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Spatial effects in a common trend model of US city-level CPI

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ABSTRACT

This paper studies relative movements in price indices of 17 US cities. We employ an unobserved common trend model where the trend can be stochastic or deterministic with possible breaks or other nonlinearities. To accommodate the spatial nature of the data we allow for spatially correlated short-run shocks. In this way, the speed of convergence to the equilibrium implied by the law of one price is estimated taking into account the effect of distances across cities. The parameters of the model are estimated using a generalized method of moments (GMM) method which incorporates moment conditions corresponding to a generalized least squares-like within estimator of regression parameters. We find a slow rate of convergence of the price levels and strong evidence of spatial effects.

1. Introduction

The law of one price (LOP), as generally understood, follows from the assumption that individuals and firms will not systematically ignore opportunities to profit from risk-free arbitrage. In the absence of transaction costs or institutional barriers, it should not be possible to buy a commodity at one price and immediately sell it for a higher price. On the contrary, so the argument goes, the very possibility of arbitrage will eliminate such price differences. Like many core ideas in economics the LOP is easy to state but by no means easy to verify empirically. To help account for the frequent rejection of the LOP, Pippenger and Phillips (2008, p. 916) identify four confounding factors in studies of commodity prices: use of retail prices, ignoring transport costs, ignoring time, and pricing non-identical products. The first three factors directly affect potential arbitrage, which requires the goods being traded to be resaleable, while the fourth is obviously fundamental. Many studies that challenge the empirical validity of the LOP, it is argued, fail to attend adequately to one or more of these details. On the other hand, when the data employed are not contaminated in this way, support for the LOP improves, a good example being the analysis of data from various multi-national internet traders by Cavallo et al. (2014). At any given time, there is always some observed price dispersion; consequently, many studies investigate whether prices can be shown to be converging to the LOP, and if so, how rapidly. The picture here is complicated by the underlying price dynamics: in many markets prices are non-stationary, and so following Johansen and Juselius (1992), testing for the presence of cointegration between two or more price series has become routine, with rejection interpreted as evidence against PPP or the LOP.

Closer in scope to the present work are studies that evaluate the size of international or internal border effects, or rates of price convergence within countries. In the first case it is necessary to distinguish between cross-border distance effects, which may be magnified by political boundaries, on the one hand, and inter- and intra-jurisdictional price distributional differences which may confound these. Surveying numerous North American studies, from Engel and Rogers (1996) onwards, Gorodnichenko and Tesar (2009) argue that much of the US–Canada border impact identified may be a side-effect of the greater price dispersion within the US. This line of argument demonstrates that price dispersion, per se, is not taken as evidence against the LOP. Studies of price convergence at the sub-national scale typically suppose that systems of states, regions or cities exhibit movement around a common trend, the point being to establish convergence towards such a trend. In an influential paper, Cecchetti et al. (2002) "believe that studying the behaviour of prices across U.S. cities will help us in understanding the likely nature of inflation convergence in the Euro area." They work with relative price indices, arguing that it is the behaviour of such aggregates that is of primary concern to monetary policy makers. Their headline result is that city

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relative price indices do not have unit roots, but that convergence is very slow, with a half-life of about 9 years, attributed to the difficulty in trading some goods. They found that relative prices between distant cities were significantly more dispersed than those between near neighbours, while convergence between cities that were closer together was faster, but not significantly so (op. cit. p. 1090 Table 3). Earlier, Parsley and Wei (1996) had also shown that the variability of relative commodity prices between U.S. cities was related to the distance separating them, while a unit root in relative prices was similarly rejected. Noting that both Cecchetti et al, and Parsley and Wei, and others, could only secure rejection of the crucial unit root null hypothesis by adopting panel unit root tests, that gloss over any individual series that might be non-stationary, Sonora (2008) repeats the analysis using a new generation of more powerful univariate tests. He finds in favour of stationarity in a majority of cases, and detects faster convergence rates than in the previous studies.

The common finding that relative price dispersion observed over time at pairs of locations increases with their physical separation suggests to us that spatial effects should be incorporated into the model, rather than being investigated separately. Although the inflation convergence literature stimulated by the creation of the Eurozone has a vigorous regional strand, and there are a number of studies of price dispersion between U.S. cities, space is generally introduced at a second stage of the analysis. In this paper, therefore, dynamic and spatial interactions in U.S. city-level prices are integrated via a panel data model with explicit spatial dependence. There are currently at least two alternative approaches to the modelling of such panels, and so the next section describes these briefly to provide some context. Section 3 introduces the model in detail, and Section 4 presents the estimation method and the asymptotic properties of the estimates. Section 5 gives a description of the data and empirical results, and finally Section 6 comments on the implications. Proofs of the theorems are set out in a separate section.

2. Estimating dynamic spatial panel models

Kelejian and Prucha (1999) propose a generalized method of moments (GMM) estimator for a static cross-section model with spatially correlated errors. This set-up is further developed by Kapoor et al. (2007) and Mutl (2006) who introduce GMM estimators for stationary dynamic panel models with temporal and spatial correlation in the disturbance handled via random effects. Baltagi et al. (2014) propose a GMM estimator for a model that also includes a temporal and spatial lag of the dependent variable, while Mutl and Pfaffermayr (2011), develop a test of the random effects assumption in a static Cliff–Ord type model. Similarly, Baltagi and Liu (2011) propose generalized least squares (GLS) estimators for panel data with fixed or random effects for a generalized spatial error components panel data model and develop a Hausman specification test. Lee and Yu (2010) review both static and dynamic spatial panel data models, providing a concise guide to recent developments in this rapidly expanding field. Following Yu et al. (2012) (YJL) the dynamic spatial panel model underlying this strand of work can be written as

$$\mathbf{Y}_{n,t} = \lambda_0 \mathbf{W}_n \mathbf{Y}_{n,t} + \gamma_0 \mathbf{Y}_{n,t-1} + \rho_0 \mathbf{W}_n \mathbf{Y}_{n,t-1} + \mathbf{X}_{n,t}\beta_0 + \mathbf{c}_{n,0} + \alpha_{t,0}\mathbf{1}_n + \mathbf{V}_{n,t} \tag{1}$$

in which $\mathbf{Y}_{n,t} = [y_{1,t},\ldots,y_{n,t}]'$ is observed at the n locations for each time period, $\mathbf{X}_{n,t}$ is an $n \times k$ matrix of exogenous covariates, $\mathbf{c}_{n,0}$ a vector of location-specific fixed effects, $\alpha_{t,0}$ a panel-wide time effect, and $\mathbf{V}_{n,t}$ an independent, identically distributed (IID) disturbance. In this structure, the vector of current endogenous variables $\mathbf{Y}_{n,t}$ is seen to be influenced by its own past, and also by a contemporaneous spill-over effect via the vector of weighted neighbouring values, $\mathbf{W}_n\mathbf{Y}_{n,t}$. To discuss the dynamics implicit in Eq. (1), first assume that the matrix, $[\mathbf{I}_n - \lambda_0\mathbf{W}_n] = \mathbf{S}_n$ is invertible, and then write, $\mathbf{A}_n = \mathbf{S}_n^{-1}[\gamma_0\mathbf{I}_n + \rho_0\mathbf{W}_n]$. With this notation the reduced form may be written,

$$\mathbf{Y}_{n,t} = \mathbf{A}_n\mathbf{Y}_{n,t-1} + \mathbf{S}_n^{-1}\left[\mathbf{X}_{n,t}\beta_0 + \mathbf{c}_{n,0} + \alpha_{t,0}\mathbf{1}_n + \mathbf{V}_{n,t}\right] \tag{2}$$

from which we obtain the Error Correction Model (ECM) representation

$$\Delta\mathbf{Y}_{n,t} = [\mathbf{A}_n - \mathbf{I}_n]\mathbf{Y}_{n,t-1} + \mathbf{S}_n^{-1}\left[\mathbf{X}_{n,t}\beta_0 + \mathbf{c}_{n,0} + \alpha_{t,0}\mathbf{1}_n + \mathbf{V}_{n,t}\right].$$

It is now easy to see that the dynamics of $\mathbf{Y}_{n,t}$ are determined by the dynamics of $\mathbf{X}_{n,t}$, $\alpha_{t,0}$, and the eigenvalues of $\mathbf{A}_n$. If $\mathbf{W}_n$ is obtained from a symmetric matrix of non-negative constants by row-normalisation, the interesting cases identified by YJL are (i) if all the eigenvalues of $\mathbf{A}_n$ have magnitude smaller than 1 the process may be stationary, (ii) if all the eigenvalues of $\mathbf{A}_n$ are equal to 1 we may have a pure unit root process without cointegration, and (iii) if some of the eigenvalues of $\mathbf{A}_n$ are equal to 1 we may have the case of "spatial cointegration". We say "may" here, because YJL assume that $\mathbf{X}_{n,t}$ is non-stochastic, while as they note, various further possibilities arise according to how $\alpha_{t,0}$ evolves. However, with the specification (1), the common time effect may be eliminated by a simple transformation, as is the case for our model introduced in Section 3. After some manipulation, YJL (2012, p. 30) show that the endogenous variable may be expressed as the sum of three components:

$$\mathbf{Y}_{n,t} = \mathbf{Y}_{n,t}^{unit} + \mathbf{Y}_{n,t}^{sta} + \mathbf{Y}_{n,t}^{\alpha} \tag{3}$$

where $\mathbf{Y}_{n,t}^{\text{unit}}$ is a non-stationary vector process, $\mathbf{Y}_{n,t}^{\text{sta}}$ is a stationary component, and $\mathbf{Y}_{n,t}^{\alpha} = \frac{1}{1-\lambda_0}\mathbf{1}_n\sum_{h=0}^{t}\alpha_{t-h,0}$ is a common trend. Furthermore, in the "spatial cointegration" case that is of greatest interest, two of these components are eliminated by the transformation, $(\mathbf{W}_n - \mathbf{I}_n)$; it can be shown that both $(\mathbf{W}_n - \mathbf{I}_n)\mathbf{Y}_{n,t}^{\text{unit}} = 0$ and $(\mathbf{W}_n - \mathbf{I}_n)\mathbf{Y}_{n,t}^{\alpha} = \mathbf{0}$ so that $(\mathbf{W}_n - \mathbf{I}_n)\mathbf{Y}_{n,t}$ is stationary, revealing that the rows of $(\mathbf{W}_n - \mathbf{I}_n)$ are cointegrating vectors, and that the rank of this matrix is the cointegrating rank of the system of related sites, in the sense that these vectors define linear combinations of the $\mathbf{Y}$ values observed at different locations that are stationary.

A somewhat different approach that introduces dependence and dynamics via observed and unobserved common factors, building on the work of Pesaran (2006), is developed in recent papers by Kapetanios et al. (2011), Chudik et al. (2011), and Pesaran and Tosetti (2011), who introduce a model of the form,

$$y_{it} = \alpha_i'\mathbf{d}_t + \beta_i'\mathbf{x}_{it} + \gamma_i'\mathbf{f}_t + e_{it} \tag{4}$$

in which $\mathbf{d}_t$ is an $m_d \times 1$ vector of observed common effects (such as time trends, or aggregate prices), $\mathbf{x}_{it}$ is a $k \times 1$ vector of observed regressors, for individual i at time t, $\mathbf{f}_t$ is an $m_f \times 1$ vector of unobservable common factors ($m_f < n$) and e_{it} is the i^{th} element of the disturbance vector, $\mathbf{e}_t$. The primary object to be estimated is the mean of the β_i coefficients. To allow for both spatial and serial autocorrelation in $\mathbf{e}_t$ the fixed matrix $\mathbf{R}_t$ is introduced, and the stationary process ε_t such that

$$\mathbf{e}_t = \mathbf{R}_t\varepsilon_t$$
$$\varepsilon_{it} = \sum_{s=0}^{\infty} a_{is}\epsilon_{i,t-s}$$

with $\epsilon_{is} \sim IID(0,1)$ with finite $4th$ moments. Evidently, the YJL and the Pesaran et al. models are different but related. Since Eq. (4) is a final form equation, their connections and differences can be seen by comparing it with the final form of YJL, Eq. (3). First consider the treatment of unobservables. In Eq. (4) both the disturbance, $\mathbf{e}_t$ and the m_f-dimensional dynamic factors, $\mathbf{f}_t$ are unobserved, and in practice, the latter are proxied by augmenting the right-hand-side with cross-section means of both y and $\mathbf{x}$ in order that the mean of the β_i may be estimated. Furthermore, there are two possible sources of spatial dependence in the unobservables: via