not overlap too strongly. We check whether estimates $\pm$ the estimated standard deviates of Tables 5 and 6 overlap. An additional check of symmetry result from the Turn and the Net models. Strong symmetry demands for a lot of probability mass around zero for the marginal posterior of the parameters in the net entry model, such that model selection excludes such prediction variables. This is only the case for GCON (see Table 7). However, GCON is also skipped in the Turn model. Strong asymmetry demands for a lot of probability mass around zero for the marginal posterior of the parameters in the turnover model, such that model selection excludes such prediction variables. This is only the case for GE (see Table 8). For GSUB, and GMES we find weak asymmetry and for GS weak symmetry. Last but not least, for GCPX we find indications of asymmetry and symmetry across the industry groupings identified by the estimation procedure. This is consistent with the interpretation that GCPX is a proxy for intangible sunk costs related to organizational capital and the knowledge base of the production process. The coefficients are not significant. This may be related to the fact that technological change is a slow process which is not well captured in our statistical model which emphasizes short and medium run dynamics.

Lagged variables: Statistical modeling demands for including the lagged explanatory variable to the set of prediction variables. From an economic point of view, these parameters can be used to characterize the long run behavior. Interestingly the estimated parameters of the lagged dependent variable have different signs for Entry and Exit. Table 5 shows a relatively small and positive parameter estimate. This implies that entries are weakly persistent, i.e. high entries yesterday result in high entries today. Contrary to the entry rate, exit rates exhibit a negative autoregressive parameter, the same is observed with the net entry rate. A negative autocorrelation can be motivated by the fact that if net entry is high in $t-1$, then due to higher competition, the profit opportunities are reduced in t; thus Net should decrease. A similar story holds for exits. Although this claim should also hold for the entry rate, this effect is perhaps overcompensated by some herd behavior such that a positive lagged parameter estimate is derived. Herd behavior can be due to irrationality or lack of information. Since the negative parameter for exits has a significantly higher absolute value than the Entry and the Net parameter estimates, the lagged parameters for Vol and Turn should be negative; the estimates of Table 8 and 9 verify this claim.

Clustering of industries: Another aspect with our the data set is the question:

> What industries i can be attributed to state or component j?

This questions can be investigated by means of MCMC output on the latent indicator S. For the entries, exits, net entries, turnover and volatility regressions the sampler provides series of $(S_{Entry}^{[m]})$,

[5]Furthermore, we would like to remark that some of the CPX_i, $i = 1, \ldots, 17$, are very close to a unit root (at a 10% significance level using a standard ADF test).

$(S^{[m]}_{Exit})$, $(S^{[m]}_{Net})$, $(S^{[m]}_{Turn})$ and $(S^{[m]}_{Vol})$, where $[m]$ is the index of the MCMC sampling step. Thus for a given model, the sampler provides us with the posterior distribution of the latent variable S_i for each industry. Therefore we are able to assign an industry to a component or state j, $j = 1, \ldots, k$, by calculating absolute frequencies from $(S_i^{[m]})$. An estimate $\hat{S}_i$ is derived by taking the component with the highest frequency. This results in a clustering of the industries. The reader should note that the MCMC sampler estimates the parameters and clusters the time series simultaneously. Therefore this procedure is also called *Bayesian clustering*. Tables 5-9 have already shown that the clustering is mainly due to the different barriers and incentives, respectively. The entry grouping captures entry barriers which are different across a class of industries. The switching intercept in the exit equation accounts for exit barriers. Especially interesting is the interpretation of the groupings in the Net and Turn equations. From the definition of symmetry and asymmetry we can conclude that the grouping in the turnover equation captures primarily barriers to mobility, while the net entry grouping accounts for common incentives and opportunities that are not accounted for by the variables used. Based on this it would be surprising to find that the clustering is uniform for the industries.

Table 10: Clustering of Industries by $\hat{S}_i$, $j = 1, \ldots, k$; (3000 MCMC steps, 1000 burn-in steps)

i	Industry	Grouping	Entry	Exit	Net	Turn	Vol
	estimated components k		3	3	2	3	3
1	stone and ceramics	intermediate	1	3	2	1	1
2	glass and glass products	intermediate	2	3	2	2	2
3	chemical industries	intermediate	1	2	2	1	1
4	manufacture of pulp and paper	intermediate	2	1	1	3	2
5	paper processing	intermediate	1	2	2	1	1
6	wood processing	consumer	2	2	2	2	2
7	food and tobacco	consumer	1	2	2	1	1
8	leather producing	consumer	2	1	1	3	2
9	leather processing	consumer	3	1	1	3	3
10	foundries	capital	1	2	2	2	1
11	metal industry except steel	capital	1	3	2	3	1
12	machinery and steel constructions	capital	1	3	2	2	1
13	transportation equipment	capital	1	3	2	1	1
14	iron and metal products	capital	1	2	2	2	1
15	electrical equipment and components	capital	2	2	2	1	2
16	textiles except clothing	consumer	2	1	1	3	2
17	clothing	consumer	3	1	1	3	3

Table 10 presents these estimates for the models and industries considered in this paper. E.g. consider the variable Entry: We observe that most industries are assigned to component/state 1, where we have a low entry rate (see estimates of the intercept $\hat{\beta}_{c,j}$ in Table 5). In this state we have a negative but low influence of the complexity variable GCPX. The industries with $i = 2, 4, 6, 15, 16$ belong to component 2, where the entry rate is slightly above component 1, however the influence of the complexity variable is low but positive for this component. Only in the leather processing and clothing industries we have a high entry rate. For the remaining variables the estimates of S_i can be interpreted equivalently. Fotopoulos and Spence (1999) studied the net entry behavior for three groups of Greek manufacturing industries - consumer, intermediate and capital goods. They found that there are significant differences in the determinants of net entry rates across industry groups. Table 10 reports in the third column the sectoral classification. We find that our Bayesian clustering is not related in a strong form to the sectoral classification, with the exception that capital goods industries seem to be more homogeneous than the other industries. However, the Bayesian clustering for the turnover behavior - according to Dunne *et al.* (1988) better suited to characterize industries than net entry rates - shows overall no relation to the sectoral grouping: Each value of the estimated component is found in each of the sectoral groupings. This result suggests that there is still high heterogeneity within the sectoral classification. It is worth noting that there is no one to one relationship between a high entry rate and a high exit rate or vice versa. By the following questions we investigate this problem in more detail:

1. Does a high entry rate in industry i imply a high net entry rate? Or more precisely, are S_{Entry}, S_{Exit}, S_{Net}, S_{Turn} and S_{Vol} independent.
2. Does a high exit rate imply a low net entry rate?
3. Are industries with high entry, exit or net entry rates more or less volatile?

As already described in the analysis of $\hat{S}_i$, these questions can be investigated by means of MCMC output on the latent indicator S. For the entries, exits, net entries, turnover and volatility regressions we get series of $(S^{[m]}_{Entry})$, $(S^{[m]}_{Exit})$, $(S^{[m]}_{Net})$, $(S^{[m]}_{Turn})$ and $(S^{[m]}_{Vol})$, where $[m]$ is the index of the MCMC sampling step. The following analysis cannot show causalities, however independence can be checked easily. By applying χ^2 contingency table tests (see e.g. Bickel and Doksum (2001)[p. 405]), we observe that the zero hypothesis S_a is independent of S_b has to be rejected - even on a 1% confidence level - for all pairs S_a, S_b taken form $\{S_{Entry}, S_{Exit}, S_{Net}, S_{Turn}, S_{Vol}\}$. Then, conditional probabilities can be obtained from MCMC output. I.e. calculate $\mathbb{P}(S_a = j \cap S_b = j')$ and $\mathbb{P}(S_b = j')$ from MCMC output, then

$$\mathbb{P}(S_a = j | S_b = j') = \frac{\mathbb{P}(S_a = j \cap S_b = j')}{\mathbb{P}(S_b = j')} \ . \tag{2}$$

Table 11 presents the estimates of these conditional probabilities. Note that Table 11 reads as follows: the conditional probability that the exit rate is in state $j = 1$ (exits are low) given that entries are low $j' = 1$ is 0.3432, etc.

Table 11 provides us with the following information: The conditional probabilities of exits given entries are not very different for entries being in class one or two. A look at the estimates of the intercept terms $\beta_{c,1}$ $\beta_{c,2}$ also confirms this results since their posteriors have relatively large overlapping regions (see Table 5). For $S_{Entry} = 3$ the probabilities of Exits | Entries are different. Stronger differences are observed with the variables entry, exit and turnover. I.e. consider the third row: If entries are in state one, then the conditional probability of low or medium turnover is high, 0.4835 and 0.3981 respectively. Approximately the same is observed with a medium entry rate, while with high entry rate ($j' = 3$) the conditional probability of low turnover is 0.1824.
For exits and entries we observe that when turnover is low then the probabilities of low and medium entry rates are high and vice versa. With net entries this effect is already present but much weaker than with the gross rates.

Table 11: Conditional probabilities $\mathbb{P}(S_a = j|S_b = j')$; (3000 MCMC steps, 1000 burn-in steps)

j'		1			2			3	
j	1	2	3	1	2	3	1	2	3
				$S_b = S_{entry}$					
Exit	0.3432	0.4179	0.2390	0.3319	0.4113	0.2568	0.4802	0.3131	0.2066
Net	0.4500	0.5500	–	0.4778	0.5222	–	0.2274	0.7726	–
Turn	0.4835	0.3981	0.1184	0.4405	0.4148	0.1447	0.1824	0.3925	0.4251
Vol	0.3317	0.3809	0.2874	0.3137	0.3708	0.3155	0.3249	0.3224	0.3527
				$S_b = S_{exit}$					
Entry	0.3870	0.3695	0.2435	0.4331	0.4210	0.1459	0.4082	0.4332	0.1587
Net	0.2643	0.7357	–	0.4327	0.5673	–	0.6357	0.3643	–
Turn	0.4492	0.3990	0.1518	0.4428	0.4266	0.1306	0.2987	0.3737	0.3276
Vol	0.3946	0.3678	0.2376	0.3135	0.3782	0.3083	0.2309	0.3433	0.4258
				$S_b = S_{Net}$					
Entry	0.4395	0.4607	0.0998	0.3893	0.3649	0.2458	–	–	–
Exit	0.2289	0.4077	0.3634	0.4617	0.3873	0.1510	–	–	–
Turn	0.3765	0.3944	0.2292	0.4352	0.4107	0.1541	–	–	–
Vol	0.2492	0.3619	0.3889	0.3768	0.3690	0.2542	–	–	–
				$S_b = S_{Trub}$					
Entry	0.4833	0.4347	0.0820	0.4045	0.4162	0.1793	0.2617	0.3159	0.4224
Exit	0.3982	0.4270	0.1748	0.3595	0.4182	0.2223	0.2975	0.2785	0.4240
Net	0.3853	0.6147	–	0.4103	0.5897	–	0.5187	0.4813	–
Vol	0.3608	0.3942	0.2450	0.3205	0.3714	0.3081	0.2459	0.2918	0.4623
				$S_b = S_{Vol}$					
Entry	0.4212	0.3933	0.1855	0.4270	0.4105	0.1625	0.3794	0.4112	0.2093
Exit	0.4443	0.3841	0.1716	0.3656	0.4090	0.2253	0.2782	0.3927	0.3291
Net	0.3240	0.6760	–	0.4155	0.5845	–	0.5257	0.4743	–
Turn	0.4583	0.4004	0.1412	0.4421	0.4098	0.1480	0.3236	0.4003	0.2761

Dunne *et al.* (1988) studied serial correlation and correlation for US manufacturing industries and found entry and exit is volatile but also indication that the high correlation between entry and exit is related to industry-specific factors. Since the variables inferred by our econometric tools are included in the entry and the exit rate model (except GCON), the dependent variables Entry and Exit are correlated. Our analysis shows that some kind of extra interdependence between the variables Entry and Exit enters via the joint distribution of the latent indicators ($S^{[m]}_{Entry}$) and ($S^{[m]}_{Exit}$).

5 Conclusions

This paper studies entry and exit dynamics for the Austrian manufacturing sector. The study is based on sector based data form 1981 to 1994, provided from the Austrian chamber of commerce. We find that our model was relatively successful in identifying the patterns of entry and exit within Austrian manufacturing. The regression results indicate that there is a strong structure effect determining the entry and exit dynamics in Austrian Manufacturing. The analysis of conditional probabilities shows that entry and exit processes are closely related. Whether this is due to symmetry or due to simultaneity is relegated to further research. We obtained a number of important insights:

1. Changes in MES, size heterogeneity and concentration are not symmetric in respect to entry and exit.

2. The growth rates in sales and employment do indicate different aspects of industry growth. The growth of industry employment is strongly asymmetric, while the growth rate of sales is weakly symmetric. This result of symmetry of an incentive mirrors the results obtained for profitability measures by Dunne and Roberts (1991) and Fotopoulos and Spence (1998).

3. Changes in complexity of operations are asymmetric for sectors with particularly low net entry rates, while they are symmetric for other industries.

4. There is a close relationship between entry and exit rates across industries in Austrian Manufacturing: The turnover of firms influences the changes in the number of competitors. Low entry rates go hand in hand with low net entry rates and a low turnover.

5. The Bayesian clustering of industries indicates that no simple classification can be made which accounts for incentives and barriers.

An interesting question remaining for further research is whether entries, exits, employment and production are truly interdependent. We want to know whether market entries stimulate economic growth and generate employment and vice versa. I.e. we want to investigate "causalities". An industry by industry analysis will prevent us from including weakly exogenous variables due to identification issues. Estimation an identification of latent class system has to be developed. As far as we know this problem has not been solved.[6] Therefore, this question has to be postponed to further research.

[6]Some first results, neglecting identification and prior construction can be found in Ansari (2000).

A Bayesian analysis of latent class models

This section briefly describes the Bayesian estimation methodology of model (1) based on Tüchler *et al.* (2001), Otter *et al.* (2002) and Frühwirth-Schnatter and Kaufmann (2002). Let us consider a latent class model (1):

$$y_{i,t} = Z_{i,t}\alpha + W_{i,t}\beta_j + \varepsilon_{i,t} \ ,$$

where $\varepsilon_{i,t}$ are independent standard normally distributed error terms with variance σ^2, i.e. $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma^2)$. The unknown variables in the model are α, $\beta = (\beta_1, \ldots, \beta_k)$, the group probabilities $\eta = (\eta_1, \ldots, \eta_k)$ and the variance term σ^2. This set of unknown variables is abbreviated by θ. The augmented set of parameters consists of θ and the latent indicator variable $S = (S_1, \ldots, S_i, \ldots, S_I)$; the set $(\theta \cup S)$ is called Ψ. $Y = \bigcup_{i,t}\{y_{i,t}, Z_{i,t}, W_{i,t}\}$ are the data available.
By the Bayes theorem (see e.g. Robert (1994) or Bickel and Doksum (2001)) we have the following relationship between the posterior $\pi(\Psi|Y)$, the likelihood $f(Y|\Psi)$ and the prior $\pi(\Psi)$:

$$\pi(\Psi|Y) \propto f(Y|\Psi)\pi(\Psi) \ , \tag{3}$$

where the symbol $\propto$ stands for "proportional to". By the model assumptions the likelihood factorizes into a product of normal densities $f_N(.)$, i.e.

$$f(Y|\Psi) = \Pi_{i=1}^{I}\Pi_{t=1}^{T}\left(\sum_{j=1}^{k}\mathbf{1}_{(S_i=j)} f_N(y_{i,t}|Z_{i,t}, W_{i,t}, \alpha, \beta_j, \sigma^2)\right) \ . \tag{4}$$

$\mathbf{1}_{(S_i=j)}$ is an indicator function. This implies that $y_{i,t} \sim \mathcal{N}(Z_{i,t}\alpha + W_{i,t}\beta_j, \sigma^2)$, for $S_i = j$.
Priors: Since we perform a Bayesian estimation of the parameters we have to define a prior distribution for Ψ, $\pi(\Psi)$. $\pi(\Psi)$ decomposes into

$$\pi(\Psi) = \pi(S|\theta)\pi(\theta) = \pi(S|\eta)\pi(\eta)\pi(\beta)\pi(\alpha)\pi(\sigma^2) \ . \tag{5}$$

Conditional on η, S_i are multinomial trials, such that $\pi(S|\theta) = \pi(S|\eta) = \Pi_{j=1}^{k}\eta_j^{D_j}$ by the model assumptions. For the remaining parameters we use conjugate priors. For η we use a Dirichlet prior $\mathcal{D}(e_{01}, \ldots, e_{0k})$. In the current analysis we set $e_{0.} = 1$, resulting in a uniform prior on the unit simplex, i.e. this prior is uninformative. For $\pi(\beta)$ and $\pi(\alpha)$ we use normal priors $\mathcal{N}(a_0, A_0)$ and $\mathcal{N}(b_0, B_0)$. We set a_0 and b_0 to vectors of zeros; the dimensions correspond to the dimensions of α and β. A_0 and B_0 are diagonal matrices of proper dimensions, the diagonal elements are set to 1000. Finally, we use the conjugate inverse gamma prior $\mathcal{IG}(\nu_0, G_0)$ for $\pi(\sigma^2)$; we set $\nu_0 = 1$ and $G_0 = 1$. By these uninformative prior assumptions the impact of the prior on the estimation results is minor.
MCMC: Since all conditional distributions of model (1) are well defined, Markow chain Monte Carlo methods can be applied easily. For more detailed information on Markov chain Monte Carlo methods the reader is referred to Albert and Chib (1993), Casella and George (1992), Greene (1997)

and Robert (1994). For the underlying model updating sweep m, from $\Psi^{[m-1]}$ to $\Psi^{[m]}$, is split up into four steps:

Step 1:	$S^{[m]}$	from	$\pi(S\|Y, \theta^{[m-1]})$
Step 2:	$\eta^{[m]}$	from	$\pi(\eta\|Y, S^{[m]})$
Step 3:	$(\alpha^{[m]}, \beta^{[m]})$	from	$\pi(\alpha, \beta\|Y, S^{[m]}, \sigma^{2\ [m-1]})$
Step 4:	$\sigma^{2\ [m]}$	from	$\pi(\sigma^2\|Y, S^m, \alpha^{[m]}, \beta^{[m]})$

The above procedure is repeated until the Markov-chain has reached or is supposed to be near its invariant distribution. In this article convergence will be checked as follows: We run the sampler for $M = 3000$ time steps and cut off the first 1000 samples of $(\Psi^{[m]})$ (*burn-in phase*). By repeating this procedure, we check whether the generated distributions derived from different runs agree. If an unrestricted sampler is applied the sampler produces or proposes candidates from only some regions of the parameter space (i.e. mixing is bad). Imposing a restriction $\mathcal{R}$ on θ, i.e. $\theta_1 < ... < \theta_j < ... < \theta_k$, clearly improves the mixing of the sampler. In this article, we follow the method of Frühwirth-Schnatter (2001) called *permutation sampling* which is very efficient from a computational point of view. To be more precise it turns out that the restriction $\mathcal{R}$ on β_c=$(\beta_{c,1}, \ldots, \beta_{c,k})'$ performs well with the underlying data; $\beta_{c,j}$ is the constant term.
Let us briefly comment on steps 1-4: For Step 1 we propose S from an uniform distribution on a discrete grid. To update S we use the Metropolis Hasting algorithm (see e.g. Robert and Casella (1999)[chapter 6]), where the reader should note that

$$\pi(S|Y,\theta) \propto \Pi_{i=1}^{I}\Pi_{t=1}^{T}\left(\sum_{j=1}^{k}\mathbf{1}_{(S_i=j)}f_N(Y_{i,t}|W_{i,t}, Z_{i,t}, \alpha, \beta_j, \sigma^2)\eta_j\right) , \tag{6}$$

$$\pi(S_i = j|Y,\theta) \propto \Pi_{t=1}^{T}\left(\sum_{j=1}^{k}\mathbf{1}_{(S_i=j)}f_N(Y_{i,t}|W_{i,t}, Z_{i,t}, \alpha, \beta_j, \sigma^2)\eta_j\right) . \tag{7}$$

Since we chose a Dirichlet prior the conditional $\pi(\eta|Y, S^{[m]})$ is once again a Dirichlet distribution with parameters $e_j = e_{0,j} + D_j$, where $D_j = \#(S_i = j)$. To sample α and β in one block, we define a vector of regression parameters $\gamma := (\alpha, \beta_1, \ldots, \beta_j, \ldots, \beta_k)'$. If α is of dimension l_α and β_j is of dimension l_β then the dimension of γ is $l_\gamma = l_\alpha + kl_\beta$. Next we construct a design matrix V as follows: $V_{i,t} = (Z_{i,t}\ W_{i,t}\mathbf{1}_{(S_i=1)}\ \ldots\ W_{i,t}\mathbf{1}_{(S_i=j)}\ \ldots\ W_{i,t}\mathbf{1}_{(S_i=k)})$. $V_i^{(T)} = (V_{i,t})_{t=1}^T$ is of dimension $[T \times q_\gamma]$. V is derived by $V = (V_1^{(T)}, \ldots, V_k^{(T)})'$, the dimension is $[TI \times q_\gamma]$. Note that y is a stacked vector consisting of $((y_{i,t}))_{t=1}^T)_{i=1}^I$. Then $y_{i,t} = V_{i,t}\gamma + \varepsilon_{i,t}$ is a standard regression model where we condition on S. Thus, we are able to use the normal priors and define $c_0 = (a_0, b_0, \ldots, b_0)'$ and $C_0 = diag(A_0, B_0, \ldots, B_0)$; b_0 and B_0 are inserted for k times into c_0 and C_0, $diag$ stands for diagonal matrix. Then (α, β) is normal with parameters c and C, where

$$C = \left(V'V/\sigma^2 + C_0^{-1}\right)^{-1} \tag{8}$$

$$c = C\left(V'y/\sigma^2 + C_0^{-1}c_0\right) . \tag{9}$$

Now (α, β) can be sampled in Step 3 from a $\mathcal{N}(c, C)$ distribution. Last but not least σ^2 is sampled from an inverse gamma distribution with parameters $\nu = \nu_0 + \frac{IT}{2}$ and $G = G_0 + \frac{1}{2}\sum(\gamma V - y)^2$. If σ^2 is large like in the data we use in our analysis, MH updates from a log normal proposal of the variance of the regression residuals turned out to be more efficient than Gibbs updates.
Model Selection: Model selection in Bayesian setting is elegant but time consuming. Therefore we pre-select some model by some standard but non-Bayesian criteria. Here, we use the adjusted coefficient of determination R^2_C the Scharz criterion. We derive the adjusted R^2_C and the Scharz criterion from MCMC output as follows: (i) Calculate the posterior means $\hat{\alpha}$ and $\hat{\sigma}^2$. (ii) Plug in $\hat{\alpha}$ to derive R^2_C; R^2 is calculated equivalently.
¿From a pure Bayesian point of view, we are interested in the posterior probabilities

$$\pi(\mathcal{M}_l|Y) \propto \pi(Y|\mathcal{M}_l)\pi(\mathcal{M}_l)$$

of some models $(\mathcal{M}_l)$, $l = 1, \ldots, L$.
¿From the Bayes theorem we know that the non-normalized posterior fulfils $\pi(\Psi|Y) \propto f(Y|\Psi)\pi(\Psi)$. The normalized posterior is derived from

$$g(\Psi|Y) = \frac{\pi(\Psi|Y)}{\int f(Y|\Psi)\pi(d\Psi)} \ ,$$

where $\int f(Y|\Psi)\pi(d\Psi)$ is the normalizing constant. This normalizing constant is nothing more than $\pi(Y|\mathcal{M}_l)$, which is required to calculate the model posterior. Thus, given a prior for a model, $\pi(\mathcal{M}_l)$, we derive the posterior probabilities of a set of models $(\mathcal{M}_l)$, $l = 1, \ldots, L$, by calculating $\pi(Y|\mathcal{M}_l)$ from MCMC output. In this paper we apply the method of importance sampling as described in Frühwirth-Schnatter (2002), to derive the desired model posterior. In the ongoing analysis we use the uninformative model prior $\pi(\mathcal{M}_l) = 1/L$, such that the posterior distribution of the models $\mathcal{M}_l$ is determined by the normalizing constants $\pi(Y|\mathcal{M}_l)$. The "best" model is the model with the highest posterior probability, i.e. we choose the model where the estimate $\hat{\pi}(Y|\mathcal{M}_l)$ peaks; the standard deviation of $\hat{\pi}(Y|\mathcal{M}_l)$ is derived by bootstrapping.

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