SPATIAL SPILLOVER IN HOUSING CONSTRUCTION

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Abstract

A model is proposed in which building contractors have regional preferences so that housing construction in different regions are imperfect substitutes. The model hypothesizes spatial and national spillovers in construction. Although the government does not engage directly in housing construction, it influences regional housing markets by auctioning land to contractors. Contractors are hypothesized to use housing-under-construction as a buffer between starts and completions. Spatial panel data for Israel are used to test the model and investigate the determinants of regional housing construction. Because the spatial panel data are nonstationary, we use spatial panel cointegration methods to estimate the model. The estimated model is used to calculate impulse responses which propagate over time and across space.

Keywords: regional housing construction, elasticity of housing supply, spatial panel cointegration,

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"Virtually every paper written on housing supply begins with the same sentence: While there is an extensive literature on the demand for housing, far less has been written about supply." DiPasquale (1999)

1. Introduction

As noted by DiPasquale and many others, the empirical determination of house prices has attracted much more empirical attention than the empirical determination of housing construction. This continues to be so even now. This asymmetry is puzzling because house prices vary inversely with the stock of housing (Smith 1969, DiPasquale and Wheaton 1994, Bar Nathan et al 1998). Therefore a complete account of house price behavior requires analysis of both sides of the housing market, the demand for housing and its supply.

The extant research on housing construction has been largely concerned with national housing construction (Ball et al 2010). In this paper, we focus on the determinants of regional housing construction. Our motivation stems from a variety of reasons. First, regional house prices and construction vary considerably and systematically. Therefore, national housing parameters might not be relevant to specific regions. Second, national aggregation of regional housing markets might be inappropriate. Indeed, it is possible to reject a hypothesis nationally due to aggregation bias, when the hypothesis is valid regionally. Third, since regional panel data are inevitably more informative than their national counterparts, it is easier to test hypotheses using regional panel data than national data. Fourth, national models of housing supply do a poor job in capturing the unique local and regional factors that bear upon supply. Finally, to our best knowledge there is no published research on regional housing construction.

Attention has recently been drawn to local phenomena such as topography, zoning and building regulations in the determination of housing construction (Meen and Nygaard 2011 and Saiz 2010). The price elasticity of supply of new housing is expected to vary inversely with the degree of inflexibility in zoning and land use policy as well as with topographical difficulties that raise the cost of construction. Since these parameters are quintessentially local, it makes more sense to estimate local or regional models rather than national models, which ignore local heterogeneity.

Regional models are not simply national models applied regionally. This is because regional housing markets are not independent islands. Construction is unlikely to be independent, especially if building contractors operate in more than one location. Building contractors may choose to operate in locations where profits are higher, or they may have local preferences so that construction in one location is not a perfect substitute for construction in another. We therefore distinguish between absolute and relative profitability in housing construction. An absolute increase in profitability in a location is hypothesized to increase construction locally. However, an increase in profitability in another location will reduce relative profitability. If construction in different locations are gross substitutes, this will reduce construction locally. On the other hand, if they are gross complements the opposite will apply. Gross complementarity may be induced, for example, by scale economies in which local building costs are affected by construction in other locations, and by advances in building technology, which encourage multi-location operations. In addition, if construction is credit constrained, this constraint may be eased when construction increases in other locations.

We distinguish between neighboring locations and other locations since for logistical reasons construction in the former might be related differently to construction between more remote locations. In practice we use spatial econometric methods to estimate spillover effects between neighboring locations, while the latter are specified at the national level. Therefore, our main contribution is to test hypotheses about housing construction using dependent regional panel data.

A second contribution is methodological. Since the data are nonstationary we use the methodology of panel cointegration to test hypotheses regarding the determination of housing construction. Standard panel cointegration tests (Pedroni 2004) assume that the panel units are independent, which in the present context means that unobserved heterogeneity is regionally independent. There have been a number of attempts to introduce dependence into panel cointegration tests. For example, Pesaran (2006) has extended panel cointegration to the case in which the panel units are dependent because they share an unobserved common factor. We

extend Pedroni's panel cointegration test statistics to the case in which the units in the panel are spatially dependent[1].

We also show that when the number of panel units is fixed, as it is in our empirical investigation, demand and supply schedules are identified without recourse to instrumental variables. Potential simultaneous equations bias that would arise in stationary data tends to vanish when the data are nonstationary and the model is panel-cointegrated. This convenient feature results from the super-consistent property of OLS estimates of cointegrating vectors. We are thus able to obtain consistent estimates of the supply schedule for housing without taking into consideration how the demand for housing is determined. The same principles enable the consistent estimation of spatial spillovers without recourse to ML or IV as would be required had the data been stationary.

We use regional panel data for Israel to test the model and to estimate spatial and national spillovers in housing construction. In previous work (Beenstock and Felsenstein 2010) on regional house prices we found that standard panel cointegration methods led to the rejection of the null hypothesis. However, spatial panel cointegration methods overturned this result. In the present paper we start by estimating a standard, non-spatial housing starts regression. Using spatial panel data we then test whether housing construction models are miss-specified if they omit spatial spillovers in housing construction. We also highlight the effect of spatial factors in the estimates of elasticity of supply for housing.

2. Theory and Methodology

2.1 The Price Elasticity of Supply of Housing Construction

The price elasticity of supply of new housing is made up of two key components. First, if house prices increase (relative to building costs) contractors have a greater incentive to build on land that is already available for housing. Marginal plots that were previously empty will be built upon and the housing stock will increase. Also, contractors will build more intensively (high rise) if building costs vary directly with the number of floors. Furthermore, marginal housing intended for re-designation (for offices, shops etc) will be retained as housing since it is more profitable, and offices

[1] Studies in housing supply typically ignore nonstationarity. For an exception see Mayer and Somerville (2000a).

and shops will be re-designated as housing. The latter does not directly affect construction but it affects the supply of housing.

Whereas the first component takes the designation of land use to be fixed, the second component assumes that land use is endogenous. If the price of housing increases, land use will be re-designated in favor of housing, which will increase new housing construction. This applies to privately owned land and publicly owned land. However, the price elasticity might be greater when land is owned privately. If land use is entirely regulated the second component will be zero because privately owned land cannot be re-designated. Also, planning permission required to build high-rise housing will adversely affect the elasticity of supply of new housing construction. However, planning permission and zoning are unlikely to be completely independent of house prices. Expensive housing makes for political unpopularity. Therefore, the second component is unlikely to be zero[2].

2.2 Models of Housing Construction

Two theoretical models have informed the empirical analysis of housing construction. The first relates construction to changes in house prices and the second to the level of house prices. The former treats housing as an asset to be supplied to the market if there is disequilibrium, expressed in changes in house prices (Blackley 1999, Hwang and Quigley 2006). The latter treats the production of new housing as any other product, which forms the basis of the "stock-flow" model originally proposed[3] by Smith (1969). This model is essentially a dynamic capital asset pricing model since the price of housing is determined in the market for housing as an asset, while the flow of this asset is determined by construction, which depends upon the level of house prices.

The basic version of the stock-flow model consists of two equations. The first is an inverted demand function in which house prices are hypothesized to vary directly with demand factors such as population and income, and to vary inversely with supply (the housing stock), which is quasi-fixed. The second equation determines housing construction, which responds to house prices. Subsequently, the housing stock adjusts over time to its long run level (Topel and Rosen 1988). The

[2] As discussed below, government tends to sell land for housing construction when house prices are high.

[3] This model dates back to Witte (1963) and has been applied in many countries including by Smith (1969) for Canada, Kearl (1979) for the United States, and Bar Nathan et al (1998) for Israel. It also features in numerous macroeconomic texts such as Dornbusch and Fischer (1990), Sachs and Larrain (1993) and Mankiw (2003).

construction industry smooths-out investment over time, and house building is a lengthy process protracted by institutional constraints due to planning delays. Investors are encouraged to smooth construction in developed sites with permits (Mayer and Somerville 2000b). In the stock-flow model new housing competes with the existing housing stock. Since the latter is much greater than the former the market power of constructors is greatly limited. It is for this reason that the in the stock-flow model it is assumed that constructors operate within a competitive environment.

2.3 Regional Housing Policy

The market for land in Israel may be unique in that 94 percent of national land is in public ownership, and is administered by the Israel Land Authority (ILA). The role of the ILA cannot be understated. It auctions land to private builders, who sell housing to the public, which hold long-term leaseholds with the ILA. These leaseholds are nominally for 49 years, but in practice are automatically renewed. These arrangements give the government long-term control over land ownership.

In Israel housing construction is entirely undertaken by private contractors. The government does not build houses directly. Nevertheless, housing construction is a major component of the government's regional policy. The government initiates housing construction in specific regions by offering for tender building rights on land vested in the ILA. It fixes a minimum price determined in large part by the location of the land, and The Ministry of Housing & Construction (MOH) encourages contractors to compete for its tenders by defraying a fraction of the development costs. In this way the government subsidizes construction in regions where it wishes to initiate construction for housing.

Given everything else, there will be more construction in regions where MOH initiates more building (denoted by G). However, such building might crowd-out private building (denoted by P). Contractors who in any case intended to build in the region might simply build MOH projects instead of private projects. On the other hand, if they are credit-constrained, the financial perks in MOH contracts might enable contractors to build private housing that otherwise would not have been possible. Therefore if MOH initiates 100 housing units, total construction will increase by less than 100 if there is crowding-out and it will increase by more than 100 if there is crowding-in.

Unfortunately there are no systematic data[4] on the subsidies embodied in MOH contracts. We assume that these subsidies vary directly with MOH-initiated housing construction. Specifically, let Z = G/B denote the share of MOH-initiated housing in total construction (B) in the region, where B = G + P. If lnB = μZ it may be shown that the coefficient of crowding-in is:

$$\frac{dP}{dG} = \frac{\mu(1-Z)-1}{1+Z\mu} \qquad (1)$$

which varies inversely with MOH's share in construction (Z). If μ(1 - Z) < 1 MOH-initiated housing (G) crowd-out private construction, otherwise it crowds-in. Alternatively, crowding-in occurs if the share of private construction (1-Z) exceeds 1/μ.

2.4 The Econometric Model

We use spatial panel data to estimate the following basic model for housing construction (B):

$$\ln B_{it} = \alpha_i + \eta \ln(P_{it}/C_{it}) + \phi \ln(\tilde{P}_{it}/\tilde{C}_{it}) + \gamma \ln(P_t/C_t) + \lambda \ln \tilde{B}_{it} + \mu Z_{it} + \pi \tilde{Z}_{it} + u_{it} \qquad (2)$$

where i = 1,2,..,N labels spatial units, t = 1,2,..,T labels time periods, P denotes house prices, C denotes building costs, and tildes denote spatial lags, e.g.:

$$\tilde{B}_i = \sum_{j \neq i}^{N} w_{ij} B_i \qquad (3)$$

where w_{ij} denote exogenous spatial weights row-summed to unity and $w_{ii} = 0$. P_t and C_t refer to house prices and building costs at the national level. The main hypotheses are that regional housing construction varies directly with profitability in the region, hence η > 0, and it varies directly with MOH regional incentives, hence μ > 0. Equation (2) includes three spatial effects. First, if profitability increases among the neighbors of region i contractors will engage in spatial substitution, hence ϕ < 0. See Meen and Nygaard (2011) for an example of such a spatial lag estimated from cross-section data. Secondly, if regional incentives received by the neighbors of region i induce spatial substitution in construction π will be negative. However, if construction in region i and its neighbors are complementary π may be positive. Third, if there are

[4] The subsidy for each MOH tender is known, but these subsidies have not been aggregated into an index.

positive spatial spillovers in construction λ will be positive. Therefore, the spatial substitution effect is ϕ and the spatial complementarity effect is λ.

The presence of λ in equation (2) implies that the unconditional elasticity differs from the elasticity conditional on construction in other locations. Since each location is its neighbors' neighbor construction in one location affects construction in its vicinity, which feeds-back onto construction in the original location. For example, η denotes the conditional price elasticity of local construction because it is conditional on $\tilde{B}_i$. Its unconditional counterpart is obtained by setting $B_i = \tilde{B}_i$ to obtain the unconditional elasticity η/(1-λ). Therefore, if $0 < \lambda < 1$ the unconditional elasticity exceeds its conditional counterpart.

Apart from these spatial effects equation (2) includes a national effect (γ). If local and neighboring profitability are given, an increase in national profitability might affect local construction in two ways. First, substitution in construction may take place beyond neighboring regions, which would make γ negative. Secondly, an increase in national profitability has a positive effect on national construction. If national and local construction are complements then γ may be positive. If national profitability increases, local construction may increase despite the fact that local profitability is unchanged.

In the "standard" specification of equation (2) there no spatial or national spillovers in which case ϕ, γ, λ and π are assumed to be zero, and each region is an island unto itself. In this case the parameters of interest are η and μ, and the conditional and unconditional elasticities are identical. In section 4 we begin by reporting results for the standard specification and test it against alternatives with spatial and national spillovers.

2.5 Cointegration in Nonstationary Spatial Panel Data

We use the IPS (Im, Pesaran and Shin 2003) statistic to determine whether the panel data are nonstationary. We prefer this test because it allows for heterogeneity in the roots of each panel unit. Since (see below) all the variables that feature in equation (2) are nonstationary but are stationary in first differences, equation (2) is panel cointegrated if the residuals (u) are stationary. If the residuals are not stationary, the parameter estimates obtained from equation (2) may be spurious (Phillips and Moon 1999, Baltagi 2008, p 287). If equation (2) is cointegrated the parameter estimates are super-consistent (Stock 1987). In the present context where N is fixed and the the data

are difference stationary with drift, this means that the parameter estimates are $T^{3/2}$ consistent instead of the usual root - T consistency, as would be the case if the data were stationary.

Conditions for identification when the data are nonstationary are different to when they are stationary. In the latter case weak exogeneity requires that the covariates in equation (1) be independent of u. For example, identification of η requires that house prices are independent of u. If there is reverse causality from housing construction to house prices η is not identified, and OLS estimates are most probably under-estimated. The same applies to estimates of λ since the spatial lagged dependent variable is positively correlated with u OLS estimates of λ are generally over-estimated (Anselin 1988). Therefore, if the data are stationary instrumental variables would be required to estimate these parameters.

We show in an appendix that matters are different if the data are nonstationary because random variables that are integrated to order d are asymptotically independent of random variables that are integrated to an order less than d. In equation (1) d = 1 for the covariates but d = 0 for u if equation (1) is cointegrated. Therefore, the covariates in equation (1) are asymptotically independent of u in which case the parameter estimates are consistent; indeed they are super-consistent. This means that when the data are nonstationary identification does not require instrumental variables for consistency. The appendix also shows that the coefficients of spatial lagged dependent variables, such as λ, are consistently estimated by OLS when the data are nonstationary. This too follows from super-consistency which vitiates the feedback from neighbors on each other.

If equation (2) is cointegrated the residuals are generally autocorrelated and mean-reverting, and the roots of the autocorrelation model are less than one by definition. The residuals may also be spatially autocorrelated in which case u_{it} is correlated with $\tilde{u}_{it}$. Spatial autocorrelation reduces efficiency but does not induce bias or inconsistency in the parameters estimates. However, more efficient estimates of the parameters may by obtained by estimating equation (2) by SUR (seemingly unrelated regression). We use the group augmented Dickey Fuller statistic (GADF), the group Phillips-Perron statistic (GPP), and the group-rho statistic suggested by Pedroni (2004) to test whether the estimated residuals are nonstationary. Note that GADF is the counterpart of the IPS statistic for testing hypotheses about panel cointegration.

We also use the panel error correction P_τ cointegration test statistic (PEC) due to Westerlund (2007), where P_τ is the t-statistic on the estimate of ρ in the panel error correction model:

$$\Delta \ln B_{it} = \psi_i + \rho \hat{u}_{it-1} + \xi \Delta \ln S_{it-1} + \zeta \Delta \ln \tilde{S}_{it} + v_{it} \qquad (4)$$

These test statistics have been transformed into the standard normal variable z:

$$z_k = \frac{\sqrt{N}[S_k - E(S_k)]}{sd(S_k)} \Rightarrow N(0,1) \qquad (5)$$

where S_k labels the particular statistic (such as IPS and GADF) and E(S) and sd(S) are the expected value and standard deviation of S obtained by Monte Carlo simulation under the assumption that the panel units are independent.

The null hypotheses tested by IPS and GADF etc are that the panel data and panel residuals are nonstationary, i.e. d =1 where d denotes the order of differencing that makes the data or residuals stationary. An alternative approach, originally suggested by Kwiatkowski, Phillips, Schmidt and Shin (1992) (KPSS) and Shin (1994) is to test the null hypothesis that the data and residuals are stationary, i.e. d = 0.Note that rejection of the former (non-stationarity) does not necessarily imply acceptance of the latter (just as failing to prove guilt does not prove innocence). Hadri (2000) has extended the KPSS statistic to test the null hypothesis that the panel data are stationary. However, there is no counterpart to Shin (1994) for testing the null hypothesis of panel cointegration. Like IPS, Hadri assumes that the panel units are independent.

As mentioned the critical values of the IPS and GADF or group-rho statistics are derived under the assumption that the panel units are independent. Baltagi et al (2007) report that panel unit root tests, such as IPS, which ignore spatial autocorrelation are reasonably sized provided that the spatial autocorrelation coefficient is sufficiently small (less than 0.4). However, they did not calculate critical values for unit root tests in spatially dependent panel data, nor did they investigate critical values for spatial panel cointegration tests such as GADF. To investigate the sensitivity of the IPS and GADF statistics to spatial dependence we report the results of a Monte Carlo simulation exercise in which spatial dependence is induced by a spatial lag. In Table 1 we report critical values for ρ-bar (the average value of ρ_i) for the following data generating process (DGP):

$$Y_{it} = \alpha_i + \rho_i Y_{it-1} + \theta_i \tilde{Y}_{it} + \varepsilon_{it} \qquad (6)$$

where θ_i induces spatial dependence in the Dickey-Fuller regression. Equation (6) is a first order ARSAR (autoregressive spatial autoregressive) model. When $\theta_i = 0$ this is equivalent to the IPS statistic expressed in terms of ρ-bar. When $\rho = 0$ it is equivalent to the BFF test statistic (Beenstock, Feldman and Felsenstein, 2012) for a spatial unit root. For example if N = T = 25 the critical value of ρ-bar is 0.661 at p = 0.05. If $\hat{\rho}$ -bar exceeds this critical value, the null hypothesis of nonstationarity cannot be rejected. If the panel data are spatially dependent the critical value of ρ-bar decreases slightly in Table 2 with θ. Table 1 shows, as expected, that the critical value of ρ-bar varies directly with T and N.

Table 1 Critical Values for Spatial Panel Unit Roots (ρ-bar)

		θ = 0			θ = 0.04			θ = 0.2		
p		1%	5%	10%	1%	5%	10%	1%	5%	10%
N=25	T=10	0.32784	0.37372	0.39774	0.080784	0.25047	0.30946	0.038446	0.20142	0.25643
	T=25	0.62973	0.66106	0.67869	0.62378	0.6583	0.67584	0.61848	0.65185	0.6696
	T=50	0.80901	0.82487	0.8328	0.80444	0.82129	0.82995	0.89654	0.9219	0.93263
N=100	T=10	0.4032	0.42749	0.440415	0.282691	0.35152	0.380629	0.238864	0.301863	0.329147
	T=25	0.67981	0.69633	0.70417	0.67849	0.69338	0.70134	0.688289	0.704241	0.712053
	T=50	0.83531	0.84227	0.84625	0.83116	0.83931	0.84327	0.950061	0.958088	0.961954
N=225	T=10	0.430558	0.447017	0.455387	0.334974	0.386037	0.405381	0.293023	0.335325	0.354018
	T=25	0.723823	0.731716	0.735764	0.707116	0.717957	0.722995	0.706853	0.717675	0.723132
	T=50	0.850728	0.855552	0.858108	0.844629	0.849745	0.852316	0.962538	0.967279	0.969512

Source: Beenstock and Felsenstein (2013). Based on 10,000 Monte Carlo trials assuming $\rho_i = 1$ and θ_i equals its tabulated value.

Table 1 suggests that if N and T are relatively small the IPS test statistic under-rejects the null hypothesis. Therefore, the results in Table 1 are conservative as far as IPS is concerned.

We have used Monte Carlo simulation to calculate the critical values for Pedroni's group-rho statistic for various values of T and N when there are two variables in the model, i.e. the dependent variable (Y) and the independent variable (X) are generated by ARSAR processes such as equation (6). Since the ε's for Y and X are drawn independently these two variables cannot be related, but they might be spuriously related. The residuals from panel regressions of Y_{it} on X_{it} must be nonstationary in which case ρ_i for these residuals is 1. Results are reported in Table

2. If the data are not spatially correlated (θ = 0) the critical value of the group-rho statistic is 0.5867 (N = 25, T = 15, p = 0.05). If the estimated value of group-rho ($\frac{1}{N}\sum_i^N \hat{\rho}_i$) is smaller than 0.5867 we may reject the null hypothesis that Y and X are not cointegrated. The critical value of group-rho increases to 0.6824 when θ = 0.2. It is therefore easier to refute the null hypothesis (no cointegration) when the data are spatially dependent.

Table 2 Critical Values for Group Rho Statistic

		θ = 0			θ = 0.04			θ = 0.2		
P		1%	5%	10%	1%	5%	10%	1%	5%	10%
N=25	T=10	0.3625	0.4101	0.4354	0.3653	0.4148	0.4398	0.4124	0.4661	0.4950
	T=15	0.5527	0.5867	0.6055	0.5557	0.5902	0.6091	0.6340	0.6824	0.7099
	T=20	0.6516	0.6817	0.6964	0.6568	0.6863	0.7010	0.7655	0.8142	0.8415
N=100	T=10	0.4481	0.4706	0.4827	0.4522	0.4734	0.4858	0.5341	0.5600	0.5743
	T=15	0.6151	0.6321	0.6409	0.6199	0.6365	0.6454	0.7654	0.7953	0.8100
	T=20	0.7025	0.7168	0.7236	0.7078	0.7230	0.7299	0.9260	0.9521	0.9680
N=225	T=10	0.4743	0.4898	0.4979	0.4777	0.4924	0.5003	0.5710	0.5899	0.6001
	T=15	0.6345	0.6455	0.6509	0.6389	0.6504	0.6558	0.8123	0.8331	0.9999
	T=20	0.7183	0.7281	0.7327	0.7256	0.7343	0.7395	0.9764	0.9946	0.9999

Source: Beenstock and Felsenstein (2013). Based on 10,000 Monte Carlo trials.

3. The Data

3.1 House Prices

Since the early 1970s Israel's Central Bureau of Statistics (CBS) has published house price indices for nine regions (see Figure 1). These indices are constructed from transactions data, which are also used by CBS to construct a hedonic price index for the country as a whole. The spatial panel data (1987-2010) are plotted in Figure 2. They show, as expected, that housing is systematically more expensive in the core than in the periphery and that the regional ranking of house prices has remained quite stable over time. During the 1990s immigration from the former USSR increased Israel's population by about 20 percent causing real house prices to double. House prices peaked in 1999-2000 after which they fell by about 30 percent. The resurgence in house prices since 2007 largely resulted from the Bank of Israel's decision to cut interest rates following the Subprime Crisis. Since we have explored these data before (Beenstock and Felsenstein 2010) we focus on housing construction.

3.2 Housing Construction

CBS publishes data on housing starts (S) and completions (C) by units and square meters. It also publishes data on housing under construction (U). In what follows we use housing starts measured in square meters. We have used these data to construct housing starts for the nine regions for which house prices are available. These data are plotted in Figure 3, which shows that with the possible exception of the Krayot area (near Haifa) construction has had a positive trend in all regions. Krayot has systematically had the least number of housing starts, whereas Tel Aviv tended to have the most. The "spaghetti" effect in Figure 3 results from the fact that, in contrast to house prices, the regional league table in housing construction has varied over time.

Figure 4 plots MOH-initiated housing starts in the nine regions, which fall into two distinct groups. The first comprises North, South, Center and Jerusalem where most of MOH starts have been concentrated (especially South). In the second group there has been relatively little MOH activity. This largely reflects the fact that public (ILA) land reserves in these regions are low. On the whole the government has been responsive to market forces; it has sold more land when house prices are more expensive. For example, following the wave of mass immigration from the former USSR in the early 1990s, the government released land for housing. This explains the spike in 1992 in Figure 4 (especially in the South).

3.3. Construction Costs

Unfortunately data on building costs (C) are only available nationally. This may not matter for materials whose prices are likely to be similar across the country (especially a small country), but it may matter for labor costs. Gyourko and Saiz (2006) report that construction costs vary widely in the United States. However, in a small country, such as Israel, this issue is likely to be less important. We assume, *force majeur*, that regional building costs have a national component, a fixed region specific component (c_i) and a random component (s_{it}), i.e. $C_{it} = c_i + C_t + s_{it}$ in which case c_i is absorbed into the specific effect in equation (2), s_{it} is absorbed into the residual, and C_t replaces C_{it} in equation (2). If the data were stationary the latter would induce attenuation bias in the parameter estimates of equation (2). However, this problem is mitigated if the data are nonstationary due to super-consistency[5].

[5] If Y and X are difference stationary and Z is stationary, omitting Z from a regression of Y on X cannot asymptotically affect the regression coefficient.

The price of land should also be a component of C. In common with most countries there are no systematic data on land prices in Israel. If relative land prices remained unchanged the unobserved effect of land prices would be picked-up by the fixed effect in equation (2) and estimates of the supply elasticities in equation (2) would be consistent. If relative land prices varied directly with house prices these elasticities would be under-estimated. However, if relative land prices happened to be stationary these estimates would be consistent since an omitted variable that is stationary is asymptotically independent of house prices, which are nonstationary.

Although there are no data on land prices for the nine regions in the study, the auction prices of the winning tenders for ILA residential building rights are published. We have used these data to construct regional land price indices for six regions during 1996-2012, which are plotted in Figure 5. These data suggest that relative regional land prices have remained reasonably stable over time. In fact these data are cointegrated suggesting that they share a common stochastic trend[6]. Therefore, the absence of systematic data on land prices might not, in practice, be serious since changes in realative land prices are stationary.

3.4 Panel Unit Root Tests

Panel unit root tests for logarithms of these variables are reported in Table 3. According to IPS one may reject the null hypothesis that the log level of construction (housing starts measured in square meters) is nonstationary since z-IPS (-2.4) is smaller than its critical value of -1.96. This is surprising since Figure 1.1 shows that the mean level of construction has, on the whole, been growing over time. By contrast Hadri's LM test clearly rejects the hypothesis that these data are stationary, since z-LMH (3.67) exceeds 1.96. Ideally these tests should be mutually consistent. However, in the case of construction they are in apparent conflict. The same apparent conflict arises, not surprisingly, in the case of housing completions. Since the log first differences of housing starts and completions are stationary according to LMH and IPS, we consider these housing construction data to be difference stationary. This conflict is less pronounced in the case of MOH construction since z-LMH is marginally smaller than its critical value. However, we also assume that MOH construction is difference stationary, which means that $\ln Z \sim I(1)$.

Table 3 Panel Unit Root Tests: 1987-2010

[6] The Dickey Fuller statistic for the regression residuals of the logarithms of land prices between each other is -4.14, suggesting that the data in Figure 5 are cointegrated.

	z – IPS		z – LMH	
	d = 0	d = 1	d = 0	d = 1
House prices	-1.53	-3.96	9.76	1.65
Housing starts	-2.40	-8.41	3.67	-0.86
Completions	-2.61	-7.78	4.42	1.17
Starts (MOH)	-3.43	-5.92	1.92	0.18
Housing under construction	-1.7	-5.61	3.07	-0.48

Notes: z-IPS is the z statistic based on Im et al (2003), and z- LMH is based on Hadri (2000). Two augmentations or lag truncations are specified. Data in logarithms (except housing under construction), and d denotes the order of differencing.

No such conflict arises in the case of house prices since according to the IPS statistic we cannot reject the null hypothesis that d = 1 and according to the LMH statistic we can reject the null hypothesis that d = 0. Since both IPS and LMH concur that house prices are stationary in first differences, we assume that they are difference stationary.

Table 3 also includes housing under active construction (U, also measured in 1000s of square meters). The relationship between this variable and starts (S) and completions (F) is:

$$U_t = U_{t-1} + S_{t-1} - F_{t-1} \qquad (7)$$

Since S and F are by definition cointegrated I(1) variables, equation (7) implies that $\Delta U \sim I(0)$ in which case $U \sim I(1)$, as indicated in Table 3 by the LMH test statistic, but not (marginally) by the IPS statistic.

The test statistics in Table 3 ignore spatial dependence in the data. The nearest case in Table 1 (N = T = 25) suggests that these test statistics are unlikely to be distorted by spatial dependence, although the IPS statistic is slightly too permissive in that it incorrectly rejects the null hypothesis that d = 1. .

4. Results

4.1 Regional Housing Starts

We begin by estimating equation (2) under the assumption that each region is an island unto itself. Hence, in equation (2) we impose the restrictions $\phi = \lambda = \pi = \gamma = 0$. This specification (standard model) assumes that each region in the panel behaves as it might have done had regional dependence been ignored. The first three restrictions assume that spatial spillovers don't matter, while the latter assumes that local

construction is independent of national construction. Subsequently, we relax the latter restriction and estimate γ. We refer to this as the "national spillover model". Thereafter, we relax the spatial restrictions, but retain the restriction $\gamma = 0$ (the spatial spillover model). Finally, all restrictions are relaxed (the general spillover model).

There are several possible outcomes. First, the standard model is supported by the data, and spatial and national spillovers are empirically unimportant. Second, the standard model is supported by the data but spillover models (national and/or spatial) are empirically superior. Third, the standard model is not supported by the data but the models with spillover are supported by the data. Finally, none of the models are supported by the data. We show that the general spillover model is supported by the data, whereas the standard model and the national spillover model are not supported by the data.

We estimate equation (2) with regional fixed effects by SUR. The latter allows the residuals (u_{it}) to be correlated, but not necessarily spatially correlated. Since the data are nonstationary the parameter estimates have non-standard distributions, in which case t – statistics do not indicate statistical significance unless the covariates happen to be strictly exogenous, which is not the case here. We therefore test for statistical significance by dropping variables from the model. If this induces cointegration failure we conclude that the variable or variables concerned are statistically significant. We use group cointegration test statistics (Pedroni 2004) designed for panel data, which allow for heterogeneity in the autoregressive behavior of the residuals (u_{it}).

We use a spatial weighting matrix that takes account of both relative size and distance. Hence:

$$w_{ij} = \frac{POP_i}{POP_i + POP_j} \times \frac{1}{d_{ij}}$$

where POP denotes the sample-mean population in the data, and d_{ij} is the Euclidean distance between i and j. The spatial weights are asymmetric ($w_{ij} \neq w_{ji}$) according to relative population sizes, so that a big region affects a small neighbor by more than does a small region affect a big neighbor. Apart from this, the effect of more distant neighbors is smaller.

Table 4 Estimates of Equation (2): Housing Starts (logarithms)

Model	η	γ	μ	ϕ	λ	π	GADF	GPP	PEC
1	0.247		1.488				-3.00	-3.61	-5.65
2	0.428	-0.031	1.321				-3.14	-3.56	-3.06
3	0.355		1.245	-0.257	0.651	-0.391	-3.45	-3.94	-4.52
4	0.312	0.495	1.098	-0.594	0.584	-0.433	-3.46	-3.87	-3.94
5	0.305	0.470	0.967	-0.548	0.515		-3.43	-3.82	-3.83
6	0.258	0.668		-0.716	0.730		-3.576	-4.010	-5.37
7	0.315			0.877	-0.265		-3.45	-4.03	

Notes: Estimation by SUR with regional fixed effects. GADF: group (1^{st} order) ADF panel cointegration z-statistic. GPP: group (1^{st} order) Phillips-Perron panel cointegration z-statistic. Their one-sided critical value is -1.65 at p = 0.05. PEC: Panel error correction statistic (P_τ in Westerlund 2007).

Results for housing starts are reported in Table 4. Model 1 refers to the standard model with no spatial or national spillovers. The estimated price elasticity of supply is 0.247 and the estimate of μ implies that MOH initiated construction increases total construction, and that crowding-in occurs according to equation (1) where the share of MOH starts is less than 33 percent. Model 1 is cointegrated according to all three panel cointegration test statistics. Recall that t-statistics are not reported because, as explained, the parameter estimates have non-standard distributions.

Model 2 refer to the national spillover model. The local price elasticity increases from 0.247 in model 1 to 0.428 and the national price elasticity is slightly negative. Although there is a slight improvement in the GADF statistic, the GPP and PEC cointegration test statistics deteriorate, suggesting that model 1 is preferable to model 2. Model 3 refers to the spatial spillover model. The local price elasticity is 0.355 and the spatial price elasticity is – 0.257. This spatial elasticity implies that housing construction in neighboring regions and local construction are close but imperfect substitutes. Indeed, what matters is largely the relative price between local house prices and house prices in neighboring regions. The same phenomenon applies to MOH building incentives; the local effect is positive (1.245) but the spatial effect is negative (-0.391). Therefore, incentives granted to neighboring regions induce contractors to transfer their business from the locality to its neighbors. Model 3 includes a spatial lagged dependent variable (0.651) implying positive spillover from neighboring construction to local construction. It also implies that the unconditional

elasticities are 2.86 times larger than their conditional counterparts. The GADF and GPP statistics of model 3 improve on their counterparts in model 1. Recall that marginal improvements in z become progressively harder as z approaches -4. However, the PEC statistic is weaker.

Model 4 specifies all the variables in equation (2) and serves as an unrestricted specification of the general spillover model. The local price elasticity of supply in model 1 is 0.312, the national price elasticity is 0.495, and the spatial price elasticity is -0.594. The latter shows that spatial substitution in construction is strong, while the former shows that national and local construction are complements. The sum of these elasticities (0.213) is similar to the local elasticity in model 1. The estimate of μ (1.098) means that MOH construction crowds-in private construction provided the MOH share in starts is less than 9 percent. The spatial lag coefficient (λ) is slightly larger than a half, so that the unconditional elesticities are slightly less than twice as large as their conditional counterparts. Finally because π is negative, MOH construction has a negative spatial spillover effect. The cointegration test statistics (GADF and GPP) greatly exceed their critical values, but are similar to their counterparts in model 3. Since the only difference between models 3 and 4 relates to national profitability (γ), this suggests that γ is not statistically significant.

Table 4 reports a number of restricted models, which indicate that the group panel cointegration test statistics are insensitive to the various restrictions tested. Model 6 omits building incentives granted by the Ministry of Housing; the cointegration test statistics hardly change, suggesting that these incentives do not significantly affect construction. Finally, Model 7 differs from other spatial models in that ϕ is positive and λ is negative; local construction varies directly with prices nearby, but there is negative spillover between local and nearby construction.

Since all the models in Table 4 are panel cointegrated, we are somewhat spoiled for choice. But some are more cointegrated than others, especially models 3 – 7, which are spatial. Although we cannot rule out the standard model in favor of models with spatial spillover, the latter models are more statistically significant because they have smaller p-values.

The panel cointegration test statistics reported in Table 4 have been calculated under the assumption that the panel data are independent. The nearest case to N = 9

and T = 23 in Table 2 (N = 25 T = 20) indicates that the tests in Table 4 are likely to be conservative, i.e. the null hypothesis in equation (2) is rejected too frequently.

Figure 6 plots the estimated residuals of model 4 in Table 4. This spaghetti graph indicates that the residuals, on the whole, mean-revert to zero. However, the residuals for Haifa are an exception, as indicated by the (1^{st} order) ADF and PP statistics reported in Table 5. Table 5 also shows that there is widespread regional heterogeneity in these mean-reverting tendencies; it is strongest in Sharon and the South and it is weakest in Haifa and the North. Table 5 further shows widespread heterogeneity in regional fixed effects. The largest fixed effect is, not surprisingly, in the North where the population is largest, and it is smallest in Krayot where the population is smallest.

Table 5 Regional Heterogeneity (Model 4)

	Fixed Effect	**ADF**	**PP**
Jerusalem	0.027	-2.95	-3.234
Haifa	-0.728	-1.061	-1.700
Tel-Aviv	-0.648	-2.007	-2.560
Dan	-0.262	-2.561	-2.840
Center	0.972	-1.524	-2.553
South	0.369	-3.081	-2.615
Sharon	0.329	-3.171	-2.673
North	1.349	-1.112	-1.799
Krayot	-1.410	-1.961	-3.100

4.3 Housing Completions

We "spatialize" the multiple cointegration model between starts and completions suggested by Bar Nathan et al (1998), which ensures that starts are eventually completed. The basic hypothesis is that completions (F) vary directly with building under construction (U) and starts (S). Contractors use buildings under construction as a buffer which lengthens when business is bad and shortens when business is good. This means that contractors slow down completion rates when business is slack and accelerate them when business is favorable. Since regional completion rates may have a spatial dimension our basic specification for completions is:

$$F_{it} = \delta U_{it} + \tau S_{it} + \omega \tilde{F}_{it} + \varsigma \tilde{U}_{it} + \nu \tilde{S}_{it} + w_{it} \qquad (7)$$

Since all the variables in equation (7) are I(1), panel cointegration requires that w ~ I(0). If completion rates increase when construction is more profitable, P_{it}/C_{it} may be

specified in equation (7). However, this effect may already be captured by starts. Notice that there is no intercept term in equation (7) because F must equal zero when S = U = 0.

Table 6 The Completions Model

Model	δ	ι	φ	ζ	υ	GADF	GPP	PEC
1	0.432	0.169	0.504	-0.074	-0.226	-4.79	-5.16	-9.28
2	0.432	0.168				-4.73	-5.12	-10.9
3	0.401	0.276[a]				-4.59	-4.99	

Notes: See notes to Table 4. Note a: private housing starts.

Model 1 in Table 6 is an unrestricted model with spatial spillovers. It states that contractors complete annually 43 percent of outstanding buildings under construction, and that current completions vary directly with starts. For every 10 square meters of starts there is an additional 1.7 square meters of completions. The spatial lag coefficient is 0.504, implying that completions increase with completions in neighboring regions. There are negative spatial spillovers from buildings under construction and starts, implying that contractors substitute completions between regions. The cointegration test statistics are highly significant. Indeed, their p-values are even smaller than their counterparts in Table 4.

Model 2 shows that dropping the spatial variables makes no difference to the cointegration test statistics. Therefore, these spatial variables are not statistically significant. By contrast, in Table 4 dropping spatial variables raised the p-values of the cointegration tests. We also carried out some further tests. For example, in model 2 completions vary directly with local house prices, suggesting that contractors accelerate completions when building is more profitable. However, the cointegration test statistics do not change. Model 3 is identical to model 2 except it used private housing starts rather than total housing starts. The effect of private housing starts on completions is greater than total starts, however, there is a slight deterioration in the panel cointegration test statistics.

Table 7 The Distribution of Completions

Year	**0**	**1**	**2**	**3**	**4**	**5**
Completions	16.8	35.9	20.4	11.6	6.6	4.0
Completion Rate	16.8	52.7	73.1	84.7	91.3	95.3

The completion lag implied by model 2 is represented in Table 7. It follows a cohort of 100 additional starts occurring in year 0. What matters is not the completion of these particular houses, but the completion of housing as a whole when contractors use housing under construction as a buffer. It is for this reason that there is an immediate effect on completions in year 0; these starts induce contractors to complete housing already under construction more rapidly. Completions peak in year1 by which the completions rate is 52.7 percent. Subsequently, the completion rate increases towards 100 percent. The mean lag is 2.7 years.

4.4 Model Properties

To illustrate the properties of the multiple cointegration housing construction model we use model 4 for housing starts from Table 4 and model 2 for housing completions from Table 6. There are spatial spillovers in the former but not in the latter. The choice is made for reasons of parsimony and the p-values of the panel cointegration tests. Notice that the starts model is in logarithms but the completions model is not. Therefore the model is nonlinear. The model is completed by using equation (6) to relate building under construction to starts and completions.

We set up a base-run by carrying out a full dynamic simulation (FDS) of the model over 1988 – 2010 in which the state variables, such as house prices and MOH starts, assume their values as in the data. Because the model contains levels of variables and their logarithms the model is nonlinear and its solutions are base dependent. We calculate impulse responses by perturbing the state variables and by comparing the perturbed FDS to the base run. In doing so, we distinguish between local, spatial and national perturbations. Due to the presence of spatial effects in the housing starts model, the impulse responses propagate over space as well as time.

The model is dynamic because of the lag between starts and completions. Since the equations for starts and completions refer to their nonstationary components, and do not embody short-term dynamics, the model refers to trend, or equilibrium behavior. A complete dynamic account would have to include error correction models for starts and completions. In the absence of error correction, the simulated impulse responses therefore refer to equilibrium responses, and their dynamics are entirely induced by the lag between completions and starts.

Table 8 Model Simulations: Housing Starts
(% change in square meters)

	Tel Aviv	Jeru-salem	Haifa	Center	Dan	Sharon	Krayot	North	South
A	0.35	0.30	0.45	0.19	0.29	0.67	0.41	8.94	0.28
B	2.27	-0.83	-0.66	-0.83	-1.5	-1.05	-0.68	-0.98	-0.73
C	-4.35	-3.08	-3.50	-2.74	-4.37	-3.84	-3.93	-3.77	-2.84

A: MOH housing starts increased in North by 200,000 square meters.
B: House prices in Tel Aviv increased by 10 percent
C: Building costs increased by 10 percent

In the first simulation we increase MOH housing starts temporarily in the North in 1995 by 200,000 square meters. This is an example of a local perturbation for the North. However, from the point of view of neighboring regions this is a spatial perturbation. In the interest of space, we focus on the response of housing starts (Table 8) and housing stocks (Table 9). The former lasts for one period only because the shock lasts for one period, and because the cointegrating vector for starts contains no dynamics. The latter, as mentioned, is dynamic because of the relationship between starts and completions. Table 9 reports the response of housing stocks up to 7 years after the shock.

The direct effect on housing starts in the North is 185,327 square meters (8.94%). Housing starts increase by less than 200,000 square meters because MOH starts crowd out private starts (simulation A). The rate of crowding out in the North in 1995 was 7.3 percent; a square meter of MOH starts crowds out 0.073 square meters of private starts. Through spatial lag effects housing starts increase in other regions. There are two types of spatial lag effect. First, there are spatial spillovers from housing starts. Second, there are spatial spillovers from MOH starts. The former spatial spillovers propagate across the regions of Israel through the spatial lagged dependent variable. Spatial spillovers for housing starts are all positive and range from 0.19 percent to 0.66 percent.

Because the perturbation is assumed to be temporary, housing starts eventually revert to their baseline solution. However, housing stocks are permanently raised, especially in the North. It takes about 4 years for the completion – starts process to dissipate after which housing stocks settle down to their new equilibrium. By implication, completions and housing-under-construction revert to their base-run solutions. By year 7 after the shock, the housing stock in the North increases by 0.43

percent, but most of this increase has already occurred within 3 years. Housing stocks gradually increase in other regions because of the spatial spillovers in starts.

Table 9 Model Simulations: Housing Stock
(% change: square meters)

	Lag	Tel Aviv	Jeru-salem	Haifa	Center	Dan	Sharon	Krayot	North	South
A	1	0.002	.005	.004	.004	.002	.011	.003	0.16	.004
	3	0.007	.012	.009	.010	.006	.025	.007	0.37	.010
	5	0.008	.013	.011	.012	.007	.029	.008	0.42	.012
	7	0.009	.014	.011	.012	.007	.030	.008	0.43	.012
B	1	0.019	-.014	-.006	-.019	-.003	-.017	-.004	-.018	-.012
	3	0.046	-.032	-.014	-.045	-.029	-.039	-.011	-.040	-.026
	5	0.055	-.038	-.017	-.052	-.035	-.046	-.013	-.046	-.031
	7	0.057	-.038	-.018	-.052	-.036	-.047	-.014	-.046	-.032
C	1	-.037	-.052	-.031	-.062	-.035	-.061	-.025	-.062	-.045
	3	-.088	-.120	-.074	-.147	-.085	-.144	-.062	-.155	-.104
	5	-.105	-.139	-.089	-.171	-.105	-.167	-.076	-.179	-.122
	7	-.108	-.141	-.093	-.171	-.106	-.171	-.080	-.180	-.125

Next (simulation B), we simulate a temporary increase of house price (10% in 1995) in the Tel Aviv region, which raises housing starts by 2.27 percent in Tel Aviv. This increase comes at the expense of housing starts elsewhere. This happens because there is spatial substitution in housing construction; there is less incentive to build outside Tel Aviv. However, this effect is mitigated by the spatial lag in housing starts. The decreases in housing starts elsewhere range from 0.68 percent to 1.5 percent. Not surprisingly, these decreases are strongest in the vicinity of Tel Aviv, especially Dan and Sharon. The spatial spillovers are large relative to their counterparts in the previous simulation (A). As in simulation A, it takes about 5 years for housing starts to find their way into the housing stock.

Finally (simulation C), we simulate a temporary increase in national construction costs in 1995. National construction costs affect starts in three ways. First, since local construction costs depend on national construction costs, local profitability in construction decreases, which adversely affects local construction in all regions. Second, if construction profitability decreases in neighboring regions, this increases local construction through the spatial lag coefficient. Third, construction profitability decreases nationally, which adversely affects local construction since local and national construction are complementary. The fist and third effects are

negative and the second effect is positive. However, the combined effect is negative as may be clearly seen in the simulation.

The adverse effects of construction costs on housing starts range from 2.74 percent in the Center and 4.34 percent in Tel Aviv. This heterogeneity stems from the spatial lag structure of the model, and because the spatial weights are asymmetric and vary. The spatial weights take account of relative size and distance. Therefore, the spatial effect of e.g. Tel Aviv on Jerusalem does not equal the effect of Jerusalem on Tel Aviv, and the effect of Jerusalem on Haifa differs from the effect of Jerusalem on Tel Aviv. As in simulations A and B it takes about 5 years for the housing stocks to adjust.

5. Conclusion

Using recent methodological advances in the econometric analysis of nonstationary spatial panel data and spatial panel data for Israel we have investigated the determinants of regional housing construction. Our main result is that the econometric specification of regional housing construction is not simply the standard national model applied regionally. This standard model assumes that each region is an island unto itself. Indeed, the standard model is not supported by the data whereas the opposite applies when this model is generalized to include spillovers that are spatial and national.

We show that although housing starts vary directly with profitability as measured by house prices relative to building costs, they vary inversely with profitability in neighboring regions, i.e. there is substantial spatial substitution in housing construction. The local price elasticity of supply is about 0.3, whereas the spatial elasticity is about -0.6 This substitution effect suggests that contractors have local building preferences since they regard neighboring regions as close substitutes but not more distant regions.

Whereas neighboring regions are substitutes, we find that local and national construction are complements. If national profitability increases, this raises local construction, as well as national construction. The local elasticity of supply with respect national house prices is about 0.5. The overall conditional price elasticity of supply is about 0.25, but its unconditional counterpart is about 0.5, i.e. a general increase in house prices of 10 percent raises construction across the country as a

whole by about 5 percent. This elasticity is somewhat larger than the one estimated by Bar Nathan et al (1998) at 0.31.

This elasticity is small. Using results from Beenstock and Felsenstein (2010) for regional house prices, population growth (2.2 percent per year) and income growth increased house prices by about 3 percent per year. Since 1967 the secular rate of growth in real house prices in Israel has been about 2 percent per year. Therefore the price elasticity of supply has reduced the rate of growth of house prices by about 1 percent per year (equal to 0.5 x 2 percent). Alternatively, because the price elasticity of supply is small, housing supply has failed to keep up with demand, which is why real house prices have been increasing. However, they have increased by 1 percent less per year than would otherwise have been the case.

Apart from the spatial substitution effect mentioned above, a further spatial effect is captured by the spatial lagged dependent variable in the model for housing starts. The estimated spatial lag coefficient implies that the local elasticity of construction with respect to construction in neighboring regions is about 0.6, suggesting that local construction and neighboring construction are complementary. We reconcile this complementarity and the substitution effect as follows. Contractors may regard neighboring regions as substitutes, but there are favorable synergies in regional construction. The cost of building in a region varies inversely with construction in its neighbors due, for example, to cost sharing in the use of capital equipment as well as perhaps in the use of labor. These spatial effects emphasize the difference between spatial and national modeling of housing supply. A regional model is not simply a national model applied regionally.

In Israel the Ministry of Housing and Construction does not directly engage in housing construction. Instead, it auctions off land for house building at preferential terms. We show that such building tends to crowd-in housing construction. The financial perks that accompany these auctions help constructors engage in other housing construction, suggesting that constructors are capital constrained. Therefore, housing construction initiated by MOH does not tend to crowd-out other housing construction. However, there is a spatial effect insofar as auctions in neighboring regions reduce local construction. Contractors will build less in a locality if MOH is initiating housing construction among its neighbors. This result is consistent with our finding that local and neighboring construction are substitutes.

We show that the lag between completions and starts varies inversely with the number of starts. This is consistent with the hypothesis that contractors use building under-construction as a buffer to smooth construction. They slow down the completion rate when business is quiet and increase it when business picks-up. Unlike in the case of housing starts, we find little in the way of spatial spillovers in housing completions. However, there may be a spatial lag in housing under-construction so that local completions vary directly with housing under-construction in neighboring regions. This effect is consistent with our previous finding that local and neighboring starts are complementary.

We use the model to simulate impulse responses across space and over time. Region specific shocks propagate at three levels. They propagate over time within regions. They propagate between regions. Finally, they propagate between regions over time. We report impulse responses for MOH initiated housing, house prices and building costs. In doing so, we distinguish between local and nation-wide shocks. The reported impulse responses express the richness of the spatial specification of the model.

Finally, we draw attention to a number of econometric issues. Since the panel data are nonstationary we have used panel cointegration to test hypotheses about housing construction. It is assumed in standard panel unit root and panel cointegration tests that the units in the panel are independent. This assumption is naturally violated in spatial panel data. We have carried out Monte Carlo simulations of the sensitivity of these tests to spatial dependence between panel units. These simulations show that provided the spatial dependence is not too pronounced the critical values for standard panel unit root and cointegration tests are reasonably reliable.

Appendix: Identification in Nonstationary Spatial Panel Data

This appendix shows that the principles of econometric identification for nonstationary data are different to when the data are stationary. Stock (1987) was the first to show that OLS parameter estimates in cointegrated models are super-consistent; they converge faster than root-T to their population counterparts. Due to super-consistency the parameter estimates of cointegrating vectors are consistent even if the variables in the model happen to be jointly determined. This means that parameter estimates that would not be consistent when the data are stationary are consistent if the data are nonstationary, provided that the variables concerned are cointegrated..

These properties carry over to nonstationary panel data when N is fixed[7]. In the present context this means that OLS estimates of the price elasticity of supply of housing construction and related parameters are consistent despite the fact that the price of housing is jointly determined with supply. Conveniently, the determinants of demand may be ignored asymptotically when testing hypotheses about supply, and the determinants of supply may be ignored when testing hypotheses about demand.

These properties also carry over to the estimation of SAR coefficients (of spatial lagged dependent variables). In the case of stationary data OLS estimates of SAR coefficients are inconsistent because the outcomes of neighbors are jointly determined. In this case, consistent estimation of SAR coefficients is by ML or IV (Anselin 1988). When the data are nonstationary, however, OLS estimates of SAR coefficients are super-consistent, as we show.

As is well known, IV and GMM are consistent estimators but biased in finite samples. The same applies to the estimation of cointegrating vectors which may be biased in finite samples (Banerjee et al 1993). However, the finite sample bias in the latter is mitigated and in many cases may be negligible, especially if the variance of the cointegrated residuals is small relative to the variance in the data.

The Identification Problem

The model to be estimated is:

$$S_{it} = b + cP_{it} + dZ^{s}_{it} + u_{it} \quad (1)$$

$$P_{it} = e + fH_{it} + gZ^{d}_{it} + v_{it} \quad (2)$$

$$H_{it} = H_{it-1} + S_{it-1} - D_{it-1} \quad (3)$$

[7] Matters are different if N is not fixed (Baltagi 2008, p 299). Notice that Baltagi's δ_{NT} tends to zero when N is fixed but T tends to infinity.

where equation (1) represents the equation for construction and equation (2) is an inverted demand schedule for housing. Z^d and Z^s are variables hypothesized to shift the demand and supply of housing. Without loss of generality the Z variables are assumed to be independent of u and v. The main parameters of interest are c and d. If the data are stationary, identification of c and d requires that P_{it} and u_{it} be independent. P is weakly exogenous if u is serially independent and uncorrelated with v, because in this makes H_{it} and P_{it} independent of u_{it} and v_{it}. In what follows we assume that these identifying restrictions do not apply, so that P_{it} and u_{it} are dependent.

Asymptotic Orders in Probability

Let the data generating process (DGP) for a difference stationary variable such as P be a random walk with drift δ (subscript i is dropped for convenience) so that P has a stochastic trend:

$$\Delta P_t = \delta + \varepsilon_t \qquad (4)$$

where ε ~ iid(0, s) without loss of generality. The general solution for P is:

$$P_t = P_0 + \delta t + \tilde{\varepsilon}_t \qquad (5)$$

$$\tilde{\varepsilon}_t = \sum_{\tau=1}^{t} \varepsilon_\tau$$

P is (covariance) nonstationary because its first two moments depend on time. Its mean is δt in equation (5), and its variance (the variance of $\tilde{\varepsilon}$) is st.

Suppose u_t is a stationary random variable. The covariance between P and u obtained by multiplying equation (5) by u_t, summing, and dividing by T:

$$\mathrm{cov}(Pu) = \tfrac{1}{T}\sum_{t=1}^{T} P_t u_t = \tfrac{1}{T}\left(\delta \sum_{t=1}^{T} t u_t + \sum_{t=1}^{T} \tilde{\varepsilon}_t u_t \right) \qquad (6)$$

This covariance has two components unless δ = 0. The asymptotic orders in probability[8] of these component are ½ and 0 respectively because (see e.g. Hendry 1995, p107, Hamilton 1994, p 485):

$$\tfrac{1}{T}\sum t u_t \sim \mathrm{O}_p(T^{½}) \qquad (7)$$

$$\tfrac{1}{T}\sum \tilde{\varepsilon}_t u_t \sim \mathrm{O}_p(T^{0}) \qquad (8)$$

[8] A random variable V has asymptotic order ν when the first two moments of $T^{-\nu}V$ are finite.

Therefore the covariance of P and u is independent of T if $\delta = 0$ and it increases with root-T otherwise.

The variances of nonstationary variables such as P increase with T if $\delta = 0$ and with T^2 otherwise, because the square of P in equation (6) depends on t^2. For similar reasons covariances between difference stationary variables increase with T^2.

Nonstationary Panel Data with Fixed N

Since Z^s and u are independent in equation (1) but P and u are not, the OLS estimate of c equals:

$$\hat{c} = c + B \qquad (9a)$$

$$B = \frac{\sum_{i=1}^{N} \operatorname{cov}(P_i u_i)}{\sum_{i=1}^{N} \left[\operatorname{var}(P_i) - r_i \operatorname{cov}(P_i Z_i^s) \right]} \qquad (9b)$$

Where r_i denotes the correlation between P_i and Z_i^s. Because N is fixed the numerator of B increases with $T^{½}$ but the denominator increases with T^2. Therefore B tends to zero with $T^{-3/2}$ in which case the OLS estimate of c is consistent. Indeed, it is super-consistent. If the variables in the model happen to be driftless[9] the numerator of B does not depend on T, but the denominator increases with T. Therefore B tends to zero with T^{-1}, which is still super-consistent.

Because parameter estimates from cointegrating vectors typically have non-standard distributions (Hendry 1995 p. 185), hypothesis tests cannot be carried using t, chi-square and F statistics, which assume that the residuals are asymptotically normally distributed. Instead, restrictions may be tested using cointegration tests. If equation (1) is panel cointegrated, but ceases to be so if Z^s is dropped from the model, this would establish that supply shifters are statistically significant, and that the estimate of equation (1) is a supply schedule. The same applies to equation (2). If it ceases to be panel cointegrated if Z^d is dropped from the model this would establish that a demand schedule had been estimated.

Spatial Lagged Dependent Variables

If spatial lagged dependent variables are specified in equations (1) and (2) and the data are difference stationary OLS estimates of SAR coefficients are consistent. To demonstrate this, assume without loss of generality that c = d = 0 and the model is:

[9] Textbooks such as Hamilton (1994) and Hendry (1995) follow Stock (1987) in assuming this case. In practice, the presence of stochastic trends in the data increases the degree of super-consistency.

$$S_{it} = a + lS_{nit} + e_{it} \qquad (10)$$
$$S_{nit} = \sum_{j \neq i}^{N} w_{ij} S_{jt}$$

S_n is the spatial lagged dependent variable where w_{ij} are spatial weights row-summed to 1. Without loss of generality e_{it} is assumed to be spatially and temporally independent. OLS estimates of the SAR coefficient are not consistent if the data are stationary, but matters are different if they are nonstationary.

The OLS estimator of the SAR coefficient is:

$$\hat{l} = l + B \qquad (11a)$$
$$B = \frac{\sum_{i=1}^{N} \mathrm{cov}(S_{ni} e_i)}{\sum_{i=1}^{N} \mathrm{var}(S_{ni})} \qquad (11b)$$

Equation (10) is vectorized as:

$$S_t = ai + lWS_t + e_t \qquad (12)$$

where S_t and e_t are N-vectors and W denotes the spatial connectivity matrix with elements w_{ij}. Solving equation (12) and pre-multiplying the result by W expresses the N-vector of spatial lagged dependent variables in terms of e_t:

$$S_{nt} = W(\mathrm{I}_N - lW)^{-1}(ai + e_t) = \Gamma(ai + e_t) \qquad (13)$$

where Γ is an NxN matrix with elements γ_{ij}. Since the data are difference stationary the counterpart to equation (5) for S_{it} is:

$$S_{it} = S_{i0} + \phi_i t + \tilde{\varepsilon}_{it} \qquad (14)$$

The covariance between S_{ni} and e_i is obtained by substituting equation (14) into equation (13) and multiplying the result by e_{it}:

$$\mathrm{cov}(S_{ni} e_i) = \sum_{i=1}^{N} \gamma_{ij} \phi_j \tfrac{1}{T} \sum_{t=1}^{T} te_{it} + \gamma_{ii} \mathrm{cov}(\varepsilon_i e_i) \qquad (15)$$

which has asymptotic order $T^{1/2}$ from equation (7). It has been assumed that ε and e are dependent within but not between spatial units.

The variance of S_{ni} is a spatially weighted average of the variances of S_j and their covariances:

$$\mathrm{var}(S_{ni}) = \sum_{j=1}^{N} \gamma_{ij}^2 \mathrm{var}(S_j) + \sum_{j=1}^{N} \sum_{k=1}^{N} \gamma_{ij} \gamma_{ik} \mathrm{cov}(S_j S_k) \qquad (16)$$

which has asymptotic order T^2. According to equations (15) and (16) B has asymptotic order $T^{-3/2}$ in which case OLS estimates of SAR coefficient l are super-consistent.

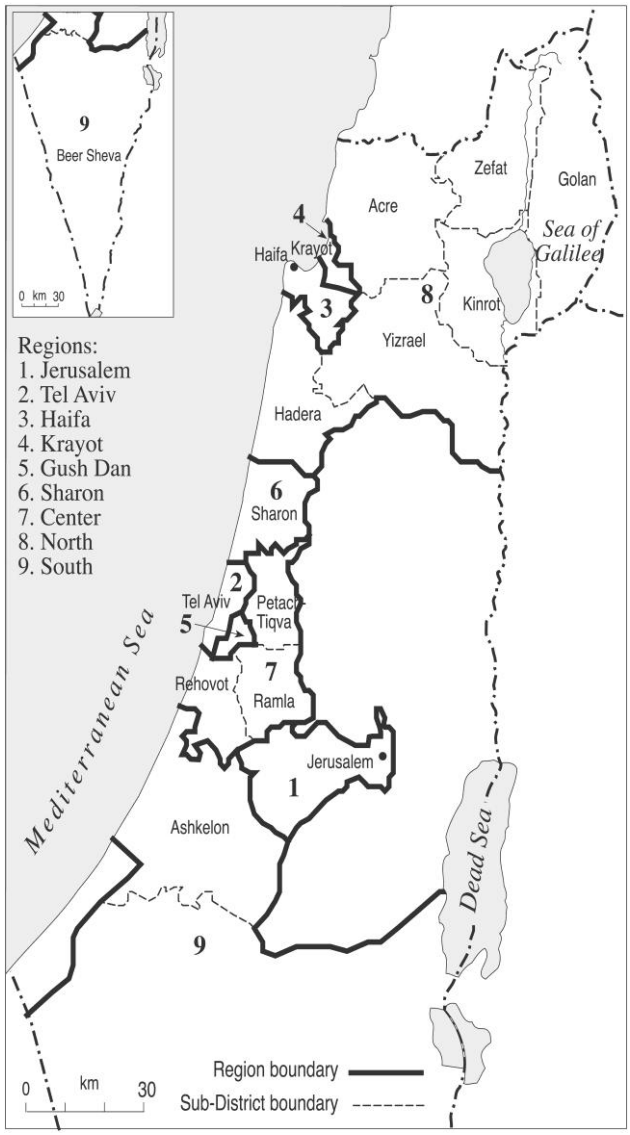


Figure 1: Map of Israeli Regions

Figure 2: Regional House Prices (Set 1991's CPI=100)

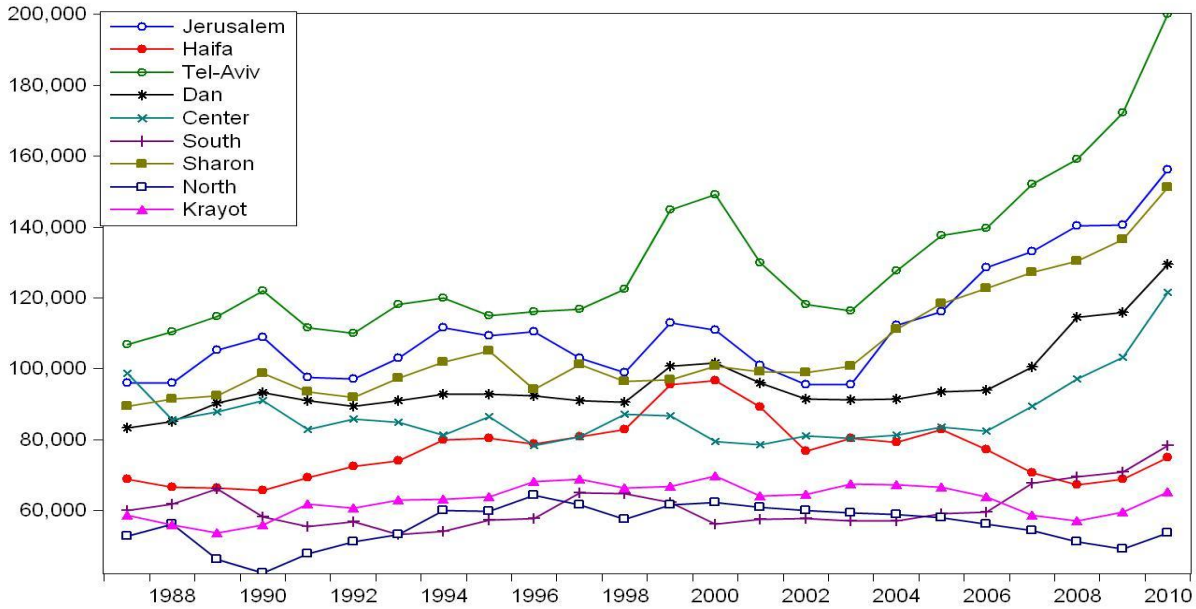


Figure 3: Housing Starts (1000's m^2), 1987-2010

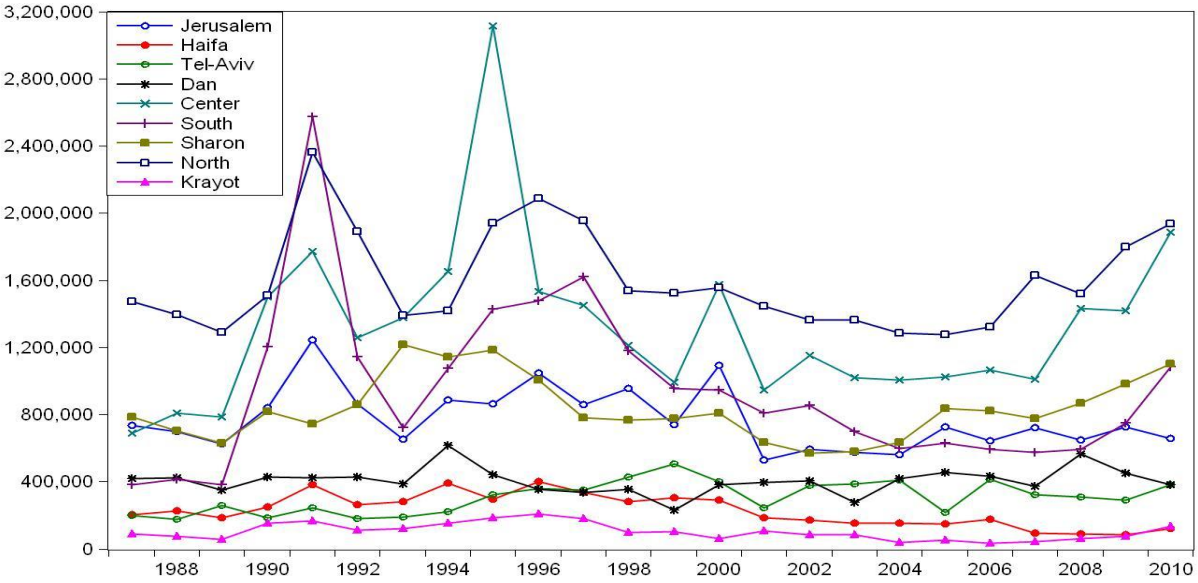


Figure 4; Public Sector Housing Starts (1000's m^2)

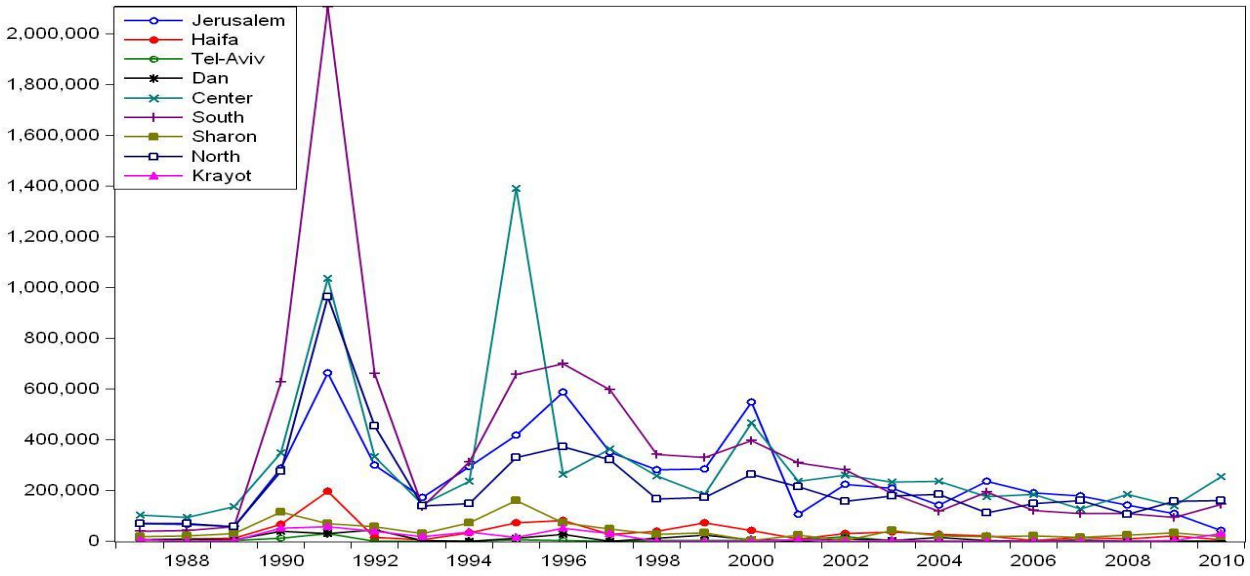


Figure 5: Relative Land Prices by District

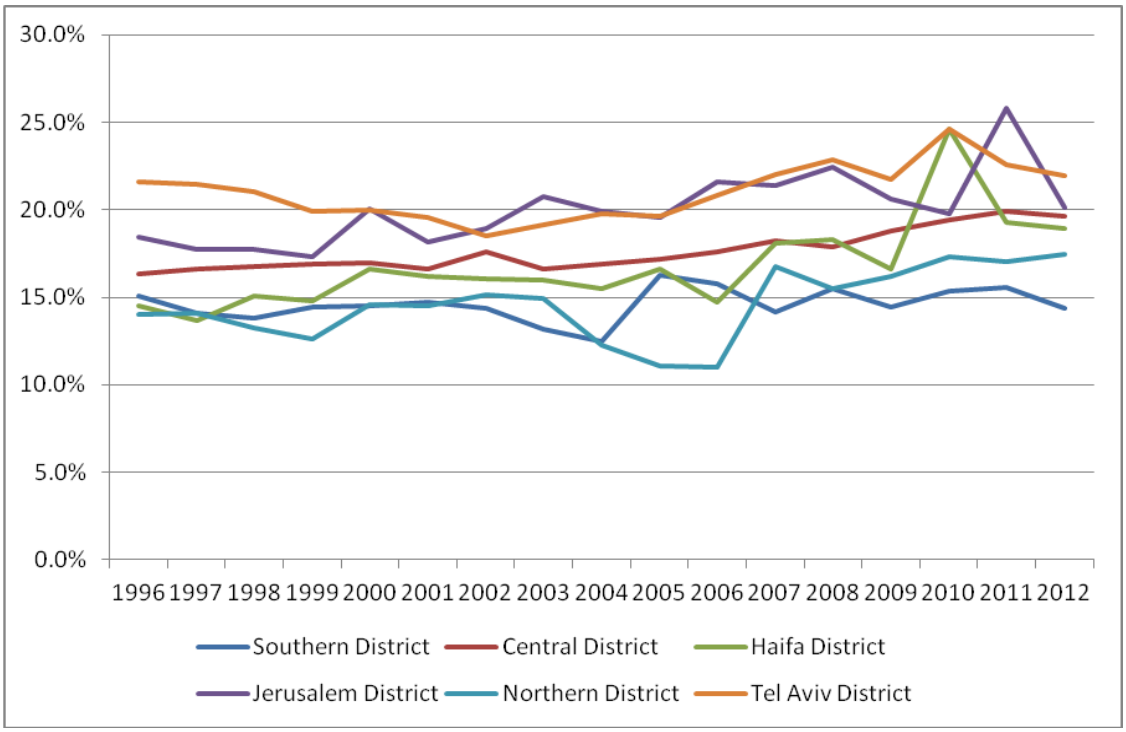
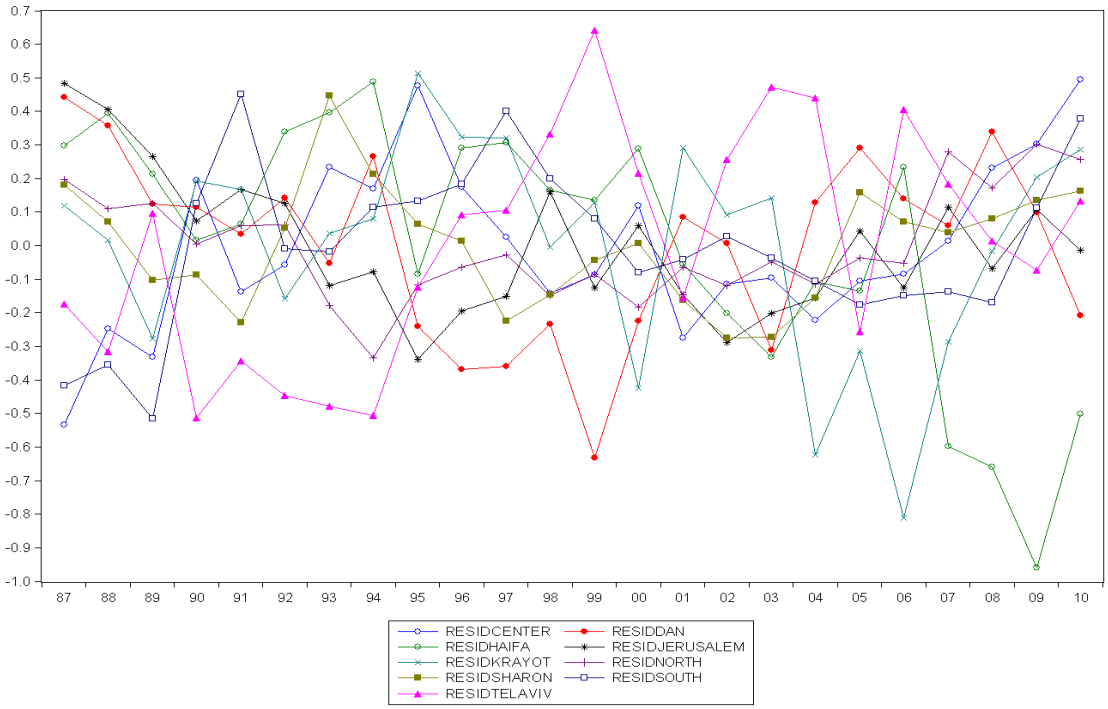


Figure 6: Residuals of Model 4



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