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SECTORAL ADJUSTMENT OF EMPLOYMENT TO SHIFTS IN OUTSOURCING AND TRADE: EVIDENCE FROM A DYNAMIC FIXED EFFECTS MULTINOMIAL LOGIT MODEL

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SUMMARY

This paper analyzes the effects of trade and outsourcing on the transition probabilities of employment between sectors, using a dynamic multinomial logit framework with fixed effects. The data cover a sample of individual Austrian male workers over the period 1988–2001. Our results strongly support the view that international economic forces are important determinants of labor market turnover. In particular, an increase in the outsourcing intensity negatively affects the probability of staying in or changing into the manufacturing sector, even more so for industries with a comparative disadvantage. Copyright © 2007 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The impact of increasing trade volumes and intensified foreign competition on the labor market has been of growing concern in recent years. International trade theory suggests that import competition (Wood, 1995) and, especially, international outsourcing (Feenstra and Hanson, 1999) affect (unskilled) workers by lowering their relative wages. Krugman (1995) emphasizes that the composition of goods trade, rather than the volume of trade, matters. In particular, he shows that the degree of outsourcing, measured by the share of intermediate goods trade, generates adverse labor market reactions. Such adverse effects of international outsourcing of unskilled labor-intensive fragments of the value-added chain are typically derived in one-sector models such as that of Feenstra and Hanson (1999). In their model, outsourcing leads to a decrease in relative demand for unskilled workers. In contrast, Heckscher–Ohlin type models with more than one sector tend to suggest the opposite, namely that the remaining fragment of the outsourcing industry, if it is still relatively (unskilled) labor intensive as compared to the other industry, actually expands, leading to a higher level of both wages and employment in this industry due to Stolper–Samuelson effects (Arndt, 1997; Egger, 2002; Egger and Egger, 2001; Egger and Falkinger, 2003). However, Kohler (2001) shows that this conclusion does not hold in a model with sector-specific capital. In the short or medium run a sector which outsources labor-intensive production stages experiences a decline

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in employment. Most of the theoretical studies on labor market effects of international outsourcing assume perfect labor markets, which seems at odds with the empirical stylized facts, especially for European economies. If labor market imperfections are considered (see Egger and Egger, 2003, for a one-sector model and Egger and Kreickemeier (2006) for a two-sector approach; Nelson 2005, (unpublished, Princeton University, 2005) provides an excellent recent survey), effects on both wages and employment may arise, pointing in the same direction.

In any case, these conclusions are based on static general equilibrium models which capture long-run effects. The corresponding short-run transitory dynamics are less understood, but are a major research topic in labor economics. Here, the nature of adjustment processes in the labor market induced by increasing trade volumes is of particular interest. At the individual level trade-related shocks may lead to job losses. Since the experience of unemployment exhibits persistent effects due to human capital loss, the labor market adjustment processes may be delayed or even prevented. In this case, it is not sufficient to investigate the long-run wage effects only. The short-run transition of workers from the sectors negatively affected by trade shocks to other, expanding sectors or to unemployment or are of particular interest.

Empirical research on short-run labor market dynamics has followed two routes (see Klein *et al*., 2003b, for an overview). One strand of the literature assesses the impact of trade-related variables, most prominently the real exchange rate, on the levels or changes in *net* employment at an aggregate level. Early research looks at the consequences of real appreciation of the US dollar on the US labor market (Grossman, 1986; Ravenga, 1992).[1] Most of the available results point to a negative impact of an exchange rate appreciation on employment and wages.

The second strand of the literature investigates the consequences of increasing trade volumes on *gross* flows of jobs or workers. Job flow studies, on the one hand, look at job creation and job destruction. Prominent examples are those of Davis *et al*. (1996), Gourinchas (1998) and Klein *et al*. (2003b). Their findings indicate that an impact of international factors on job flows is hard to detect, specifically if low-frequency data are used. Most of the work is based on US data. However, there is now also evidence on gross job flows in Europe, pointing to comparable job reallocation rates as in the USA. Among the European countries, Germany (Boeri and Cramer, 1992) exhibits somewhat lower turnover rates than countries like Sweden (Persson, 2000) or Austria (Hofer *et al*., 2001). However, Stiglbauer *et al*. (2003) find that Austrian worker flows are smaller than previously argued. The worker flow approach, on the other hand, studies employment movements of individual workers and 'has the advantage of identifying the impact of international factors on gross labor flows at a more fundamental level ... than job flows' (Klein *et al*., 2003a, p. 22). Goldberg *et al*. (1999) and Kletzer (2002) are two recent examples in this regard. Goldberg *et al*. (1999) find that exchange rate movements have no overall significant effect on employment stability. Their impact is rather concentrated in specific sectors and may have different effects depending on whether they arise through the export or import channel. Kletzer (2000, 2002) finds that higher export sales reduce displacement rates, while import competition does not seem to affect displacement rates significantly.

The present paper takes a closer look at the impact of trade on employment in a worker flow approach and concentrates on the short-run employment dynamics. Using a detailed database of individual Austrian male workers over the period 1988–2001, we investigate whether and how growth in goods imports, exports, a change in the terms of trade, and the intensification of

[1] Burgess and Knetter (1998) were the first in assessing this effect in a larger cross-section of countries (the G-7). More recent studies are Campa and Goldberg (2001) and Goldberg (2004).

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outsourcing affect individual transition probabilities between six different states of employment and unemployment/out of labor force. However, we also consider the role of technical change as a driving force of labor market adjustment.

From a European perspective, Austria is a prime example for studying the impact of trade liberalization (Aiginger *et al.*, 1996; Hofer and Huber, 2003). Due to the opening up of Eastern Europe at the beginning of the 1990s we observed a marked increase in trade and outsourcing volumes during the last decade. In addition, the Austrian labor market is characterized by highly centralized wage bargaining. Under these circumstances labor market turnover is the main channel of adjustment to external industry-specific shocks.

The contribution of this paper is twofold. First, in contrast to the previous literature, which concentrated on the impact on job loss or displacement rates mostly in a cross-section, we formulate a more concise model, which also incorporates the longitudinal dimension. In this set-up it is possible to model the full transition matrix between states/sectors. Furthermore, we are able to assess the impact of international trade and outsourcing on job creation in the manufacturing sector, controlling for unobserved individual characteristics of workers. Thereby we distinguish between comparative advantage (CA) manufacturing industries and those with a comparative disadvantage (CDA). The analysis at the individual level is especially important, since trade-displaced workers might exhibit different patterns of labor market adjustment depending on their personal characteristics. Kletzer (2000, p. 26f) argues that 'the source of the difficulty is their otherwise disadvantaged characteristics, not the characteristics of the displacement industry'. The transition matrix between labor market states is specified as a dynamic multinomial logit model, for which Honoré and Kyriazidou (2000) propose a fixed effects estimator. With this estimation methodology it is possible to reduce the bias from time-invariant unobservable individual specific influences (like ability), part of which may be state specific.

Second, we propose a generalization of the Honoré and Kyriazidou (2000) estimation procedure by allowing heterogeneous effects of the explanatory variables depending on the state of origin. With this more general model we can investigate whether the impact of trade on labor market transitions depends on the previous labor market state.

2. A MODEL FOR INDIVIDUAL LABOR MARKET TRANSITIONS

We model employment adjustment by individual labor market transitions. The aim is to estimate the impact of outsourcing and trade on those transitions. In our model, we consider direct transitions between industry sectors as well as transitions which take unemployment or out of labor force as an intermediate step. We distinguish between six different labor market states:

- employment in the service sector;
- employment in sales sector;
- employment in CA manufacturing sector;
- employment in CDA manufacturing sector;
- unemployment;
- out of labor force.

The comparative advantage of an industry is defined according to the revealed comparative advantage index, $RCA_{it} = \ln[(x_{it}/m_{it})/(X_t/M_t)]$, where $x_{it}(m_{it})$ are goods exports (imports) of

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industry i at time t and $X_t(M_t)$ are overall goods exports (imports) at time t. We classify a manufacturing industry as having a comparative advantage, if $RCA_{it} > 0$ for all t;[2] the remaining industries are classified as comparative disadvantage manufacturing industries.[3]

An important aspect in modeling individual labor market transitions is state dependence. For labor market states, as for many other situations, we observe that an individual who has experienced an event in the past is more likely to experience that event in the future than an individual who has not. Heckman (1981) discusses two explanations for this phenomenon. The first one is the presence of 'true state dependence', in the sense that the lagged state enters the model in a structural way as an explanatory variable. The second explanation maintains that individuals differ in some unmeasured propensity to experience the event and this propensity is either stable over time or the values of the propensity are autocorrelated. Heckman calls the latter source of serial correlation 'spurious state dependence'. To disentangle both effects it is necessary to have longitudinal information on an individual basis. We model transitions by a first-order Markov chain[4] and allow for unobserved heterogeneity, thus capturing the spurious state dependence.

We also include time-varying explanatory variables. To assess the importance of increased trade openness and import competition on worker flows and sectoral adjustment, we use the growth in real goods imports and exports as explanatory variables (the export and import price indices use 1995 as the base year). The inclusion of real goods export and import values guarantees that these variables do not simply capture nominal effects such as the impact of inflation. These variables directly affect labor demand and the pace and structure of job creation and destruction. This set-up follows Kletzer (2000, 2002), who provides a comprehensive discussion of the role of trade variables in explaining changes in employment. Regarding the use of import growth as an explanatory variable for job destruction, Kletzer (2000) notes that—depending on the supply elasticities and the competitiveness of domestic firms relative to foreign ones—increasing imports may be associated with falling or rising import shares. Davidson and Matusz (2004, p. 5) note that a surge of imports reduces employment, but that only 'changes in trade flows, not levels of trade flows, cause changes in turnover rates' and, accordingly, in the transition probabilities in employment between sectors.

Similar to Goldberg *et al.* (1999), we also introduce a real exchange rate measure in an alternative specification. We follow Goldberg (2004) and construct a real (export plus import) trade-weighted Austrian exchange rate at the industry level, i.e. as a weighted, real effective exchange rate measure. A real appreciation is usually found to reduce labor demand and to raise the probability of job losses.

In all model specifications, we also account for the share of outsourcing in an industry. Previous research on international factors of job destruction predominantly focuses on overall (final plus intermediate) goods trade. We know from the recent trade and wages debate that components trade (cross-border fragmentation of production or international outsourcing) significantly affects wages and accounts for part of the rise in the US skilled-to-unskilled workers' wage gap. But to the best of our knowledge, Kletzer (2000, 2002) is the first to distinguish between final goods and intermediate goods trade in a worker flow approach. Trade theory is equivocal about the

[2] We argue that sticking to a time-variant measure of comparative advantage could be prone to endogeneity problems.

[3] Although it might be preferable to include not only goods trade but also trade in services in its definition, our measure of comparative advantage relies on goods trade only because of the lack of disaggregated service trade data over the covered period.

[4] Magnac (2000) and D'Addio and Honoré (2002) model duration dependence in a second-order Markov model. As we only consider transitions at an annual frequency, we argue that a first-order framework should be sufficient.

impact of outsourcing on employment at the sectoral level. Heckscher–Ohlin-based work á la Arndt (1997) supports the view that outsourcing of labor (rather than capital)-intensive production stages leads to an expansion of the labor-intensive sector in terms of both output and employment. Thereby, complete inter-sectoral mobility of all production factors is assumed, which makes the approach more suited for analyzing long-run effects. Viewing capital as sector specific in the short or medium run, Kohler (2001) illustrates that outsourcing of a sector's labor-intensive production stages is associated with a decline of this sector's employment. The results in Kletzer (2000, 2002) are in line with the latter reasoning. She provides evidence for the USA that outsourcing is indeed positively related to job loss.

Additionally, we introduce the growth of labor productivity as an—admittedly crude—indicator of technical change. From a theoretical point of view, the impact of labor productivity on labor demand and, hence, on job flows is not clear a priori.[5] On the one hand, we would expect that an increase in labor productivity reduces labor demand. On the other hand, if the increase is higher than that of the competing firms or industries abroad, domestic industries should be able to gain market shares, all else equal. Since we also control for terms of trade effects, the former effect should be relevant and we expect a negative impact on worker flows in a sector, which has been witnessing productivity gains. Furthermore, the productivity variable should pick up the long-term trends, like employment growth in the services sector and a reduction in the other sectors. Lastly, we control for age effects by introducing three age classes with age class >35 years forming the reference group to account for less mobility of older people.

In contrast to the trade and wages studies at the industry level (Feenstra and Hanson, 1999; Ravenga, 1992) all industry-specific variables enter our model as exogenous variables. We argue that from the Austrian perspective major changes in the trade variables during the 1990s may have been induced by the opening of the Eastern European countries. This can be seen as an exogenous influence. Furthermore, we are less worried about endogeneity of the trade variables because reactions at the individual level are unlikely to exert an impact on industry aggregates.

To formulate the econometric model, we adopt the latent propensity framework á la McFadden (1974). At each period, the latent variable y^*_{kit} describes the propensity level to be in state k out of states $0, \ldots, m$ for individual i at time t. In our case states are out of labor force $k = 0$, unemployment, and employment in four different sectors, so that $m = 5$. We observe n individuals i at $T + 1$ points in time $t = 0, \ldots T$. The propensity function is determined by

$$y^*_{kit} = x_{kit}\beta_k + z_{it}\gamma_k + \sum_{j=0}^{m} \delta_{jk}\mathbf{1}\{y_{i(t-1)} = j\} + \alpha_{ki} + \varepsilon_{kit} \tag{1}$$

where x_{kit} is a vector of state-specific individual characteristics (in our case trade and technology), and z_{it} is a vector of person-specific individual characteristics (age groups), $\mathbf{1}$ is the indicator function, $y_{i(t-1)}$ indicates the lagged state, $y_{i(t-1)} = j$ if the individual was in state j at $t - 1$, α_{ki} is an unobservable individual specific effect and ε_{kit} is an unobservable error term. Note that we model unobserved individual heterogeneity as state dependent so that each individual exhibits a specific propensity for each alternative. The parameters of interest to be estimated are $\beta = \{\beta_k\}^m_{k=0}$ and $\gamma = \{\gamma_k\}^m_{k=0}$ and δ the coefficient on the lagged endogenous variable. The parameter $\delta = \{\delta_{jk}\}^m_{j,k=0}$ is allowed to depend upon both the lagged state and the current state, so

[5] See Stoneman (1983) for an early statement of the argument and Vivarelli *et al.* (1996) for a more recent one.

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that there are in total m^2 feedback parameters. δ_{jk} is the feedback effect if the state j at $t-1$ is followed by the state k at time t.

The link between the latent and the observed variables is given by the assumption that the observed state has maximal propensity:

$$y_{it} = k \quad \text{if} \quad y^*_{kit} = \max_l (y^*_{lit})$$

As a consequence, if we assume that the underlying errors ε_{kit} are independent across alternatives and over time conditional on $(x_i, z_i, \alpha_i, y_{i0})$ and identically distributed according to the Type 1 extreme value distribution, the probability of individual i of being in state k at time t, is given by

$$P(y_{it} = k | y_{i(t-1)} = j, x_i, z_i, \alpha_i) = \frac{\exp(x_{kit}\beta_k + z_{it}\gamma_k + \delta_{jk} + \alpha_{ki})}{\sum_{l=0}^{m} \exp(x_{lit}\beta_l + z_{it}\gamma_l + \delta_{jl} + \alpha_{li})} \tag{2}$$

with $\alpha_i = \{\alpha_{ki}\}_{k=0}^m$ and $x_i = \{\{x_{kit}\}_{k=0}^m\}_{t=0}^T$, $z_i = \{z_{it}\}_{t=0}^T$. This implies that the transition matrix of this first-order Markov process is heterogeneous between individuals.

The model so far assumes that the effects of the exogenous variables are homogeneous with respect to the state of origin from which the transition is made. For example, a change in outsourcing in the CA manufacturing sector exerts the same effect for all individuals entering into this sector irrespective of whether they were previously unemployed, out of labor force, or employed in any of the sectors. As an extension we specify a more general model in which the parameters on the state-specific exogenous variables β are allowed to depend on the state of origin. Specifically, we consider the following generalization to (2):

$$P(y_{it} = k | y_{i(t-1)} = j, x_i, z_i, \alpha_i) = \frac{\exp(x_{kit}\beta_{jk} + z_{it}\gamma_k + \delta_{jk} + \alpha_{ki})}{\sum_{l=0}^{m} \exp(x_{lit}\beta_{jl} + z_{it}\gamma_l + \delta_{jl} + \alpha_{li})} \tag{3}$$

with $\beta = \{\beta_{jk}\}_{j,k=0}^m$ giving the influence of the observed covariates x on the probability of being in state k for each lagged state j.

3. ECONOMETRIC ESTIMATION APPROACH

When specifying and estimating (2) or (3) one is faced with the choice between a random effects approach and a fixed effects approach. There is a trade-off between these two settings: In the random effects model, one specifies the distribution of (α_i, δ_{0i}). The main advantage of this approach is that it delivers a completely specified model. As a consequence all probabilities of interest under any 'what-if' scenario can be estimated, provided that the model remains true. However, one has to make assumptions about the interrelation of the distribution of (α_i, δ_{0i}) with the time-varying explanatory variables in all periods, which may be inconsistent with the distribution of these variables. Further, there is the initial conditions problem which requires to specify the distribution of (α_i, δ_{0i}) conditional on (y_{0i}, x_i, z_i).[6] In a multinomial framework like

[6] See Honoré (2002) for a discussion of these points.

ours, the random effects specification leads to the evaluation of multiple integrals, which is a major computational challenge. The fixed effects approach attempts to estimate the (β, γ)'s and δ's without making any assumptions on the distribution of (α_i, δ_{0i}), and on the way they depend on (x_i, z_i). Only in special cases is it possible to estimate nonlinear models with fixed effects. The estimation method we use here, proposed by Honoré and Kyriazidou (2000), places restrictions on the support of the time-varying explanatory variables. Drawbacks of this approach are, first, that the semi-parametric nature of fixed effects models may lead to estimates that are much less precise than the corresponding random effects estimates. Second, the parameter estimates by this approach do not allow one to calculate objects such as the average effect of the explanatory variables on the probability that y_{it} equals a certain state, because this will depend on the distribution of (α_i, δ_{0i}). In this paper we pursue the fixed effects approach.

The individual fixed effects parameters α_{ik} in models (2) and (3) cannot be estimated consistently. Unlike in linear models the problem of incidental variables cannot be overcome by differencing. The idea applied by Chamberlain (1984) for fixed effects logit estimation has been to derive a set of conditional probabilities that do not depend on the individual effects. Honoré and Kyriazidou (2000) pick up this approach and present a method to estimate panel data fixed effects discrete choice models where the set of explanatory variables includes strictly exogenous variables, lags of the endogenous dependent variable as well as unobservable individual specific effects. Their estimation method is also extended to the case of multinomial discrete choice variables, and so covers our model of labor market transitions. Honoré and Kyriazidou (2000) consider events where the state variable y switches from, say, state k to state l between two points in time, say, s and t with $1 \leq t < s \leq T - 1$. Conditional on such a switch and on the constancy of the explanatory variables in the following periods $(x_{i(t+1)}, z_{i(t+1)}) = (x_{i(s+1)}, z_{i(s+1)})$, where $x_{it} = \{x_{kit}\}_{k=0}^{m}$, the probabilities of the events are independent of the individual effects. For continuous explanatory variables the exact equality condition is replaced by weighting the differences with a kernel function, giving the observations with smallest differences the highest weights. The likelihood function for model (2) is given in Appendix A. Appendix B derives the likelihood for the generalized model (3) with origin-specific effects of the exogenous regressors.

Honoré and Kyriazidou (2000) show that the estimator is consistent and asymptotically normally distributed, with a rate of convergence $\sqrt{n\sigma_n^k}$, where k is the dimensionality of x_{it} and σ_n is the kernel bandwidth (see Appendix A).

The method allows only for time-varying exogenous variables x, z with a positive probability of staying constant over time, i.e. $P((x_{it} - x_{is}) = 0) > 0$, $P((z_{it} - z_{is}) = 0) > 0$. For this reason time dummies are not included. Furthermore, the constant and the fixed individual effects cannot be estimated in the model. Therefore, it is impossible to calculate the probabilities in the transition matrix with the estimated parameters.

The estimator defined by minimizing the likelihood function (equation (4) in Appendix A) depends on a bandwidth and a kernel to be chosen. The choice of kernel is usually less critical than the choice of bandwidth in applications of semi- and non-parametric methods. We choose the Epanichnikov kernel given by

$$K(u) = \max\{0, 1 - u^2\}$$

$K(.)$ has a bounded support which implies that many terms in the objective function are 0. We will experiment with different values of bandwidth, since the choice of bandwidth is more important than the choice of kernel.

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4. DATA

We use a random sample of males drawn from the Austrian social security records, which collects detailed information on all workers in Austria with the exception of self-employed, civil servants and marginal workers. These data contain information on the labor market status of individuals on a daily basis covering the years 1988–2001. We distinguish between the states employed, unemployed and out of the labor force (e.g., education, maternity leave). For individuals with regular employment we also know the employer's industry sector at the 4-digit level according to NACE classification. We classify employment by four different industrial sectors. Specifically, we distinguish between two types of manufacturing (CA versus CDA industries), sales, and service sector. To establish a consistent classification, we consider only those manufacturing industries as comparatively advantaged, which did not switch from comparative advantage to comparative disadvantage within the whole period.[7]

We evaluate the labor market status on May 31 of each year[8] and exclude all individuals from the sample who were never employed during the whole period. Further, individuals who are younger than 16 in 2001 and older than 64 in 1988 are dropped from the sample. We are only interested in analyzing movements between industrial sectors, allowing for intermediate steps in unemployment or out of labor force. Transitions from education to the labor force or transitions to retirement should therefore not be considered. For any individual above the age of 55, we define a series of observations in state out of labor force which reaches the end year 2001 as retirement. Analogously, for an individual below age 27, we define a series of out of labor force observations which starts in the first year (1989) as education. Those observations are excluded from the estimation. Finally, we obtain an unbalanced panel of 38 349 male workers.

Table I shows the distribution of individuals over the defined states in the first and the last year of the sample. Employment is largest in the service sector. About 32% of the manufacturing sector employment is in comparative advantage industries.[9] We can see a slight employment shift over

Table I. Descriptive statistics, Austrian males by labor market states

Years	1989		2001	
	N	%	*N*	%
Out of labor force	2 623	9.89	3 971	14.53
Unemployed	954	3.6	1 655	6.06
Manufacturing CDA	7 193	27.11	6 056	22.16
Manufacturing CA	4 957	18.68	3 887	14.22
Sales	3 630	13.68	3 274	11.98
Service	7 177	27.05	8 488	31.06
Blue collar worker	15 179	57.21	15 816	57.87
	Mean	SD	Mean	SD
Age in years	36.01	10.97	39.92	9.74
Total	26 534	100	27 331	100

Note: CA, comparative advantage manufacturing industry; CDA, comparative disadvantage manufacturing industry.

[7] We are grateful to Deborah Swenson for this suggestion. However, our results prove also robust, if we relax this condition.
[8] This implies that all movements within a year are left out.
[9] Manufacturing with comparative disadvantage also includes the construction industry.

time from the manufacturing to the service sector, but this has to be interpreted with caution as the age distribution of individuals is not representative over the sampling period.[10]

Table II exhibits the annual transition frequencies between the employment states. There appears to be a high persistence in all employment states. To a large extent, transitions from unemployment and out of labor force occur to the service sector, while transitions to CA manufacturing are relatively rare. There are direct transitions between the sectors, but unemployment or out of labor force as an intermediate step seems to be quite frequent. A comparison of transition frequencies over time again suffers from the non-representative age distribution. Persistency in all states increases as a consequence of the aging sample population, but apart from that no big shifts can be detected.

Next, we match the information on individual labor market states and industrial sectors with industry-level data. Information on trade flows comes from Statistics Austria. They comprise the annual growth rates of real goods imports and exports, where the deflators are based on industry-level unit values. The trade-weighted industry-specific real exchange rate is calculated similar to that proposed in Goldberg (2004) using exports plus imports of an industry as weights. From the IMF database we construct trade-weighted bilateral real exchange rates by multiplying a country's nominal exchange rate index (Austrian shillings per local currency using the year 2000 as base) with ratio of consumer price indices of the partner country against the Austrian price index, again with base year 2000.[11] Hence, an increase of this index implies a real depreciation of the Austrian schilling or a deterioration of the Austrian terms of trade. Furthermore, we use the share of intermediate goods imports in total imports at the industry level as a measure of outsourcing. Intermediate goods imports are classified according to the Broad Economic Categories revision 3 classification

Table II. Frequencies of yearly transitions between employment states of Austrian males

Origin state	Destination state					
	Olf	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
1989–1990						
Olf	0.63	0.07	0.12	0.04	0.04	0.10
Unemployed	0.31	0.21	0.13	0.10	0.08	0.17
Manufacturing CDA	0.10	0.02	0.83	0.02	0.01	0.02
Manufacturing CA	0.07	0.01	0.04	0.85	0.01	0.01
Sales	0.09	0.02	0.03	0.02	0.81	0.02
Service	0.09	0.02	0.02	0.01	0.02	0.83
2000–2001						
Olf	0.79	0.05	0.04	0.02	0.03	0.08
Unemployed	0.11	0.49	0.13	0.05	0.07	0.16
Manufacturing CDA	0.03	0.02	0.91	0.01	0.01	0.02
Manufacturing CA	0.02	0.01	0.02	0.91	0.02	0.02
Sales	0.03	0.03	0.02	0.01	0.87	0.03
Service	0.04	0.03	0.02	0.01	0.01	0.89

Note: Olf, out of labor force; CA, comparative advantage manufacturing industry; CDA, comparative disadvantage manufacturing industry; number of individuals: 26 534 in 1989/1990; 27 331 in 2000/2001.

[10] The exact sampling procedure is the following: random samples of 50 000 individuals each were drawn from the social security records for the years 1992 and 1996. All these individuals were followed from 1984 to 2001. Of course, this sampling procedure leads to an age bias in the panel, e.g., too many young workers at the beginning and older workers over-represented at the end of the period.

[11] For the periods after the introduction of the euro we use the fixed exchange rates underlying the euro for the members of the euro-currency union.

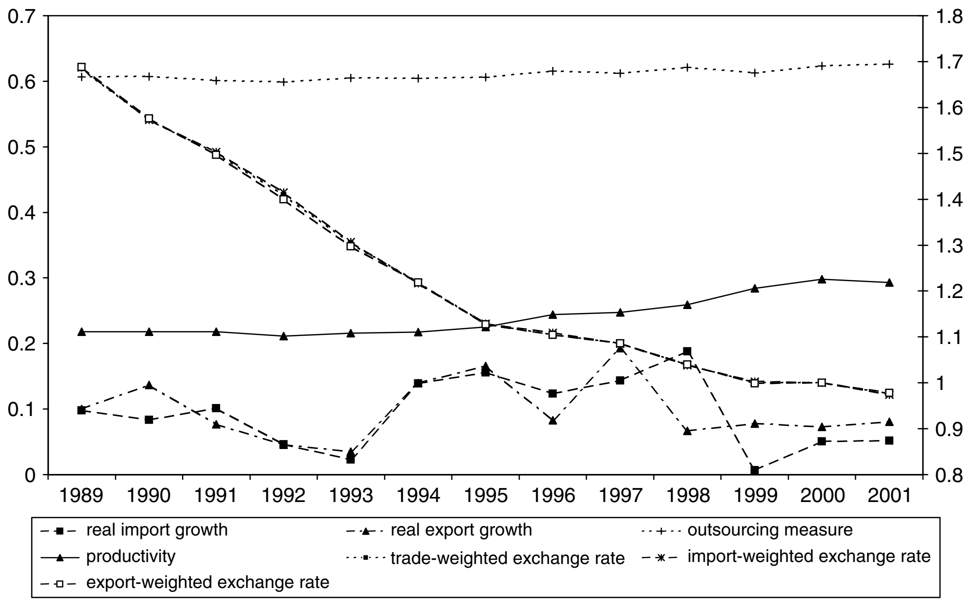

Figure 1. Trade variables and labor productivity, yearly mean values at individual level. Note: right axis refers to the exchange rate measures

of the United Nations, applied to the World Trade Database. We also consider technical change measured as real value-added over employment. These figures have been provided by the Austrian Institute of Economic Research and they are available at the 2-digit level only, while all the other industry-specific variables refer to 3-digit NACE level. The time-path of the mean values of the trade variables and the technical progress (productivity) variable are shown in Figure 1.

5. EMPIRICAL RESULTS

We estimate model (2) with labor market states as the dependent variable, and the set of trade and technical change variables as the determinants of interest. To account for the age structure in the panel we add dummy variables for three age groups as further explanatory variables (an alternative would have been to estimate separate models for age groups). As the reference category we choose the out of labor force state. Age is a person-specific explanatory variable in the sense that it does not depend on the state of an individual. The trade variables are alternative specific exogenous determinants. Therefore, for every individual at every point in time a vector $x_{it} = (x_{0it}, \ldots, x_{mit})$ has to be defined. For state k, in which the individual actually is at period t, we use the explanatory variables defined by the employer's industry. For the remaining states these variables remain unobserved; hence, we impute the expected values (state-specific mean values over all individuals). Note that the trade variables refer to goods transactions and they are only available for the manufacturing industries. We have to assume that in the other industries no goods trade takes place and, therefore, we set the trade variables equal to zero in these industries. As a consequence, β coefficients are not identified in the alternative states unemployment, service, and sales.[12] The variable for labor productivity is set to the (individual) mean value over all industries if the state is unemployment or out of labor force. To assess whether there is a significant impact of trade on individual movements between sectors we test the hypothesis $\beta = 0$ using the Wald test. Such a test is justified in the sense that it follows the usual χ^2 distribution under the null, even if the bandwidth is a fixed constant (see D'Addio and Honoré, 2002).

Table III reports the estimation results of the basic specification (Model 1), while Table IV presents the results of an alternative specification using the industry-specific real exchange rate instead of import and export growth to measure the impact of trade exposure (Model 2). There are two corresponding specifications given in Table V, which only consider transitions to the

Table III. Model 1, yearly transitions 1989–2001

	Destination state				
	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
Origin state					
Unemployment	1.837	0.586	0.770	0.980	1.275
	(0.099)	(0.245)	(0.526)	(0.273)	(0.175)
Manufacturing CDA	1.326	4.788	2.162	1.177	1.790
	(0.135)	(0.234)	(0.717)	(0.431)	(0.316)
Manufacturing CA	1.535	2.299	6.034	1.827	1.748
	(0.236)	(0.572)	(0.793)	(0.667)	(0.566)
Sales	1.437	1.666	1.887	4.563	1.642
	(0.191)	(0.482)	(0.819)	(0.278)	(0.326)
Service	1.463	1.623	1.403	1.187	4.140
	(0.123)	(0.318)	(0.614)	(0.360)	(0.170)
Trade variables					
Real import growth		−0.465	−0.775		
		(0.371)	(1.253)		
Real export growth		−1.312	1.411		
		(0.352)	(1.307)		
Outsourcing		−2.948	−0.370		
		(0.215)	(0.437)		
Technical progress					
Productivity	18.418	−0.098	−0.738	−1.538	−0.544
	(4.568)	(0.380)	(0.341)	(0.689)	(0.043)
Age					
Age <25	0.771	1.321	1.529	1.084	0.252
	(0.546)	(0.727)	(1.759)	(1.130)	(0.550)
Age 25–30	0.450	0.824	0.821	1.007	−0.006
	(0.464)	(0.618)	(1.624)	(1.015)	(0.451)
Age 30–35	0.101	0.286	0.701	0.634	−0.116
	(0.362)	(0.442)	(1.147)	(0.864)	(0.356)
Mean log-likelihood	−0.0740502				
Number of individuals	32 703				
Number of cases	66 158				
Wald test $\chi^2(11)$	400.782				

Note: Fixed effects logit model estimated with conditional ML, Austrian males; standard errors in parentheses; Wald test for joint significance of trade and technical change variables.

[12] We have trade information for some of the industries in the service sector with non-zero values for about 10% of individuals. Alternative estimation results for $\beta \neq 0$ in the service sector are available upon request.

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Table IV. Model 2, yearly transitions 1989–2001

	Destination state				
	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
Origin state					
Unemployment	1.903	0.848	0.767	1.183	1.314
	(0.087)	(0.278)	(0.480)	(0.279)	(0.183)
Manufacturing CDA	1.318	5.662	2.035	1.915	2.056
	(0.143)	(0.359)	(0.793)	(0.487)	(0.417)
Manufacturing CA	1.316	2.487	6.328	1.906	2.230
	(0.219)	(0.764)	(0.543)	(0.718)	(0.645)
Sales	1.542	2.286	1.630	5.344	2.080
	(0.181)	(0.688)	(0.825)	(0.401)	(0.353)
Service	1.499	2.261	1.768	1.828	4.788
	(0.117)	(0.443)	(0.798)	(0.419)	(0.193)
Trade variables					
Industry-level trade-weighted exchange rate		−1.194	1.036		
		(0.187)	(1.435)		
Outsourcing		−0.694	−0.548		
		(0.288)	(0.491)		
Technical progress					
Productivity	24.750	−0.214	−2.173	−1.514	−0.588
	(3.916)	(0.400)	(0.431)	(0.661)	(0.045)
Age					
Age <25	0.160	0.338	−0.286	−0.019	0.061
	(0.505)	(0.766)	(1.320)	(1.019)	(0.538)
Age 25–30	0.201	0.384	0.083	0.699	0.190
	(0.386)	(0.607)	(1.093)	(0.847)	(0.433)
Age 30–35	−0.089	0.162	0.44	0.387	−0.016
	(0.276)	(0.414)	(0.721)	(0.643)	(0.338)
Mean log-likelihood	−0.108346				
Number of individuals	32 703				
Number of cases	40 897				
Wald test $\chi^2(9)$	342.157				

Note: Fixed effects logit model estimated with conditional ML, Austrian males; standard errors in parentheses; Wald test for joint significance of trade and technical change variables.

two manufacturing sectors by adding all remaining transitions to the reference group. Further, we consider the robustness of the results in Tables III and IV by looking at alternative kernel bandwidths of 0.05 and 0.20 and by using the sign of the industry-specific trade balance in all periods as an alternative criterion to define CA and CDA, respectively. The corresponding estimates of the trade and technical change impact on transition probabilities for the two types of models as in Tables III and IV are given in Table VI.[13] In all specifications the trade and technical change variables are jointly significant according to the Wald test. Since the estimation results prove robust in all essential respects, it suffices to base the discussion of our findings on Tables III and IV.

We do not find an impact of increasing import competition measured in terms of real import growth on the inflows of workers into manufacturing as compared to the baseline (out of labor force), either for CDA or for CD industries (Table III). The coefficient on real export growth turns out negative, but significantly so only in CDA industries. This result seems puzzling and may

[13] Of course, a substantial reduction of the kernel bandwidth results in a considerable decline in the number of observations.

Table V. Models 1 and 2, transitions to the manufacturing industries only, yearly transitions 1989–2001

	Destination state			
	Model 1		Model 2	
	Manuf. CDA	Manuf. CA	Manuf. CDA	Manuf. CA
Origin state				
Unemployment	−0.331	−0.261	0.002	−0.301
	(0.202)	(0.374)	(0.211)	(0.373)
Manufacturing CDA	4.306	1.795	5.058	1.560
	(0.213)	(0.648)	(0.317)	(0.759)
Manufacturing CA	1.762	5.618	1.953	6.077
	(0.559)	(0.754)	(0.693)	(0.504)
Sales	−0.699	−0.442	−0.201	−0.625
	(0.263)	(0.459)	(0.286)	(0.476)
Service	−0.767	−0.708	−0.516	−0.865
	(0.204)	(0.410)	(0.220)	(0.403)
Trade variables				
Real import growth	−0.605	−0.451		
	(0.334)	(1.039)		
Real export growth	−0.955	1.505		
	(0.344)	(1.216)		
Industry-level trade-weighted exchange rate			−0.888	1.308
			(0.172)	(1.203)
Outsourcing	−2.813	−0.526	−1.094	−0.607
	(0.198)	(0.399)	(0.261)	(0.445)
Technical progress				
Productivity	−0.222	−0.959	−0.315	−2.417
	(0.331)	(0.301)	(0.328)	(0.392)
Age				
Age <25	1.416	1.753	1.414	0.701
	(0.643)	(1.463)	(0.652)	(1.184)
Age 25–30	0.884	0.967	0.981	0.539
	(0.544)	(1.337)	(0.522)	(1.001)
Age 30–35	0.376	0.594	0.520	0.690
	(0.385)	(0.968)	(0.362)	(0.694)
Mean log-likelihood	−0.142243		−0.212525	
Number of individuals	32 703			
Number of cases	66 158		40 897	
Wald test	260.741		166.787	

Note: Fixed effects logit model estimated with conditional ML, Austrian males; standard errors are in parentheses; Wald test for joint significance of trade and technical change variables.

reflect that restructuring CDA industries have been able to increase productivity, simultaneously reducing employment and increasing exports. The industry-weighted exchange rate is significantly negative for the CDA industries but not in CD industries. This finding indicates that manufacturing industries do not take advantage of a real deprecation. Rather, it suggests that CDA industries suffer from higher prices of intermediate imports. All else equal, this result implies that the probability that a person works in CDA industries and, specifically, that job changers find a job in these industries is significantly lowered as compared to the option to go out of the labor force. The findings on the impact of real import growth and of changes in the terms of trade is not in line with other studies, which to a large extent use higher aggregated data. Ravenga (1992) finds for the USA that changes in import prices primarily affect employment rather than

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Table VI. Robustness checks: varying bandwidths and definition of CA industries

	Model version 1				Model version 2			
	Exchange rate	Outsourcing	Productivity		Imp.growth	Exp. growth	Outsourcing	Productivity
RCA, *bandwidth* = 0.05		15 121 cases				14 368 cases		
Manufacturing CDA	−1.412	−1.366	0.014		−2.901	−5.372	−4.249	−0.757
	(0.561)	(0.799)	(1.620)		(2.240)	(1.103)	(0.667)	(1.662)
Manufacturing CA	4.024	−0.638	−1.506		−0.280	2.149	−0.589	−0.781
	(4.999)	(1.420)	(1.559)		(5.455)	(4.386)	(1.474)	(1.178)
RCA, *bandwidth* = 0.20		93 464 cases				169 495 cases		
	Manufacturing CDA	−0.895	−0.688	−0.247	−0.528	−0.824	−2.363	−0.089
	(0.086)	(0.146)	(0.190)		(0.144)	(0.140)	(0.101)	(0.158)
Manufacturing CA	−0.514	−0.536	−2.250		−0.309	0.597	−0.448	−1.167
	(0.381)	(0.224)	(0.205)		(0.479)	(0.452)	(0.181)	(0.139)
Trade balance, *bandwidth* = 0.10		40 867 cases				66 077 cases		
	Manufacturing CDA	−1.203	−0.701	−0.178	−0.451	−1.314	−3.038	−0.074
	(0.185)	(0.286)	(0.400)		(0.369)	(0.353)	(0.215)	(0.390)
Manufacturing CA	1.240	−0.138	−1.885		−0.566	1.748	−0.145	−0.421
	(1.723)	(0.507)	(0.464)		(1.307)	(1.433)	(0.457)	(0.371)

Note: Fixed effects logit model estimated with conditional ML, Austrian males, yearly transitions 1989–2001; standard errors are in parentheses.

wages. She argues that the reason for this evidence is that workers are relatively mobile between industries. We suspect that this should be even more relevant for countries with a high degree of unionization such as Austria. However, Kletzer (2000, p. 9) notes that in unionized labor markets the employment effect may eventually be dampened, since 'the presence of rents may leave room for wage concessions'.

As a very robust result, we find a significant negative impact of outsourcing on the transition probabilities to the CDA manufacturing sector. With the exception of Kletzer (2000, 2002), who reports a positive effect on displacements, the impact of outsourcing on workers' mobility has not been previously considered. Our result is at odds with the long-run Heckscher–Ohlin view of outsourcing, but supports Kohler's (2001) specific factors model view, which predicts a reduction of employment in the outsourcing sector. Note, there is no significant impact of outsourcing on the CA industries.

Lastly, in both Models 1 and 2 there are pronounced negative labor productivity effects, which are all significant. Only CDA industries are an exception, where this effect is insignificant. One reason for this finding might be that technical progress is primarily labor augmenting and capital and labor are complementary in the CDA industries but substitutive in the other sectors. Since we observe a negative impact of technical progress in almost all sectors, the significant positive impact on unemployment is a natural consequence. Technical progress or investment in capital, materialized in an increased labor productivity, reduces the probability to stay in the job or find a job in any of the industries relative to the probability of moving out of the labor force. By the same argument technical progress increases the likelihood of becoming unemployed.

Tables VII and VIII display the results from models with state of origin dependent effects of trade and technology on transition probabilities. For both the trade and technical change variable we test parameter homogeneity across all states of origin. It turns out that the null of identical origin-specific effects on the transitions into CDA industries is only rejected for the trade-weighted exchange rate, outsourcing and productivity. The most important results from these tables may be summarized as follows.

First, an increase in the trade-weighted exchange rate (a real depreciation) is mainly at the expense of transitions from CDA manufacturing industries into themselves. Second, outsourcing significantly reduces the probability of transitions into the CDA manufacturing industries, and especially so for men previously out of labor force and the unemployed and workers previously employed in a CDA industry (see Tables VII and VIII). In contrast, outsourcing does not impede transition into or staying in the CA industries. Third, technical change in terms of rising labor productivity in CA manufacturing industries tends to harm transitions from other labor market states into those industries. In addition it increases the likelihood of becoming unemployed (see the negative signs of the effects in the third coefficient column as compared to the first one in Tables VII and VIII). Furthermore, men out of labor force or unemployed ones are less likely to find jobs in CA manufacturing, sales or service industries, if technical progress raises the productivity of all workers in the market.

6. CONCLUSION

This paper investigates the consequences of increasing trade and, especially, of outsourcing on gross flows of workers. In contrast to the literature that concentrates on static long-run effects, we investigate the short-run labor market dynamics. In particular, we investigate the determinants of

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Table VII. Origin-specific effects of trade and technical change variables, Model 1

Origin state	Destination state				
	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
Real import growth					
OLF		0.776	−0.930		
		(0.957)	(2.339)		
Unemployed		0.182	−0.933		
		(1.024)	(4.387)		
Manuf. CDA		−0.599	0.440		
		(0.577)	(3.206)		
Manuf. CA		−8.022	−0.842		
		(15.134)	(5.193)		
Sales		0.141	2.012		
		(4.282)	(4.523)		
Service		−0.100	−2.821		
		(2.155)	(4.344)		
Wald test $\chi^2(5)$		1.910	0.700		
Real export growth					
OLF		−1.245	3.528		
		(0.991)	(2.742)		
Unemployed		−0.345	3.043		
		(1.287)	(4.834)		
Manuf. CDA		−1.876	−0.166		
		(0.478)	(4.461)		
Manuf. CA		0.227	−1.419		
		(3.595)	(5.765)		
Sales		3.088	0.462		
		(3.783)	(4.107)		
Service		−0.121	0.692		
		(1.792)	(7.364)		
Wald test $\chi^2(5)$		3.847	1.104		
Outsourcing					
OLF		−3.030	−0.566		
		(0.379)	(0.771)		
Unemployed		−3.375	−1.115		
		(0.591)	(1.960)		
Manuf. CDA		−3.832	0.584		
		(0.400)	(1.665)		
Manuf. CA		0.976	0.183		
		(3.317)	(1.279)		
Sales		−1.830	−1.575		
		(1.567)	(2.043)		
Service		0.076	−1.414		
		(0.943)	(2.096)		
Wald test $\chi^2(5)$		17.015	1.272		
Productivity					
OLF	25.725	0.029	−0.138	−1.552	−3.203
	(5.629)	(1.055)	(0.667)	(1.178)	(0.116)
Unemployed	−2.003	−1.369	−2.55	−3.362	−4.754
	(5.641)	(1.607)	(1.371)	(1.736)	(0.141)
Manuf. CDA	13.707	−0.056	−3.476	1.742	0.185
	(8.706)	(0.478)	(1.482)	(2.457)	(0.232)
Manuf. CA	10.631	−4.169	0.268	−0.314	−0.236
	(15.388)	(8.384)	(1.094)	(5.208)	(0.354)
Sales	7.261	−0.859	−4.524	−1.831	−0.012
	(10.479)	(0.904)	(1.743)	(1.150)	(0.317)

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Table VII. (*Continued*)

Origin state	Destination state				
	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
Service	11.161	3.410	−6.621	−1.585	−0.540
	(6.543)	(2.552)	(3.145)	(1.898)	(0.068)
Wald test $\chi^2(5)$	31.205	3.535	15.255	3.014	1047.896
Mean log-likelihood	−0.0709221				
Number of individuals	32 703				
Number of cases	66 158				

Note: See Table VIII.

the transition probabilities of employment into both other sectors and unemployment/out of labor force, using a dynamic multinomial logit framework with fixed effects of Honoré and Kyriazidou (2000). In this way, we are able to explicitly take care of individual heterogeneity as well as of state dependence. Furthermore, we generalize the model to account for origin-specific effects of the trade variables. The database contains information on individual Austrian male workers over the period 1988–2001.

Our results support the view that international factors are important for labor market turnover, and even more so for net importing industries with a comparative disadvantage. Specifically, increases in outsourcing as share in total trade negatively affect the probability of staying in or changing into the manufacturing sector. First, in each and any estimated model the reduction in the transition probability parameters is largest for outsourcing, irrespective of whether we additionally control for other sources of changes in labor productivity. Second, in all cases the reductions in transition probabilities are lower for employment in the comparative advantage group of manufacturing industries. However, for the latter class of industries, we do not find a negative impact of real import growth, rising terms of trade or outsourcing. This finding points to a relative low elasticity of substitution between domestic output and imports. To some extent our results support the findings in previous empirical research, based on static econometric specifications.

APPENDIX A: LIKELIHOOD FUNCTION FOR THE DYNAMIC MULTINOMIAL LOGIT MODEL WITH FIXED EFFECTS

Define the binary variable $y_{hit} = 1$ if the individual is in state $h \in \{0, 1, \ldots, m\}$ in period t and zero otherwise. The estimation of model (2) with state-specific individual characteristics x_{kit}, person-specific individual characteristics z_{it}, and fixed individual effects α_{ki} can be based on the maximization of the following likelihood function:

$$L = \sum_{i=1}^{n} \sum_{1 \le t < s \le T-1} \sum_{k \ne l} \mathbf{1}\{y_{kit} + y_{kis} = 1\}\mathbf{1}\{y_{lit} + y_{lis} = 1\} \times \mathbf{1}\{z_{i(t+1)} = z_{i(s+1)}\} K\left(\frac{x_{i(t+1)} - x_{i(s+1)}}{\sigma_n}\right) \ln \frac{\exp(D_1)}{1 + \exp(D_1)} \mathbf{1}\{s - t = 1\} \tag{4}$$

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Table VIII. Origin-specific effects of trade and technical change variables, Model 2

Origin state	Destination state				
	Unempl.	Manuf. CDA	Manuf. CA	Sales	Service
Trade-weighted exchange rate					
OLF		−0.468	4.784		
		(0.424)	(2.606)		
Unemployed		−0.426	5.026		
		(0.528)	(5.271)		
Manuf. CDA		−2.029	5.509		
		(0.310)	(6.490)		
Manuf. CA		−0.881	−2.537		
		(1.601)	(3.812)		
Sales		1.233	6.246		
		(1.467)	(6.440)		
Service		−1.231	5.503		
		(0.750)	(4.302)		
Wald test $\chi^2(5)$		14.688	4.636		
Outsourcing					
OLF		−1.408	0.102		
		(0.660)	(1.400)		
Unemployed		−1.488	−2.654		
		(0.734)	(1.528)		
Manuf. CDA		−0.334	−1.640		
		(0.447)	(1.383)		
Manuf. CA		0.829	−0.598		
		(3.135)	(0.871)		
Sales		−1.557	−1.733		
		(2.331)	(2.973)		
Service		0.781	−0.961		
		(1.303)	(2.007)		
Wald test $\chi^2(5)$		4.665	2.258		
Productivity					
OLF	38.785	0.828	−1.713	−3.02	−0.861
	(5.459)	(1.231)	(1.218)	(1.309)	(0.084)
Unemployed	10.637	−4.105	−15.045	−3.379	−7.759
	(5.276)	(1.457)	(3.578)	(1.599)	(0.212)
Manuf. CDA	47.826	−0.239	−9.09	2.059	0.195
	(9.1)	(0.62)	(4.053)	(2.386)	(0.313)
Manuf. CA	22.196	−1.107	−0.782	−1.016	−2.995
	(17.016)	(2.241)	(0.711)	(5.27)	(0.896)
Sales	29.368	−0.59	−7.071	−1.594	−0.013
	(10.876)	(1.815)	(4.53)	(1.175)	(0.373)
Service	29.899	3.462	−4.348	0.577	−0.614
	(6.819)	(2.347)	(2.845)	(1.92)	(0.082)
Wald test $\chi^2(5)$	29.168	10.492	21.354	6.073	1067.512
Mean log-likelihood	−0.102591				
Number of individuals	32 703				
Number of cases	40 897				

Note: Fixed effects logit model estimated with conditional ML, Austrian males, yearly transitions 1989–2001; standard errors are in parentheses; Wald tests for equality of origin-specific effects, critical value 11.07.

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$$+\sum_{i=1}^{n}\sum_{1\leq t<s\leq T-1}\sum_{k\neq l}\mathbf{1}\{y_{kit}+y_{kis}=1\}\mathbf{1}\{y_{lit}+y_{lis}=1\}$$
$$\times\,\mathbf{1}\{z_{i(t+1)}=z_{i(s+1)}\}K\left(\frac{x_{i(t+1)}-x_{i(s+1)}}{\sigma_n}\right)\ln\frac{\exp(D_2)}{1+\exp(D_2)}\mathbf{1}\{s-t>1\}$$

with

$$\begin{aligned}D_1 = {} & (x_{kit}-x_{kis})\beta_k-(x_{lit}-x_{lis})\beta_l+(z_{it}-z_{is})(\gamma_k-\gamma_l)\\ & +\delta_{y_{i(t-1)}k}+\delta_{kl}+\delta_{l\,y_{i(s+1)}}-\delta_{y_{i(t-1)}l}-\delta_{lk}-\delta_{k\,y_{i(s+1)}}\end{aligned}$$

and

$$\begin{aligned}D_2 = {} & (x_{kit}-x_{kis})\beta_k-(x_{lit}-x_{lis})\beta_l+(z_{it}-z_{is})(\gamma_k-\gamma_l)\\ & +\delta_{y_{i(t-1)}k}+\delta_{k\,y_{i(t+1)}}+\delta_{y_{i(s-1)}l}+\delta_{l\,y_{i(s+1)}}\\ & -\delta_{y_{i(t-1)}l}-\delta_{l\,y_{i(t+1)}}-\delta_{y_{i(s-1)}k}-\delta_{k\,y_{i(s+1)}}\end{aligned}$$

In the objective function $K(.)$ is a kernel and σ_n is a bandwidth which approaches 0 as the number of observations increase to ∞, $x_{it}=\{x_{kit}\}_{k=0}^{m}$. We impose the following identification restrictions:

$$\begin{aligned}(\beta_0,\gamma_0)&=0\\ \delta_0=(\delta_{00},\ldots,\delta_{m0})&=0\\ \delta_{0k}&=0\ \forall\ k=1,\ldots,m\\ \alpha_{i0}&=0\ \forall\ i=1,\ldots,n\end{aligned}$$

which means that all parameters with respect to the reference state $k=0$ are equal to zero.

APPENDIX B: LIKELIHOOD FUNCTION FOR THE MODEL WITH ORIGIN-SPECIFIC EFFECTS OF EXOGENOUS VARIABLES

As an extension to the multinomial case of dynamic logit model presented in Honoré and Kyriazidou (2000), we consider the case where the effect of the time-varying exogenous variables is allowed to depend on the state of origin. The model is

$$P(y_{it}=k|y_{i(t-1)}=j,x_i,z_i,\alpha_i)=\frac{\exp(x_{kit}\beta_{jk}+z_{it}\gamma_k+\delta_{jk}+\alpha_{ki})}{\sum_{l=0}^{m}\exp(x_{lit}\beta_{jl}+z_{it}\gamma_l+\delta_{jl}+\alpha_{li})}$$

Here the parameter on β_{jk} on state-specific individual characteristics x_{kit} are allowed to depend on both the state of origin j and the current state k.

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To derive the likelihood function we proceed analogously to Honoré and Kyriazidou (2000) and consider the events

$$\begin{aligned} A = \{&y_{i0} = d_0, \ldots, y_{it-1} = j, y_{it} = k, y_{it+1} = q, \ldots, \\ &y_{is-1} = p, y_{is} = l, y_{is+1} = r, \ldots, y_{iT} = d_T\} \end{aligned}$$

and

$$\begin{aligned} B = \{&y_{i0} = d_0, \ldots, y_{it-1} = j, y_{it} = l, y_{it+1} = q, \ldots, \\ &y_{is-1} = p, y_{is} = k, y_{is+1} = r, \ldots, y_{iT} = d_T\} \end{aligned}$$

where $1 \leq t < s \leq T-1$, and $j, k, q, p, l, r, d_0, d_T \in \{0, \ldots, m\}$ with $k \neq l$. Then we verify that, if $x_{jit+1} = x_{jis+1}$ for all $j = 0, \ldots, m$ and $z_{it+1} = z_{is+1}$, then

$$Pr\ (A|x_i, z_i, \alpha_i, A \cup B, \{x_{jit+1} = x_{jis+1}\}_{j=0}^{m}, z_{it+1} = z_{is+1})$$

does not depend on α_i. The estimation can be based on a likelihood function of the same structure as in (4), and the expressions for D_1 and D_2 in the likelihood function are given by

$$\begin{aligned} D_1 = {} & x_{kit}\beta_{y_{i(t-1)}k} + x_{lis}\beta_{kl} + x_{y_{i(s+1)}i(s+1)}\beta_{l\,y_{i(s+1)}} \\ & - x_{lit}\beta_{y_{i(t-1)}l} + x_{kis}\beta_{lk} + x_{y_{i(s+1)}i(s+1)}\beta_{k y_{i(s+1)}} \\ & + (z_{it} - z_{is})(\gamma_k - \gamma_l) \\ & + \delta_{y_{i(t-1)}k} + \delta_{kl} + \delta_{l\,y_{i(s+1)}} - \delta_{y_{i(t-1)}l} - \delta_{lk} - \delta_{k y_{i(s+1)}} \end{aligned}$$

and

$$\begin{aligned} D_2 = {} & x_{kit}\beta_{y_{i(t-1)}k} + x_{y_{i(t+1)}i(t+1)}\beta_{k y_{i(t+1)}} \\ & + x_{lis}\beta_{y_{i(s-1)}l} + x_{y_{i(s+1)}i(s+1)}\beta_{l\,y_{i(s+1)}} \\ & - x_{lit}\beta_{y_{i(t-1)}l} - x_{y_{i(t+1)}i(t+1)}\beta_{l\,y_{i(t+1)}} \\ & - x_{kis}\beta_{y_{i(s-1)}k} + x_{y_{i(s+1)}i(s+1)}\beta_{k y_{i(s+1)}} \\ & + (z_{it} - z_{is})(\gamma_k - \gamma_l) \\ & + \delta_{y_{i(t-1)}k} + \delta_{k y_{i(t+1)}} + \delta_{y_{i(s-1)}l} + \delta_{l\,y_{i(s+1)}} \\ & - \delta_{y_{i(t-1)}l} - \delta_{l\,y_{i(t+1)}} - \delta_{y_{i(s-1)}k} - \delta_{k y_{i(s+1)}} \end{aligned}$$

We impose the following identification restrictions:

$$\begin{aligned} (\beta_{00}, \ldots, \beta_{m0}) &= 0 \\ \gamma_0 &= 0 \\ \delta_0 = (\delta_{00}, \ldots, \delta_{m0}) &= 0 \\ \delta_{0k} &= 0\ \forall\ k = 1, \ldots, m \\ \alpha_{i0} &= 0\ \forall\ i = 1, \ldots, n \end{aligned}$$

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