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Kaiser, Ulrich; Kongsted, Hans Christian

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True Versus Spurious State Dependence in Firm Performance: The Case of German Exports

Ulrich Kaiser, Hans Christian Kongsted

Centre for Industrial Economics
Department of Economics, University of Copenhagen
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True versus spurious state dependence in firm performance: the case of German exports[§]

Ulrich Kaiser* and Hans Christian Kongsted**

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Abstract: This paper analyzes the persistence of firms' exporting behavior in a panel of German manufacturing firms using dynamic binary choice models. We distinguish between true and spurious state dependence in exports and apply fixed effects methods that allow us to verify the robustness of our results to critical assumptions on firms' initial export status. We find robust evidence of state dependence in the current export status of firms. We also document an important role of unobserved permanent firm heterogeneity ("spurious state dependence") and quantify the relative importance of different export determinants. Our results, which are consistent with the findings of previous studies on firms in developing countries and in the United States, show the presence of important sunk costs in export market entry and a depreciation of knowledge and experience in export markets.

JEL classification: $C23, D21$

Keywords: state dependence, export activity, dynamic binary choice models, fixed effects

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*University of Southern Denmark at Odense, Department of Business and Economics, Campusvej 55, 5230 Odense M, Denmark; email: uka@sam.sdu.dk, internet: http://www.sam.sdu.dk/staff/uka; Centre for Economic and Business Research at Copenhagen Business School, Centre for European Economic Research and Centre for Industrial Economics at the University of Copenhagen.

**University of Copenhagen, Department of Economics, Studiestræde 6, 1455 Copenhagen K, Denmark; email: Hans.Christian.Kongsted@econ.ku.dk, internet: http://www.econ.ku.dk/kongsted/; Centre for Economic and Business Research at Copenhagen Business School and Centre for Applied Microeconometrics at the University of Copenhagen. The activities of the Centre for Applied Microeconometrics are financed by a grant from the Danish National Research Foundation.

1 Introduction

The export performance of the domestic economy is usually regarded as a key component of the competitiveness of both developed and developing economies. It is therefore unsurprising that the body of economic literature on firms' behavior on export markets is large and steadily growing. Important theoretical papers are Baldwin (1988) and Dixit (1989), who emphasized the role of sunk costs associated with the efforts a firm undertakes in entering a foreign market. A main empirical contribution is Roberts and Tybout (1997; R&T hereafter) which also is the main reference of our paper. They conclude that sunk costs are important determinants of the dynamics of exports and also identify unobserved permanent firm effects as an important determinant of the overall persistence in exports.

Recent empirical work along the lines of R&T has produced evidence on the dynamics of exporting activities of firms and plants in a variety of regions and countries including Colombia (R&T), the United States (Bernard and Jensen, 2004; B&J hereafter) and Lower Saxony, a region in Northern Germany (Bernard and Wagner, 2001; B&W hereafter). These studies consistently find a very high degree of persistence in export status: current export activity at the firm or plant level is strongly and positively related to past export activity. The focus of the present paper is to further investigate the sources of such persistence. The core question is whether the very fact that a firm has previously been an exporter changes its probability of being an exporter in the current period, or if it is mainly permanent factors inherent to the firm and unobserved to the econometrician that are behind the persistent nature of exports. To put it in the terms of Heckman (1981): is the observed persistence a consequence of "true" state dependence, or is it "spurious" state dependence due to permanent unobserved firm effects that determines the intertemporal relationship?

This paper seeks to quantify both the extent to which current export activity is affected by the past and the extent to which true state dependence is the driving force behind such dynamics. Our study complements R&T and other empirical studies that build on their framework in several different respects: First, we provide new evidence for a particularly relevant developed economy, Germany, which is often termed the “world export champion”.[1] Existing empirical studies on the export activity of German plants either do not consider dynamics (Wagner 1993, 1995, 2002, 2003; Bernard and Wagner 1997) or specify state dependence by a linear probability model with lagged endogenous variables and fixed effects (B&W), an approach also taken by B&J in a study of U.S. manufacturing plants. As the authors acknowledge themselves, linear probability models do not generate well defined transition probabilities which is why we consider proper binary choice models throughout this paper. Secondly, we extend recent estimators suggested by Wooldridge (2005) for dynamic logit models to a case that allows for state dependence in exports to depreciate over time. A final contribution of our paper is that it complements the existing literature by investigating the dynamics of exports based on business survey data. Such data is more readily available than the Census-like data underlying previous studies. We demonstrate the feasibility of using the data for this analysis and find that our results are broadly in line with previous literature.

Our empirical investigations use both a “random effects” approach (RE hereafter) and a “fixed effects” approach (FE hereafter). The RE approach is an extension of a recent and computationally convenient specification suggested by Wooldridge (2005). A potential drawback of such RE–type dynamic binary choice models is that consistency hinges upon the correct specification of the relationships between the unobserved firm–specific permanent effects, the explanatory variables, and the initial export status. This is the “initial conditions” problem pointed out by Heckman (1981). We address this issue by using the conditional FE estimator developed by Honoré and Kyriazidou (2000, hereafter H&K) for dynamic binary choice models. The H&K estimator does not impose assumptions on the nature of permanent unobserved firm heterogeneity or its relationship with exogenous variables or initial conditions.

While the H&K estimator does identify the presence (or absence) of true state dependence, it is (i) not informative with respect to the quantitative and qualitative effects of many other factors that potentially influence differences in performance across firms,[2] (ii) requires the dependent variable to be independent of time ef-

[1]Frankfurter Allgemeine Zeitung, web-edition dated October 21, 2004.

[2]Only the coefficients of time-varying variables are identified by FE methods. One way to get around this problem is to include interactions of time–invariant and time–varying variables.

fects and (iii) is very demanding with respect to the time series dimension of panel data, as we discuss in greater detail in Section 3. We therefore primarily use the H&K estimation results to confirm our central RE-based findings.

The main result of this paper is that we find statistically significant and quantitatively important state dependence in exports. Both the first and the second lag of export status are statistically significant and positive with the first lag being quantitatively larger than the second lag. Our FE results serve to verify that the findings are robust to general specifications of the relation between firms' initial export state and permanent unobserved firm effects. The estimated lag structure indicates the existence of significant sunk costs in entering an export market and that knowledge and experience acquired upon entry depreciates significantly over two years. Our findings could suggest a scope for policy measures with lasting effects directed at export performance even for firms in a developed and already highly export-oriented economy.

2 Data

This section discusses the nature of our data, the pattern of export market transitions in the data, and the export determinants to be included as exogenous variables in our empirical model. We follow closely the existing studies in selecting the variables in order to enhance the comparability of our work with existing results.

2.1 Data source

Our analysis is based on waves 1 to 13 of the "Mannheim Innovation Panel" (MIP) collected between 1993 and 2004.[3] We concentrate on goods–producing

See Lee and Tae (2005) for a general treatment.

[3] Each wave refers to the respective prior year. The most recent information we have at our disposal hence refers to the year 2003 while the information related to 1992 (and 1993 in some model specifications) is lost once we use lagged variables.

sectors and leave out the sectors construction and utilities from the MIP data.[4]

The MIP is a business survey 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 the same way since 1993. All of the variables used in our study are based on MIP questions that remained unchanged. A detailed description of the data is provided by Janz et al. (2001).

The MIP is the German contribution to the "Community Innovation Survey" (CIS), which provides the statistical basis for innovation policy of the European Union and its member states. A total of 17 European countries (both EU and non–EU countries) participate in the survey;[5] all countries use the same standardized questionnaire. Even though CIS takes place only every four years, many countries collect data annually so that our paper can in principle be re–estimated for other countries as well.

The target population of the MIP covers all legally independent German firms with at least five employees from the sectors mining and quarrying, manufacturing, electricity, gas and water supply as well as construction. Germany does not maintain a business register. Data taken from Germany's leading credit rating agency, Creditreform, therefore served as the sampling frame. The MIP is a stratified random sample. The stratifying variables are firm size (eight size classes defined by the number of employees), sector classification (defined by two–digit sector classification codes) and region (East and West Germany). The sampling is disproportional, i.e. the sampling probabilities vary between cells: large firms, firms from East Germany and firms from strata where labor productivity is particularly heterogeneous are over–sampled.

[4]Export activity is very low in both sectors so that including sector dummy variables for construction and utilities almost perfectly predicts export activity.

[5]These are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Norway, Portugal, Spain, Sweden, the Netherlands and the United Kingdom.

The MIP is a voluntary mail survey that can also be filled out online. Questionnaires are sent to the sampled firms in early spring with two mail reminders in late spring and early summer. Selected firms are also contacted by phone. The response rates vary between 23.7 percent and 20.6 percent which is at the average of business surveys carried out in Germany. A non–response survey with 1,000 realized interviews is carried out after the mail survey is completed. Tests for non–response tend not to reveal biases with respect to firm size, sector or regional affiliation (Janz et al. 2003).

As a panel data set, the questionnaires are sent to the same set of firms every year. The sample is refreshed every second year by a stratified random sample of newly founded firms and other firms that moved into the frame population for example because they exceed the five employee threshold. The MIP sampling scheme has changed in 1998 for cost reasons. In even years, a shortened questionnaire is sent to a sub–sample of firms which have previously answered the questionnaire at least once or firms that have been added to the sample in the preceding year. The full sample scheme is used every odd year. Additionally, the most relevant variables are asked retrospectively for the preceding even year to maintain the panel structure of annual waves.

Our data differs in many respects from the data used by our most important references, R&T, B&W and B&J. A potentially important difference is that we use firm–level data while existing studies use plant–level data. We have no direct information on how this difference affects the comparability of our study. We do think, however, that the firm constitutes an appropriate level of analysis since it is likely that export decisions are reached at the firm–level rather than at the plant–level. B&W for example argue that firm-level data is preferable and include a dummy variable for multi–plant to capture such effects in their plant–level study.

A second difference between the data sources is that the MIP is based on a business survey, whereas existing studies use Census–like data. Again, we lack any direct evidence on the likely effects of this difference in data sources but, as we already noted, previous non-response analyzes of the MIP data do usually not reveal significant biases. The fact that we consider firms rather than plants and that large firms are oversampled in our sample does account, however, for differences in the average number of employees in our study compared to plant–level descriptive statistics contained in Bernard and Wagner (1997) for Lower Saxony. The mean number of employees reported in Bernard and Wagner (1997, Table 2) for 1992 is 257 employees for exporters and 67 employees for non–exporters; our corresponding mean number of employees for 1992 is 1,316 (median 200) for exporters and 181 for non–exporters (median 32). In terms of export activity, Bernard and Wagner (1997, Table 1) report export shares for each of the industrial sectors they consider. Some of those sectors coincide completely with ours. Our export shares in Plastics (72 per cent in Bernard and Wagner 1997/72 per cent in our data for 1992), Wood processing (49 percent/49 percent) and Textiles (75 percent/76 percent) are very similar to those presented in Bernard and Wagner (1997) while they are different in Electrical Equipment (48 percent/71 percent). The different export ratios for some sectors could well be due to the fact that our data covers Germany as a whole and not just Lower Saxony.

A final data–related issue is that the MIP primarily is an innovation survey and has not been collected for the analysis of export activity *per se*. It has, however, right from the start been designed for the analysis of issues that are not primarily innovation–related. As a consequence, papers based on the MIP data cover a wide range of other topics. For example, Ebling and Janz (1999) as well as Arnold and Hussinger (2005a,b) analyze export behavior; Hempell (2005) and Czarnitzki (2005) analyze labor productivity; and Falk and Seim (2000a,b) as well as Kaiser (2000, 2001) study the demand for heterogeneous labor.

2.2 Descriptive statistics

Our data initially comprises of an unbalanced gross sample of 25,335 observations on 7,278 firms. We have excluded observations on firms which do not report their export status, report zero employees, have no labor costs, or report having been part of a merger during the year of observation. Table 1 displays descriptive statistics of the variables involved in our estimations and the share of exporters in the total number of observations by industry. The table differentiates between exporting firms and non–exporting firms. It is shown that exporting firms (i) employ a higher number of employees, (ii) pay higher wages per worker and (iii) are older than non–exporting firms. All these differences are statistically highly significant. Findings (i) and (ii) are consistent with other studies on export activity, most importantly with B&W and Bernard and Wagner (1997).

Table 1 shows that the share of exporters is higher than the share of non–exporters in all sectors but Food and tobacco.[6] Export activity is highest in Machinery where 82.6 percent of all firms export, followed by Petrochemicals (82.4 percent) and Transport (78.3 percent). It is lowest in Food and tobacco (46 percent), Wood processing (54 percent) and Nonmetallics (56.5 percent). Around three quarters of the firms at any point in our data are exporters.

Insert Table 1 about here!

Table 2 presents descriptive statistics of export status and time-varying explanatory variables involved in the estimation. As usual, the between variation of the explanatory variables is much larger than the within variation. There in fact is quite little within–variation in both the number of employees and labor cost per worker (relative to the between variation).

Insert Table 2 about here!

2.3 Export market transitions

Our definition of firms' export status is based on the MIP survey question "How large were your exports in [the year the question refers to]". If a firm reports

[6]We have abbreviated the sector names throughout this paper. The appropriate sector names and their abbreviations in parenthesis are: manufacture of food products, beverages and tobacco (Food & tobacco); manufacture of textiles and textile products (Textiles); manufacture of wood and wood products (Wood processing); manufacture of coke, refined petroleum products and nuclear fuel (Petrochemicals); manufacture of rubber and plastic products (Plastics); manufacture of other non–metallic mineral products (Nonmetallics); manufacture of basic metals and fabricated metal products (Metallics); manufacture of electrical and optical equipment (Electrics); manufacture of medical, precision and optical instruments, watches and clocks (Medical equipment); manufacture of transport equipment (Transport); manufacture of furniture (Furniture); and manufacture of machinery and equipment (Machinery).

zero exports, it is defined as a non–exporter; if positive values are reported, the firm is defined as an exporter. A small number of firms do not report the value of their exports whereas they do respond to a question directly targeted at their export status ("Did you have no exports in [the year the question refers to]"). The transformation of the value of exports into a simple dummy variable makes it possible to use both pieces of information. Our procedure is clearly discarding valuable information since it converts a continuous variable into a binary one, but it is in keeping with the overall focus of the paper on the firm's binary decision to participate in the export market. In effect, we infer the presence of true state dependence from the dynamic behavior of the main export status "switchers".

The maximum number of times a firm has participated in the survey is twelve, 20 per cent of the firms participated six times or more (denoted 6+), and 38 per cent have participated four times or more (4+). The 4+ firms account for 17,310 observations of the total number of observations or approximately two-thirds of the total in the gross sample.

A first look at persistence in exporting is provided by Table 3. Panel A refers to the transitions in the gross sample of 25,335 observations. The transitions are between exporting and non–exporting in adjacent time periods, $t-1$ and t. There is clear evidence of persistence in exporting status. Both exporters (97 per cent) and non-exporters (88.4 per cent) are very likely to remain in their current state between periods $t-1$ and t. This means that there are fairly few "switchers" in the sample.

Panels B and C of Table 3 classify the transitions between $t-1$ and t by the exporting status of firms in the previous period, $t-2$, if three or more consecutive observations are available. For example, consider a firm that was a non-exporter in period $t-1$. If the firm had not been exporting in the previous period, $t-2$, it is quite unlikely to switch to exporting in t (panel B); only 10.3 per cent of observations on firms in such circumstances are reported as active exporters (328 out of 3,186 observations). On the contrary, a much higher proportion of non-exporting firms return to exporting in t if the firm was an exporter in $t-2$ (70 out of 300 observations, or 23.3 per cent, according to panel C). A similar pattern holds for firms exporting in $t-1$: non-exporters in $t-2$ are quite likely to return to non-exporting after a single period of exporting (17.2 per cent, panel B); a switch to non-exporting takes place with very low probability for firms with a history of exporting prior to $t-1$ as only 2.2 per cent of firms with exports both in $t-2$ and $t-1$ become non-exporters in t (panel C).

The pattern of transitions is suggestive of both first- and second-order dependence in exports. Lagged export status matters for current exports and the amount of time previously spent in a particular state (two or more periods *versus* just one period) apparently also affects the likelihood of leaving a state in any given period. Specifically, the evidence in Table 3 suggests there is negative duration dependence in switching out of a particular state: the longer a firm has been a non–exporter, the less likely it is to shift to the other state and become an exporter; a similar pattern of negative duration dependence holds for moves out of exporting. While the raw transitions are suggestive they do not identify if the apparent persistence is truly due to state dependence or to permanent unobserved firm heterogeneity. The aim of our econometric modelling is to sort out the relative contributions of either to assessing their statistical and economic significance.

Insert Table 3 about here!

2.4 Determinants of export market participation

Our point of departure in selecting which exogenous variables to include is the seminal study by R&T. They derive a dynamic theoretical model of firms' entry and exit decision with sunk costs involved in entering (or exiting) the export market. From their model they obtain a fairly parsimonious specification in terms of exogenous variables. We briefly motivate their variables and refer to R&T for details:

- $\ln(wage)$: The natural logarithm of labor cost per worker is primarily included as a proxy variable for the competitiveness of domestic firms in foreign markets, although it could also be regarded as a measure for workforce qualifications since labor costs are an increasing function of qualifications.

- $\ln(empl)$: Firm size is measured by the log of the number of employees. Larger firms are more likely to export than smaller ones because they might be more efficient due to scale effects, might have easier access to capital markets, and be more likely to detect export opportunities. R&T use the firm's capital stock as a measure of size. Since this alternative measure is not available in our data, we use employment.

- $\ln(age)$: Older firms are more likely to export since they have learned through time how to successfully conduct business at home and how to adjust business strategies to changing environments.

- *Corp*: Being a part of a corporation is likely to affect export activity due to access to complementary assets and information from other firms within the corporation. We use corporation status at sample entry as our explanatory variable.

- *East*: We control for geographical location by including a dummy for the firm being located in the former East German Länder. We use location at sample entry as our explanatory variable.

- Sector dummy variables: Our specification also includes a set of sector dummy variables since there are inherent differences in export activity across sectors.

- Time dummy variables: We allow for possible business cycle and exchange rate effects by including a set of year dummy variables.

The only explanatory variable missing in our specification compared to R&T is export price. We do not have this piece of information in our data. Since the aggregate price fluctuations are captured by the time dummies and the individual firms' export prices turn out insignificant in all of R&T's specifications, we do not expect this omission to be a significant source of bias.

The MIP data in principle allows 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.

The usable sample size differs both according to the estimation method being used and as a result of item-nonresponse in the survey. Random effects-type estimators require a complete specification of cross-sectional determinants. This could be associated with a significant loss of data due to item–nonresponse in the exogenous variables, and the actual reduction of the sample varies according to specification choice. The fixed effects-type estimators that we also consider, see Section 3, do not need time-invariant determinants of exporting activity but they do rely on samples of consecutive observations of at least four observations per firm (or six observations depending on the generality of the dynamics of the model). This will be another source of sample reduction. We will exploit the data to the fullest extent possible although this will imply that somewhat different samples are used for different estimators.

3 Model specification and estimation

This section sets up the basic model and discusses some specification and estimation issues. We consider in particular the relative merits of fixed effects (FE) and random effects (RE) approaches to the estimation of a dynamic binary response panel data model. This section also provides the details on the implementation of these approaches.

Our basic model is given by Equation (1) and Equation (2) below. We model the binary indicator of exporting activity, y_{it}, for firm i in year t as a function of (i) a vector of strictly exogenous observables, $\boldsymbol{X_{it}}$ (some of which may be time–invariant); (ii) state dependence through lagged export status indicators, y_{it-1} and y_{it-2}; (iii) permanent unobserved heterogeneity as modelled by the component α_i; and (iv) an idiosyncratic error term, u_{it}:

$$y_{it} = 1\{\boldsymbol{X_{it}}'\boldsymbol{\beta} + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \alpha_i + u_{it} > 0\}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T, \quad (1)$$

where $1\{\ \}$ is the indicator function. The conditional probability of firm i exporting in year t is

$$P(y_{it} = 1 | \boldsymbol{X_i}, \alpha_i, y_{i,-1}, y_{i0}, y_{i1}, \ldots, y_{it-1}) = F(\boldsymbol{X_{it}}'\beta + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \alpha_i), \quad (2)$$

where we specify the link function F as a cumulative distribution function (cdf). $\boldsymbol{X_i} = (\boldsymbol{X_{i1}, ..., X_{iT}})$ is the set of exogenous variables observed in-sample over $t = 1, 2, \ldots, T$, and $y_{i,-1}$ and y_{i0} denote pre–sample observations at $t = -1$ and $t = 0$, respectively. The conditioning on $y_{i,-1}$ is in the two–period model only.[7] The specification of lagged export terms in Equation (1) differs from that adopted by R&T. While both capture second-order dependence in export status, R&T include a dummy variable that is coded 1 if the firm last exported in $t-2$ and 0 otherwise since this is consistent with their theoretical sunk costs model. We decided to use the actual export status at $t-2$ since it allows us to use the two-lag FE estimator of Chamberlain (1985) as well as d'Addio and Honoré (2004).

To complete the model specification, we need assumptions regarding the link function and the idiosyncratic error term. Common choices in terms of F are logit or probit.[8] Each has its own specific limitations in this context. The FE estimation strategy has the virtue of not making any assumptions on the unobserved permanent effect, α_i. This requires the use of a logit specification because there are no other parametric specifications that allow fixed effects estimation in dynamic binary choice models as discussed by Honoré (2002).[9]

For RE estimation it is further required that a particular distribution is specified for α_i. Both logit and probit specifications could be used here. The RE probit specification could furthermore be extended to allow for serial correlation in u_{it}. Such an extension was considered by R&T, although they found it to be insignificant in their sample of Colombian firms. This extension is not available for the dynamic logit model, as discussed by Honoré and Kyriazidou (2000) in the context of state dependence modelling and serial correlation in individual unobservables.

We are essentially facing a trade-off between being able to allow for serial correlation in the error term u_{it} at the cost of making distributional assumptions, and

[7]Although the empirical analysis uses an unbalanced panel we outline the balanced case here in order not to obscure the notation.

[8]In specifying F as a cdf we excluded the use of a linear link function since it does not produce well–defined choice probabilities.

[9]See, however, Honoré and Kyriazidou (2000) for a semi-parametric approach.

the possibility to use a FE estimate which is less restrictive in terms of assumptions on α_i. The existing empirical evidence in R&T does not suggest significant evidence of serial correlation. Since our paper's main focus is on the relative importance of true and spurious state dependence, we will make this inference with minimal assumptions on unobserved permanent heterogeneity, α_i, and give preference to the logit assumption.[10] In effect, we maintain the assumptions of a logistic link function F and an idiosyncratic error term, u_{it}, which is i.i.d. and independent of $\boldsymbol{X_i}$, α_i, and the pre-sample observations on export status.

In specifying our RE estimators we follow recent suggestions by Wooldridge (2005). In his approach, the initial conditions problem inherent in the dynamic nature of Equation (1) and the need to condition on pre-sample observations is taken into account by specifying a particular distribution for the unobserved individual effect, given the exogenous regressors, $\boldsymbol{X_i}$, and the initial export status of the firm, and integrating out the error in the unobserved firm effect from the likelihood function. If correctly specified, the RE estimator provides consistent and efficient estimates of all aspects of the model, including the marginal effects of time–varying observable export determinants on the probability of export market participation at different levels of the distribution of unobservables and the average of such effects.

We also generalize the one–lag case treated in Wooldridge (2005) to a two–lag case with $\gamma_2 \neq 0$. This is in order to capture second-order dependence as suggested by the raw transitions in Table 3. Previous studies of export market dynamics, including R&T, B&J and B&W, also find evidence for second–order effects. For the two–lag model we adopt a linear representation of the unobserved permanent component, α_i, in terms of exogenous variables and pre–sample values of export status,

$$\alpha_i = \gamma_0 + \rho_1 y_{i0} + \rho_2 y_{i,-1} + \rho_3 \boldsymbol{X_i} + \eta_i \tag{3}$$

where η_i is distributed as $N(0, \sigma_\eta^2)$ and is independent of $y_{i,-1}$, y_{i0} and $\boldsymbol{X_i}$. This is a convenient representation that allows the term η_i to be integrated out of the likelihood function as in a standard RE logit specification.[11] For the one-lag case, the conditioning is on a single pre-sample observation. In order to apply the

[10]None of our RE–based conclusions are affected when we specify a dynamic probit model.

[11]Wooldridge (2005) used a probit specification although as noted above we specify a logit model.

estimator to unbalanced samples, we include the time-varying exogenous variables only in terms of their in-sample averages, $\overline{\boldsymbol{X_i}}$.

The FE estimation approach for a dynamic logit model, Equation (1) and Equation (2), with time–varying exogenous regressors has been suggested by Honoré and Kyriazidou (2000), who extend the conditional logit approach of Cox (1958) and Rasch (1960). For a one-lag case without exogenous regressors ($\gamma_2 = 0$, $\beta = 0$), the state dependence parameter γ_1 can be identified without making any assumptions on α_i if $T \geq 3$ (with one pre-sample observation on y). Identification relies on the fact that the number of periods that an individual firm is active in the export market is a sufficient statistic for γ_1. Conditioning on this statistic produces a conditional likelihood which does not depend on α_i. Intuitively, if no first-order state dependence is present, we observe strings with longer runs of active or inactive periods to be no more prevalent than sequences in which the firm frequently switches between states. The relative frequencies of runs and switches is informative about γ_1. By construction, the distribution of α_i or other model features that depend on this distribution are not identified.

Honoré and Kyriazidou (2000) show that this basic conditioning argument also identifies the coefficients of time-varying exogenous variables in $\boldsymbol{X_{it}}$, if their values can be properly matched in certain periods and if — conditional on this match — there is enough variation in $\boldsymbol{X_{it}}$ in other periods. For discrete regressors the match can be exact whereas kernel weighting needs to be applied for continuous regressors. This means that, in practical terms, only a single continuous regressor is feasible and that convergence of the estimator will be slower than the usual $\sqrt{N}$ rate. Moreover, the need to match the values of $\boldsymbol{X_{it}}$ over time for some firms means that e.g. time dummies cannot be accomodated by this method.

Model extensions to allow for duration effects have been examined by Honoré and Kyriazidou (2000) and by d'Addio and Honoré (2004). Their two-lag FE approach identifies γ_2 and the components of β which correspond to time-varying variables. The first-order state dependence parameter is treated similarly to α_i as a nuisance parameter, γ_{1i}, which is allowed to vary unrestrictedly across i. For the two-lag case, identification needs that $T \geq 4$ (and two pre-sample observations on y). For the special case without exogenous variables, $\boldsymbol{X_{it}}$, the conditional logit approach reduces to the dynamic logit FE estimator proposed by Chamberlain (1985). This estimator will then identify the parameter related to duration dependence, γ_2.

The FE approach allows us to stay completely agnostic about the relationship between the initial export status, y_{i0} and $y_{i,-1}$, the unobserved permanent component, α_i, and the exogenous regressors, $\boldsymbol{X_i}$. Given the validity of the other model assumptions (which are common to both our RE and FE approaches), the FE estimator is thus consistent independently of the initial conditions specification. In this way, a comparison between RE and FE estimates provides a specification check on the assumptions regarding α_i that underlie the RE estimator.

4 Results

Our empirical results consist of three parts. First, we estimate Wooldridge-type correlated random effect (RE) models of export status. The RE estimation approach provides us with a fully specified model, including a distribution of unobserved permanent firm heterogeneity. Next, we produce fixed effect (FE) estimates of the model parameters related to state and duration dependence for comparison with the RE estimates. Finally, in order to quantify the relative importance of different determinants of persistence in firms' export status, we calculate predicted export probabilities using the RE estimates of the full model.

4.1 Random effects results

The RE estimates of the export participation equation, Equation (1), are reported in Table 4.[12] Similar to R&T, we let the time-varying variables enter with a lag in order to avoid simultaneity problems. The columns labelled "One-lag models" report the results for specifications that impose $\gamma_2 = 0$. The columns labeled "Two-lag models" add the twice lagged export dummy to the model. All models treat the initial conditions problem according to Equation (3) by allowing unobserved permanent firm heterogeneity to be dependent on the initial values of export status and the firm-specific averages of the time-varying regressors. For

[12]The coefficients of time and industry dummies are reported in the Appendix.

the one-lag models only one initial value of export status enters Equation (3).

Insert Table 4 about here!

The unrestricted one-lag model reported in the first column shows few significant exogenous variables. Such insignificant results in this model are, however, to some degree related to the limited within-variation evident from Table 2. This creates near-collinearity between terms that involve the supposedly time-varying variables, $\ln wage_{t-1}$, $\ln empl_{t-1}$ and $\ln age_{t-1}$, and their corresponding firm-specific averages. Once we exclude the time-varying terms (but keep the firm-specific averages),[13] our qualitative findings are very similar to R&T's: the average employment effect is highly significant (we regard employment as a proxy for size and compare it to R&T's estimate on capital) and there is a positive and significant effect of average wages. With regard to state dependence, there is a positive and highly significant impact of last period's export status. Unobserved permanent firm heterogeneity accounts for a significant part of the overall variance. This is indicated by the significance of σ_η. There is ample evidence of time effects. The years 1996 and 2003 are associated with a significantly higher propensity to export than the reference year, 1993, whereas firms on average had a comparatively low propensity to export in 1997. Industry effects are also highly significant which is why we include a full set of industry dummies throughout.

While the one-lag models show clear evidence of true state dependence via the strongly significant presence of lagged export status, they do not allow the amount of time spent exporting or non-exporting to play a role. In columns three and four of Table 4, we extend our model to accommodate this. Similar to previous studies, including R&T, B&W and B&J, second-order dependence turns out to be empirically relevant since the second lag is highly significant and positive. The extension reduces the size of the coefficient estimate on the first lag, although it remains highly significant. The averages of firms' wages and employment over the sample are positively significant. The negative effect associated with firms being located in East Germany is no longer significant in the two-lag model. Otherwise, the qualitative findings are basically unaltered compared to the one-lag model.

[13]The model reduction cannot be formally rejected. A Wald test of the exclusion restrictions yields a test with a p-value of 0.16.

In column four we specify our final model by excluding variables which previously were insignificant at a five per cent level.[14] The model reduction lowers somewhat the coefficients on twice lagged exports although it remains positive and highly significant. The coefficients related to first-order state dependence, average firm size, and average wages are almost unaffected by the model reduction. This is our final model which we will use for quantifying the empirical importance of state dependence and duration dependence in Subsection 4.3.

4.2 Fixed effects results

Next, we produce fixed effect (FE) estimates of the basic model parameters related to state and duration dependence, γ_1 and γ_2, and some time-varying exogenous variables.

There are a few caveats to the practical use of FE estimation in these data. First, as noted in Section 3, the conditional logit approach requires the absense of any time effects. The RE results in Table 4 provide, however, evidence of significant time effects. We will therefore report additional results for the longest subperiod that is free of time effects, 1998 to 2002.[15] The second caveat is that our RE results indicate limited within-variation in the exogenous variables. The FE approach is likely to exacerbate this problem since the identification of coefficients of exogenous variables relies exclusively on variations over time. Our preliminary investigations using the Honoré—Kyriazidou and d'Addio—Honoré estimators did not provide evidence of significant effects of the time–varying variables and we found the coefficients of main interest, γ_1 and γ_2, to vary little between specifications based on different exogenous variables. We will therefore only report a representative set of results using firm size as the time–varying exogenous variable in the model.

The upper part of Table 5 reports the Honoré—Kyriazidou and d'Addio—Honoré

[14]The model reduction cannot be formally rejected. A Wald test of the exclusion restrictions yields a test with a p-value of 0.63.

[15]Table 4 reports Wald tests of equality of the coefficients of time dummies for the years from 1998 to 2002. None of the corresponding p–values is less than 0.17 so we cannot reject the hypothesis that time effects are equal during this period.

estimates of models that include a time-varying term in firm size. The lower part reports results obtained using the Chamberlain (1985) estimator in a model without exogenous variables.

From Table 4 we would expect to find second-order dependence so we rely primarily on the results presented for the two-lag model in Table 5. In the two-lag case the conditional logit approach identifies γ_2, whereas the first-lag effect is treated as a nuisance parameter, γ_{1i}, that varies unrestrictedly across firms similar to α_i. The FE estimate of γ_2 is 0.832 and hence very close to our final RE estimate of 0.78, although estimated with less precision. The coefficient estimate on firm size is negative and insignificant.[16] It is similar to the estimate that was obtained when we included time-varying exogenous variables in the RE model. When firm size is excluded, the estimate of γ_2 is somewhat lower as evidenced by the Chamberlain estimate of 0.69.

Having arrived at the preferred FE estimate of γ_2 of 0.69 we can assess the significance of the difference to the second-order coefficient of 0.78 as obtained for the preferred RE specification in Table 4. We employ a Hausman test as suggested by Chay and Hyslop (2000) and find that the final two-lag RE model cannot be rejected based on the common parameter, γ_2. The Hausman test yields a test statistic of 0.08 which is distributed as $\chi^2(1)$ under the null of a correctly specified RE model. It must be noted that the first caveat applies: because the two-lag FE estimators need six or more observations, we have used the full sample and thus face potential inconsistency of the FE estimates due to neglected time effects.

Insert Table 5 about here!

For the one-lag models we report two sets of estimates of γ_1 in Table 5. Both are obtained from samples of four or more observations: a full sample estimate and a 1998-2002 subsample estimate. *A priori*, we expect both to suffer from bias due

[16] The overall loss of precision in FE estimation is due to the conditional nature of these estimators and the requirement of six or more observations for the two-lag FE estimator. This sample size restriction also explains why we cannot apply the two-lag FE estimators to the 1998-2002 subsample which includes only five periods.

to omission of a second lag in export status and a formal comparison based on Hausman tests is therefore not valid. The sub–sample FE estimate is 3.86 (and hence very close to the 3.95 obtained from the final RE specification in Table 4) and statistically highly significant for a sample without major time effects. The insignificance of firm size effects again suggest the relevance of the Chamberlain estimate which is 3.89 for the sub–sample and thus even closer to the RE estimate. The full sample estimates of γ_1, on the other hand, are considerably lower at 2.9. This indicates a negative bias due to the neglect of time effects by the full–sample FE estimates.

In sum, we find that although the FE approach evidently loses much precision in estimation, we take the results as confirming the validity of the estimates of the fully specified model obtained by the RE approach in Subsection 4.1.

4.3 Quantifying export determinants

This subsection quantifies the effects of three distinct determinants of persistence in firms' export status, state dependence, unobserved heterogeneity, and observable exogenous determinants. Similar to R&T we present the predicted period t probability of exporting based on the final estimates of the restricted two-lag model from Table 4.

Insert Table 6 about here!

Firms are characterized in three different dimensions. First, going across each panel in Table 6 corresponds to firms being at the 25th, 50th, or 75th percentile when ranked according to their observables.[17] Secondly, firms are characterized by their recent exporting histories, (y_{it-2}, y_{it-1}), within each of the four panels: no exports during a period of (at least) two years prior to t, (0,0); having been an exporter at $t-2$ but not at $t-1$, (1,0); having been an exporter at $t-1$ but

[17]In our restricted two-lag specification, the index of observables includes time dummies, sector dummies, and the term $\hat{\rho}_1 y_{i0} + \hat{\rho}_2 y_{i,-1} + \overline{X_i}' \hat{\rho}_3$ to approximate the unobserved firm effect.

not at $t-2$, (0,1); or having been an exporter for at least two years prior to t, (1,1). Finally, the rows of the table show the effects of being located at various points in the distribution of unobserved firm effects, η_i.

Exporting is the likely outcome for most combinations in Table 6. This reflects a comparatively high share of exporters in our sample. The share of exporters among German firms varies between 68 and 78 per cent over the sample period which is in contrast to e.g. the R&T sample of Colombian plants for which the share of exporters ranges between 11 and 14 per cent. The B&J sample of U.S. plants is an intermediate case with about half of the plants actively exporting. For the German firms, it apparently takes a history of consistent non-exporting during a period of two years, or one year of no exports in combination with a low propensity due to unobserved heterogeneity or observed exogenous export determinants, for the probability of exporting to drop below a half.

State dependence is prominent for all combinations in Table 6. As an example, consider a firm which is at the 50th percentile in terms of its estimated index of observables and has an unobserved permanent effect of zero, $\eta_i = 0$. Assume also that the firm did not export at time $t-2$. Then, if the firm was *not* an exporter at $t-1$ its predicted probability of exporting this period is 0.329; if the firm *did* export in period $t-1$, the probability of exporting increases to 0.962. This is a marked increase in the propensity to export of 0.63, or almost two-thirds, due to the effect of positive first-order state dependence. The effects of state dependence are smaller for firms which are in any case very likely to export either because they exported at $t-2$ (a change from 0.517 to 0.982), or due to their unobserved firm characteristics. Still, the smallest difference in the current propensity to export between exporters and non-exporters at $t-1$ is a 9 per cent increase. This is for exporters at $t-2$ which are at the 75th percentile in terms of observables with an unobserved firm effect of $+2\sigma_\eta$ (plus two standard deviations of the unobserved permanent firm effect). The statistical significance of lagged export status is thus reflected by a quantitatively important effect of first-order state dependence in determining predicted export probabilities. This is in line with previous findings of the importance of state dependence in exports for plants in Colombia (R&T), the U.S. (B&J), and Lower Saxony (B&W).

The statistical significance of the second lag in export status establishes a role for duration dependence in exports. The quantitative effects can be gauged from Table 6. Consider again a firm at the 50th percentile of the estimated index of observables with a zero unobserved effect, $\eta_i = 0$, but now assume that the firm did export at $t-1$. The current propensity to export is only 0.020 higher if the firm was also an exporter at $t-2$ (predicted probability 0.982) rather than having been a non-exporter (predicted probability 0.962). Basically, a firm with those particular characteristics is in any case very likely to export due to the effect of first-order state dependence. Somewhat larger effects of duration dependence are found for firms which are otherwise less export-prone. If the firm did not export at $t-1$, its probability of exporting changes from 0.329 to 0.517 depending on whether it was an exporter at $t-2$. Again, larger effects can be found the otherwise least export-prone firms with low levels of observable and unobservable export determinants.

Both the exogenous export determinants and the unobserved permanent firm-specific effects remain potent and quantitatively important determinants of current export status. This is evident from comparing the predicted export propensities between the three panels or between the rows in Table 6. To obtain a more direct comparison of the relative importance of true and spurious state dependence, consider again a firm at the 50th percentile in terms of the observables index and without exports two periods prior to t. If this firm happens to be in the upper tail of the distribution of unobservables (at $+2\sigma_\eta$) rather than in the lower tail (at $-2\sigma_\eta$), its predicted export probability improves from 0.096 to 0.693. The difference of 0.60 is close to the effect of 0.63 due to first-order state dependence which was recorded above for a firm with similar observable characteristics and $\eta_i = 0$. According to this comparison, it takes an extreme difference in unobservables to produce a difference in export propensities similar to the effect associated with being already established in the export market during the period prior to t.

5 Conclusions

We study state and duration dependence in the export activity of German manufacturing firms between 1993 and 2003 using dynamic logit models. State dependence is identified by the random effects type estimators due to Wooldridge (2005) and the fixed effects estimator suggested by Honoré and Kyriazidou (2000). Using our fixed effects estimates we indeed cannot reject the validity of the assumptions imposed by the computationally convenient Wooldridge-type estimator.

Our main conclusion is that there is substantial state dependence in the export activity of German firms. Moreover, we find that state dependence in exports depreciates over a period of two years which indicates duration dependence. Finally, we find that spurious state dependence — unobserved permanent firm heterogeneity — also plays an important role in determining the export status of German firms.

Even though both our econometric approach and our data differ substantially from existing studies, our finding of positive state dependence confirms existing studies, most notably those by Roberts and Tybout (1997) for Colombia, Bernard and Jensen (2004) for the U.S. as well as Bernard and Wagner (2001) for firms from an area in Northern Germany.

Our finding of true state dependence in export activity may have economic policy implications since it means that if economic policy successfully turns non–exporters into exporters, the effect is likely to be lasting.

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Table 1: Descriptive statistics

	All	Exporters	Non–exporters	# of obs.
A. Mean characteristics of exporters and non–exporters				
# of employees	782.7996	1041.1410	126.4205	25,203
Wage per worker	0.0637	0.0680	0.0531	19,469
Age	19.3321	21.4521	14.0707	24,122
B. Share of exporters by industry				
All sectors	0.7166			25,335
Food & tobacco	0.4597			1,701
Textile	0.7588			1,484
Wood processing	0.5400			1902
Petrochemicals	0.8241			1,836
Plastics	0.7769			2,062
Nonmetallics	0.5646			1,332
Metallics	0.6498			3,958
Machinery	0.8259			4,342
Electrics	0.7778			2,345
Medical equipment	0.7622			2,027
Transport	0.7827			1,298
Furniture	0.7739			1,048

Panel A displays the means of the explanatory variables involved in the estimation separately for exporting firms and non–exporting firms. All differences are statistically highly significant as indicated by *t*–tests. The number of observations corresponds to all firms, exporters and non–exporterts. Wage per worker is measured as total labor cost (in 1,000 Euro) per employee and year. **Panel B** shows the share of exporters in the total number of observations by industry.

Table 2: Descriptive statistics

		Mean	Std. Dev.	# of obs.
Export status	overall	782.7996	7882.5990	25,335
	between		6194.0370	
	within		3606.6650	
Wage per worker	overall	0.0637	0.0295	19,469
	between		0.0283	
	within		0.0144	
# of employees	overall	0.7166	0.4506	25,203
	between		0.4378	
	within		0.1754	

Table 3: Export status transitions

A. All transitions

		status in t		
		non–exporter	exporter	Total
status in $t-1$	non–exporter	4,477	590	5,067
		88.4	*11.6*	*100.0*
	exporter	393	12,597	12,990
		3.0	*97.0*	*100.0*
	Total	4,870	13,187	18,057
		27.0	*73.0*	*100.0*

B. Non-exporters at $t-2$

		status in t		
		non–exporter	exporter	Total
status in $t-1$	non–exporter	2,858	328	3,186
		89.7	*10.3*	*100.0*
	exporter	72	346	418
		17.2	*82.8*	*100.0*
	Total	2,930	674	3,604
		81.3	*18.7*	*100.0*

C. Exporters at $t-2$

		status in t		
		non–exporter	exporter	Total
status in $t-1$	non–exporter	230	70	300
		76.7	*23.3*	*100.0*
	exporter	196	8,873	9,069
		2.2	*97.8*	*100.0*
	Total	426	8,943	9,369
		4.5	*95.5*	*100.0*

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

Table 4: Dynamic logit models with Wooldridge-type correlated random effects specification. Dependent variable: y_{it} (year t export status of firm i).

	One-lag models		*Two-lag models*	
y_{it-1}	4.443***	4.403***	3.966***	3.950***
	(0.140)	(0.138)	(0.187)	(0.183)
y_{it-2}	—	—	0.869***	0.782***
			(0.207)	(0.203)
$\ln(wage)_{it-1}$	0.120	—	—	—
	(0.238)			
$\ln(empl)_{it-1}$	-0.358	—	—	—
	(0.178)			
$\ln(age)_{it-1}$	-0.142	—	—	—
	(0.231)			
$y_{i,-1}$	—	—	0.949***	0.994***
			0.218)	(0.215)
y_{i0}	1.567***	1.592***	0.800***	0.825***
	(0.160)	(0.159)	(0.241)	(0.236)
$\overline{\ln(wage)_{i,-1}}$	0.148	0.276*	0.547***	0.522***
	(0.279)	(0.146)	(0.172)	(0.153)
$\overline{\ln(empl)_{i,-1}}$	0.634***	0.277***	0.244***	0.228***
	(0.182)	(0.042)	(0.053)	(0.048)
$\overline{\ln(age)_{i,-1}}$	0.065	-0.073	-0.126	—
	(0.237)	(0.070)	(0.096)	
$Corp_i$	0.118	0.119	-0.018	—
	(0.152)	(0.151)	(0.196)	
$East_i$	-0.314**	-0.310**	-0.089	—
	(0.132)	(0.132)	(0.161)	
Equality of time effects				
1998 — 2002	[0.23]	[0.27]	[0.17]	[0.24]
σ_η	0.780***	0.784***	0.762***	0.763***
	(0.058)	(0.057)	(0.079)	(0.077)
$\ln L$	-1,932.24	-1,934.75	-1,230.98	-1,284.42
Number of observations	11,056	11,056	7,607	7,963

Note: All models include a full set of industry dummies, time dummies, and a constant term (estimates are reported in the Appendix). Numbers in parentheses are standard errors. Numbers in brackets are p–values of Wald tests. Models are estimated using a Gaussian quadrature. ***, ** and * denote significance at the one per cent, five per cent, or ten per cent level, respectively. The term $\overline{\ln(empl)_{i,-1}}$ denotes the firm average of lagged employment and similar for the wages and age variables.

Table 5: Fixed effect estimates of dynamic logit models. Dependent variable: y_{it} (year t export status of firm i).

	One-lag model		*Two-lag model*
	4+ observations *Full sample*	*4+ observations* *1998-2002 sample*	*6+ observations* *Full sample*
A. Honoré-Kyriazidou/d'Addio-Honoré estimates			
y_{it-1}	2.953***	3.861***	—[a]
	(0.181)	(0.710)	
y_{it-2}	—	—	0.832**
			(0.381)
$\ln empl_{it-1}$	0.180	0.446	-0.580
	(0.205)	(0.860)	(0.581)
B. Chamberlain estimates			
y_{it-1}	2.924***	3.892***	—[a]
	(0.180)	(0.714)	
y_{it-2}	—	—	0.693*
			(0.369)
Number of observations	11,589	3,439	6,233

Note: Numbers in parentheses are quasi–MLE standard errors calculated as in d'Addio and Honoré (2004). The bandwith parameter for Honoré-Kyriazidou/d'Addio-Honoré estimates is set at $bn^{-1/5}$ with $b = 10$ and n denoting the number of firms available for estimation. Results are found to be qualitatively unaffected when b is varied in a range between 2 and 20. ***, ** and * denote significance at the one per cent, five per cent, or ten per cent level, respectively. [a]: Parameter varies unrestrictedly over firms.

Table 6: Predicted probabilities of exporting (based on the estimates of the restricted two-lag model in Table 4).

Firm Effect	25th percentile of the observables index				50th percentile of the observables index				75th percentile of the observables index			
	(y_{it-2}, y_{it-1})				(y_{it-2}, y_{it-1})				(y_{it-2}, y_{it-1})			
σ_η	(0,0)	(1,0)	(0,1)	(1,1)	(0,0)	(1,0)	(0,1)	(1,1)	(0,0)	(1,0)	(0,1)	(1,1)
$-2\sigma_\eta$	0.031	0.065	0.623	0.783	0.096	0.189	0.847	0.924	0.170	0.309	0.914	0.959
$-\sigma_\eta$	0.064	0.130	0.780	0.886	0.186	0.333	0.922	0.963	0.305	0.489	0.958	0.980
0	0.128	0.242	0.884	0.943	0.329	0.517	0.962	0.982	0.484	0.673	0.980	0.991
$+\sigma_\eta$	0.239	0.407	0.942	0.973	0.512	0.697	0.982	0.992	0.668	0.815	0.991	0.996
$+2\sigma_\eta$	0.402	0.595	0.972	0.987	0.693	0.831	0.992	0.996	0.812	0.904	0.996	0.998

Note: Each table entry is the predicted probability of exporting in period t given the recent exporting history, (y_{it-2}, y_{it-1}), the error in the unobserved firm effect, η_i, and the index of observables, $\boldsymbol{X_{it}}'\hat{\boldsymbol{\beta}} + \hat{\gamma}_0 + \hat{\rho}_1 y_{i0} + \hat{\rho}_2 y_{i,-1} + \overline{X_i}'\hat{\rho}_3$.

Appendix: time and industry effects of dynamic logit models of Table 4

	One-lag models		*Two-lag models*	
$D1994$	-0.063	-0.075	—	—
	(0.208)	(0.207)		
$D1995$	-0.038	-0.038	0.336	0.277
	(0.216)	(0.212)	(0.268)	(0.261)
$D1996$	0.749***	0.741***	0.994**	0.927***
	(0.243)	(0.236)	(0.271)	(0.265)
$D1997$	-0.714***	-0.718***	-0.575**	-0.544**
	(0.239)	(0.232)	(0.263)	(0.258)
$D1998$	-0.136	-0.149	-0.001	-0.014
	(0.218)	(0.204)	(0.272)	(0.266)
$D1999$	0.330	0.301	0.578	0.495**
	(0.258)	(0.242)	(0.275)	(0.268)
$D2000$	0.071	0.034	0.290	0.232
	(0.231)	(0.212)	(0.246)	(0.239)
$D2001$	0.225	0.172	0.407	0.402
	(0.276)	(0.253)	(0.286)	(0.278)
$D2002$	-0.026	-0.068	0.043	0.037
	(0.249)	(0.227)	(0.261)	(0.255)
$D2003$	1.143***	1.098***	1.470***	1.425***
	(0.286)	(0.259)	(0.292)	(0.286)
Food, beverages, tobacco	-0.935***	-0.941***	-0.778***	-0.848***
	(0.224)	(0.224)	(0.280)	(0.276)
Textiles	-0.609**	-0.608**	-0.488	-0.527*
	(0.255)	(0.255)	(0.327)	(0.317)
Wood products	-1.134***	-1.136***	-1.132***	-1.126***
	(0.216)	(0.216)	(0.264)	(0.257)
Petrochemical	-0.190	-0.197	-0.378	-0.440
	(0.246)	(0.245)	(0.309)	(0.300)
Rubber and plastic	-0.254	-0.256	-0.582**	-0.620**
	(0.222)	(0.222)	(0.267)	(0.261)
Other non-metallic mineral	-0.753***	-0.748***	-0.485	-0.527*
	(0.241)	(0.241)	(0.300)	(0.293)
Metal products	-0.616***	-0.622***	-0.547**	-0.574**
	(0.180)	(0.180)	(0.222)	(0.219)
Electrical and optical	-0.200	-0.200	-0.246	-0.186
	(0.220)	(0.220)	(0.281)	(0.277)
Instruments	-0.300	-0.294	-0.175	-0.173
	(0.229)	(0.229)	(0.282)	(0.275)
Transportation equipment	-0.172	-0.181	0.045	0.018
	(0.269)	(0.269)	(0.347)	(0.343)
Furniture	-0.085	-0.088	0.056	0.041
	(0.290)	(0.290)	(0.377)	(0.365)
Constant	-1.883***	-1.846***	-1.378***	-1.684***
	(0.557)	(0.547)	(0.638)	(0.572)

The reference year is 1993 for the one-lag models and 1994 for the two-lag models. The reference industry is manufacture of machinery and equipment. ***, ** and * denote significance at the one per cent, five per cent, or ten per cent level, respectively.