Determinants of Firm-level Domestic Sales, Exports, and Foreign-firm Presence with Spillovers: Evidence from China*

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Abstract: This paper studies the determinants of firm-level revenues, as a measure of the performance of firms in China's domestic and export markets. The analysis of the determinants of the aforementioned outcomes calls for a mixed linear-nonlinear econometric approach. The paper proposes specifying a system of equations which is inspired by Basmann's work and recent theoretical work in international economics and conducts comparative static analyses regarding the role of exogenous shocks to the system to flesh out the relative importance of transmissions across outcomes.

Key Words: Spatial econometrics; Spillovers; Panel-data econometrics; Nonlinear systems; Firm-level sales; Chinese firms

JEL Classification: C23; C31; D24; L65

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*This paper is prepared in honor of Bob Basmann's contributions in theoretical and applied econometrics. Basmann's work on systems of equations in structural model estimation (Basmann, R.L., 1957, A generalized classical method of linear estimation of coefficients in a structural equation. Econometrica 25, 77-83; Basmann, R.L., 1959, The computation of generalized classical estimates of coefficients in a structural equation. Econometrica 27, 72-81) and on observational equivalence issues in testing for causation (Basmann, R.L., 1988, Causality tests and observationally equivalent representations of econometric models, Journal of Econometrics, 39(1-2), 69-104) are guiding lights on performing rigorous estimation of systems of equations.

1 Introduction

An important strand of Robert Basmann's early work was devoted to the estimation of simultaneous equations (see Basmann, 1957, 1959, 1961, or 1963, to mention a few). Examples of simultaneous systems of equations in economics are the study of the domestic and foreign demand of outputs across firms, of the consumption of different goods and services across households, or the behavior of different workers within firms or sectors. A host of economic problems at various levels of aggregation involves panel data and systems of equations. Two problems which complicate the analysis of such data considerably in conjunction are that data broadly speaking may be missing in the sense of censoring or truncation and that they are cross-sectionally dependent (e.g., see Pinkse and Slade, 1998; McMillen, 2002; Smith and LeSage, 2004; Pinkse, Slade, and Shen, 2006; Klier and McMillen, 2008; Smirnov, 2010; Conley and Topa, 2007; Case, 1992; Wang, Iglesias, and Wooldridge, 2013; for approaches towards estimating problems with cross-sectionally dependent binary outcome variables; or LeSage, 2000; Flores-Lagunes and Schnier, 2012; Xu and Lee, 2015a; Xu and Lee, 2015b; LeSage and Pace, 2009; for cross-section approaches towards a wider range of models with cross-sectionally dependent, censored or truncated and other limited dependent variables). While the literature on spatial and social-interaction models has formulated and analyzed models for systems of equations (see, e.g., Cohen and Morrison Paul, 2004, 2007; Kelejian and Prucha, 2004; Wang, Li, and Wang, 2014; Baltagi and Deng, 2015; Wang, Lee, and Bao, 2015), in these approaches the structural form of the model is linear in parameters, and, except for Cohen and Morrison Paul (2004) and Baltagi and Deng (2015), the approaches are designed for an analysis of cross sections of units.

The present paper proposes an approach towards estimating panel-data processes of systems of cross-sectionally dependent data with potentially mixed continuous and censored dependent variables. It outlines a Bayesian estimation approach, puts forward simulations to illustrate the performance of the estimators in small samples, and provides an application with Census-type firm-level data on manufacturers of textiles in China's province of Guangdong, analyzing domestic and foreign (i.e., export) demand towards firms.

According to the simulation exercises presented below, the Bayesian approach works well in small samples of 500 and 1,000 cross-sectional units. Ignoring the censoring clearly leads to a bias in the estimated parameters, according to that evidence. This bias is aggravated in a spatial or social-interactions model relative to a model where the reduced form of the model is a linear index, since censored observations feed back onto the outcomes of uncensored units. Ignoring that this feedback occurs by way of the true rather than the censored outcomes leads to a substantive parameter bias, depending on the relative importance of the censored units in the data.

Since its gradual opening up in the 1970s and, in particular, since the country's entering of the World Trade Organization (WTO) in 2001, firm performance has been soaring in China. Clearly, foreign demand through exports and foreign-firm presence through foreign-affiliate operation in China have been drivers of this process. This paper studies the linkages between domestic selling and exporting on the one hand and among domestic versus exporting sellers on the other hand in China's textiles production. The analysis of the problem calls for an approach to estimate a set of mixed linear and nonlinear seemingly unrelated or even simultaneous equations, since domestic sales of firms are continuous, while exports are censored. Considering panel data and allowing for correlations of the disturbances across equations calls for a panel-data systems approach. The paper proposes specifying a system of equations which is inspired by recent theoretical work in international economics and conducts comparative static analyses regarding the role of exogenous shocks to the system to assess the relative importance of shocks across outcomes as well as firms.

The insights from the empirical analysis based on the data employed here may be summarized as follows. First, there is censoring of log exports (for about 6% of the observations). Second, the parameter estimates lead us to reject models which disregard spatial or network effects among textiles producers. Third, there is an indication that success at export markets positively influences domestic sales but there is no evidence of the opposite. Fourth, the results point to the relevance of time-invariant unobservable factors which affect domestic and export sales of textiles producers. These results suggest that the data at hand call for econometric models of the kind proposed and analyzed in this paper. With this approach we identify (broadly-defined) productivity as a key driver of both domestic and export sales of textiles and ad-valorem tariffs as the second-most important determinant of textiles exports at the firm level in Guangdong province. Other important factors relate to factor-market competition among all domestic sellers and exporters and to spillovers from other domestic sellers on domestic sales and from other exporters on export sales of a firm. The findings indicate that spatial or network effects among firms account for up to about one-third to almost one-half of the total impact for the median firm and some of the determinants of domestic sales and exporting. The inter-quartile range of the total impact effects is estimated to amount to slightly less than one-half of the effect on the median firm. This heterogeneity of the impact effects is due to the interdependence of domestic and export selling, respectively.

The remainder of the paper is organized as follows. The subsequent section introduces the econometric model for panel data with systems of mixed continuous and limited dependent variables, Section 3 outlines the estimation procedure, and Section 4 provides some eclectic evidence on the small-sample performance of the estimation approach. Section 5 summarizes Census-type panel data on various characteristics of Chinese textiles manufacturers in Guangdong province, including the outcomes of interest, domestic and export sales, and it reports on estimation results based on an application of the aforementioned procedure on the respective data. The last section concludes.

2 An econometric spatial panel-data model of a system of mixed censored and continuous equations

Let us use indices i and t to denote firms and time periods, and let N and T denote the unique number of firms and years in the data.

For each firm in the data, we observe log domestic sales, y_{it}^d. For exporters, we observe log exports, y^e_{it}. Whereas log domestic sales are continuous, log exports are censored. These two variables may be represented as to be generated from a two-equation system of corresponding latent variables y^{d*}_{it} and y^{e*}_{it}. Using a generic notation for equation $g, h \in \{d, e\}$, the two equations of the latent variables are specified as

$$\begin{aligned} y^{g*}_{it} &= \gamma_g y^{h*}_{it} + \lambda_g \sum_{j \in \mathcal{N}_t} w^g_{ijt} y^{g*}_{jt} + x^g_{it}\beta_g + u^g_{it} \\ &= \gamma_g y^{h*}_{it} + \lambda_g \overline{y}^{g*}_{it} + x^g_{it}\beta_g + u^g_{it} \end{aligned} \tag{1}$$

where $\overline{y}^{g*}_{it}$ is the spatial lag of the gth latent dependent variable, y^{h*}_{it} denotes the latent dependent variable of the other equation, x^g_{it} is a row vector of exogenous, explanatory variables of the gth latent dependent variable, λ_g is a scalar spatial-lag parameter, γ_g is a scalar parameter, β_g is a conformable parameter vector, and u^g_{it} is an error term. With left censoring at zero,[1] we may define the two observed outcome variables as

$$y^d_{it} = y^{d*}_{it} \tag{2}$$

$$y^e_{it} = I(y^{e*}_{it} \geq 0) y^{e*}_{it}. \tag{3}$$

To the Bayesian econometrician, who can sample the latent continuous variables, the problem at stake is fully characterized by two latent processes and two corresponding equations. The corresponding system of equations is one of mixed censored and uncensored, spatially correlated panel data.[2]

Regarding the disturbances, we assume for the generic equation $g \in \{d, e\}$

$$u^g_{it} = \alpha^g_i + \nu^g_{it}, \tag{4}$$

where α^g_i denotes an individual-specific, time-invariant unobserved effect and ν^g_{it} the idiosyncratic error. In what follows, we will consider α^g_i and ν^g_{it} to be structurally

[1] It would be straightforward to allow the censoring point to happen at an arbitrary other value, or to consider right censoring of the data on the dependent variable(s). However, since left censoring at zero is the relevant case for the application below, we outline the econometric model accordingly.

[2] Note that under the assumptions adopted here, namely that there is (spatial or social-network) interdependence in latent outcomes rather than observed outcomes, the difference between censoring and truncation vanishes with Bayesian sampling of latent outcomes.

correlated across equations. For this, let us introduce the two 2×1 vectors $\alpha_i = (\alpha_i^d, \alpha_i^e)'$ and $\nu_{it} = (\nu_{it}^d, \nu_{it}^e)'$. Both vectors are assumed to be multivariate normal each with α_i potentially having a non-zero mean and ν_{it} having mean zero, with variance-covariance matrix

$$E[\zeta_{it}\zeta_{it}^*] = \begin{pmatrix} \sigma_{\zeta^d\zeta^d} & \cdot \\ \sigma_{\zeta^e\zeta^d} & \sigma_{\zeta^e\zeta^e} \end{pmatrix} \text{ for } \zeta \in \{\alpha, \nu\}, \tag{5}$$

where ζ_{it} corresponds to either the time-invariant α_i or the time-variant ν_{it}. Moreover, we assume that $E[\alpha_i^g \alpha_j^g] = 0$ for all $i \neq j$, $E[\alpha_i^g \nu_{jt}^h] = 0$ for all $\{g, h, i, j, t\}$, and $E[\nu_{is}^g \nu_{jt}^g] = 0$ for all $\{g, i, j, s, t\}$.

As is common in panel-data models featuring spatial dependence or a social-network structure (see, e.g., Kapoor, Kelejian, and Prucha, 2007), the observations are stacked such that i is the fast index and t the slow index. After defining the $TN \times TN$ spatial or social-interactions weights matrix $W^g = (w_{ijt}^g)$, the model for the latent variable for equation g in (1) may be written as

$$y^{g*} = \gamma_g y^{h*} + \lambda_g W^g y^{g*} + X^g \beta_g + \iota_T \otimes \alpha^g + \nu^g, \tag{6}$$

for $g, h \in \{d, e\}$ where y^{g*}, y^{h*}, and ν^g are of dimension $TN \times 1$.[3] The matrix X^g is of dimension $TN \times k^g$ and its parameter vector β_g is $k^g \times 1$. The $TN \times TN$ weights matrix W^g is block-diagonal with $W^g = diag(W_t^g)$ and contains zero diagonal elements. The off-diagonal elements of W_t^g are possibly nonzero, reflecting the neighborliness or network relations between two cross-sectional units at time t. Moreover, we assume the elements of W^g to be normalized so that the admissible parameter space of λ_g can be characterized more straightforwardly. For instance, a convenient normalization is dividing each element in W^g by the corresponding sum of all elements in a row (see Anselin, 1988; and see Kelejian and Prucha, 2010, for alternative normalizations).[4] The

[3]Notice that we could write $W^g y^{g*} = \overline{y}^{g*}$ instead. However, the notation in equation (6) will turn out to be useful towards outlining the reduced form of the system of equations.

[4]With a time-invariant, normalized, $N \times N$ spatial weights matrix $\overline{W}^g$, $W^g = I_T \otimes \overline{W}^g$, where I_T is an identity matrix of dimension T and $\overline{W}^g = (w_{ij}^g)$.

vector α^g is of dimension $N \times 1$.

Stacking both equations for $g \in \{d, e\}$ below one another yields the following equation system

$$y^* = (\Gamma \otimes I_{TN})y^* + (\Lambda \otimes I_{TN})Wy^* + X\beta + A\alpha + \nu, \tag{7}$$

where $y^* = (y^{d*\prime}, y^{e*\prime})'$ denotes the $2TN \times 1$ vector of stacked latent variables. The $2TN \times 2TN$ spatial weights matrix is given by $W = diag_g(W^g)$. The 2×2 diagonal matrix of the spatial autocorrelation (or social interaction) parameters is given by $\Lambda = diag_g(\lambda_g)$, and the 2×2 matrix Γ contains the respective γ parameters off the diagonal. The regressors are subsumed in the $2TN \times k$ matrix $X = diag_g(X^g)$ with corresponding $k \times 1$ parameter vector $\beta = (\beta_g)$, where $k = \sum_{g \in \{d,e\}} k^g$. The unobserved, time-invariant heterogeneity of the cross-sectional units is subsumed in the $2N \times 1$ vector $\alpha = (\alpha^g)$, and the innovations are subsumed in the $2TN \times 1$ vector $\nu = (\nu^g)$. The other matrices are defined as follows: $A = I_2 \otimes \iota_T \otimes I_N$, with ι_T being a column vector of ones of dimension T, and I_{TN} being an identity matrix of dimension TN. The operator $\otimes$ denotes the Kronecker product.

Based on this notation, the reduced form of the system of equations in (7) can be written as

$$y^* = L^{-1}(X\beta + A\alpha + \nu),$$

with $L = (I_{2TN} - (\Gamma \otimes I_{TN}) - (\Lambda \otimes I_{TN})W) \equiv \begin{pmatrix} L^{dd} & L^{de} \\ L^{ed} & L^{ee} \end{pmatrix}$, where $L^{dd} = I_{TN} - \lambda_d W^d$, $L^{ee} = I_{TN} - \lambda_e W^e$, $L^{de} = -\gamma_d I_{TN}$ and $L^{ed} = -\gamma_e I_{TN}$. Notice that the case of a spatial seemingly unrelated system of equations is covered by this expression, as only the off-diagonal elements of Γ would then be zero, and in turn both L^{de} and L^{ed} would be $0_{TN \times TN}$.

3 Estimation

3.1 Bayesian MCMC in general

Standard simultaneous systems of equations can be estimated by maximum likelihood (see, e.g., Haavelmo, 1944; Hood and Koopmans, 1953; among others), two-stage least squares (see Basman 1957, 1959; Theil, 1958) or Bayesian methods (see Zellner, 1971; or Drèze and Richard, 1983, for an overview).

The equation system of interest to this paper is characterized by three types of dependencies: cross-sectional dependence among the individual units due to spatial (or network) interactions and the presence of Wy^* in equation (7); cross-equation dependence due to the presence of y^* on the right-hand side of (7); and cross-equation dependence through the assumptions about the time-invariant and time-variant unobservables in (5). Furthermore we have a mixed-system where one equation is linear whereas the other one is censored.

In particular, the presence of Wy^* as a determinant of y^* precludes the estimation of the model parameters by the maximum likelihood estimator, in particular, for large samples.[5] Moreover, the censoring of the data in one equation does not permit an analysis of the model by customary instrumental-variables generalized-method-of-moments estimators which are designed for problems where the data are fully observed.[6]

To account for the different forms of interdependence and the non-linearity of some of the dependent variables, we follow a Bayesian Markov-chain Monte Carlo (MCMC) approach which has been used in earlier work mainly to study single-equation, cross-section-data, unlimited and limited-dependent-variable models (see, for example, LeSage, 2000; LeSage and Pace, 2009; Parent and LeSage, 2012, who analyze a univariate linear spatial dynamic random effects model. Also, Baltagi, Egger, and Kesina, 2016, who analyze a bivariate probit panel-data model with spatial or social network interactions). None of

[5] This is due to the interdependence of the units in the reduced form of the model.

[6] Clearly, either ignoring Wy^* on the right-hand side of the model or replacing it by Wy (i.e., using censored rather than true values of the outcome) would lead to biased parameter estimates.

this work considers the case of simultaneous equations with cross-sectional dependence, limited dependent variables, and panel data, which is the focus of the present paper.

With Bayesian MCMC simulation, the posterior distribution of all parameters is estimated by combining prior information on them with the likelihood for the respective model. Each parameter is sampled sequentially from its conditional distribution – either by Gibbs or Metropolis Hastings sampling, depending on the nature of the conditional distribution of the sampled parameter (see the next subsections for details).

Bayesian MCMC simulation is suitable for simultaneous equation systems with cross-sectional dependence as the one described in the previous section for several reasons. First, it avoids calculating and evaluating multidimensional integrals as they occur in maximum-likelihood models with spatial or social network interactions. Second, with Bayesian MCMC estimation, the treatment of limited-dependent-variable models is facilitated. Utilizing the approach of Albert and Chib (1993) for non-spatial, cross-sectional, univariate probit models and LeSage (2000) and LeSage and Pace (2009) for spatial, cross-sectional, univariate and multivariate probit models, the latent variables of non-linear dependent variables may be introduced as additional parameters to the model. Compared to maximum-likelihood estimation, this simplifies the estimation as conditioning on latent variables yields simpler conditional distributions than not doing so.[7] In particular, this data-augmentation approach of Bayesian MCMC estimation facilitates the computation of moments and the associated confidence intervals of the effects of exogenous explanatory variables on outcome.

Let us use the following convention for the notation in this section. Let us subsume all parameters in $\theta = \{\beta, \lambda_g, \gamma_g, \Sigma_\nu, y^*, \alpha, \mu_\alpha, V_\alpha\}$ for $g \in \{d, e\}$, where $\beta = (\beta_d', \beta_e')'$ and $y^* = (y^{d*\prime}, y^{e*\prime})'$. The variance-covariance matrix of the idiosyncratic errors is denoted by Σ_ν. The vector μ_α and the matrix V_α relate to the conditional distribution of α and will be described in more detail in the subsequent subsections. Using $y = (y^{d\prime}, y^{e\prime})'$

[7] For example, in the application below, we fully observe log domestic sales of textile producers in China while their log exports are censored from below at zero. However, one could imagine more general circumstances of bigger systems of equations with truncation as well as censoring.

to denote the vector of observed dependent variables, the joint posterior distribution is given by

$$
\begin{aligned}
& p(\theta|y, X, W) \\
\propto \; & p(y|y^*, X, W)p(y^*|\beta, \lambda_g, \gamma_g, \Sigma_\nu, \alpha, \mu_\alpha, V_\alpha, X, W) \\
& p(\beta)p(\gamma_g|\lambda_g)p(\lambda_g)p(\Sigma_\nu)p(\alpha|\mu_\alpha, V_\alpha)p(\mu_\alpha)p(V_\alpha).
\end{aligned}
$$

The first expression in the second line relates the observed dependent variables to their latent counterparts, the second expression represents the likelihood of the model, and the third line denotes the priors. The expression for the joint posterior distribution turns out to be intractable as such. Therefore, we calculate the conditional distributions for all model parameters given the data and the other parameters, which we denote by $\theta_\ell|\theta_{-\theta_\ell}$. In what follows, we will use the convention to denote posterior distributions by an overline and prior distributions by an underline.

3.2 Prior distributions and likelihood

Using $\mathcal{N}$ and $\mathcal{W}$ to denote the normal and Wishart distributions, we specify the prior distributions for β and Σ_ν as

$$
\begin{aligned}
\beta &\sim \mathcal{N}(\underline{\beta}, \underline{V}_\beta) \quad \text{where} \quad \underline{\beta} = 0_{k\times 1} \quad \text{and} \quad \underline{V} = I_k \cdot 1e^{12}, & (8) \\
\Sigma_\nu^{-1} &\sim \mathcal{W}(\underline{V}_{\Sigma_\nu}^{-1}, \underline{v}_{\Sigma_\nu}) \quad \text{where} \quad \underline{V}_{\Sigma_\nu}^{-1} = I_2 \quad \text{and} \quad \underline{v}_{\Sigma_\nu} = 2, & (9)
\end{aligned}
$$

where the above assumptions imply a very diffuse (or uninformative) prior about the elements of β and also a relatively diffuse prior about the elements of Σ_ν. The time-invariant, unobserved heterogeneity captured by $\alpha = (\alpha_d', \alpha_e')'$, is modelled by means of a hierarchical structure, whereby all elements $\alpha_i = (\alpha_{di}, \alpha_{ei})'$ utilize a distribution, which has some parameters in common, which we label as *hyper-parameters* and which are drawn in a previous step and utilized when drawing α_i. These hyper-parameters are the associated mean μ_α and the variance-covariance matrix V_α, which have the following priors:

$$\begin{aligned} \mu_\alpha &\sim \mathcal{N}(\underline{\mu}_{\mu\alpha}, \underline{V}_{\mu\alpha}) \quad \text{where} \quad \underline{\mu}_{\mu\alpha} = 0_{2\times 1} \quad \text{and} \quad \underline{V}_{\mu\alpha} = I_2 & (10)\\ V_\alpha^{-1} &\sim \mathcal{W}(\underline{V}_{V\alpha}^{-1}, \underline{v}_{V\alpha}) \quad \text{where} \quad \underline{V}_{V\alpha}^{-1} = I_2 \quad \text{and} \quad \underline{v}_{V\alpha} = 2. & (11)\end{aligned}$$

By this choice, the priors for the elements in α are relatively diffuse.

The prior distributions for γ_g and λ_g exhibit also a hierarchical structure of the form

$$\begin{aligned} \gamma_g|\lambda_g &\sim U(-1+|\lambda_g|, 1-|\lambda_g|), & (12)\\ \lambda_g &\sim U(-1,1), & (13)\end{aligned}$$

reflecting dependence of the spatial-lag (or social-interaction) parameters λ_g and the parameters on the endogenous variables γ_g to ensure identifiability of the system.[8]

As all of the aforementioned priors are relatively uninformative, in calculating the posterior distribution relatively little weight is placed on the priors and much on the data.

The joint distribution of y^* is given by

$$y^* \sim \mathcal{N}(\mu_{y^*}, \Omega_{y^*}), \tag{14}$$

with

$$\begin{aligned} \mu_{y^*} &= L^{-1}(X\beta + A\alpha)\\ \Omega_{y^*} &= L^{-1}(\Sigma_\nu \otimes I_{TN})L^{-1\prime},\end{aligned}$$

where μ and Ω are partitioned as $\mu = \begin{pmatrix} \mu^d \\ \mu^e \end{pmatrix}$ and $\Omega = \begin{pmatrix} \Omega^{dd} & \Omega^{de} \\ \Omega^{ed} & \Omega^{ee} \end{pmatrix}$.

The likelihood stated in terms of the latent variables y^* is given by

$$p(y^*|\theta, X, W) = \frac{|L|}{(2\pi)^{2TN/2}|\Sigma|^{TN/2}} exp\left[-\frac{1}{2} tr\left(B\Sigma_\nu^{-1}\right)\right],$$

where tr denotes the trace and B is a 2×2 matrix containing the elements

$b^{dd} = (L^{dd}y^{d*} + L^{de}y^{e*} - X^d\beta_d - \iota_T \otimes \alpha^d)'(L^{dd}y^{d*} + L^{de}y^{e*} - X^d\beta_d - \iota_T \otimes \alpha^d)$,

[8] Clearly, this identifiability eventually requires putting exclusion restrictions on the variables in X across the equations in the system. The associated conditions are standard in models with systems of equations (see Kelejian and Prucha, 2004).

$$b^{de} = (L^{dd}y^{d*} + L^{de}y^{e*} - X^d\beta_d - \iota_T \otimes \alpha^d)'(L^{ed}y^{d*} + L^{ee}y^{e*} - X^e\beta_e - \iota_T \otimes \alpha^e),$$
$$b^{ed} = (L^{ed}y^{d*} + L^{ee}y^{e*} - X^e\beta_e - \iota_T \otimes \alpha^e)'(L^{dd}y^{d*} + L^{de}y^{e*} - X^d\beta_d - \iota_T \otimes \alpha^d),$$
$$b^{ee} = (L^{ed}y^{d*} + L^{ee}y^{e*} - X^e\beta_e - \iota_T \otimes \alpha^e)'(L^{ed}y^{d*} + L^{ee}y^{e*} - X^e\beta_e - \iota_T \otimes \alpha^e).$$

3.3 Conditional distributions

Conditional distribution of $\boldsymbol{\beta}$

The conditional distribution of β given the other parameters is

$$\beta|\theta_{-\beta} \sim \mathcal{N}(\overline{\beta}, \overline{V}_\beta), \tag{15}$$

where

$$\begin{aligned} \overline{\beta} &= \overline{V}_\beta \left(X' \left(\Sigma_\nu^{-1} \otimes I_{TN}\right)(Ly^* - A\alpha) + \underline{V}^{-1}\underline{\beta}\right), \\ \overline{V}_\beta &= \left(X' \left(\Sigma_\nu^{-1} \otimes I_{TN}\right) X + \underline{V}^{-1}\right)^{-1}. \end{aligned}$$

Accordingly, we may apply Gibbs sampling to draw values for β.

Conditional distribution of $\boldsymbol{\alpha}$

The conditional distribution of the $2N \times 1$ vector α is

$$\alpha|\theta_{-\alpha} \sim \mathcal{N}(\overline{\alpha}, \overline{V}_\alpha),$$

where

$$\begin{aligned} \overline{\alpha} &= \overline{V}_\alpha \left(A' \left(\Sigma_\nu^{-1} \otimes I_{TN}\right)(Ly^* - X\beta) + (V_\alpha^{-1} \otimes I_N)(\mu_\alpha \otimes \iota_N)\right), \\ \overline{V}_\alpha &= \left(A'(\Sigma_\nu^{-1} \otimes I_{TN})A + V_\alpha^{-1} \otimes I_N\right)^{-1}, \end{aligned}$$

which are based on the hyper-parameters μ_α and V_α. The latter are drawn as

$$\mu_\alpha|\theta_{-\alpha} \sim \mathcal{N}(\overline{\mu}_\alpha, \overline{V}_{\mu_\alpha}),$$

using

$$\begin{aligned} \overline{\mu}_\alpha &= \overline{V}_{\mu_\alpha} \left((V_\alpha^{-1} \otimes \iota_N')\alpha + \underline{V}_{\mu_\alpha}^{-1}\underline{\mu}_\alpha\right), \\ \overline{V}_{\mu_\alpha} &= \left(NV_\alpha^{-1} + \underline{V}_{\mu_\alpha}^{-1}\right)^{-1}, \end{aligned}$$

and

$$V_\alpha^{-1}|\theta_{-\alpha} \sim \mathcal{W}(\overline{V}_{V_\alpha}, \overline{v}_{V_\alpha}),$$

with

$$\begin{aligned}
\overline{v}_{V_\alpha} &= \underline{v} + N, \\
\overline{V}_{V_\alpha} &= (M + \underline{V}_{V_\alpha})^{-1},
\end{aligned}$$

and the 2×2 matrix $M = (m^{gh})$ containing the elements $m^{gh} = (\alpha^g - \iota_N \mu_\alpha^g)'(\alpha^{h'} - \iota_N \mu_\alpha^{h'})$, where ι_N is an $N \times 1$ vector of ones. All of these parameters have known distributions. Accordingly, we apply Gibbs sampling, drawing the hyper-parameters μ_α and V_α first and then using those in drawing the elements of α.

Conditional distribution of $\boldsymbol{\Sigma_\nu}$

The conditional distribution of the 2×2 matrix Σ_ν^{-1} is given by

$$\Sigma_\nu^{-1}|\theta_{-\Sigma_\nu^{-1}} \sim \mathcal{W}(\overline{V}_{\Sigma_\nu}, \overline{v}_{\Sigma_\nu}),$$

with

$$\begin{aligned}
\overline{v}_{\Sigma_\nu} &= \underline{v}_{\Sigma_\nu} + TN, \\
\overline{V}_{\Sigma_\nu} &= (B + \underline{V}_{\Sigma_\nu})^{-1},
\end{aligned}$$

which is of the Wishart form. Therefore, we use Gibbs sampling for drawing the respective parameters.

Conditional distributions of $\boldsymbol{\lambda_g}$ and $\boldsymbol{\gamma_g}$

The conditional distributions of λ_g and γ_g for $g \in \{d, e\}$ are given by

$$\lambda_g|\theta_{-\lambda_g} \propto |L| exp\left[-\frac{1}{2} tr\left(B\Sigma_\nu^{-1}\right)\right], \tag{16}$$

$$\gamma_g|\theta_{-\gamma_g} \propto |L| exp\left[-\frac{1}{2} tr\left(B\Sigma_\nu^{-1}\right)\right], \tag{17}$$

where $|L| = |(I_{TN} - \lambda_d W^d)(I_{TN} - \lambda_e W^e) - \gamma_d \gamma_e I_{TN}|$. These distributions have an unknown form and therefore a Metropolis-Hastings sampling procedure is applied. Since we use the same approach for drawing $\lambda_g|\theta_{-\lambda_g}$ and $\gamma_g|\theta_{-\gamma_g}$, it is sufficient to outline it exemplarily for $\lambda_g|\theta_{-\lambda_g}$. Following LeSage and Pace (2009), a proposal candidate λ_{gc} is drawn by $\lambda_{gc} = \lambda_g + c_{\lambda_g} \cdot N(0,1)$, with λ_g denoting the previous value and c_{λ_g} a tuning parameter. We only use proposal candidates that are in the admissible parameter range. Using (16), and $\{\lambda_g, \lambda_{gc}\}$, an acceptance probability is calculated to decide whether keeping λ_g or using the new candidate λ_{gc}. The tuning parameter c_{λ_g} is adapted to ensure an acceptance probability between 40% and 60%.

Conditional distribution of $\mathbf{y^{e*}}$

In the application in Section 5 below, y^d represents the (log of) domestic sales, which are fully observed for all firms and time periods. Thus, $y^{d*} = y^d$, and we do not have to take draws for this dependent variable. In contrast, y^{e*}, which represents the (log of) exports are not fully observed but censored for some percentage of the observations from below at zero. We calculate the conditional distribution of y^{e*} using the joint distribution in equation (14) as

$$y^{e*}|\theta_{-y^{e*}} \sim \mathcal{N}(\mu_{y^{e*}}, \Omega_{y^{e*}}), \tag{18}$$

with

$$\begin{aligned} \mu_{y^{e*}} &= \mu^e + \Omega^{ed}(\Omega^{dd})^{-1}(y^d - \mu^d), \\ \Omega_{y^{e*}} &= \Omega^{ee} - \Omega^{ed}(\Omega^{dd})^{-1}\Omega^{de}. \end{aligned}$$

We draw the censored values of log export sales from a truncated multivariate normal, which is truncated from the right at zero using the method suggested by Geweke (1991).

4 Simulation analysis

4.1 Simulation design

Before turning to the applications, we provide some evidence on the applicability of the proposed estimation routine in small to medium-sized samples of $N \in \{500; 1,000\}$ and $T = 3$. Specifically, we provide evidence of two types of systems each of which consists of two equations, one corresponding to a panel tobit and one to a linear panel-data model. In one case, we consider the case of a seemingly-unrelated-regression error structure, where Γ is a 2×2 matrix of zeros (SUR), and in another case, we consider the case of a simultaneous system of equations (SSE). Since both types of models contain a spatial lag of the dependent variable to account for cross-sectional spillovers among firms, we will refer to them as SSUR and SSSE in this section. For each type of model, we consider two parameter configurations regarding $\{\lambda_1; \lambda_2\}$, namely $\{0.4; 0.4\}$ and $\{0.1; 0.3\}$.

For each model and configuration, we generate an $N \times N$ raw weights matrix W_0 which has a wrap-around structure of a neighbors before and a neighbors behind every unit i in a row, where $a = 10$. Hence, for the 11-th cross-sectional unit, all units $1, ..., 10$ and all units $12, ..., 21$ are neighbors; for the first unit, units $2, ..., 11$ and units $N - 10, ..., N$ are neighbors; and for the N-th unit, units $N - 11, ..., N - 1$ as well as units $1, ..., N$ are neighbors; etc.

We employ three exogenous variables $\{X_{it}^{g1}; X_{it}^{g2}; X_{it}^{g3}\}$ which we generally draw identically and independently from univariate normal distributions with mean zero and variance two. Their coefficients are set to $\beta_{g1} = (1, 1, 1)'$, $\beta_{g2} = (1, 1, 1)'$, $\beta_{g3} = (1, 1, 1)'$.

We draw the elements of the 2×1 vector ν_{it} independent of $\{X_{it}^{g1}; X_{it}^{g2}; X_{it}^{g3}\}$ and of α_i^g and identically and independently within equation g from a bivariate normal with $\nu_{it} \sim N(0_{2\times1}, \Sigma_\nu)$ where $\Sigma_\nu = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}$. Similarly, we draw the elements of the 2×1 vector α_i identically and independently within equation g from a bivariate normal with $\alpha_i \sim N(\mu_\alpha, \Sigma_\alpha)$ with $\Sigma_\alpha = \begin{pmatrix} 2 & 0.8 \\ 0.8 & 2 \end{pmatrix}$. With a few exceptions, we set $\mu_\alpha = (1.5; 2.5)'$. However, to assess the importance of the relative amount of censored observations in the data on y_2, we allow $\mu_{\alpha 2}$ to vary in Design 1.

For the sake of better readability, we summarize the parameters for the SSUR and the SSSE models under the different designs in Table 1. In each case, we generate one Markov chain of 30,000 parameter draws with 5,000 burn-ins and a thinning rate of 10 (i.e., using every $10-th$ draw after discarding the burn-in draws). In the next subsection, we report the results obtained from each of those Markov chains.

In all designs, we consider the case where one outcome is fully observed whereas a second one is censored, where the fraction of censored values is reported in the notes of each table. In the table, we report the posterior mean and standard deviation for each parameter. The terms m_{α_1} and m_{α_2} refer to the averages across the thinned Monte Carlo draws of the draw-specific averages of the posterior α_1 and α_2, respectively. Similarly, $\{s_{\alpha 11}, s_{\alpha 12}, s_{\alpha 22}\}$ correspond to the averages across Monte Carlo draws of the draw-specific posterior variance terms of $\{\alpha_1, \alpha_2\}$.

We assess the validity of the thinned chains for statistical inference by way of Geweke's (1992) test.[9]

4.2 Simulation results

We present the results for the four combinations of N and $\{\lambda_1; \lambda_2\}$ for the SSUR model in Tables 2-6 and for the SSSE model in Tables 7-9. The findings from these simulations can be summarized as follows.

– Tables 2-6 about here –

First of all, the simulation results in Tables 2-6 indicate that the SSUR model works well in samples of 500 and even more so in ones of 1,000 cross-sectional units. As expected, the parameters can be estimated at greater precision with a larger sample of 1,000 than with a smaller one of 500 cross-sectional units. Tables 2-5 are all based on Design 1. However, in Tables 2-4 we vary the fraction of censored observations in y_2

[9]This test splits the sample of the MCMC draws after thinning and discarding burn-in draws into three parts and tests the equality of the sample means based on the first 20% and the last 50% of the draws of the chain.

by changing $\mu_\alpha = (1.5; 2.5)'$ as used in Tables 2 and 5-9 to $\mu_\alpha = (1.5; 4)'$ in Table 3 (low degree of censoring; see the respective table footnote) and $\mu_\alpha = (1.5; 1)'$ in Table 4 (high degree of censoring; see the respective table footnote). According to these results, the routine works well, especially for a sample size of 1,000 cross-sectional units for all considered degrees of censoring.

Table 5 is an interesting benchmark case which Table 2 should be compared with. While the censored values of y_2 are drawn in Table 2, they are set at zero in Table 3, so that y_2 instead of y_2^* is used in estimation. The results in Table 5 clearly indicate that ignoring the fact that some of the information on outcome y_2 is censored leads to parameter bias (e.g., consider the point estimates of $\{\beta_{21}, \beta_{22}, \beta_{23}\}$ or of λ_2 in the case of $N = 1,000$. Hence, addressing the missing information in a suitable way as in Table 2 is particularly relevant with interdependent data (such as ones on spatial units of social networks).

– Tables 7-9 about here –

The results for the SSSE models in Tables 7-9 suggest that, given everything else, the estimation of simultaneous-equations models of the proposed kind, where we permit $\gamma_1 \neq 0$ and $\gamma_2 \neq 0$, leads to a change in the signal-to-noise ratio so that one would wish to have a somewhat larger number of cross-sectional units available. This can be seen from the point estimates of λ_1 and λ_2, e.g., in Table 7, in particular for the smaller sample. However, overall, the estimator appears to work quite well, and small-sample problems tend to vanish even in panel data-sets with moderately-large cross-sections.

5 Empirical analysis of firms' domestic sales and exports in China's textiles industry

In the course of the 1990s and certainly since the country's accession to the World Trade Organization in 2001, China has become a key player on global textiles markets. Apart from easier access to foreign markets through lower tariffs abroad and access to foreign capital in China, spillovers through contact with foreign textile producers on export markets as well as local technology spillovers among producers in China appear to be important determinants of supply of and demand for China's textiles products.

In the present paper, we focus on textiles sales of firms in Guangdong province which is located on the coast of south-eastern China. According to the census of 2014, the province is the most populous one in China with almost 110 million people, accounting for almost eight percent of China's population. The major settlements in the province are its administrative capital, Guangzhou, and the economic hub of Shenzhen both of which feature among the most populous cities in China. With the fourth-highest average per-capita income among all the provinces, Guangdong is also the largest one in terms of GDP in China. The manufacture of textiles is among the most significant economic activities in Guangdong province.

Trade is very important to Guangdong. It has numerous economic and technological development zones in place – most but not all of them in Guangzhou, Huizhou, Shenzhen, and Zhuhai. Many of these zones provide easy access to global markets, and they lead to a clustering of the emergence of firms in space, stimulating spillovers among firms. Much of the export activity and of production in general is situated in or in close neighborhood to the Pearl River Delta, for which the Port of Guangzhou – the largest port in South China – serves as the key economic and transport nod.

In the remainder of this section, we will introduce the data-set used in the present paper, report on descriptive statistics of the variables employed, and summarize the associated regression results.

5.1 Firm-level census panel data on textiles producers in Guangdong province

We employ panel data on domestic sales and exports of textiles producers in Guangdong province over the period 2004-2007. During that time span, approximately 8.5% of total sales in the Chinese textiles industry are produced in Guangdong. However, of all domestic textiles sales by Chinese producers, firms in Guangdong contribute only 6%, while their exports account for about 14% of China's export volume in the textiles sector, indicating the province's strong orientation towards export markets. All over China's manufacturing, foreign capital (ownership) is concentrated in exporting firms. For instance, 48% of China's manufacturing exporters (and 20% of all manufacturers) were partly foreign owned in 2004-2007. However, 70% of Guangdong's manufacturing exporters (and 44% of all manufacturers) were partly foreign owned over the same time span. All of this suggests that Guangdong is a province of primary interest to study domestic and export performance of firms, in particular, in the textiles sector.

We refer to the dependent variables used in the subsequent empirical analysis as log domestic sales_{it} (or y^d_{it}) and log exports_{it} (or y^e_{it}), respectively. Log exports sales are censored at zero.[10]

We generally employ lagged determinants as adjusting supply occurs with some lag. Accordingly, exogenous independent variables range from 2004 to 2006 and the corresponding dependent variables are measured in 2005-2007. For each producer, we know the exact geographical location, which permits determining the distance to other producers and whether a producer is located in the Pearl River Delta or not. Moreover, we know the density of all firms as well as of textiles producers – in particular of domestic sellers versus exporters of any goods and of textiles – in the same zip code. For all producers, we observe their overall employment, the wage costs per employee, the interest rate paid for capital, the material costs, the value added per employee as a crude measure of productivity, and the share of foreign capital in all capital invested in a firm. By the association with a specific textiles subsector,[11] we may also compute the weighted average tariff rate applied to China's exports abroad, where the weights (China's overall exports by subsector, destination country and year) and partner country tariffs are

[10] In the data, censoring may occur due to mis-reporting or non-reporting of small export volumes, due to indirect exporting of small export quantities through whole salers, etc. It is well known that countries impose thresholds for the requirement of reporting exports to statistical offices and not all textiles producers report positive exports. See Wakelin (1998) or Berthou and Fontagné (2008) for estimating firm-level exports with censored regression models.

[11] Our data set consists of firms from two subsectors: Textile processing and textile manufacturing. These consist of 24 4-digit subsectors, which we based our merge with the tariff rates on.

available from the World Bank's WITS database.[12]

All variables are in logs except for the interest rate – the ratio of interest expenditures and total debt for the same textiles subsector and year –, the binary indicator for the location in the Pearl River Delta, the share of domestic market sellers of any products among all firms in the same zip code, the share of domestic sellers in all textiles producers in the same zip code, the share of export market sellers of any products among all firms in the same zip code, and the share of exporters in all textiles producers in the same zip code.

Firm size (employment$_{it-1}$), productivity$_{it-1}$, and cost variables (wage per worker $_{it-1}$, materials per worker$_{it-1}$, and interest rate$_{it-1}$) capture aspects of technology at the level of the firm. On the contrary, the firm number variables (number of all firms in zip code$_{it-1}$, number of all textile firms in zip code$_{it-1}$, share of domestic market sellers in all firms in zip code$_{it-1}$, share of domestic market sellers in all textile producers in zip code$_{it-1}$, share of exporters in all firms in zip code$_{it-1}$, and share of exporters in all textile producers in zip code$_{it-1}$) capture aspects of the market environment (the required labor pool, the potential of competition as well as of spillovers). Fixed time effects in each equation reflect aspects of domestic and foreign demand potential, and the ad-valorem tariff$_{it-1}$ captures foreign-market access costs. Finally, the foreign capital share$_{it-1}$ captures another aspect of foreign-market access costs (and, possible, of technology transfer).

Factor costs, productivity and profitability (both of which are captured by the variable value added per employee as used here), and the economic and geographical environment are standard determinants of firm overall sales (see, e.g., Baltagi, Egger, and Kesina, 2016, for evidence on China) as well as exports (see Kneller and Pisu, 2005; Greenaway and Kneller, 2007).[13] However, a customary assumption introduced by the-

[12]In a sector such as textiles, which does neither involve large-scale import activity of intermediate products nor large-scale final-product competitive imports from elsewhere by China, it seems natural to focus on the role of import tariffs abroad on Chinese exports. However, in other sectors, this is not the case, as has been demonstrated by Van Biesebroeck and Yi, 2012.

[13]Defever, Heid, and Larch (2015) showed that, across all industries, Chinese firms tend to enter

oretical work that most of the empirical literature relies upon is that individual firms are atomistic (see Eaton and Kortum, 2002; Melitz, 2003; Kneller and Yu, 2016), so that shocks to individual operations do not induce effects on other firms. The spillover (or spatial- or network-lag) terms introduced by the presence of $(\Lambda \otimes I_{TN})Wy^*$ among the explanatory variables in the proposed empirical model means that individual firms are important-enough so that shocks to them induce effects on other firms in the geographical neighborhood (e.g., through literal productivity spillovers, effects on market power, or factor flows across firms). Hence, empirical evidence of Λ being nonzero would challenge this assumption. Though based on different econometric methods than the ones applied here, some exemplary earlier work suggests that firms are indeed not operating independently of each other (see, e.g., Smarzynska Javorcik, 2004, for evidence from Lithuania; the findings in Greenaway and Kneller, 2008, for the United Kingdom indicate that the presence of other exporting firms in the neighborhood induces positive effects on a firm's propensity to export; the evidence in Manova and Yu, 2016, and Manova, Wei, and Zhang, 2015, for China suggests that firms are related to each other through processing and multinational relationships). Another customary assumption introduced by the same theoretical work that most of the empirical literature relies upon is that – conditional on firm-level productivity, market power, and factor costs – any change in the success on export markets is irrelevant for success of the same firm on domestic markets and vice versa. The presence of $(\Gamma \otimes I_{TN})y^*$ in the empirical model permits a departure from this hypothesis, and evidence of Γ to be non-zero would be a challenge for the respective theoretical assumption. Again, some exemplary earlier work suggests that also firms' non-exporting outcomes may benefit from their exports (see, e.g., Berman, Berthou, and Héricourt, 2011; Wang, Wei, Liu, Wang, and Lin, 2014).

We collect all of the explanatory variables into the two vectors X_{it}^d and X_{it}^e for domestic sales and exports, respectively. Both X_{it}^d and X_{it}^e include: employment$_{it-1}$;

export markets in a contagious way, which is consistent with the theoretical results and the evidence in Albornoz, Calvo Pardo, Corcos, and Ornelas, 2012. However, this issue is only loosely related to the interest in this paper, which is about spatial and network effects among the export sales anywhere abroad versus domestic sales anywhere in China of Chinese textiles producers.

productivity$_{it-1}$; wage per worker$_{it-1}$; materials per worker$_{it-1}$; interest rate$_{it-1}$; number of all firms in zip code$_{it-1}$; number of all textile firms in zip code$_{it-1}$; and fixed time effects for 2006 and 2007. Only X_{it}^d additionally includes: share of domestic sellers in all firms in zip code$_{it-1}$; and share of domestic sellers in all textile producers in zip code$_{it-1}$. And only X_{it}^e includes: share of exporters in all firms in zip code$_{it-1}$; share of exporters in all textile producers in zip code$_{it-1}$; ad-valorem tariff$_{it-1}$; and foreign capital share$_{it-1}$. Altogether, our study includes 630 textiles producers which are scattered across 288 zip codes. Table 10 summarizes main features of the dependent and the independent variables.

– Table 10 about here –

According to the table, (log) domestic sales are on average slightly higher than (log) exports. The zip code specific variables indicate the concentration of firms in some zip code areas. Textiles producers are more strongly oriented towards export markets than firms on average in Guangdong province. The numbers in the table suggest that, for the years 2005-2007, the share of textiles exporters in all textiles producers in the data is much larger than the share of exporters in all firms in the same 288 zip codes where textiles producers are located. Conversely, the share of domestically selling textiles producers in all textiles producers in the data is smaller than the share of domestic sellers in all manufacturing firms in the same zip codes and years. More than 80% of the textile producers in the data are located within the Pearl River Delta which points to some geographical concentration of firms in this area, and provides easy access to export markets. A foreign capital share of 0.647 for those textile producers and years indicates a relatively high presence of foreign firms, at least as partial owners, in Guangdong's textile sector.

5.2 Estimation results

In this subsection, we present results based on a number of different econometric models, all of which consider censoring in log exports y^e. Table 11 presents the results of single-equation models, where y^d and y^e are estimated as separate, univariate, spatial models with y^e being censored and y^d being not. Tables 12 and 13 contain the SSUR (assuming that both $\gamma_d = 0$ and $\gamma_e = 0$) and SSSE models.

– Table 11-13 about here –

Since the reduced forms of the estimated models are nonlinear for potentially two important structural reasons, namely that domestic sales and exporting may have an impact on each other and that the success of textile firms at the domestic and the foreign market may depend on the one of other firms, the parameters in Tables 11-13 should not be interpreted. Therefore, we refrain from such a detailed discussion here and focus on a comparison of the results in the tables by way of impact effects in the subsequent subsection. However, we can point out a few general findings here.

First, the posterior means of $\sigma_{\nu_{de}}$ are -0.758 (with standard deviation 0.069) for SSUR in Table 12, and -2.168 (with standard deviation 0.214) for SSSE in Table 13. This suggests that efficiency gains can be had from estimating the two equations jointly, rather than estimating them separately as in Table 11.

Second, all the specifications in Tables 11-13 point to an interdependence in both domestic sales and exports (with $\hat{\lambda}_g$ being generally positive and statistically significant from zero). These results suggest that there are positive spillovers among both domestic sellers and exporters which are potentially related to the understanding of consumer markets and to productivity.

Third, firm-specific effects appear to be quite important, according to the estimates $\widehat{m}_{\alpha d}$ and $\widehat{m}_{\alpha e}$ as well as the associated variances $\widehat{\sigma}_{\alpha dd}$ and $\widehat{\sigma}_{\alpha ee}$. This suggests that one should not ignore the presence of producer-specific unobserved attributes in estimation.

Fourth, a comparison of the results of SSUR and SSSE in Tables 12 and 13, respectively, leads to the conclusion that an increase in export sales has, on average, positive repercussions on a textile producer's domestic sales but not vice versa: γ_d is estimated with a posterior mean of $\widehat{\gamma}_d = 0.178$ and an associated small standard deviation of 0.019, while γ_e is estimated with a posterior mean of $\widehat{\gamma}_e = 0.042$ with a large standard deviation of 0.114. This suggests that the SSUR model is rejected against the SSSE model. We devote the subsequent subsection to a discussion of the parameter estimates by way of impact estimates based on the reduced form of the SSSE model.

5.3 Impact effects of regressors

Let us consider the effects of a change in a single element of x_{it}, namely covariate $x_{k,it}$, which may be part of X^d only, of X^e only, or of both of them. It will be useful to refer to a one-standard-deviation change in this covariate, which is scaled by the corresponding parameter estimate, $\widehat{\beta}_{dk}$ in equation d and $\widehat{\beta}_{ek}$ in equation e, by $\widehat{\Delta}_k^d$ and $\widehat{\Delta}_k^e$, both of which are scalars. Moreover, let us define the vectors of equation-to-equation estimated direct effects, $\widehat{d}^{gh,d}$, of effects on others, $\widehat{d}^{gh,o}$, of effects from others, $\widehat{d}^{gh,f}$, and of total effects, $\widehat{d}^{gh,t}$, as

$$\begin{aligned}
\widehat{d}_k^{gh,d} &= diag[L_{gh}^{-1}(\widehat{\Delta}_{hk}) \otimes I_{TN}], && (19)\\
\widehat{d}_k^{gh,o} &= [L_{gh}^{-1}(\widehat{\Delta}_{hk}) \otimes I_{TN}]\iota_{TN} - \widehat{d}_k^{gh,d}, && (20)\\
\widehat{d}_k^{gh,f} &= [L_{gh}^{-1}(\widehat{\Delta}_{hk}) \otimes I_{TN}]'\iota_{TN} - \widehat{d}_k^{gh,d}, && (21)\\
\widehat{d}_k^{gh,t} &= \widehat{d}_k^{gh,d} + \widehat{d}_k^{gh,f}, && (22)
\end{aligned}$$

where a superscript $\{gh, l\}$ with any vector $\widehat{d}_k$ indicates a subvector pertaining to effects of type $l \in \{d, o, f, t\}$ of a shock in the exogenous explanatory variable k in equation of outcome $h \in \{d, e\}$ on outcome $g \in \{d, e\}$. Averages of such impact effects have been proposed in different types of models with spatial or network interactions in LeSage and Pace (2009). Notice that the elements of $\widehat{d}_k^{gh,l}$ vary across the observations it, depending on these observations' location and economic geography in the textiles sector. In the above expressions, L_{gh}^{-1} denotes the gh-th block of L^{-1}. Whenever $g = h$, the effects pertain to within-outcome responses, whereas for $g \neq h$ they pertain to across-outcome responses.

– Tables 14-15 about here –

Tables 14 and 15 summarize moments of the distribution of the impact effects of a one-standard-deviation increase in an explanatory variables (which enters only one or both equations) at a time on log domestic sales and log exports, respectively. As to the moments of these distributions, we generally report the minimum (*Min*), the 25-th percentile (*p25*), the 50-th percentile (*p50*), the 75-th percentile (*p75*), the Maximum (*Max*), and the average (*Avg*).[14] The horizontal organization of the tables is such that own-outcome effects, $\widehat{d}_k^{gg,l}$, are followed by cross-outcome effects, $\widehat{d}_k^{gh,l}$. Vertically, every table contains the impact effects for those determinants at the top, which enter both equations, followed by the equation-specific ones. The normalization of the shocks to one standard deviation permits a quantitative comparison of the estimates both across tables as well as across entries within a table.

In the subsequent discussion, we focus, for the sake of brevity, on shocks on log productivity$_{it-1}$ (as a common determinant of log domestic sales$_{it}$ and log exports$_{it}$) and on the share of domestic market sellers in all firms in zip code$_{it-1}$, the share of domestic market sellers in all textile producers in zip code $_{it-1}$, the share of exporters in all firms in zip code$_{it-1}$, the share of exporters in all textile producers in zip code$_{it-1}$, the log ad-valorem tariff$_{it-1}$, and the foreign capital share$_{it-1}$ (as equation-specific determinants of the considered outcomes). The corresponding effects may be summarized as follows:

First, among all the impact-effect estimates the variability of the direct effects and of the effects on others is relatively small, while the effects from other producers is relatively large. This is largely owed to the row normalization of the weights matrix W. Accordingly, the variance in the (own- and cross-equation) total effects largely flows from the variability of the impact effects from other firms.

Second, what we call a positive shock on productivity (in a broad sense, as it includes changes in total-factor productivity as well as in prices) tends to lead to a shift away from selling abroad to selling in China. The signs of the impact effects differ across the blocks in the tables. For example, positive direct effects on domestic sales across all moments in the distribution in the left block of Table 14 (the own-equation effects) go hand in

[14]In general, these moments are evaluated at the posterior mean of the respective parameter estimates $\widehat{\beta}_{dk}$ and $\widehat{\beta}_{ek}$. Clearly, computing the standard deviations of these moments across the draws in the Monte Carlo chain is straightforward. We refrain from reporting these standard deviations (as estimates of the standard errors) due to space constraints.

hand with negative direct effects on export sales across all moments in the distribution in the left block of Table 15. The cross-equation effects in the right block of results in Tables 14 and 15 differ in sign from the own-equation effects in the respective left block, and they are quite sizable, at least for domestic sales. For instance, more than one-half of the total effect on the median producer in Table 14, which is estimated at 0.423, is undone by the effect on export sales which induces an impact on log domestic sales of -0.251. This covariate induces the largest impact effects among all the determinants included in the models.

The impact-effect estimates of the share of domestic market sellers in all firms in zip code$_{it-1}$ on log domestic sales and of the share of export market sellers in all firms in zip code$_{it-1}$ on log export sales are negative. In contrast, the ones of the share of domestic market seller in all textile producers in zip code$_{it-1}$ on log domestic sales and of the share of exporters in all textile producers in zip code$_{it-1}$ on log export sales are positive. These results suggest that there are positive spillovers (arguably from learning about the market) from other sellers with the same orientation (domestic selling and exporting), while a greater presence of domestic sellers and exporters in general tend to weaken the outcomes of textiles producers, probably through greater competition for factors and less competitive pressure in other sectors than in textiles. In general, such effects are stronger for exporting than for domestic selling, and the (factor-market) competitive effects from all sellers of the same type are stronger than the positive spillover effects from other textiles producers which are domestically selling (in Table 14) or exporting (in Table 15) across all moments of the distribution of impact effects.

Third, in comparison to other explanatory variables, a shock in the log ad-valorem tariff rate$_{it-1}$ in the same textiles sub-sector as firm i induces the second-largest impact effect on log exports in absolute value, according to Table 15. Finally, a higher foreign-capital share$_{it-1}$ raises the level of exports, but the impact is relatively modest, at least in this sector and province, in comparison to other determinants of log exports.

6 Conclusions

This paper conducts an analysis of the determinants of domestic and export sales of individual textiles producers in Guangdong province over the years 2004-2007. Features of the data, evidence of spatial and network effects among Chinese producers in earlier work, and evidence of learning from exporting in earlier work on firms call for an econometric model, which permits analyzing a panel-data system of simultaneous equations with cross-sectionally (or spatially) dependent outcomes of which some are censored and others are not.

We outline an estimation approach based on Bayesian Markov-chain Monte Carlo simulation. We conduct simulations which suggest that this approach can be used in small to moderately-large samples of 1,000 cross-sectional units or less.

The application suggests that all features of the econometric model which we account for are important: time-invariant heterogeneity in terms of unobservables must not be ignored; export success boosts domestic sales; domestic sales success of other firms and export success of other firms induce positive spillovers on domestic sellers and exporters of textiles, respectively.

One advantage of the utilized MCMC approach is its flexibility in allowing for various forms of interdependence and the treatment of non-linear models in a unified framework. Analyzing systems with multiple non-linear equations can be simplified by formulating a latent variable model representation and drawing the unobserved values.

Future work in this context may be devoted to incorporating other forms of cross-sectional correlation such as the presence of spatial or social-network interdependence in unobservables as captured by the disturbances. Moreover, future work might consider time-wise interdependence of the data in somewhat longer panels than studies here, e.g., through the presence of time lags of latent variables on the right-hand side of the model or a serial correlation of the disturbances.[15]

[15] E.g., the importance of time-wise dependence in data has been addressed in Basmann (1985), Basmann, Richardson, and Rohr (1974a, 1974b).

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Table 1: Overview of simulation designs - True parameter values

	SSUR Design 1	SSUR Design 2	SSSE Design 3	SSSE Design 4	SSSE Design 5
β_{11}	1.000	1.000	1.000	1.000	1.000
β_{12}	1.000	1.000	1.000	1.000	1.000
β_{13}	1.000	1.000	1.000	1.000	1.000
β_{21}	1.000	1.000	1.000	1.000	1.000
β_{22}	1.000	1.000	1.000	1.000	1.000
β_{23}	1.000	1.000	1.000	1.000	1.000
λ_1	0.400	0.100	0.400	0.100	0.400
λ_2	0.400	0.300	0.400	0.300	0.400
γ_1	-	-	-0.100	-0.100	-0.300
γ_2	-	-	0.100	0.100	0.100
$\sigma_{\nu_{11}}$	2.000	2.000	2.000	2.000	2.000
$\sigma_{\nu_{12}}$	1.000	1.000	1.000	1.000	1.000
$\sigma_{\nu_{22}}$	2.000	2.000	2.000	2.000	2.000
m_{α_1}	1.500	1.500	1.500	1.500	1.500
m_{α_2}	2.500	2.500	2.500	2.500	2.500
$s_{\alpha_{11}}$	2.000	2.000	2.000	2.000	2.000
$s_{\alpha_{12}}$	0.800	0.800	0.800	0.800	0.800
$s_{\alpha_{22}}$	2.000	2.000	2.000	2.000	2.000

Table 2: SSUR Design 1 - the fraction of censored observations in y_2 is medium, $N = 500$ and $N = 1,000$

	True	$N = 500$			$N = 1,000$		
		Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	0.980	0.019	0.480	1.015	0.013	0.262
β_{12}	1.000	0.989	0.018	0.322	0.998	0.013	0.386
β_{13}	1.000	1.030	0.019	0.562	1.008	0.013	0.796
β_{21}	1.000	0.995	0.024	0.464	1.005	0.015	0.599
β_{22}	1.000	0.975	0.024	0.484	1.010	0.015	0.625
β_{23}	1.000	1.001	0.025	0.701	1.024	0.015	0.508
λ_1	0.400	0.373	0.031	0.660	0.395	0.021	0.414
λ_2	0.400	0.335	0.136	0.484	0.386	0.081	0.605
$\sigma_{\nu_{11}}$	2.000	1.928	0.088	0.857	2.007	0.062	0.172
$\sigma_{\nu_{12}}$	1.000	0.940	0.081	0.667	1.051	0.053	0.294
$\sigma_{\nu_{22}}$	2.000	2.319	0.372	0.855	2.084	0.134	0.202
m_{α_1}	1.500	1.560	0.094	0.520	1.552	0.062	0.534
m_{α_2}	2.500	2.636	0.503	0.460	2.512	0.327	0.590
$s_{\alpha_{11}}$	2.000	1.751	0.105	0.703	2.044	0.083	0.199
$s_{\alpha_{12}}$	0.800	0.670	0.091	0.453	0.794	0.068	0.778
$s_{\alpha_{22}}$	2.000	1.938	0.146	0.408	2.070	0.094	0.640

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.155 for $N = 500$ and $3,000$ and 0.156 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 3: SSUR Design 1 - the fraction of censored observations in y_2 is low, $N = 500$ and $N = 1,000$

	True	$N = 500$			$N = 1,000$		
		Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	0.996	0.019	0.451	1.013	0.013	0.470
β_{12}	1.000	0.970	0.019	0.306	1.001	0.013	0.849
β_{13}	1.000	1.000	0.019	0.728	0.987	0.013	0.334
β_{21}	1.000	0.995	0.021	0.591	0.974	0.017	0.510
β_{22}	1.000	1.000	0.022	0.188	1.036	0.016	0.478
β_{23}	1.000	0.993	0.022	0.983	0.994	0.016	0.263
λ_1	0.400	0.388	0.033	0.285	0.422	0.027	0.361
λ_2	0.400	0.353	0.130	0.317	0.379	0.118	0.864
$\sigma_{\nu_{11}}$	2.000	2.046	0.091	0.342	1.974	0.063	0.470
$\sigma_{\nu_{12}}$	1.000	1.074	0.083	0.189	1.008	0.055	0.407
$\sigma_{\nu_{22}}$	2.000	2.358	0.491	0.106	2.273	0.433	0.636
m_{α_1}	1.500	1.559	0.100	0.455	1.518	0.076	0.536
m_{α_2}	4.000	4.307	0.827	0.340	4.274	0.776	0.631
$s_{\alpha_{11}}$	2.000	2.095	0.120	0.189	1.926	0.080	0.595
$s_{\alpha_{12}}$	0.800	0.657	0.095	0.326	0.926	0.067	0.240
$s_{\alpha_{22}}$	2.000	1.864	0.154	0.920	2.116	0.125	0.774

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.060 for $N = 500$ and $3,000$ and 0.050 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 4: SSUR Design 1 - the fraction of censored observations in y_2 is high, $N = 500$ and $N = 1,000$

	True	$N = 500$			$N = 1,000$		
		Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	1.021	0.020	0.806	1.003	0.013	0.805
β_{12}	1.000	1.003	0.020	0.173	1.014	0.013	0.495
β_{13}	1.000	0.991	0.020	0.793	1.007	0.014	0.373
β_{21}	1.000	1.067	0.029	0.109	1.003	0.019	0.694
β_{22}	1.000	1.050	0.030	0.437	1.022	0.018	0.370
β_{23}	1.000	1.056	0.030	0.215	1.027	0.019	0.796
λ_1	0.400	0.380	0.030	0.419	0.385	0.021	0.441
λ_2	0.400	0.335	0.115	0.464	0.341	0.090	0.548
$\sigma_{\nu_{11}}$	2.000	2.026	0.094	0.731	2.052	0.065	0.162
$\sigma_{\nu_{12}}$	1.000	0.968	0.090	0.113	1.112	0.061	0.939
$\sigma_{\nu_{22}}$	2.000	2.429	0.167	0.219	2.175	0.110	0.479
m_{α_1}	1.500	1.651	0.095	0.382	1.647	0.062	0.619
m_{α_2}	1.000	1.049	0.181	0.438	1.144	0.167	0.765
$s_{\alpha_{11}}$	2.000	2.437	0.129	0.674	1.933	0.083	0.524
$s_{\alpha_{12}}$	0.800	1.085	0.113	0.222	0.708	0.069	0.392
$s_{\alpha_{22}}$	2.000	2.037	0.179	0.376	1.989	0.107	0.166

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.346 for $N = 500$ and $3,000$ and 0.335 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 5: SSUR Design 1 - the fraction of censored observations in y_2 is medium and no drawing of y_2 occurs, $N = 500$ and $N = 1,000$

		$N = 500$			$N = 1,000$		
	True	Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	0.982	0.019	0.841	1.026	0.014	0.595
β_{12}	1.000	0.987	0.019	0.443	1.001	0.014	0.117
β_{13}	1.000	1.031	0.020	0.144	1.005	0.014	0.688
β_{21}	1.000	0.827	0.025	0.432	0.853	0.021	0.551
β_{22}	1.000	0.811	0.027	0.657	0.847	0.019	0.360
β_{23}	1.000	0.843	0.033	0.139	0.857	0.018	0.883
λ_1	0.400	0.371	0.043	0.384	0.392	0.034	0.264
λ_2	0.400	0.256	0.279	0.362	0.306	0.262	0.391
$\sigma_{\nu_{11}}$	2.000	1.934	0.087	0.705	2.011	0.065	0.917
$\sigma_{\nu_{12}}$	1.000	0.842	0.108	0.454	0.860	0.071	0.694
$\sigma_{\nu_{22}}$	2.000	3.329	1.822	0.978	3.188	1.707	0.385
m_{α_1}	1.500	1.565	0.124	0.425	1.560	0.094	0.229
m_{α_2}	2.500	3.177	0.955	0.234	3.086	0.970	0.393
$s_{\alpha_{11}}$	2.000	1.748	0.107	0.780	2.041	0.083	0.090
$s_{\alpha_{12}}$	0.800	0.536	0.090	0.867	0.687	0.068	0.371
$s_{\alpha_{22}}$	2.000	1.246	0.191	0.606	1.363	0.178	0.252

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.155 for $N = 500$ and $3,000$ and 0.156 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 6: SSUR Design 2 - $N = 500$ and $N = 1,000$

		$N = 500$			$N = 1,000$		
	True	Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	0.999	0.019	0.764	0.968	0.014	0.772
β_{12}	1.000	0.973	0.019	0.706	0.991	0.013	0.869
β_{13}	1.000	1.002	0.020	0.490	1.003	0.013	0.962
β_{21}	1.000	1.000	0.025	0.498	1.007	0.017	0.793
β_{22}	1.000	1.000	0.024	0.423	1.013	0.016	0.766
β_{23}	1.000	1.010	0.026	0.332	0.994	0.016	0.900
λ_1	0.100	0.081	0.043	0.132	0.077	0.029	0.874
λ_2	0.300	0.249	0.160	0.814	0.282	0.087	0.531
$\sigma_{\nu_{11}}$	2.000	2.043	0.092	0.392	1.964	0.063	0.651
$\sigma_{\nu_{12}}$	1.000	1.071	0.083	0.754	0.981	0.054	0.687
$\sigma_{\nu_{22}}$	2.000	2.347	0.396	0.327	2.248	0.131	0.789
m_{α_1}	1.500	1.561	0.090	0.238	1.580	0.057	0.984
m_{α_2}	2.500	2.659	0.518	0.712	2.553	0.305	0.521
$s_{\alpha_{11}}$	2.000	2.098	0.118	0.995	2.007	0.080	0.241
$s_{\alpha_{12}}$	0.800	0.650	0.095	0.756	0.835	0.068	0.261
$s_{\alpha_{22}}$	2.000	1.817	0.154	0.666	2.032	0.102	0.904

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.180 for $N = 500$ and $3,000$ and 0.181 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 7: SSSE Design 3 - $N = 500$ and $N = 1,000$

	True	$N=500$ Mean	Std.dev	GT p-value	$N=1,000$ Mean	Std.dev	GT p-value
β_{11}	1.000	0.992	0.019	0.390	0.988	0.014	0.947
β_{12}	1.000	1.018	0.020	0.113	1.016	0.014	0.121
β_{13}	1.000	1.008	0.019	0.679	1.015	0.014	0.376
β_{21}	1.000	1.021	0.023	0.770	1.005	0.015	0.254
β_{22}	1.000	1.040	0.023	0.696	0.978	0.015	0.912
β_{23}	1.000	1.001	0.021	0.227	0.998	0.016	0.389
λ_1	0.400	0.448	0.029	0.982	0.387	0.021	0.155
λ_2	0.400	0.346	0.031	0.231	0.371	0.021	0.761
γ_1	-0.100	-0.101	0.012	0.535	-0.116	0.009	0.544
γ_2	0.100	0.102	0.014	0.951	0.101	0.009	0.460
$\sigma_{\nu_{11}}$	2.000	1.902	0.089	0.126	2.009	0.066	0.319
$\sigma_{\nu_{12}}$	1.000	0.950	0.081	0.615	0.937	0.057	0.204
$\sigma_{\nu_{22}}$	2.000	2.102	0.108	0.416	2.030	0.073	0.726
m_{α_1}	1.500	1.422	0.083	0.993	1.661	0.060	0.159
m_{α_2}	2.500	2.760	0.148	0.345	2.614	0.101	0.671
$s_{\alpha_{11}}$	2.000	2.250	0.119	0.769	2.150	0.088	0.512
$s_{\alpha_{12}}$	0.800	0.866	0.104	0.587	0.923	0.074	0.512
$s_{\alpha_{22}}$	2.000	2.061	0.133	0.913	2.207	0.096	0.915

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.156 for $N = 500$ and $3,000$ and 0.136 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 8: SSSE Design 4 - $N = 500$ and $N = 1,000$

	True	$N=500$ Mean	Std.dev	GT p-value	$N=1,000$ Mean	Std.dev	GT p-value
β_{11}	1.000	0.993	0.019	0.974	0.987	0.013	0.542
β_{12}	1.000	1.020	0.020	0.230	1.015	0.014	0.456
β_{13}	1.000	1.010	0.019	0.685	1.015	0.014	0.146
β_{21}	1.000	1.010	0.023	0.747	1.005	0.016	0.258
β_{22}	1.000	1.039	0.023	0.785	0.974	0.016	0.183
β_{23}	1.000	0.994	0.022	0.806	0.996	0.016	0.914
λ_1	0.100	0.168	0.038	0.856	0.080	0.028	0.967
λ_2	0.300	0.237	0.035	0.371	0.276	0.024	0.420
γ_1	-0.100	-0.101	0.012	0.621	-0.115	0.010	0.638
γ_2	0.100	0.100	0.014	0.721	0.099	0.009	0.398
$\sigma_{\nu_{11}}$	2.000	1.904	0.091	0.377	2.004	0.066	0.502
$\sigma_{\nu_{12}}$	1.000	0.939	0.080	0.881	0.928	0.057	0.765
$\sigma_{\nu_{22}}$	2.000	2.079	0.108	0.109	2.005	0.070	0.651
m_{α_1}	1.500	1.426	0.078	0.463	1.652	0.054	0.706
m_{α_2}	2.500	2.770	0.141	0.434	2.584	0.096	0.306
$s_{\alpha_{11}}$	2.000	2.254	0.123	0.131	2.143	0.085	0.773
$s_{\alpha_{12}}$	0.800	0.861	0.105	0.822	0.907	0.072	0.633
$s_{\alpha_{22}}$	2.000	2.021	0.132	0.600	2.186	0.097	0.900

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.193 for $N = 500$ and $3,000$ and 0.173 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 9: SSSE Design 5 - $N = 500$ and $N = 1,000$

	True	$N = 500$			$N = 1,000$		
		Mean	Std.dev	GT p-value	Mean	Std.dev	GT p-value
β_{11}	1.000	0.993	0.019	0.449	0.987	0.014	0.506
β_{12}	1.000	1.020	0.020	0.717	1.014	0.014	0.979
β_{13}	1.000	1.009	0.019	0.515	1.014	0.013	0.319
β_{21}	1.000	1.022	0.023	0.206	1.006	0.015	0.109
β_{22}	1.000	1.045	0.023	0.189	0.981	0.016	0.844
β_{23}	1.000	1.004	0.023	0.812	0.997	0.016	0.529
λ_1	0.400	0.447	0.028	0.690	0.391	0.020	0.274
λ_2	0.400	0.342	0.031	0.832	0.375	0.023	0.868
γ_1	-0.300	-0.296	0.012	0.312	-0.315	0.009	0.518
γ_2	0.100	0.103	0.014	0.764	0.100	0.009	0.216
$\sigma_{\nu_{11}}$	2.000	1.887	0.090	0.440	2.001	0.067	0.434
$\sigma_{\nu_{12}}$	1.000	0.951	0.080	0.105	0.943	0.058	0.685
$\sigma_{\nu_{22}}$	2.000	2.121	0.108	0.516	2.037	0.072	0.658
m_{α_1}	1.500	1.463	0.064	0.700	1.636	0.048	0.825
m_{α_2}	2.500	2.764	0.138	0.827	2.588	0.103	0.909
$s_{\alpha_{11}}$	2.000	2.265	0.123	0.329	2.149	0.087	0.611
$s_{\alpha_{12}}$	0.800	0.876	0.105	0.959	0.918	0.072	0.754
$s_{\alpha_{22}}$	2.000	2.070	0.133	0.881	2.202	0.095	0.928

Notes: The total number of observations TN and the fraction of censored observations on y_2 are $1,500$ and 0.165 for $N = 500$ and $3,000$ and 0.143 for $N = 1,000$. GT p-value denotes the p-value of the Geweke (1992) test.

Table 10: Descriptive statistics

	Mean	Std.dev	Min	Max
Domestic sales (in logs)	10.350	1.732	2.590	14.610
Exports (in logs)	10.109	2.976	0	14.590
Wage per worker (in logs)	2.632	0.453	0.194	5.162
Interest rate	0.029	0.088	0.000	0.773
Materials per worker (in logs)	4.624	0.909	0.593	7.218
Productivity (in logs)	4.969	0.819	2.637	7.501
Employment (in logs)	5.586	0.982	2.565	8.731
Pearl River Delta	0.832	0.374	0	1
Number of all firms in zip code (in logs)	3.861	1.228	0	5.935
Number of all textile firms in zip code (in logs)	2.211	1.251	0	4.635
Share of domestic market sellers in all firms in zip code	0.811	0.151	0.250	1
Share of domestic market sellers in all textile producers in zip code	0.780	0.202	0.143	1
Share of exporters in all firms in zip code	0.528	0.194	0	1
Share of exporters in all textile producers in zip code	0.723	0.237	0	1
Ad-valorem tariff (in logs)	0.048	0.012	0.041	0.100
Foreign capital share	0.647	0.450	0	1

Table 11: Spatial univariate regression results for domestic sales and exports

	Mean	Std.dev	GT p-value
Dependent variable: Domestic sales			
β_d			
Wage per worker (in logs)	-0.066	0.061	0.935
Interest rate	-0.260	0.305	0.209
Materials per worker (in logs)	-0.126	0.089	0.105
Productivity (in logs)	0.226	0.102	0.112
Employment (in logs)	0.056	0.020	0.411
Pearl River Delta	-0.104	0.130	0.846
Number of all firms in zip code (in logs)	-0.002	0.027	0.962
Number of all textile firms in zip code (in logs)	-0.003	0.027	0.573
Share of domestic market sellers in all firms in zip code	-0.744	0.365	0.345
Share of domestic market sellers in all textile producers in zip code	-0.017	0.255	0.168
λ_d	0.370	0.048	0.124
$\sigma_{\nu dd}$	0.737	0.030	0.770
$m_{\alpha d}$	6.515	0.496	0.124
$s_{\alpha dd}$	2.126	0.065	0.252
Dependent variable: Exports			
β_e			
Wage per worker (in logs)	0.413	0.152	0.111
Interest rate	1.990	0.818	0.912
Materials per worker (in logs)	0.589	0.235	0.408
Productivity (in logs)	-0.641	0.265	0.145
Employment (in logs)	0.247	0.071	0.463
Pearl River Delta	-0.190	0.197	0.885
Number of all firms in zip code (in logs)	-0.122	0.090	0.564
Number of all textile firms in zip code (in logs)	0.006	0.089	0.467
Share of exporters in all firms in zip code	-1.636	0.528	0.263
Share of exporters in all textile producers in zip code	0.247	0.425	0.482
Ad-valorem tariff (in logs)	-15.966	7.260	0.324
Foreign capital share	0.277	0.131	0.572
λ_e	0.480	0.075	0.663
$\sigma_{\nu ee}$	7.534	0.315	0.243
$m_{\alpha e}$	5.200	0.760	0.651
$s_{\alpha ee}$	1.778	0.253	0.239

Notes: All regressors are one period lagged. We include year dummies. GT p-value denotes the p-value of the Geweke (1992) test.

Table 12: Domestic sales and exports - SSUR results

	Mean	Std.dev	GT p-value
β_d			
Wage per worker (in logs)	-0.072	0.045	0.727
Interest rate	-0.175	0.296	0.315
Materials per worker (in logs)	-0.094	0.058	0.896
Productivity (in logs)	0.153	0.067	0.940
Employment (in logs)	0.017	0.017	0.872
Pearl River Delta	-0.020	0.055	0.914
Number of all firms in zip code (in logs)	-0.015	0.026	0.757
Number of all textile firms in zip code (in logs)	0.006	0.025	0.204
Share of domestic market sellers in all firms in zip code	-0.219	0.156	0.778
Share of domestic market sellers in all textile producers in zip code	-0.017	0.115	0.477
β_e			
Wage per worker (in logs)	0.458	0.137	0.244
Interest rate	2.042	0.827	0.892
Materials per worker (in logs)	0.569	0.231	0.661
Productivity (in logs)	-0.627	0.262	0.730
Employment (in logs)	0.233	0.063	0.905
Pearl River Delta	-0.124	0.177	0.525
Number of all firms in zip code (in logs)	-0.113	0.086	0.508
Number of all textile firms in zip code (in logs)	0.007	0.086	0.448
Share of exporters in all firms in zip code	-1.788	0.538	0.950
Share of exporters in all textile producers in zip code	0.258	0.432	0.809
Ad-valorem tariff (in logs)	-16.476	7.280	0.365
Foreign capital share	0.261	0.118	0.375
λ_d	0.511	0.041	0.115
λ_e	0.506	0.104	0.885
$\sigma_{\nu_{dd}}$	0.730	0.029	0.677
$\sigma_{\nu_{de}}$	-0.758	0.069	0.764
$\sigma_{\nu_{ee}}$	7.530	0.318	0.230
m_{α_d}	5.063	0.420	0.118
m_{α_e}	4.952	1.051	0.892
$s_{\alpha_{dd}}$	2.163	0.063	0.481
$s_{\alpha_{de}}$	0.101	0.122	0.411
$s_{\alpha_{ee}}$	1.783	0.256	0.150

Notes: All regressors are one period lagged. We include year dummies. GT p-value denotes the p-value of the Geweke (1992) test.

Table 13: Domestic sales and exports - SSSE results

	Mean	Std.dev	GT p-value
β_d			
Wage per worker (in logs)	-0.144	0.059	0.340
Interest rate	-0.494	0.366	0.391
Materials per worker (in logs)	-0.211	0.088	0.365
Productivity (in logs)	0.304	0.100	0.271
Employment (in logs)	-0.008	0.020	0.110
Pearl River Delta	0.036	0.066	0.823
Number of all firms in zip code (in logs)	0.002	0.030	0.799
Number of all textile firms in zip code (in logs)	0.010	0.031	0.286
Share of domestic market sellers in all firms in zip code	-0.373	0.177	0.782
Share of domestic market sellers in all textile producers in zip code	0.091	0.126	0.197
β_e			
Wage per worker (in logs)	0.454	0.148	0.451
Interest rate	2.033	0.815	0.811
Materials per worker (in logs)	0.570	0.237	0.969
Productivity (in logs)	-0.658	0.269	0.737
Employment (in logs)	0.190	0.059	0.965
Pearl River Delta	-0.180	0.168	0.873
Number of all firms in zip code (in logs)	-0.102	0.082	0.457
Number of all textile firms in zip code (in logs)	0.039	0.085	0.173
Share of exporters in all firms in zip code	-1.558	0.484	0.421
Share of exporters in all textile producers in zip code	0.748	0.368	0.536
Ad-valorem tariff (in logs)	-17.624	6.749	0.886
Foreign capital share	0.127	0.094	0.259
λ_d	0.405	0.047	0.801
λ_e	0.348	0.103	0.723
γ_d	0.178	0.019	0.801
γ_e	0.042	0.114	0.771
$\sigma_{\nu_{dd}}$	1.259	0.093	0.768
$\sigma_{\nu_{de}}$	-2.168	0.214	0.867
$\sigma_{\nu_{ee}}$	7.661	0.369	0.921
m_{α_d}	4.371	0.494	0.726
m_{α_e}	6.096	1.691	0.472
$s_{\alpha_{dd}}$	2.121	0.083	0.706
$s_{\alpha_{de}}$	-0.240	0.270	0.616
$s_{\alpha_{ee}}$	1.785	0.258	0.128

Notes: All regressors are one period lagged. We include year dummies. GT p-value denotes the p-value of the Geweke (1992) test.

Table 14: Effects estimates of one std.dev. increase in explanatory variables - domestic sales

		$d^{dd,d}$	$d^{dd,o}$	$d^{dd,f}$	$d^{dd,t}$	$d^{de,d}$	$d^{de,o}$	$d^{de,f}$	$d^{de,t}$
Wage per worker	Min	-0.068	-0.046	-0.078	-0.144	0.037	0.056	0.011	0.048
	p25	-0.066	-0.046	-0.056	-0.122	0.037	0.060	0.047	0.085
	p50	-0.066	-0.046	-0.045	-0.111	0.038	0.060	0.058	0.095
	p75	-0.066	-0.046	-0.037	-0.104	0.038	0.060	0.073	0.111
	Max	-0.066	-0.044	-0.009	-0.074	0.041	0.060	0.105	0.142
	Avg	-0.066	-0.046	-0.046	-0.112	0.038	0.060	0.060	0.097
Interest rate	Min	-0.043	-0.029	-0.049	-0.091	0.032	0.049	0.009	0.041
	p25	-0.042	-0.029	-0.035	-0.077	0.032	0.051	0.041	0.073
	p50	-0.042	-0.029	-0.028	-0.070	0.032	0.052	0.050	0.082
	p75	-0.042	-0.029	-0.024	-0.065	0.033	0.052	0.063	0.095
	Max	-0.042	-0.028	-0.005	-0.047	0.035	0.052	0.090	0.123
	Avg	-0.042	-0.029	-0.029	-0.071	0.032	0.051	0.051	0.084
Materials per worker	Min	-0.200	-0.136	-0.228	-0.422	0.094	0.143	0.027	0.121
	p25	-0.194	-0.135	-0.164	-0.357	0.095	0.151	0.119	0.216
	p50	-0.193	-0.135	-0.131	-0.325	0.095	0.151	0.146	0.242
	p75	-0.193	-0.135	-0.109	-0.303	0.095	0.152	0.186	0.280
	Max	-0.193	-0.128	-0.025	-0.218	0.103	0.152	0.266	0.361
	Avg	-0.194	-0.135	-0.135	-0.329	0.095	0.151	0.151	0.246
Productivity	Min	0.251	0.167	0.033	0.283	-0.107	-0.158	-0.275	-0.374
	p25	0.251	0.175	0.142	0.394	-0.099	-0.158	-0.193	-0.291
	p50	0.252	0.176	0.171	0.423	-0.099	-0.157	-0.152	-0.251
	p75	0.252	0.176	0.213	0.464	-0.098	-0.157	-0.124	-0.224
	Max	0.260	0.177	0.297	0.549	-0.098	-0.148	-0.028	-0.126
	Avg	0.252	0.175	0.175	0.427	-0.099	-0.157	-0.157	-0.256
Employment	Min	-0.007	-0.005	-0.008	-0.015	0.033	0.050	0.010	0.042
	p25	-0.007	-0.005	-0.006	-0.013	0.033	0.053	0.042	0.075
	p50	-0.007	-0.005	-0.005	-0.012	0.033	0.053	0.051	0.084
	p75	-0.007	-0.005	-0.004	-0.011	0.033	0.053	0.065	0.098
	Max	-0.007	-0.005	-0.001	-0.008	0.036	0.053	0.093	0.126
	Avg	-0.007	-0.005	-0.005	-0.012	0.033	0.053	0.053	0.086
Pearl River Delta	Min	0.014	0.009	0.002	0.016	-0.013	-0.019	-0.034	-0.046
	p25	0.014	0.010	0.008	0.022	-0.012	-0.019	-0.024	-0.036
	p50	0.014	0.010	0.010	0.024	-0.012	-0.019	-0.019	-0.031
	p75	0.014	0.010	0.012	0.026	-0.012	-0.019	-0.015	-0.027
	Max	0.014	0.010	0.017	0.031	-0.012	-0.018	-0.003	-0.015
	Avg	0.014	0.010	0.010	0.024	-0.012	-0.019	-0.019	-0.031
Number of all firms in zip code	Min	0.003	0.002	0.000	0.003	-0.025	-0.036	-0.063	-0.086
	p25	0.003	0.002	0.002	0.004	-0.023	-0.036	-0.044	-0.067
	p50	0.003	0.002	0.002	0.005	-0.023	-0.036	-0.035	-0.058
	p75	0.003	0.002	0.002	0.005	-0.023	-0.036	-0.028	-0.051
	Max	0.003	0.002	0.003	0.006	-0.022	-0.034	-0.007	-0.029
	Avg	0.003	0.002	0.002	0.005	-0.023	-0.036	-0.036	-0.059
Number of all textile firms in zip code	Min	0.012	0.008	0.002	0.014	0.009	0.013	0.002	0.011
	p25	0.012	0.008	0.007	0.019	0.009	0.014	0.011	0.020
	p50	0.012	0.008	0.008	0.020	0.009	0.014	0.013	0.022
	p75	0.012	0.008	0.010	0.022	0.009	0.014	0.017	0.026
	Max	0.012	0.008	0.014	0.026	0.009	0.014	0.024	0.033
	Avg	0.012	0.008	0.008	0.020	0.009	0.014	0.014	0.023

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Table 14 continued: Effects estimates of one std.dev. increase in explanatory variables - domestic sales

		$d^{dd,d}$	$d^{dd,o}$	$d^{dd,f}$	$d^{dd,t}$	$d^{de,d}$	$d^{de,o}$	$d^{de,f}$	$d^{de,t}$
Share of domestic market sellers in all firms in zip code	Min	-0.059	-0.040	-0.068	-0.125				
	p25	-0.057	-0.040	-0.048	-0.106				
	p50	-0.057	-0.040	-0.039	-0.096				
	p75	-0.057	-0.040	-0.032	-0.090				
	Max	-0.057	-0.038	-0.007	-0.065				
	Avg	-0.057	-0.040	-0.040	-0.097				
Share of domestic market sellers in all textile producers in zip code	Min	0.018	0.012	0.002	0.020				
	p25	0.018	0.013	0.010	0.028				
	p50	0.018	0.013	0.012	0.030				
	p75	0.018	0.013	0.015	0.033				
	Max	0.019	0.013	0.021	0.040				
	Avg	0.018	0.013	0.013	0.031				

Notes: The columns denote the within-equation direct effects, $d^{dd,d}$, effects on others, $d^{dd,o}$, effects from others, $d^{dd,f}$, and total effects, $d^{dd,t}$, and the across-equation direct effects, $d^{de,d}$, effects on others, $d^{de,o}$, effects from others, $d^{de,f}$, and total effects, $d^{de,t}$ of one-standard deviation changes of the regressors. The rows contain the minimum, the 25-th, 50-th, and 75-th percentile, maximum, and average for each effect.

Table 15: Effects estimates of one std.dev. increase in explanatory variables - exports

		$d^{ee,d}$	$d^{ee,o}$	$d^{ee,f}$	$d^{ee,t}$	$d^{ed,d}$	$d^{ed,o}$	$d^{ed,f}$	$d^{ed,t}$
Wage per worker	Min	0.209	0.110	0.022	0.230	-0.003	-0.004	-0.008	-0.011
	p25	0.209	0.115	0.094	0.304	-0.003	-0.004	-0.005	-0.008
	p50	0.209	0.115	0.112	0.321	-0.003	-0.004	-0.004	-0.007
	p75	0.209	0.115	0.139	0.348	-0.003	-0.004	-0.004	-0.006
	Max	0.214	0.116	0.191	0.400	-0.003	-0.004	-0.001	-0.004
	Avg	0.209	0.115	0.115	0.324	-0.003	-0.004	-0.004	-0.007
Interest rate	Min	0.180	0.095	0.019	0.199	-0.002	-0.003	-0.005	-0.007
	p25	0.180	0.099	0.081	0.262	-0.002	-0.003	-0.003	-0.005
	p50	0.180	0.099	0.097	0.277	-0.002	-0.003	-0.003	-0.004
	p75	0.181	0.100	0.120	0.300	-0.002	-0.003	-0.002	-0.004
	Max	0.185	0.100	0.165	0.345	-0.002	-0.003	-0.001	-0.002
	Avg	0.180	0.099	0.099	0.280	-0.002	-0.003	-0.003	-0.005
Materials per worker	Min	0.528	0.278	0.055	0.584	-0.009	-0.013	-0.023	-0.031
	p25	0.529	0.291	0.239	0.769	-0.008	-0.013	-0.016	-0.024
	p50	0.530	0.292	0.285	0.814	-0.008	-0.013	-0.013	-0.021
	p75	0.530	0.292	0.353	0.883	-0.008	-0.013	-0.010	-0.019
	Max	0.543	0.293	0.484	1.015	-0.008	-0.012	-0.002	-0.010
	Avg	0.530	0.291	0.291	0.821	-0.008	-0.013	-0.013	-0.021
Productivity	Min	-0.563	-0.304	-0.502	-1.052	0.011	0.016	0.003	0.014
	p25	-0.550	-0.303	-0.366	-0.915	0.011	0.017	0.013	0.024
	p50	-0.550	-0.303	-0.295	-0.845	0.011	0.017	0.016	0.027
	p75	-0.549	-0.302	-0.248	-0.798	0.011	0.017	0.021	0.032
	Max	-0.548	-0.289	-0.057	-0.605	0.012	0.017	0.030	0.041
	Avg	-0.550	-0.302	-0.302	-0.852	0.011	0.017	0.017	0.028
Employment	Min	0.185	0.097	0.019	0.204	-0.000	-0.000	-0.001	-0.001
	p25	0.185	0.102	0.083	0.269	-0.000	-0.000	-0.001	-0.001
	p50	0.185	0.102	0.100	0.285	-0.000	-0.000	-0.000	-0.001
	p75	0.186	0.102	0.123	0.309	-0.000	-0.000	-0.000	-0.001
	Max	0.190	0.103	0.169	0.355	-0.000	-0.000	-0.000	-0.000
	Avg	0.185	0.102	0.102	0.287	-0.000	-0.000	-0.000	-0.001

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Table 15 continued: Effects estimates of one std.dev. increase in explanatory variables - exports

		$d^{ee,d}$	$d^{ee,o}$	$d^{ee,f}$	$d^{ee,t}$	$d^{ed,d}$	$d^{ed,o}$	$d^{ed,f}$	$d^{ed,t}$
Pearl River Delta	Min	-0.069	-0.037	-0.062	-0.129	0.001	0.001	0.000	0.001
	p25	-0.068	-0.037	-0.045	-0.113	0.001	0.001	0.001	0.001
	p50	-0.068	-0.037	-0.036	-0.104	0.001	0.001	0.001	0.002
	p75	-0.067	-0.037	-0.030	-0.098	0.001	0.001	0.001	0.002
	Max	-0.067	-0.035	-0.007	-0.074	0.001	0.001	0.002	0.002
	Avg	-0.068	-0.037	-0.037	-0.105	0.001	0.001	0.001	0.002
Number of all firms in zip code	Min	-0.130	-0.070	-0.115	-0.242	0.000	0.000	0.000	0.000
	p25	-0.126	-0.070	-0.084	-0.210	0.000	0.000	0.000	0.000
	p50	-0.126	-0.070	-0.068	-0.194	0.000	0.000	0.000	0.000
	p75	-0.126	-0.069	-0.057	-0.183	0.000	0.000	0.000	0.000
	Max	-0.126	-0.066	-0.013	-0.139	0.000	0.000	0.000	0.000
	Avg	-0.126	-0.069	-0.069	-0.196	0.000	0.000	0.000	0.000
Number of all textile firms in zip code	Min	0.048	0.025	0.005	0.053	0.001	0.001	0.000	0.001
	p25	0.048	0.027	0.022	0.070	0.001	0.001	0.001	0.001
	p50	0.048	0.027	0.026	0.074	0.001	0.001	0.001	0.001
	p75	0.048	0.027	0.032	0.081	0.001	0.001	0.001	0.002
	Max	0.050	0.027	0.044	0.093	0.001	0.001	0.001	0.002
	Avg	0.048	0.027	0.027	0.075	0.001	0.001	0.001	0.001
Share of exporters in all firms in zip code	Min	-0.316	-0.170	-0.282	-0.590				
	p25	-0.308	-0.170	-0.205	-0.513				
	p50	-0.308	-0.170	-0.166	-0.473				
	p75	-0.308	-0.169	-0.139	-0.447				
	Max	-0.307	-0.162	-0.032	-0.339				
	Avg	-0.308	-0.169	-0.169	-0.478				
Share of exporters in all textile producers in zip code	Min	0.181	0.096	0.019	0.200				
	p25	0.182	0.100	0.082	0.264				
	p50	0.182	0.100	0.098	0.279				
	p75	0.182	0.100	0.121	0.303				
	Max	0.186	0.101	0.166	0.348				
	Avg	0.182	0.100	0.100	0.282				
Ad-valorem tariff	Min	-0.217	-0.117	-0.194	-0.406				
	p25	-0.212	-0.117	-0.141	-0.353				
	p50	-0.212	-0.117	-0.114	-0.326				
	p75	-0.212	-0.116	-0.095	-0.308				
	Max	-0.211	-0.111	-0.022	-0.233				
	Avg	-0.212	-0.117	-0.117	-0.329				
Foreign capital share	Min	0.058	0.031	0.006	0.064				
	p25	0.058	0.032	0.026	0.085				
	p50	0.058	0.032	0.031	0.090				
	p75	0.058	0.032	0.039	0.097				
	Max	0.060	0.032	0.053	0.112				
	Avg	0.058	0.032	0.032	0.090				

Notes: The columns denote the within-equation direct effects, $d^{ee,d}$, effects on others, $d^{ee,o}$, effects from others, $d^{ee,f}$, and total effects, $d^{ee,t}$, and the across-equation direct effects, $d^{de,d}$, effects on others, $d^{de,o}$, effects from others, $d^{de,f}$, and total effects, $d^{de,t}$ of one-standard deviation changes of the regressors. The rows contain the minimum, the 25-th, 50-th, and 75-th percentile, maximum, and average for each effect.