True versus spurious state dependence in firm performance: the case of West German exports[§]

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Abstract: This paper analyzes the persistence of firms' exporting behavior in a panel of West German manufacturing firms. Dynamic binary choice models allow us to distinguish between true and spurious state dependence in firm performance. Using random effects models as well as a recent fixed effect approach which imposes few restrictions on unobservables, we find robust evidence of state dependence in the current export status of firms. Unobserved permanent firm heterogeneity ("spurious state dependence") is found to be less important than suggested by earlier studies. The existence of true state dependence in exports has direct economic policy implications: if policy successfully turns non–exporters into exporters, the effect is likely to be lasting.

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1 Introduction

Governments all over the world spend large resources on promoting the performance of domestic firms. It is not clear if these promotion activities are effective and empirical research has just started to evaluate the impacts of government support on firm performance. Even if government support programmes were *statically* effective, it is unknown if they have any *lasting* effects on firm performance.

The main aim of this paper is to answer the following question using a large panel data set of West German manufacturing firms: is firm performance state dependent in the sense that becoming a "good performer" today changes the probability of "good performance" in the future? This would be the case of "true" state dependence which suggests that even a temporary (but successful) government support measure could have an effect on performance in future periods. Or is it the case that "good firm performance" is primarily caused by factors inherent to the firm but not easily affected by policy measures, such as management abilities. For example, some firms are — for whatever reasons permanently more "export-prone" than others, independently of their past export performance. That would be a case of "spurious state dependence" and a policy measure that aims at turning a non-exporting firm into an exporter will not change its future performance. The distinction between spurious and true state dependence is crucial for economic policy: if state dependence is spurious, firm performance is clearly unlikely to be durably influenced by economic policy. Just the reverse holds for true state dependence. If firm performance is truly state dependent, then a statically successful governmental policy has lasting effects on firm performance. For example, a governmental policy that is able to turn nonexporting firms into exporters at some point in time, will induce a permanent change in a firm's export status if firm performance is truly state dependent.

Many aspects of firm performance — such as being an exporter or not — are empirically found to be highly persistent over time. This observation leaves open the question if persistence is caused by true state dependence or merely by spurious effects due to permanent unobserved (to the econometrician) firm heterogeneity. True state dependence might be caused by sunk costs, for example by the efforts a firm undertook to enter a foreign market. Export activity is indeed our measure of firm performance and the subject of the empirical analysis. It is just one of many possibilities to measure firm performance as pointed out by Van Phu et al. (forthcoming). Export activity is, however, an important ingredient of the performance of many developed economies. This is even more true for Germany as the world export champion where, according to the German Federal Ministry of Economics and Labour (2004), every fifth workplace directly depends on exports. Unsurprisingly, many empirical studies on the export activity of German firms exist, most notably those by Wagner (1994, 2002, 2003). Governments, and in particular the German government, frequently influence export activity by export counselling, export subsidization, export (re–) financing, risk sharing and export credits. These forms of export promotion are currently also high on the agenda of the World Trade Organization since they put less developed countries at a disadvantage.

The fundamental difficulty in the estimation of the effects of past firm performance on current firm performance is the "initial conditions" problem described by Heckman (1981): in panel data sets that typically have a short time dimension the treatment of the initial state of the firm and its relation to unobserved firmspecific effects will matter critically for the consistency of coefficient estimates. Most existing studies on firms' dynamic export performance, including our key reference, Roberts and Tybout (1997) (R&T hereafter), use random effects binary choice models. The potential drawback of random effects–type dynamic binary choice models is that consistency hinges on the specified relationships between the distribution of unobserved firm–specific permanent effects, the explanatory variables, and the initial export status.

The application of fixed effects models turns out not to be straightforward in nonlinear models such as binary choice models. One reaction to this is the approach taken by Bernard and Jensen (forthcoming). They use fixed effects linear probability models with a lagged endogenous dummy variable. However, the linear probability model, as the authors acknowledge themselves, is not very satisfactory for the same reason as in static models: the transition probabilities that this model generates are not proper probabilities.

We instead suggest to use the fixed effects estimator recently developed by Hon-

ore and Kyriazidou (2000) for a dynamic binary choice model. As a proper binary choice model, we believe it is a preferred alternative to the linear probability fixed effect model of Bernard and Jensen. Since its consistency does not hinge upon a particular specification of initial conditions, it delivers a specification check of the random effect approaches. We consider also two random effect approaches: a Heckman-type model which is close to that used by R&T and a recent and more convenient alternative suggested by Wooldridge (2002a). Validation of a random effects model is of great interest here since, in practice, the Honore and Kyriazidou fixed effects model specification allows for only one explanatory variable in addition to the lagged endogenous dummy variable. Hence, while the fixed effects approach does identify the presence (or absence) of true state dependence, it is not informative with respect to the quantitative and qualitative effects of many factors that potentially influence firm performance.

Another potential practical problem with the Honore and Kyriazidou estimator is that it requires the dependent variable to be independent of time effects. Previous specification checks using the two random–effects type models have shown, however, that there are highly significant time effects in the export status of East German firms. This is unsurprising since most sectors of the East German economy were in a state of transition during the 1990s with traditional export markets collapsing after 1990 and slowly recovering after 1996. The empirical analysis of this paper therefore deals exclusively with West German firms.

Our main results are that the persistence in firms' export status is significantly driven by true state dependence, suggesting a scope for economic policy intervention with lasting effects. The fixed effects approach validates the random effects model of Wooldridge (2002a). The Heckman-type approach used in R&T, on the other hand, appears to be rejected by our data. Permanent unobserved firm heterogeneity, and thus "spurious" state dependence, is found to explain a comparatively smaller part of the overall variance in our data. Overall, we find that the assumptions on the initial export status matter critically for the random effects findings. Finally, there is mixed evidence on the relationship between firm size (as measured by employment) and exporting activity. We will leave further clarification of this issue for future research.

2 Data and empirical specification

2.1 Data

Our analysis is based on all nine waves of the "Mannheim Innovation Panel" (MIP) that are available for academic research. They were collected between 1993 and 2001 and refer to the respective prior year. The most recent information we have at our disposal hence refers to the year 2000 while the most distant information is related to 1992 (which is of course completely lost once we use lagged dependent variables).¹ The MIP data cover both East Germany and West Germany but we leave out East Germany for reasons already outlined in the introduction. Moreover, we concentrate on goods-producing sectors and leave out the construction sector and utilities from the MIP data since export activity is very low in both sectors so that including sector dummy variables for construction and utilities almost perfectly predicts export activity.

The MIP is a business survey that is collected by the Centre for European Economic Research on behalf of the German Ministry of Education, Research, Science and Technology. The MIP survey obeys to the methodological and implementation issues for innovation surveys described in the OECD "OSLO–manual" (OECD 1994). One of the great merits of the MIP data is that most of the questions have been asked in exactly the same way since 1992. All of the variables that we use in our study are based on MIP questions that remained completely unchanged.

The MIP data has previously been used to evaluate innovation promotion programs (Almus and Czarnitzki 2003), research joint ventures (Kaiser 2002) and firms' patenting activity (Licht and Zoz 1998). We omit a detailed description of the data here and concentrate on the variables used in the estimations. Janz et al. (2001) describe the data in greater detail.

We base the definition of firms' export status on the MIP survey question "How large were your exports in xxxx?" (where xxxx is to be replaced by the year

 $^{^{1}}$ We have posted our data set and the software codes we use in the estimations on the internet at http://www.ulrichkaiser.com/papers/export.html.

the question refers to). If a firm reports zero exports, it is defined as a nonexporter, if positive values are reported, the firm is defined as an exporter. Our transformation of exports into a simple dummy variable means that we potentially throw away a lot of information. Firms' export volumes of course vary both between firms and within firms. We choose to neglect this information, first of all because the focus of the paper is on the firm's binary participation decision and also because of a practical econometric issue: dynamic tobit models do not exist in the existing literature so that turning to a tobit model instead of the dynamic binary choice models does not help us to answer questions regarding state dependence.

Our data initially comprises of a total of 16,065 observations on 4,542 firms. The maximum number of times a firm has participated in the survey is nine, five percent of the firms have participated eight times, 25 percent have participated five or more times, half of the firms has participated three or more times and 75 percent have participated at least two times.

The usable sample size reduces considerably due to (i) item-nonresponse in the dependent variable (reduction by 2,241 observations), (ii) the requirement of at least four consecutive observations per firm for one of the estimators we apply (reduction by 5,723 observations) and (iii) item-nonresponse in the exogenous variables (reduction varies according to specification choice). Item (i) and (ii) lead to a total reduction in sample size of 6,979 observations (43.4 percent of the initial sample).

In order to further illustrate our data, we will hereafter differentiate between a "gross sample" which consists of all firms that participated in the MIP survey at least two consecutive times (we use two consecutive participations since we use lagged endogenous variables) and a "net sample" that meets the full data requirements of all three estimators applied. These are (i) participation in the MIP survey at least four consecutive times and (ii) no item–nonresponse in the explanatory variables. The net sample hence is the sample that we eventually use in our analyzes.

A first empirical look at persistence in export activity is provided by Table 1 that displays the observed transitions between exporting and non–exporting of

the firms in our data. The upper panel refers to the gross sample while the lower panel is related to the net sample. Both panels provide first evidence for a very strong degree of persistence. The share of non-exporters in period t that remain being non-exporters in period t + 1 is around 90 percent. Likewise for firms that are exporters in t: 98 percent remain exporters in t + 1. Table 1 also shows that the structure of export status transitions is very similar between our two samples.

Insert Table 1 about here!

2.2 Empirical specification

The empirical specification that we employ to model firms' current export status is chosen to be very similar to the one used by R&T. They derive the estimation equation from a dynamic theory model of firms' entry and exit decision with sunk costs involved in entering (or exiting) the export market. Since R&T's empirical specification also is parsimonious in terms of exogenous variables, our point of departure is to replicate as closely as possible the R&T results on West German data.

The MIP data in principle allow for a much broader model specification that takes into account issues such as credit rationing, innovative activity, skill mix of workers, or research and development. Item–nonreponse in the MIP data is, however, a severe problem so that incorporating all the additional variables that one might think of affecting export activity would very considerably reduce our sample size. Moreover, we use a fixed effects estimator for which consistency does not rely on a full specification of cross-sectional determinants of exports in order to validate the results.

We do not motivate our empirical specification in detail and instead refer to R&T. Below we simply list what variables are included and briefly describe why they are considered:

• ln(*labor cost p.c.*): The natural logarithm of labor cost per worker is a proxy variable for the competitiveness of domestic firms in foreign markets. This

variable is also a measure for workforce qualifications since labor costs are an increasing function of qualifications.

- ln(*empl*): Firm size is included as the log of the number of employees since larger firms are more likely to export than smaller ones because they might be more efficient due to scale effects than smaller firms. They also might have easier access to capital markets and are more likely to detect export opportunities.
- $\ln(age)$: Older firms are more likely to export since they have learned through time how to successfully conduct business and how to adjust business strategies to changing environments. We use firm age at sample entry as the explanatory variable.
- *Dep*: Being a subsidiary firm is likely to affect export activity due to access to complementary assets and information from the mother company. We use a dummy variable for subsidiary firms in our specification.
- Sector dummy variables: Our specification also includes a set of sector dummy variables since there are inherent differences in export activities across sectors.²
- Time dummy variables: We allow for possible business cycle and exchange rate effects by including a set of year dummy variables.

Table 2 presents descriptive statistics of the continuous explanatory variables involved in the estimation. As usual, the between variation of the explanatory variables is much larger than the within variation. There is quite considerable within-variation in $\ln(labor \ cost \ p.c.)$ while there is much less within-variation in $\ln(empl)$.

²The following sectors are included in our analysis: manufacture of food products, beverages and tobacco, manufacture of textiles and textile products, manufacture of wood and wood products, manufacture of coke, refined petroleum products and nuclear fuel, manufacture of rubber and plastic products, manufacture of other non-metallic mineral products, manufacture of basic metals and fabricated metal products, manufacture of electrical and optical equipment, manufacture of medical, precision and optical instruments, watches and clocks, manufacture of transport equipment, manufacture of furniture, and manufacture of machinery and equipment.

Although not reported in the table, item–nonresponse is quite considerable even for those two elementary variables. Information of workforce size is missing 224 times while labor cost information is missing 4,004 times in the gross sample, an issue that is likely due to the fact that the question on workforce size is asked at the very beginning of the questionnaire while the wage bill question is asked at its very end.

Insert Table 2 about here!

3 Estimation

Our basic model of the current export status of a firm is a dynamic binary response panel data model. The binary indicator of exporting activity outcome, y_{it} , for firm *i* in year *t* is modelled as a function of observed heterogeneity in terms of a vector of strictly exogenous variables, X_{it} (some of which may be timeinvariant), "true" first-order state dependence through the lagged export status, y_{it-1} , "spurious" state dependence through permanent unobserved heterogeneity as modelled by the component α_i , and an idiosyncratic error term, u_{it} :

$$y_{it} = 1\{ \boldsymbol{X_{it}}'\boldsymbol{\beta} + \gamma y_{it-1} + \alpha_i + u_{it} > 0 \}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T-1.$$
(1)

$$P(y_{it} = 1 | \mathbf{X}_i, \alpha_i, y_{i0}, y_{i1}, \dots, y_{it-1}) = F(\mathbf{X}_{it}'\beta + \gamma y_{it-1} + \alpha_i), \quad t = 1, 2, \dots, T-1, \quad (2)$$

where 1{ } is the indicator function, $X_i = (X_{i0}, X_{i1}, ..., X_{iT-1})$, P denotes a probability, and F denotes a cumulated density function.

Throughout we maintain a first-order lag in y_{it} and a logistic link function F.³ Moreover, we assume that u_{it} is i.i.d. logistic and independent of y_{i0} , X_i , and α_i . A total of T observations on the dependent variable is available for the analysis.⁴

³The logit specification is chosen since it allows a fixed effect estimator if $T \ge 3$. Fixed effect estimators for higher-order state dependence have been developed by Chamberlain (1985) for a case with no exogenous regressors and by D'Addio and Honore (2003) for a case with exogenous variables.

⁴Although the empirical analysis will use an unbalanced panel we outline the balanced case here in order not to obscure the notation.

Three different estimators of model (1) are considered. They differ in terms of their treatment of the initial export status, y_{i0} , its relation to the firm-specific unobserved permanent component, α_i , and the exogenous variables, X_i . First, a Heckman (1981)-type approach (hereafter H–RE) is considered. It specifies a distribution of y_{i0} given α_i and the exogenous regressors, X_i , and maintains that α_i is not correlated with the time-varying variables in X_i .

A second estimator we use is the RE model that has recently been proposed for dynamic binary choice models by Wooldridge (2002a) (herafter W–RE). It treats the initial condition by specifying a convenient distribution for the unobserved individual effects, α_i , given y_{i0} and the exogenous regressors, X_i , and allows for correlation between α_i and X_i .

The final estimator we consider is a fixed effects (hereafter FE) estimator which has recently been developed for the dynamic logit model with strictly exogenous regressors by Honore and Kyriazidou (2000). Their approach will allow us to stay completely agnostic about the relationship between the initial export status, y_{i0} , the unobserved permanent component, α_i , and the exogenous regressors, X_i .

Each RE estimator will be consistent and efficient if (and only if) the model is correctly specified whereas the FE estimator is consistent independent of the initial conditions. This is why we can use comparisons between each set of RE estimates and the FE estimates as a specification check of the random effects estimators.

The H–RE approach applies a flexible characterization of the distribution of the initial conditions in terms of initial values of observables and the unobserved permanent component, $f(y_{i0}|\mathbf{X}_{i0}, \alpha_i)$. Specifically, the distribution of the initial export status is a "reduced form" expression in terms of the initial values of the exogenous regressors and the unobserved permanent firm-specific component, $y_{i0} = 1\{X'_{i0}\beta_0 + \delta_0\alpha_i + u_{i0} > 0\}$. Moreover, it is assumed that α_i is distributed as $N(0, \sigma_{\alpha}^2)$ and independently of \mathbf{X}_i , and that u_{i0} is i.i.d. logistic. Then

$$P(y_{i0} = 1|X_i, \alpha_i) = \frac{\exp(X'_{i0}\beta + \delta_0\alpha_i)}{1 + \exp(X'_{i0}\beta + \delta_0\alpha_i)}$$
(3)

and α_i can be integrated out of the likelihood function for $y_{i0}, y_{i1}, \ldots, y_{iT-1}$ given

 $X_{i0}, X_{i1}, \ldots, X_{iT-1}$. This is very similar to the estimator applied by R&T.⁵

The W-RE approach reverses the conditioning argument and specifies $f(\alpha_i|y_{i0}, \mathbf{X}_i)$. This conditional distribution is unrestricted and a particular choice of $f(\alpha_i|y_{i0}, \mathbf{X}_i)$ enables inference on the model parameters by maximizing the likelihood function for y_{i1}, \ldots, y_{iT-1} conditional on y_{i0} and \mathbf{X}_i . For the logit specification a convenient choice is to assume that

$$\alpha_i = \gamma_0 + \gamma_1 y_{i0} + \gamma_2 \boldsymbol{X_i} + \eta_i \tag{4}$$

where η_i is independent of y_{i0} and X_i , and distributed as $N(0, \sigma_{\alpha}^2)$. Wooldridge (2002a) provides further details and suggests that X_i may substituted by timeaverages to conserve degrees of freedom. This model allows for correlation between α_i and X_i according to (4). Again the term η_i can be integrated out of the likelihood function as in a standard RE logit specification.

Finally, we apply a fixed effect approach to the estimation of Equation (1). For the logit model, Cox (1958) and Chamberlain (1985) consider the case with no exogenous regressors and showed that the parameter measuring state dependence, γ , can be identified without making any assumptions on α_i or its relationship with y_{i0} and \mathbf{X}_i . The FE approach uses the fact that the number of periods that an individual firm is active in the export market, $s_i = \sum_{t=0}^{T-1} y_{it}$, is a sufficient statistic for γ . Conditional on the number of active periods in a string of observations for firm *i* and under the absence of true first-order state dependence, strings with runs of active or inactive periods should be no more prevalent than strings in which the firm frequently switches between states. The relative frequencies of runs and switches then identify γ and the coefficients of time-varying variables in \mathbf{X}_i . The FE estimator does not identify the coefficients of time-invariant variables or the distribution of α_i by construction.

The FE approach has been extended to the logit case with exogenous regressors by Honore and Kyriazidou (2000). They show that a similar conditioning argument will work with a proper matching of the values of exogenous variables, X_{it} , in certain periods if — conditional on this match — there is enough variation in X_{it} in other periods. For discrete regressors the match can be exact whereas for

⁵R&T consider a probit case that also allows for serial correlation in u_{it} but they find no evidence of significant serial correlation.

continuous regressors kernel weighting needs to be applied. This means that, in practical terms, only a single continuous regressor is feasible and that convergence of the estimator will be slower than that the usual \sqrt{n} rate. Moreover, the need to match the values of X_{it} over time means that e.g. time dummies cannot be allowed by this method.

The large data requirements of the FE approach and its practical limitations seem to intensify the concerns with FE estimation usually encountered in the analysis of linear panel data models. However, there are data-related concerns that weigh in favor of the FE approach when a survey–based panel data set is used. We showed in Section 2 that item–nonresponse causes a considerable decline in usable sample size (although the remaining "net" sample does make the FE approach feasible, as we will see in the next section). Further explanatory variables could possibly either be time–invariant or have low within-variation. The effects of the additional explanatory variables will then be absorbed by the fixed effects so that there is no informational gain in adding these variables. If adding further explanatory variables leads to a substantial reduction in sample size due to item–nonresponse, the informational advantage of the RE approach is even smaller.⁶

4 Results

Table 3 reports our main findings. For each RE estimator we report results for the unrestricted specification outlined in Section 2 and a restricted specification that leaves out grossly insignificant variables. We also report FE results for a model that includes lagged employment along with the lagged export status of the firm. The estimations are based on an unbalanced sample of 2,524 observations on a total of 459 firms.

As discussed in Section 3, a practical limitation of the FE approach is that

⁶The within–variation in the explanatory variables included in the actual empirical specification seems sufficient. A simple static fixed effects logit model of current export status leads to highly significant effects of wages and firm size. The specification in addition included a set of time dummies, a set of sector dummies, firm age and a dummy for being a subsidiary firm.

only one time-varying continuous exogenous variable is feasible due to the nonparametric matching involved by this approach. Clearly, consistency of the FE estimator depends on the inclusion of the proper time-varying effects. We choose employment as the time-varying exogenous regressor in the FE estimation so as to be consistent with existing studies on firms' export activity, for example Bernard and Jensen (forthcoming) and Wagner (2003).⁷

Insert Table 3 about here!

The H–RE estimates for the West German case are broadly consistent with the results that R&T obtained for export–oriented Columbian firms using a similar estimation approach. We find positive effects of the time–varying explanatory variables (labor cost per capita and employment) as well as a significant coefficient of lagged export status.⁸ The effects of subsidiary status (Dep_i) and age are positive and industry effects are also significant. The results differ mainly in terms of the time effects which were quite significant in R&T but not in our model, and the more dominant role of permanent unobserved heterogeneity. The variance of α_i accounted for approximately 69 per cent of the overall error variance according to R&T whereas the comparable figure in our estimation would be above 90 per cent.

The W-RE estimates confirm the presence of a significant effect of lagged export status. They also show that time effects do not play a significant role in our data. Just as in R&T and in our H-RE estimates, the effect of employment is positive. Although the figures are not strictly comparable due to the conditioning on y_{i0} and X_i in Equation (4), the W-RE results indicate a smaller role for unobserved firm heterogeneity which explains a share of approximately 40 per cent of the overall error variance.

The FE estimates confirm that there is empirical evidence of true state dependence. The coefficient of lagged export status, $\hat{\gamma}$, is very close to that obtained

⁷The fact that time dummies cannot be included in the FE model seems less of a problem according to the RE results presented below.

⁸R&T use a probit specification so an approximate factor of 1.6 should be applied to correct for the different normalizations, e.g. Wooldridge (2002b, p. 466). The logit estimate of $\hat{\gamma} = 1.78$ is thus slightly larger than the R&T probit estimate of 0.885.

by the W-RE approach although less significant with a p-value around 13 per cent. The short-run effect of lagged employment is found to be slightly negative but the estimate is insignificant. The standard errors of both coefficients have increased markedly. This is mainly due to the fact that the identification of the FE comes from a total number of strings used in the estimation — compare Section 3 — which is only 114.

Our FE estimates gain in precision if we increase the sample size by also including observations that have missing values in explanatory variables other than lagged export status and lagged employment, which then disallows for comparisons between the FE model and the RE models since they are based on entirely different samples.

Considering *all* observations with non-missing values in lagged employment and lagged export status (and not requiring that these observations have non-missing values in the other variables used in the RE models as well) the sample size increases by more than 50 per cent with 3,969 observations on 717 firms being available for the analysis. The empirical identification is based on 171 usable strings. Our results (with bootstrapped standard errors in parentheses) are an estimated coefficient on lagged exports of 3.05 (1.65) which is now significant at the ten per cent level, and a coefficient on employment of -0.13 (0.92) which remains insignificant.

Finally, we use the FE estimates in Table 3 as a specification check for the RE approaches. Hausman tests on the parameters that are identified by both the RE and the FE estimators⁹ show that, formally, we can reject neither of the RE specifications.¹⁰ However, due to the relative imprecision of the FE estimates we expect these test not to be very powerful. An informal comparison of the RE approach should be rejected on these data whereas the W–RE approach appears to be validated. Our conclusions below will thus be based on the latter approach.

⁹The use of Hausman tests in the context of dynamic logit models was suggested by Chay and Hyslop (2000).

¹⁰The test statistics of 0.18 and 1.72 for W-RE and H-RE, respectively, are far from being significant. They are asymptotically distributed as $\chi^2(2)$ with p-values of 0.91 and 0.42, respectively.

5 Conclusions

The main conclusion of the empirical analysis is that the persistence in firms' export status is significantly driven by true state dependence. This result is very robust across specifications.

We also find that the Wooldridge (2002a)-type random effects estimate of the state dependence parameter is much larger than in our reference study on state dependence in export activity by Roberts and Tybout (1997). The Wooldridge (2002a)-type random effects estimates are validated by the fixed effects estimator of Honore and Kyriazidou (2000) which, in contrast to the random effects estimators, remains consistent independently of the assumptions on the initial conditions. Moreover, our finding of significant true state dependence is robust to any time-invariant cross-sectional determinant of export status.

Our results also indicate that the importance of "spurious" state dependence, that is, permanent unobserved firm heterogeneity, is overstated by the Heckman (1981)-type random effects approach. We reject the Heckman-type model and validate the Wooldridge-type approach for our data. This suggests that a "pure" random effects assumption of uncorrelated permanent individual-specific effects is not tenable. We have shown that a proper binary choice FE approach is feasible on these data and how it can be used as a misspecification check on the random effects results.

Our finding of true state dependence in export activity has direct economic policy implications: if policy successfully turns non–exporters into exporters, the effect is likely to be lasting.

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| Gross sample | | | | | | | |
|---------------|--------------|-----------------|----------|-------|--|--|--|
| | | status in $t+1$ | | | | | |
| | | non-exporter | exporter | Total | | | |
| | non-exporter | 1,539 | 165 | 1,704 | | | |
| status in t | | 90.3 | 9.7 | 100 | | | |
| | exporter | 142 | 6,826 | 6,968 | | | |
| | | 2.0 | 98.0 | 100 | | | |
| | Total | 1,681 | 6,991 | 8,672 | | | |
| | | 19.4 | 80.6 | 100 | | | |
| | | | | | | | |
| Net samp | le | | | | | | |
| | | status in $t+1$ | | | | | |
| | | non-exporter | exporter | Total | | | |
| | non-exporter | 284 | 43 | 327 | | | |
| status in t | | 86.7 | 13.2 | 100 | | | |
| | exporter | 36 | 1,702 | 1,738 | | | |
| | | 2.0 | 98.0 | 100 | | | |
| | Total | 320 | 1,745 | 2,065 | | | |
| | | | | | | | |

| | Table 1: | Export | status | transition | matrices | |
|---|----------|--------|--------|------------|----------|--|
| _ | | | | | | |
| | | | | | | |

Note: straight numbers are absolute frequencies, numbers in italics are relative frequencies.

15.5

84.5

100

| Gross sample | | | | | | | |
|--------------|---------|--------|----------|----------|----------|-------|------------|
| | | | | | Ratio | | |
| | | | | Ratio | between/ | | |
| | | | | mean | within | | # of |
| | | Mean | Std.dev. | std.dev. | std.dev. | | obs. |
| ln(W/L) | overall | -2.737 | 0.475 | -5.76 | | Ν | 10,673 |
| | between | | 0.430 | -6.37 | 1.57 | n | $3,\!112$ |
| | within | | 0.274 | -9.99 | | T-bar | 3.430 |
| ln(L) | overall | 4.781 | 1.789 | 2.67 | | Ν | $13,\!654$ |
| | between | | 1.816 | 2.63 | 6.90 | n | 3,222 |
| | within | | 0.263 | 18.18 | | T–bar | 4.238 |
| Net sam | ple | | | | | | |
| | - | | | | Ratio | | |
| | | | | Ratio | between/ | | |
| | | | | mean | within | | # of |
| | | Mean | Std.dev. | std.dev. | std.dev. | | obs. |
| ln(W/L) | overall | -2.697 | 0.348 | -7.75 | | Ν | 2,524 |
| | between | | 0.296 | -9.11 | 1.52 | n | 459 |
| | within | | 0.195 | -13.83 | | T-bar | 5.499 |
| ln(L) | overall | 4.707 | 1.524 | 3.09 | | Ν | 2,524 |
| | between | | 1.542 | 3.05 | 9.18 | n | 459 |
| | within | | 0.168 | 28.02 | | T-bar | 5.499 |

Table 2: Descriptive statistics of the continuous variables involved in the estimation

Note: "N" denotes the total number of cases for which the corresponding variable is nonmissing, "n" denotes the total number of firms for which the corresponding variable is nonmissing and "T-bar" denotes the average number of firm-years for which the corresponding variable is non-missing.

| | H-RE | | W- | W-RE | | |
|-------------------------|---------|---------|---------|---------|---------|--|
| y_{it-1} | 1.800 | 1.779 | 2.772 | 2.671 | 2.531 | |
| | (0.366) | (0.305) | (0.403) | (0.369) | (1.689) | |
| $\ln(wage)_{it}$ | 0.773 | | 0.700 | | | |
| | (0.492) | | (0.583) | | | |
| $\ln(empl)_{it}$ | 2.390 | 2.231 | 0.994 | 0.692 | -0.184 | |
| | (0.345) | (0.312) | (0.652) | (0.608) | (2.145) | |
| $\ln(age)_i$ | 1.600 | 1.467 | 0.181 | | | |
| | (0.367) | (0.394) | (0.210) | | | |
| Dep_i | 2.453 | 2.551 | -0.132 | | | |
| | (0.567) | (0.448) | (0.450) | | | |
| Time dummies | Yes | | Yes | | | |
| | [0.059] | | [0.094] | | | |
| Industry dummies | Yes | Yes | Yes | Yes | | |
| | [0.000] | [0.000] | [0.286] | [0.246] | | |
| $\ln \sigma_{\alpha}^2$ | 4.108 | 3.958 | 1.123 | 1.094 | | |
| | (0.283) | (0.295) | (0.389) | (0.371) | | |
| $\ln L$ | -397.30 | -405.45 | -292.19 | -299.79 | | |

Table 3: Dynamic logit models. Dependent variable: y_{it} (export status in year t). Number of firms: 459. Total number of observations: 2524.

Note: numbers in parentheses for the RE estimators are quasi-MLE standard errors. For the FE estimates they are based on 10,000 bootstrap replications. A total of 114 usable strings are used in the FE estimation. Numbers in brackets are p-values of Wald tests of exclusion. RE models are estimated using a Gaussian quadrature. H–RE applies a Heckman (1981) type correction based on initial values of exogenous variables. W-RE applies the Wooldridge (2002a) correction by including y_{i0} and the individual time-averages, $\overline{\ln(wage)_{i,-1}}$ and $\overline{\ln(empl)_{i,-1}}$, as additional regressors.