Modeling Spatial Interdependence in Comparative and International Political Economy with an Application to Capital Taxation

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Introduction

This paper examines globalization and capital taxation, emphasizing the implied strategic dependence among countries in fiscal policymaking and the resultant spatial interdependence (contemporaneous correlation) of capital tax rates in time-series-cross-sectional data. Methodologically, we evaluate common strategies for modeling empirically this interdependence and propose our own alternatives. Substantively, we find that several recently published studies understate the degree of spatial interdependence in capital taxes. Our arguments, which apply broadly to empirical studies in comparative and international political economy, will help applied researchers better assess the relative importance of internal (domestic) versus external (international) determinants of tax policy as well as other important political and economic variables.

There are currently two basic approaches to addressing spatial interdependence. Some scholars treat the interdependence as "substance" to be modeled using spatial lags as right-hand-side variables. Great care is taken to identify the nature of the spatial dependence and the underlying mechanisms that create it (e.g., Basinger and Hallerberg 2004, Simmons and Elkins 2004). These studies use theoretically informed spatial weights to generate their spatial lags, which then are used to test hypotheses about strategic interdependence or policy diffusion more generally.

Others treat the spatial interdependence in their data as a "nuisance." Most often the spatial interdependence is relegated to the stochastic component of the regression model and standard error estimates are corrected to account for non-spherical disturbances (e.g., Garrett and Mitchell 2001, Swank and Steinmo 2002). Some studies employ spatial lags but treat them solely as nuisance controls, rather than interpreting them (also) as models of diffusion, which is analogous to using (temporally) lagged dependent variables as nuisance controls for serial correlation and ignoring their implications as models of dynamics. Simple, arbitrary spatial weights such as 1/(N-1) are used frequently is these studies (e.g., Franzese 2002, Hays 2003).

We argue scholars should not confine the spatial dependence in their data to the error term because it is likely to be ignored when it comes to interpreting their regression results.[1] If spatial dependence is overlooked, studies will be biased toward finding domestic, internal factors are more important that international, external ones. Moreover, scholars who use spatial lags as "nuisance" controls should provide some theoretical and (or) empirical justification for their spatial weights. Arbitrary weights produce lags that fail to capture adequately the spatial interdependence in the data.

For those whose expertise or interests lie primarily in the relationships between domestic variables, and are therefore inclined to treat spatial interdependence as a "nuisance", we offer a simple middle-of-the-road approach to generating *empirically* grounded spatial lags that can be used to implement either the spatial-OLS or spatial-2SLS estimators (Franzese and Hays 2004). We recommend this to the standard "nuisance" estimator: non-spatial OLS with panel corrected standard errors (Beck and Katz 1995). Spatial OLS (S-OLS) with PSCE's often outperforms non-spatial OLS with PCSE's (OLS-PCSE) in terms of efficiency with very little cost in terms of overconfidence. The advantages of the spatial estimators over non-spatial OLS are much more pronounced under other conditions. For those who are already estimating models with spatial lags (e.g., Franzese 2002, Hays 2003, Basinger and Hallerberg 2004), we evaluate and, under most circumstances, recommend the use of spatial 2SLS (Franzese and Hays 2004).[2]

[1] For a similar argument about temporal dependence, see Beck and Katz (1996).

[2] See Franzese and Hays (2004) for a lengthy discussion of the spatial 2SLS estimator. In short, this estimator uses spatially weighted X's as instruments for the endogenous spatial lag.

Our paper is organized as follows. We begin with a brief review of the empirical debate over the relative importance of internal and external determinants of capital tax policy. Then, in the second section, we present one of Persson and Tabellini's models of capital tax competition to illustrate the strategic interdependence in fiscal policymaking and to motivate our concern with spatial dependence. Section three briefly discusses the performance of non-spatial OLS to S-OLS under conditions most favorable to the former—that is, when the spatial dependence in the true data generating process is limited to the error term and completely uncorrelated with the systematic component (i.e., with anything else in the model). We then reanalyze the tax regressions in Swank and Steinmo (2002) using the S-OLS estimator. In section four we consider the case where there is spatial dependence in both the systematic and stochastic components of the dependent variable. We finish section four by reestimating the capital tax regressions in Hays (2003) and Basinger and Hallerberg (2004) using spatial 2SLS (S-2SLS). Section five concludes.

Internal and External Determinants of Capital Tax Policy

Are capital tax policies driven more by the internal characteristics of countries such as their domestic institutions, partisan balance of power, debt burdens, and demographics or external factors such as increasing international capital mobility, strategic policy interdependence, and common external shocks? In theory, strong inter-jurisdictional competition can undermine the tax policy autonomy of individual tax authorities, especially when heavy taxes are levied upon more mobile assets such as capital. Inter-jurisdiction competition intensifies as capital and other mobile assets become more liquid and more mobile across borders. Indeed, many scholars of domestic and international fiscal-competition (e.g., Zodrow and Mieszkowski 1986, Wilson

1986, Wildasin 1989; Oates 2001, Wilson 1999 review) expect intense inter-jurisdiction competition to cause socially inefficient under-taxing of mobile assets. As a central exemplar, most scholarly and casual observers see the striking post-1970s rise in international capital mobility and steady postwar increase in trade integration as forcing welfare/tax-state retrenchment and a shift in tax-burden incidence from relatively mobile assets (e.g., capital, especially financial) toward more immobile ones (e.g., labor, especially less-flexibly-specialized types). Growing capital-market integration and asset mobility across jurisdictions enhances such pressures, the argument holds, by sharpening capital's threat against domestic governments to flee "excessive and inefficient" welfare/tax systems. This account stresses the importance of international, external factors in determining countries' capital tax policies.

Several notable recent studies of the comparative and international political economy of tax policy change over this period have examined the empirical support for this argument. That globalization in general and capital mobility in particular has actually constrained public policies broadly and capital tax policy specifically is highly contested. Hines (1999), after reviewing the empirical economics literature, concludes that national tax systems do affect the investment location decisions of multinational corporations, though he points to a number of other factors that influence these decisions as well. Rodrik (1997), Dehejia and Genschel (1999), Genschel (2002), and others argue that this has increasingly constrained governments' policy-latitude in recent years.

Quinn (1997), Swank (1998, 2002), Swank and Steinmo (2002), Garrett and Mitchell (2001), and others, however, do not find these trends to have constrained governments' tax policies much or at all. The theoretical explanation for such results, occasionally implicit, seems that other cross-national differences also importantly affect investment-location decisions, affording governments some room to maneuver. Hines (1999:308), e.g., found commercial, regulatory, and other policies, and labor-market institutions, intermediate-supply availability, final-market proximity among other factors key in corporate investment-location decisions. Swank (2002:252-6, esp.), e.g., argues that corporate and capital tax rates are a function of funding requirements of programmatic outlays, macroeconomic factors like inflation and economic growth, and partisan politics.

Swank and Steinmo (2002) reach similar conclusions about the importance of domestic factors for tax policy reform—particularly budgetary dynamics, the level of public sector debt, and macroeconomic performance. They also find a limited number of external factors, specifically a country's capital account and trade openness, are important determinants of tax reform. Some of their findings are surprising—for example, that increased capital mobility and trade put downward pressure on marginal statutory corporate tax rates but not on effective capital tax rates and that increased capital mobility leads to lower effective tax rates on labor. Swank and Steinmo treat the spatial dependence in their data as a "nuisance." We conduct a reanalysis of their tax regressions below and conclude, among other things, that because of their methodological approach they underemphasize the importance of external factors when it comes to explaining capital tax policy.

But first, in the next section, we present one of Persson and Tabellini's models of capital tax competition to illustrate the strategic interdependence in fiscal policymaking and to motivate our concern with modeling spatial dependence. This model helps us make the case that spatial interdependence in capital tax policy should not be viewed as a "nuisance."

A Stylized Theoretical Model of Capital Tax Competition

We leverage Persson and Tabellini's (2000:ch. 12) formal-theoretical model to demonstrate that tax competition implies spatial interdependence. The model's essential elements are as follows. In two jurisdictions (i.e., countries), denote the domestic and foreign capital-tax rates τ_k and τ_k^*. Individuals can invest in either country, but foreign investment incurs mobility costs (M).[3] Taxation follows the source (not the residence) principle. Governments use revenues from taxes levied on capital and labor to fund a fixed amount of spending. Individuals differ in their relative labor-to-capital endowment, denoted e^i, and make labor-leisure, l and x, and savings-investment, $s = k + f$ (k =domestic; f =foreign), decisions to maximize quasi-linear utility, $\omega^i = U(c_1^i) + c_2^i + V(x^i)$, over leisure and consumption and in the model's two periods, subject to a time constraint, $1 + e^i = 1 + x^i$, and budget constraints in each period, $c_1^i + k^i = 1 - e^i$ and $c_2^i = (1-\tau_k)k^i + (1-\tau_l)l^i$.

The equilibrium economic choices of citizens in this model are as follows:

$$s^i = S(\tau_k) \equiv 1 - U_c^{-1}(1-\tau_k) \quad (1);$$

$$f^i = F(\tau_k, \tau_k^*) \equiv M_f^{-1}(\tau_k - \tau_k^*) \quad (2);$$

$$k^i = K(\tau_k, \tau_k^*) = S(\tau_k) - F(\tau_k, \tau_k^*) \quad (3).$$

With labor, $L(\tau_l)$, leisure, x, and consumption, c_1, c_2, implicitly given by these conditions, this leaves individuals with indirect utility, W, defined over the policy variables, tax rates, of:

$$\begin{aligned} W(\tau_l, \tau_k) = U(1 - S(\tau_k)) + (1-\tau_k)S(\tau_k) + (\tau_k - \tau_k^*)F(\tau_k, \tau_k^*) - \\ M(F(\tau_k, \tau_k^*)) + (1-\tau_l)L(\tau_l) + V(1 - L(\tau_l)) \end{aligned} \quad (4)$$

Facing an electorate with these preferences over taxes, using a Besley-Coate (1997) citizen-

[3] It is assumed that the function M, which captures the mobility costs of foreign investment, has the properties: $M(0) = 0, M_f > 0$ if $f > 0$, and $M_{ff} > 0$.

candidate model wherein running for office is costly and citizens choose whether to enter the race by an expected-utility calculation, some citizen candidate will win and set tax rates to maximize his/her own welfare. The model's stages are: 1) elections occur in both countries, 2) elected citizen-candidates set their respective countries' tax rates, and 3) all private economic decisions are made. In this case, the candidate who enters and wins will be the one with endowment e^p such that s/he desires to implement the following Modified Ramsey Rule:

$$\frac{S(\tau_k^p)-e^p}{S(\tau_k^p)}\left[1+\varepsilon_l(\tau_k^p)\right]=\frac{L(\tau_l^p)+e^p}{L(\tau_l^p)}\left[1+\frac{S_\tau(\tau_k^p)+2F_\tau^*(\tau_k^{p*},\tau_k^p)\tau_k}{S_\tau(\tau_k^p)}\right] \qquad (5)$$

Equation (5) gives the optimal capital-tax-rate policy for the domestic policymaker to choose, which, as one can see is a function of the capital tax-rate chosen abroad. The game is symmetric, so the optimal capital tax-rate for the foreign policymaker to choose looks identical from his/her point of view and, importantly, depends on the capital tax-rate chosen domestically. That is, equation (5) gives best-response functions $\tau_k = T(e^p, \tau_k^*)$ and $\tau_k^* = T^*(e^{p*}, \tau_k)$ for the foreign and domestic policymaker, respectively. In words, the domestic (foreign) capital-tax rate depends on the domestic (foreign) policymaker's labor-capital endowment and the foreign (domestic) capital tax rate—i.e., capital taxes are strategically interdependent. The slope of these functions, $\partial T/\partial \tau_k^*$ and $\partial T^*/\partial \tau_k$ can be either positive or negative. Thus, the model does not predict a "race to the bottom." An increase in foreign tax-rates induces capital flows into the domestic economy, but the domestic policymaker may use the increased tax-base to lower tax-rates or to raise them (the latter to seize the greater revenue opportunities created by the decreased elasticity of this base). Figure 1 graphs these reaction functions assuming that both slope positively. The illustrated comparative static shows an increase in the domestic policymaker's labor-capital endowment. This change shifts the function T outward, raising the equilibrium capital-tax rate in both countries.

<Figure 1 About Here>

This theoretical model of capital tax competition, and related ones that illustrate the strategic interdependence in fiscal policymaking, motivates our concern with modeling spatial dependence. Clearly, anyone interested in testing the relative importance of internal versus external factors on capital taxation should not treat the spatial dependence in their data as a "nuisance." These spatial relationships have substantive importance in this debate.

In the next section, we explore in greater detail the OLS-PCSE approach to spatial dependence and the implicit model that underlies it. We develop a new and simple middle-of-the-road strategy to generate *empirically* grounded spatial lags that, in turn, can be used to implement either the spatial-OLS or spatial-2SLS estimators (Franzese and Hays 2004). This method does not require the analyst to theorize about or model the mechanisms that generated the spatial dependence.

Spatial Error Models

Those who take the standard "nuisance" approach to spatial dependence (OLS-PCSE) assume, hopefully correctly, that the spatial dependence in the true data generating process is limited to the error term and completely uncorrelated with the systematic component (i.e., with anything else in the model). Thinking in terms of Persson and Tabellini, this would imply that only unexpected changes in other countries tax policies would cause governments to reform their own.[4] In this case, we have what is referred to in the spatial econometrics literature as a spatial error or spatial moving average model, which takes the form

[4] Perhaps capital flows are more sensitive to unexpected tax policy changes.

$$\begin{aligned} &\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\varepsilon}, \text{ where} \\ &\boldsymbol{\varepsilon} = \boldsymbol{\lambda\varepsilon} + \mathbf{u} \qquad . \\ &\boldsymbol{\lambda} = \rho\mathbf{W} \end{aligned} \tag{6}$$

In the time-series-cross-sectional (TSCS) version of this model, **y** is an *NTx1* vector of observations on the dependent variable stacked by unit (i.e., unit 1, time 1 to *T*, then unit 2, time 1 to *T*, *etc.* through unit *N*), and **W** is an *NTxNT* block-diagonal spatial-weighting matrix (with elements w_{ij}). Thus, **λε** is an *NTx1* matrix of spatially correlated disturbances. The *NTx1* matrix **u** contains i.i.d. disturbances. The diagonal elements of the off-diagonal *TxT* blocks in **W**, which reflect the contemporaneous effect of the column unit on the row unit, are the w_{ij} that reflect the degree of connection from unit *j* to *i*—so, unlike a variance-covariance matrix, **W** need not be symmetric. The spatial autoregressive coefficient, ρ, reflects the impact of the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}, on the outcome in *i*. Thus, ρ gauges the overall strength of diffusion (spatial dependence), whereas the w_{ij} describe the relative magnitudes of the diffusions paths (spatial dependence) between the sample units.

The coefficients in this model can be estimated consistently using OLS. However, the standard error estimates are biased downward. Moreover, OLS is inefficient. The feasible generalized least squares (FGLS) estimator, developed for the TSCS context by Parks (1967), is efficient, but very few political scientists use Parks FGLS since the publication of Beck and Katz (1995). Beck and Katz argued, and demonstrated with Monte Carlo simulations, that Parks' method underestimates the true variance of the FGLS estimator's sampling distribution when N and T are small. Moreover, they argued the efficiency gains are modest in sample sizes typical in political science research. They concluded that the small efficiency gains come at a high cost in terms of overconfidence (i.e., significantly underestimating the true standard errors). Their recommendation, which is widely followed, is to report OLS coefficient estimates with their robust panel corrected standard errors (PCSE's).

A problem with both Parks-FGLS and OLS-PCSE is that because the spatial dependence is relegated to the error term of the model, it is almost always ignored by analysts. We propose a simple spatial OLS estimator (S-OLS) that uses the spatial interdependence in the data to create a spatial lag that, for each unit in the dataset, is a weighted average of the contemporaneous OLS residuals from the other units.

More specifically, our approach to S-OLS, which is only appropriate when the conditions in (6) hold, follows four steps:

1) Estimate the regression of $\mathbf{y}$ on $\mathbf{X}$ using non-spatial OLS
2) Use the OLS residuals from step one to estimate $\hat{\boldsymbol{\varepsilon}} = \boldsymbol{\lambda}\hat{\boldsymbol{\varepsilon}} + \mathbf{u}$ again using OLS
3) Implement S-OLS by regressing $\mathbf{y}$ on $\mathbf{X}$ and $\hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\varepsilon}}$
4) Estimate panel corrected standard errors (Beck and Katz 1995)

Using the experimental design from Beck and Katz (1995), Franzese and Hays (2005) show this estimator matches most of the efficiency gains of Parks-FGLS in small samples without the problem of overconfidence, in part because S-OLS can be combined with PCSE estimates. The main results from their study are provided in the appendix (Tables A1 and A2).

Replication and Reanalysis (Swank and Steinmo)

Swank and Steinmo stress the importance of domestic factors—particularly budgetary dynamics, the level of public sector debt, and macroeconomic performance—in their empirical study of tax policy reform. They also find some external factors, specifically a country's capital account and trade openness, are important determinants of tax reform. A few of their findings are counterintuitive—for example, that increased capital mobility and trade put downward pressure on marginal statutory corporate tax rates but not on effective capital tax rates and that increased capital mobility leads to lower effective tax rates on labor. They argue this is because statutory rate reductions are combined with the elimination of specific investment incentives leaving effective tax burdens unaffected. The finding that increased capital mobility leads to lower effective tax rates on labor income is explained by arguing that labor taxes raise the non-wage costs of employment, cutting into profits. Swank and Steinmo recognize their data are spatially interdependent—they report panel corrected standard errors—but they treat this dependence as a "nuisance" rather than as additional evidence of the importance of external factors in determining tax policy.

Swank and Steinmo implicitly assume that any spatial dependence is limited to the error term in their model. For the purposes of our reanalysis we accept their assumption about the nature of the spatial dependence as true and therefore estimate a model that includes a weighted average of the OLS residuals from the other units (countries in this case) as a spatial lag. We focus on the results for effective tax rates on capital income, labor income, and consumption that are reported in Table 2 from their appendix (pp. 653-4). Their sample covers 13 countries over the period 1981-1995 (N=13 and T=15).

<Table 1 About Here>

Table 1 presents the results of our replication and reanalysis. We follow the steps for S-OLS outlined above with one notable exception. We assume that the pattern of spatial dependence in countries' capital, labor, and consumption taxes are similar and, therefore, pool the OLS residiuals from all three of Swank and Steinmo's tax regressions to estimate the spatial weighting matrix (λ). This gives us KxT observations (3*15 = 45) instead of T to estimate the

N-1 independent non-zero elements in each country's *TxNT* block row of $\boldsymbol{\lambda}$.[5] Comparing the original OLS-PCSE results with our S-OLS (PCSE) results suggest there are efficiency gains with the spatial lag model. There are thirty-three common coefficients estimates. For twenty-eight of these coefficients, the standard errors are smaller with S-OLS (PCSE) than with OLS-PCSE.[6] Most importantly, we come to different conclusions about the importance of international factors for capital taxes.[7] In each model, the coefficient estimate on the spatial lag is statistically significant. In discussing their results, Swank and Steinmo (2002, 650) write, "[they] are consistent with the argument that while internationalization has influenced the shift in the content of tax policy, the combined effect of statutory tax rate cuts and base-broadening reductions in investment incentives has left the effective tax burden on capital largely unchanged." They come to this conclusion because they largely ignore the spatial dependence in their data except to make standard error corrections for their coefficient estimates. The spatial dependence is "out of sight, and out of mind." When a spatial lag is included on the right-hand-side of their regression model we see this conclusion about the effects of international, external factors is likely incorrect. Unexpected changes in effective capital tax rates in one country have statistically significant consequences for effective capital tax rates in other countries.

Spatial Lag Models

The standard spatial lag model takes the form

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[5] In our estimation of $\boldsymbol{\lambda}$ we allowed the OLS residuals from each tax regression to have separate means and variances.

[6] Part of this change is attributable to the overconfidence of S-OLS (PCSE). Distinguishing overconfidence from increased efficiency, in these results, is not an easy task.

[7] Interestingly, the S-OLS (PCSE) estimates lead to a very different set of conclusions about the determinants of effective tax rates on consumption in that we find statistically significant unemployment and partisan effects on these tax rates. This could be due to either omitted variable or simultaneity biases.

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \qquad (7)$$

where **y** is an *NTx1* vector of observations on the dependent variable stacked by unit (i.e., unit 1, time 1 to *T*, then unit 2, time 1 to *T*, *etc.* through unit *N*), and **W** is an *NTxNT* block-diagonal spatial-weighting matrix (with elements w_{ij}). Thus, **Wy** is the spatial lag. Again, the diagonal elements of the off-diagonal *TxT* blocks in **W** are the w_{ij} that reflect the degree of connection from unit *j* to *i*. The spatial autoregression coefficient (ρ) reflects the impact of the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}, on the outcome in *i*. Thus, ρ gauges the overall strength of diffusion (spatial dependence), whereas the w_{ij} describe the relative magnitudes of the diffusions paths (spatial dependence) between the sample units.

Spatial lag models have been used in one of two ways. Some scholars treat the spatial lags as substantively interesting right-hand-side variables (e.g., Simmons, Dobbin, and Garrett 2004) and use theoretically informed spatial weights (e.g., Basinger and Hallerberg 2004, Simmons and Elkins 2004) to generate their spatial lags. For example, operationalization of the tax-competition argument would be weights, w_{ij}, based on the trade or capital-flow shares of countries *j* in country *i*'s total. The inner product of that vector of weights with the stacked dependent variable **y**, then gives the weighted sum (or average) of **y** in the other countries *j* that time-period as a right-hand-side variable in the regression. The matrix **Wy** just gives the entire set of these vector inner-products—in this case, the trade- or capital-flow-weighted averages—for all countries *i*. Others employ spatial lags but treat them solely as nuisance controls. Simple, arbitrary spatial weights like 1/(N-1) are used (e.g., Franzese 2002, Hays 2003).

The estimation of spatial lag models, both the "substance" and "nuisance" varieties, is plagued by endogeneity problems. We show below, in the simplest possible case (one domestic factor, *X*; two countries, 1 and 2; and conditionally *i.i.d.* errors, **ε**) that *OLS* estimates of *(7)* will suffer simultaneity bias, and, obviously, that *OLS* estimates of *(7)* omitting the spatial lag will suffer omitted-variable bias, and we specify those biases insofar as possible.

This simple case is represented by equations (8) and (9):

$$Y_1 = \beta_1 X_1 + \rho_{12} Y_2 + \varepsilon_1 \qquad (8);$$

$$Y_2 = \beta_2 X_2 + \rho_{21} Y_1 + \varepsilon_2 \qquad (9).$$

The left-hand side of (8) is on the right-hand side of (9) and *vice versa*: textbook endogeneity. In words, country 2 affects country 1, but country 1 also affects country 2. Assuming for convenience that X_1 is exogenous and has a variance of 1, the resultant bias in *OLS* estimates of ρ_{12} can be shown to equal:

$$\hat{\rho}_{12} = \rho_{12} + \frac{\rho_{21} Var(\varepsilon_1)(1-\rho_{21}\rho_{12})}{\beta_2^2 + \rho_{21}^2 Var(\varepsilon_1) + Var(\varepsilon_2)} \qquad (10),$$

which, assuming $\rho_{12}\rho_{21}<1$, implies that *OLS* estimates of diffusion from country *j* to *i* will have bias of the same sign as the diffusion from *i* to *j*. This means that, if "feedback" from *j* to *i* and *i* to *j* reinforce (both positive as in Figure 1, or both negative), then *OLS* estimates of interdependence will be inflated. If feedback is dampening (e.g., opposite slopes in Figure 1), which is probably less likely in most substantive contexts (but possible in Persson and Tabellini's model, as noted), *OLS* estimates will be attenuated. We can also show, moreover, that this bias in the estimated strength of interdependence, ρ, induces an attenuation bias in the estimate of β_1, the effect of *X* (i.e., domestic and/or exogenous-external factors):

$$\hat{\beta}_1 = \beta_1 - \frac{\beta_1 Var(\varepsilon_1)\rho_{21}^2}{\beta_2^2 + \rho_{21}^2 Var(\varepsilon_1) + Var(\varepsilon_2)} \qquad (11).$$

Thus, typically, *OLS* estimates of spatial lag models will tend to over-estimate the importance of interdependence—e.g., tax competition—and underestimate the importance of other factors.

On the other hand, *OLS* estimates of equation (7) that ignore interdependence, i.e., that omit spatial lags, will suffer the converse omitted-variable biases, which (using the usual omitted-variable-bias formula) is equal to:

$$\hat{\beta}_1 = \beta_1 + \frac{\rho_{12}\rho_{21}\beta_1}{1-\rho_{12}\rho_{21}} \qquad (12).$$

Again, if the feedback is reinforcing (same-signed ρ_{12}, ρ_{21}), these are inflation biases, and, if the feedback is dampening, these are attenuation biases. Thus, in the positive-feedback case that we suspect is more common, *OLS* estimates that ignore *interdependence* will tend to over-estimate the power of the variables in $\mathbf{X}$. This conclusion holds as a matter of degree also: insofar as *interdependence* is inadequately specified, absolutely and relatively to the alternative argument specification, the latter will tend to be overestimated and the former underestimated, and *vice versa*. Therefore, when spatial lags are generated with arbitrary weights, the coefficient estimates on these lags are likely to be biased downwards. We return to this point in the reanalysis of Hays (2003) below. Note that the bias in equation (12) is based on the assumption X_1 and X_2 are independent. If they are correlated, the biases are larger. For example, if the X's represent common shocks (i.e., $X_1 = X_2$), the OLS estimate for β_1 will be

$$\hat{\beta}_1 = \beta_1 + \frac{\rho_{21}\beta_2 + \rho_{12}\rho_{21}\beta_1}{1-\rho_{12}\rho_{21}} \qquad (13).$$

In other words, analysts will overestimate the importance of (common) shocks, if they omit the spatial lag. The reverse holds as well. Omitting common shock variables in this case will lead to analysts to overestimate spatial lag coefficients. Assuming X_1 and X_2 are equal, the OLS estimate for ρ_{12} will be

$$\hat{\rho}_{12} = \rho_{12} + \frac{\beta_1\beta_2 + \rho_{21}\beta_1^2}{(1-\rho_{12}\rho_{21})(\beta_2^2 + \beta_1^2\rho_{21}^2 + \rho_{21}^2\ \mathrm{var}(\varepsilon_1) + \mathrm{var}(\varepsilon_2))} \qquad (14).$$

While this bias will typically be inflating (reinforcing feedback), there is one important case when it is attenuating: when the spatial lag is differenced and lagged temporally:

$$\Delta Y_{1,t} = \rho_{12}\Delta Y_{2,t-1} + \Delta\varepsilon_{1,t} \qquad (15);$$

$$\Delta Y_{2,t} = \rho_{21}\Delta Y_{1,t-1} + \Delta\varepsilon_{2,t} \qquad (16);$$

$$\hat{\rho}_{12} = \rho_{12} + \frac{\text{cov}[Y_{2,t-1} - Y_{2,t-2}, \varepsilon_{1,t} - \varepsilon_{1,t-1}]}{\text{var}[Y_{2,t-1} - Y_{2,t-2}]} \qquad (17).$$

In this case, if the error terms are i.i.d, the estimate of ρ_{12} will be unbiased. However, if countries 1 and 2 experience common shocks (i.e., $\text{cov}[\varepsilon_{1,t}, \varepsilon_{2,t}] > 0$), the numerator from the second term on the right-hand-side of equation (17) will be negative, and S-OLS will underestimate the degree spatial dependence. This attenuating bias shows up in our reanalysis of Basinger and Hallerberg (2004) below. Note that, if ΔY_2 in equation (15) is contemporaneous with the dependent variable and countries 1 and 2 experience common shocks, S-OLS will overestimate the degree of spatial dependence.

To sum, the simple case represented by equations (8) and (9) demonstrates that the OLS and S-OLS estimators have a hard time separating the effects of common shocks and diffusion (spatial dependence) modeled with spatial lags. If one's dependent variable is caused by both, most of the time, omitting (observable) common shocks will cause spatial lag coefficients to be overestimated and omitting spatial lags will lead to inflated common shock coefficients. One exception to this rule is when the spatial lag is differenced and lagged temporally (equations (15) and (16)). Along these lines, to the extent that the spatial interdependence is inadequately specified (e.g., when arbitrary spatial weights are used to generate lags), absolutely and relatively to the alternative common shocks variable, the latter will tend to be overestimated and the former underestimated, and *vice versa*. Finally, spatial lags are generally endogenous and, therefore, the S-OLS estimator suffers from a simultaneity bias. Under the most reasonable conditions, the bias leads analysts to overestimate the degree of spatial dependence and underestimate the importance of other regressors. Again, the effects of this simultaneity bias are most severe for common shock variables.

Using Monte Carlo experiments, Franzese and Hays (2004) show these basic results extend to common sample sizes (N&T) from empirical studies in comparative and international political economy. The main results from these experiments are reported in the appendix (Tables A3-A6).

Replication and Reanalysis (Hays and Basinger and Hallerberg)

Although all theoretical models of and arguments regarding tax competition, and, indeed, the very substance of its supposed process, clearly imply the spatial interdependence of capital taxes, few scholars have empirically modeled such interdependence directly. Two recent exceptions, Hays (2003) and Basinger and Hallerberg (2004), however, do estimate spatial-lag models of international capital-tax competition, using *OLS*. In the next section, we discuss the empirical work in these two papers and then conduct a reanalysis of their respective regression models. Our results suggest that both studies underestimate the degree of international interdependence in capital tax policymaking, though for very different reasons: Hays uses arbitrary weights to generate his spatial lag and Basinger and Hallerberg ignore that their spatial lag is likely endogenous.[8]

Hays (2003) argues that the effect of globalization—specifically increased international

[8] Overall, Hays probably overestimates the coefficient on his spatial lag variable. This is because the simultaneity bias in his S-OLS estimates, which he also ignores, is inflating.

capital mobility—on a country's capital tax rate depends on its capital endowment and political institutions. An exogenous increase in international capital mobility affects the capital tax rate in two ways. First, it shifts the revenue maximizing tax rate downward. And second, by making the supply of capital less (more) elastic, it increases the marginal gain from increasing (decreasing) the capital tax rate when it is below (above) the revenue maximizing level. How far globalization shifts the revenue maximizing tax rate downward is a function of a country's capital endowment: the drop is large for capital rich countries and relatively small for capital poor ones. The impact of changes to the elasticity of the supply of capital on tax rates depends on a country's political institutions. The capital-supply elasticity determines the marginal revenue-gain from changing tax rates while political institutions determine the marginal cost. Hays argues that increased international capital mobility will have the greatest negative impact on capital tax rates in relatively closed and capital-rich countries with majoritarian political institutions (e.g., the U.K.).

To test his hypothesis, Hays estimates a spatial-lag model with a temporal lag and fixed country effects. He uses the Mendoza et al. (1994, 1997) capital tax rates as the dependent variable. The key independent variables are the degree of capital mobility—measured by Quinn's (1997) indices of capital and financial openness—and capital mobility interacted with a measure of each country's capital endowment and its consensus democracy score (Lijphart 1999).[9] For each country, Hays uses the average tax rate, i.e., the average of the dependent variable, **y**, in the N-1 other countries as the spatial lag. In other words, all the off-diagonal elements of the spatial weighting matrix from (7) are set to 1/(N-1). For Hays' purposes, the spatial lag controls for the possibility that the observed changes in capital taxation are being

[9] The capital endowment data are provided in the Penn World Table. Hays uses the capital stock per worker in 1965 as a measure of each country's initial capital endowment.

driven by tax competition between countries.[10] Hays estimates the model using OLS and reports panel corrected standard errors (S-OLS with PCSE's).

Basinger and Hallerberg (2004) estimate spatial-lag models to test the following hypotheses derived from their theoretical model of tax competition: 1) countries will undergo tax reform more frequently if the political costs of such reforms are low and/or the decisiveness of reforms in determining the patterns of investment flows is high, 2) countries will engage in tax reform when the political costs of reform in competitor countries is low, 3) the domestic political costs of reform and the decisiveness of reform will determine the sensitivity of countries' tax-policies to tax changes in their competitors. Basinger and Hallerberg (2004) include both spatially weighted **X**'s and spatially weighted **Y**'s (i.e., spatial lags) on the right-hand-side of their regression models. Hypothesis 1 is operationalized with a set of domestic **X**'s; they test Hypothesis 2 using a set of spatially weighted **X**'s and Hypothesis 3 with spatial lags interacted with domestic **X**'s.

The dependent variable in their empirical analysis is the change in the *capital tax rate*. In addition to the Mendoza et al. capital-tax rates, the same variable used by Swank and Steinmo (2002) and Hays (2003), Basinger and Hallerberg include the top marginal capital-tax rates (both central government and overall). They identify two kinds of domestic political costs as independent variables: transaction and constituency costs. *Ideological distances* between veto players are used to measure transaction costs. The greater the ideological distance between political actors that can block policy change the harder it is to alter the status quo (in this case,

[10] While Hays' regression models allow for tax competition his theoretical model does not. He makes a small country assumption so the global net-of-tax return to capital is exogenous. Tax competition is not inconsistent with the theory, but Hays' focus is on strategic interaction (among producer groups) within countries rather than on tax competition between countries.

adopt capital-tax reform). *Partisanship* is used to measure constituency costs; the constituency costs associated with capital tax reform will be higher when left governments are in power. A third independent variable of interest, the degree of capital mobility, is measured using *capital controls* on outflows. The degree of capital mobility determines the decisiveness of capital taxes in determining the location of international investments.

Basinger and Hallerberg use four different spatial weighting matrices: a symmetric 1/(N-1) weighting matrix (the same one used by Hays), which makes the spatial lag for each unit equal to the simple average of the **Y**'s in the other units, and three weighted averages using GDP, FDI, and Fixed Capital Formation (FCF) as weights. For each row, the last three spatial weighting matrices have cell entries that differ across columns, but the rows themselves are identical. In other words, for every country in the sample, the US—because of its large GDP, capital stock, and flows of FDI—is weighted more heavily than Finland, but the effect of American tax rates on other tax rates is the same for all countries. American tax rates have the same effect on Canada as they do on Austria, for example. The spatial weights are time varying. Basinger and Hallerberg (2004) include fixed country effects in their models, but, unlike Hays, do not lag the dependent variable directly. The do include the lagged level of the tax rate, though, which makes their model with changes as the dependent variable essentially the same as a partial-adjustment (lagged-dependent-variable) model in levels. The models are estimated using OLS; panel corrected standard errors are reported. In our reanalysis, we focus on Hypothesis 3 (Tables 3-5 from Basinger and Hallerberg). In these models, the spatial lag is differenced and lagged temporally. (See discussion of equations (15) and (16) above.)

Both Hays (2003) and Basinger and Hallerberg (2004) find the coefficient on the spatial lag is positive and statistically significant. The problem with both sets of analyses is they do not account for the fact that the spatial lag is endogenous making the *S-OLS* estimator biased and inconsistent. Both may have underspecified *common-conditions* sorts of arguments also.

We conduct a reanalysis of Hays' (2003:99)[11] regressions using a new spatial-weights matrix and two consistent estimators—spatial two-stage least squares and spatial maximum likelihood (Tables 2 and 3). As with our earlier reanalysis of Swank and Steinmo, we assume that Hays' spatial lag specification is the correct one. Overall, the results of our reanalysis with respect to the spatial lag are mixed. Given Hays' setup, the endogeneity and measurement-induced biases are pushing his coefficient estimates in different directions. This is clear from Table 2, which presents our renalaysis of the capital-account openness models. The original estimates are reported in the second column labeled "Spatial OLS" and "Symmetric Diffusion." By symmetric diffusion we mean that Hays used a spatial weighting matrix with off-diagonal elements that all take a value of 1/(N-1). In our reanalysis, we also include an asymmetric weighting matrix based on observed cross-national correlations in capital tax rates. For each country's row in the spatial weights matrix we enter ones for the countries with which its capital tax rates have a statistically significant positive correlation. We then row-standardize the spatial weighting matrix.[12] The weighting matrix is asymmetric because country 1's importance in determining country 2's capital tax rate may not be the same as Country 2's importance in determining Country 1's tax rate.[13]

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[11] The original estimates are reported in Hays' Table 2.

[12] Standardization is done by replacing the ones in each country's row in the weighting matrix with 1/N, where N is the number of countries with which its tax rate is correlated. In other words, if a country's capital tax rate is positively correlated with five other countries, the appropriate cells in the weighting matrix take a value of 0.2.

[13] If Country 1's tax rate is correlated with five other countries and Country 2's tax rate is only correlated with Country 1, the importance of Country 1's tax rate (i.e., its weight in the spatial weighting matrix) in

We report non-spatial *OLS* estimates in the first column of Table 2 to demonstrate that there is omitted variable bias when the spatial lag is left out of the model. Most importantly, the non-spatial *OLS* estimate for the consensus democracy interaction term is about 35% smaller than the original *S-OLS* estimate and statistically insignificant. Two things worry us about Hays' original estimates in the second column. First, he uses *S-OLS*, which, because the spatial lag is endogenous, is likely to give an inflated estimate of the coefficient. This simultaneity bias can induce bias in the other coefficient estimates (Franzese and Hays 2004). Second, Hays uses an arbitrary spatial weighting matrix. Each country's capital tax rate in the sample is assumed to be important (and equally so) in determining every other country's tax rate. This convenient assumption gives a simple unweighted average of the capital tax rates in the other countries as the spatial lag. If this assumption is wrong, which it almost certainly is, the spatial lag contains measurement error, which may cause attenuation bias in the spatial-lag coefficient estimate.[14] Note that these biases work in opposite directions.

<Table 2 About Here>

The estimates in the third and fourth columns are consistent with our expectations. When we estimate using *S-2SLS* the estimate on the spatial lag drops from .280 to .221 (a 21% reduction) and when we use the asymmetric spatial weighting matrix the estimate increases to .316 (+13%). Both "corrections" (asymmetric spatial weighting matrix and consistent estimator) are made in columns 5 (S-2SLS) and 6 (S-ML). Overall, these results, which are very similar across the two estimators, suggest that Hays overestimated the coefficient on the spatial lag (simultaneity bias) and underestimated the coefficients on the capital-mobility variable and the capital-

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determining Country 2's tax rate will be greater than the reverse.

[14] There is no strong reason to think this measurement error would be systematic. See Franzese and Hays (2004) for a discussion of this attenuation bias.

mobility*consensus-democracy interaction variable (induced biases). In other words, because of the endogeneity of the spatial lag, Hays likely overestimated the importance of international factors (tax competition) at the expense of domestic (consensus democracy) and common external factors (capital mobility), which is what we would expect. Our reanalysis of the financial openness model in Table 3 tells a similar story.

<Table 3 About Here>

First, non-spatial *OLS* produces serious omitted variable bias (Column 1, Table 3). And second, Hays (2003) probably overestimates the coefficient on the spatial lag and underestimates the coefficients on the capital mobility and consensus democracy interaction variables (Columns 5 and 6 vs. Column 2).

Next, we do a reanalysis of several regressions from Basinger and Hallerberg's Tables 3, 4, and 5. We focus on the regressions that use the Mendoza et al. capital tax rates and levels of fixed capital formation (FCF) for the dependent variable and spatial weights matrix respectively.[15] In these regressions, the dependent variable is the one period change and the spatial lag is differenced and lagged one period. This particular specification raises the concern that unmodeled common shocks are causing Basinger and Hallerberg to underestimate the degree of spatial interdependence. We address this potential problem in two ways—we estimate the model using S-2SLS, which purges the spatial lag of it correlation with the omitted common shocks, and we estimate a model with fixed period effects. The results are reported in Table 4.

<Table 4 About Here>

As expected, we find that Basinger and Hallerberg underestimate the sensitivity of countries' capital tax policies to changes in competitor countries when the cost of capital tax reform

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[15] Our results are similar across dependent variables and weighting schemes.

domestically is low. Specifically, when the ideological distance between veto players is 0, the coefficient estimate for the spatial lag increases to .33 and .81 (from .21) with the S-2SLS and fixed period estimators respectively. When the government leans right (partisanship score of 0.8), these same estimate increases from .30 to .57 and .84. For countries with no capital controls, the estimate rises from .23 to .37 and .79.

Conclusion

We have argued that spatial dependence in capital tax data is substantively interesting because it suggests the importance of external factors in determining tax policy and should not be treated as a "nuisance." For this reason, those conducting empirical research on capital taxation (and other areas of comparative and international political economy) should consider estimating spatial lag models with non-arbitrary lags generated from theoretically and (or) empirically justified spatial weights. This choice can be defended on econometric grounds alone when the degree of spatial dependence in the data is strong and the sample size—particularly the T dimension—is relatively large.

There is one significant caveat. It is important to know whether the spatial dependence in one's data is limited to the stochastic portion of the model or present in both the systematic and random components. This has implications for how one generates the appropriate spatial lag and estimates the model. We have sidestepped this issue completely. In the experiments, of course, we knew what the true data generating process was and, in our reanalyses, we assumed the authors correctly specified their models. Applied research that takes spatial dependence seriously must employ a battery of specification and diagnostic tests and use the results to inform and guide their analyses. (See Anselin 1988 and Aselin et al. 1996 for a discussion of the relevant tests.)

In empirical studies of capital taxation, the debate over the relative importance of internal versus external determinants is an important one. The degree of spatial dependence in capital taxes has important implications for this debate. We have identified three reasons recently published studies have understated this dependence: the spatial relationships are treated as a methodological "nuisance" (Swank and Steinmo, Hays), arbitrary spatial weights are used to generate lags (Hays), and the endogeneity problem is ignored (Basinger and Hallerberg). These issues should not be overlooked in future research.

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Figure 1. Best Response Functions (Persson and Tabellini 2000, 334)

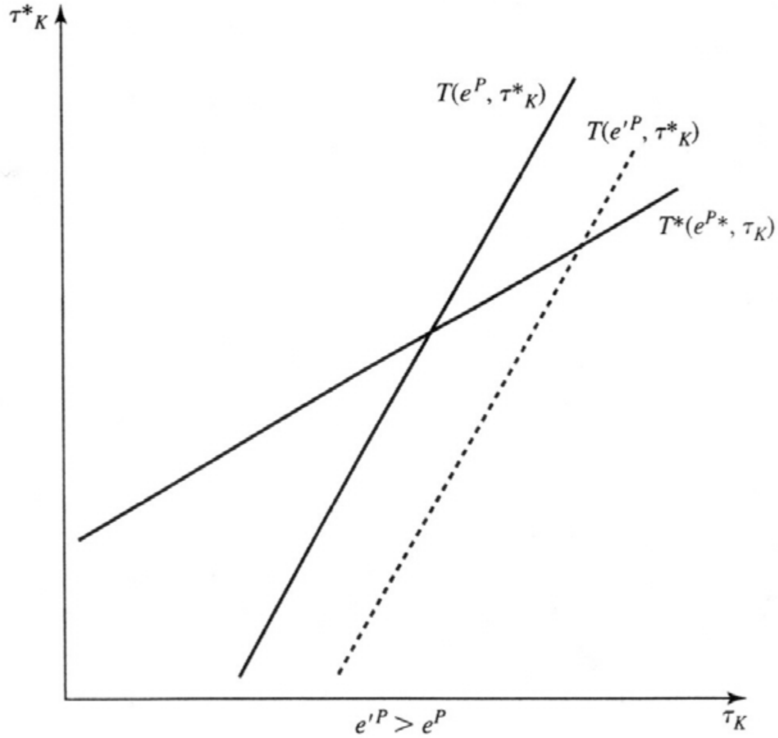

Figure 12.4

Table 1. Replication and Reanalysis of Swank and Steinmo (Appendix, Table 2)

	Effective Tax Rate on Capital		Effective Tax Rate on Labor		Effective Rate on Consumption	
	Repl.	Reanal.	Repl.	Reanal.	Repl.	Reanal.
Liberalization	1.146	1.165	-0.261**	-0.256**	-0.033	0.057
	(0.991)	(0.945)	(0.126)	(0.107)	(0.211)	(0.184)
Trade	-0.018	-0.022	-0.009	-0.009	0.000	-0.001
	(0.073)	(0.062)	(0.031)	(0.027)	(0.016)	(0.013)
Structural Unemployment	-1.147***	-0.943***	-0.359	-0.244	0.147	0.303***
	(0.292)	(0.273)	(0.26)	(0.211)	(0.117)	(0.088)
Public Sector Debt	0.089**	0.059	0.053***	0.051***	-0.007	-0.012*
	(0.044)	(0.037)	(0.017)	(0.015)	(0.01)	(0.007)
Elderly Population	1.264**	1.297**	-0.018	-0.026	0.05	-0.005
	(0.594)	(0.534)	(0.227)	(0.219)	(0.133)	(0.117)
Temporal Lag	0.809***	0.788***	0.671***	0.658***	0.73***	0.677***
	(0.072)	(0.069)	(0.082)	(0.068)	(0.075)	(0.058)
Growth	0.23	0.259	-0.008	-0.016	0.038	0.032
	(0.176)	(0.175)	(0.054)	(0.046)	(0.036)	(0.025)
% Change Profits	0.127*	0.168**				
	(0.073)	(0.075)				
Domestic Investment	0.066	0.062				
	(0.066)	(0.063)				
Inflation			0.115**	0.104**	-0.041	-0.026
			(0.05)	(0.048)	(0.033)	(0.029)
Unemployment			0.28**	0.257***	-0.114	-0.161***
			(0.114)	(0.090)	(0.07)	(0.042)
Left Government	0.018*	0.017	0.008**	0.009**	-0.003	-0.005*
	(0.011)	(0.013)	(0.004)	(0.003)	(0.003)	(0.003)
Christian Democratic Gov	0.041**	0.038**	0.001	0.003	-0.004	-0.011**
	(0.016)	(0.018)	(0.009)	(0.010)	(0.007)	(0.006)
Spatial Lag		0.595***		0.569***		0.985***
		(0.160)		(0.136)		(0.134)

Nostes: The country and year dummy variable coefficients are omitted to save space.

Table 2. Capital Tax Rates and International Capital Mobility (Capital Account Openness)

Independent Variables	Capital Account Openness	Capital Account Openness	Capital Account Openness	Capital Account Openness	Capital Account Openness	Capital Account Openness
Capital Mobility	1.918**	2.223**	2.159**	1.620*	1.695*	1.729*
	(.919)	(.930)	(1.045)	(.859)	(.996)	(1.013)
Capital Mobility Interacted with:						
Capital Endowment	-.070*	-.069*	-.069**	-.033	-.0425	-.048
	(.040)	(.040)	(.033)	(.039)	(.030)	(.040)
Consensus Democracy	.484	.746*	.691	1.245***	1.053**	1.121**
	(.431)	(.434)	(.472)	(.428)	(.485)	(.534)
Corporatism	-1.186	-2.229	-2.008	-3.047**	-2.578*	-2.453
	(1.339)	(1.359)	(1.399)	(1.318)	(1.357)	(1.641)
Left Government	.370*	.286	.304	.304	.321	.331
	(.196)	(.195)	(.209)	(.186)	(.196)	(.215)
Population	-1.79e-07	-9.77e-06**	-7.74e-06*	5.79e-07	3.88e-07	.001
	(3.49e-06)	(3.98e-06)	(4.03e-06)	(3.30e-06)	(3.60e-06)	(.004)
European Union	-.204	-.465***	-.410**	-.520***	-.440**	-.442***
	(.161)	(.170)	(.185)	(.161)	(.176)	(.168)
Temporal Lag	.834***	.754***	.771***	.686***	.723***	.706***
	(.034)	(.039)	(.028)	(.043)	(.031)	(.038)
Spatial Lag		.280***	.221***	.316***	.237***	.267***
		(.066)	(.048)	(.049)	(.035)	(.044)
Obs.	465	465	465	465	465	465
Estimation	Non-spatial OLS	Spatial OLS	Spatial 2SLS	Spatial OLS	Spatial 2SLS	Spatial ML
Diffusion		Symmetric	Symmetric	Asymmetric	Asymmetric	Asymmetric

Notes: The regressions were estimated with fixed country effects. (Coefficients for country dummies not shown.)
Parentheses for the OLS estimates contain panel corrected standard errors.
Parentheses for the 2SLS estimates contain robust standard errors clustered by year.
Parentheses for the ML estimates contain robust standard errors.
** * Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 3. Capital Tax Rates and International Capital Mobility (Financial Openness)

Independent Variables	Financial Openness	Financial Openness	Financial Openness	Financial Openness	Financial Openness	Financial Openness
Capital Mobility	.858***	.988***	.958**	.725**	.758**	.741**
	(.338)	(.342)	(.359)	(.313)	(.345)	(.322)
Capital Mobility Interacted with:						
Capital Endowment	-.029*	-.034**	-.033**	-.024*	-.025**	-.028*
	(.015)	(.016)	(.013)	(.014)	(.011)	(.014)
Consensus Democracy	.209	.306*	.283*	.422***	.369**	.369**
	(.154)	(.157)	(.165)	(.151)	(.161)	(.168)
Corporatism	-.534	-.817*	-.751	-.888**	-.799	-.656
	(.471)	(.490)	(.603)	(.451)	(.567)	(.612)
Left Government	.099*	.085	.088	.089*	.0916	.095
	(.054)	(.054)	(.057)	(.051)	(.055)	(.059)
Population	2.45e-07	-2.10e-06*	-1.55e-06	2.13e-07	2.21e-07	.000
	(1.04e-06)	(1.23e-06)	(1.11e-06)	(9.83e-07)	(9.79e-07)	(.001)
European Union	-.075*	-.148***	-.131**	-.156***	-.136***	-.131***
	(.046)	(.050)	(.050)	(.045)	(.045)	(.044)
Temporal Lag	.825***	.751***	.768***	.682***	.718***	.702***
	(.036)	(.040)	(.030)	(.044)	(.031)	(.038)
Spatial Lag		.261***	.200***	.309***	.231***	.261***
		(.066)	(.053)	(.047)	(.036)	(.043)
Obs.	465	465	465	465	465	465
Estimation	Non-spatial OLS	Spatial OLS	Spatial 2SLS	Spatial OLS	Spatial 2SLS	Spatial ML
Diffusion		Symmetric	Symmetric	Asymmetric	Asymmetric	Asymmetric

Notes: The regressions were estimated with fixed country effects. (Coefficients for country dummies not shown.)
Parentheses for the OLS estimates contain panel corrected standard errors.
Parentheses for the 2SLS estimates contain robust standard errors clustered by year.
Parentheses for the ML estimates contain robust standard errors.
** * Significant at 1%, ** Significant at 5%, * Significant at 10%

Table 4. Replication and Reanalysis of Basinger and Hallerberg (Mendoza et al. Tax Rates, FCF Weights)

	Repl-ication	Reanalysis		Repl-ication	Reanalysis		Repl-ication	Reanalysis	
Regression Coefficients									
Coefficient, change in competitor $countries_{t-1}$	.21** (.10)	.33 (.21)	.81** (.35)	-.22 (.33)	-.64 (.57)	.46 (.42)	.23** (.08)	.37* (.19)	.79** (.35)
Coefficient, change in competitor countries*distance, party, cap controls	-39 (.50)	-.55 (.81)	-.36 (.51)	.63 (.53)	1.51 (.94)	.48 (.54)	-.75 (.64)	-1.40 (1.26)	-.58 (.73)
Conditional Coefficients									
0 distance (United Kingdom, 1980-97)	.21** (.10)	.33 (.21)	.81** (.35)						
S.75 distance (Denmark, 1991-92)	.17** (.07)	.28* (.16)	.77** (.34)						
0.2 distance (Netherlands, 1982-88)	.13* (.07)	.22 (.15)	.74** (.33)						
0.3 distance (Italy, 1981)	.09 (.10)	.17 (.17)	.70** (.33)						
0.5 distance (Finland, 1996-97)	.01 (.18)	.06 (.30)	.63* (.36)						
0 partisanship (no country)				-.22 (.33)	-.64 (.57)	.46 (.42)			
0.2 partisanship (Norway, 1989)				-.10 (.23)	-.34 (.39)	.56 (.36)			
0.4 partisanship (Netherlands, 1982-88)				.03 (.13)	-.04 (.22)	.65** (.33)			
0.6 partisanship (Austria, 1987-97)				.15** (.06)	.27* (.15)	.75** (.33)			
0.8 partisanship (Ireland, 1990-92)				.30** (.11)	.57** (.26)	.84** (.37)			
0 capital controls (United States, 1980-97)							.23** (.08)	0.37** (.19)	.79** (.35)
0.25 capital controls (France, 1980-89)							.04 (.12)	0.02 (.24)	.65** (.32)
0.5 capital controls (Portugal, 1980-85)							-.15 (.27)	-0.33 (.53)	.50 (.38)
0.75 capital controls (Greece, 1981)							-.34 (.43)	-0.68 (.83)	.36 (.50)
S-2SLS	No	Yes	No	No	Yes	No	No	Yes	No
Period Dummies	No	No	Yes	No	No	Yes	No	No	Yes

Notes: See Basinger and Hallerberg (2004), Tables 3-5.

Appendix

Monte Carlo Experiments from Franzese and Hays (2005)

We replicate and extend the simulations in Beck and Katz (1995), focusing our attention on the overconfidence and efficiency issues addressed in their Tables 4 and 5 respectively. (See pages 638-9 for a detailed discussion of their experimental design.) Beck and Katz use a restricted version of the equations in (6) above to generate their experimental data, which feature disturbances that are both contemporaneously correlated across units and panel heteroscedastic. The contemporaneous correlation or spatial dependence is experimentally manipulated through $\boldsymbol{\lambda}$ while panel heteroscedasticity is created by allowing the variance of $\mathbf{u}$ to be unit specific.

Table A1. Replication and Extension of Beck and Katz (1995, Table 4)

			Overconfidence (%)		
T	Heterosce-dasticity	Contempo-raneous Correlation	OLS	PCSE	S-OLS (PCSE)
10	0	0	101	102	NA
10	0	0.25	136	105	NA
10	0.3	0	114	100	NA
10	0.3	0.25	145	104	NA
20	0	0	102	102	102
20	0	0.5	220	107	115
20	0.3	0	123	106	106
20	0.3	0.5	224	106	109
30	0	0	96	97	97
30	0	0.5	214	102	115
30	0.3	0	115	99	99
30	0.3	0.5	232	108	113
40	0	0	99	99	99
40	0	0.5	214	101	118
40	0.3	0	114	98	98
40	0.3	0.5	227	104	110

Notes: The spatial weighting matrix (W) was estimated using the OLS residuals. This matrix cannot be estimated unless T > N. S-OLS includes a spatial lag of the dependent variable on the right-hand-side (W*Y). These results are based on 1,000 trials. The number of units was fixed at 16 as opposed to 15

Table A2. Replication and Extension of Beck and Katz (1995, Table 5)

		Relative Efficiency of Parks and S-OLS to OLS (Over 100% indicates superiority of OLS)							
		Contemporaneous Correlation of the Errors							
N	T	0.0		0.25		0.5		0.75	
		Parks	S-OLS	Parks	S-OLS	Parks	S-OLS	Parks	S-OLS
10	10	102	NA	102	NA	99	NA	97	NA
	20	112	110	104	106	91	95	73	82
	30	110	110	104	102	86	88	66	73
	40	111	110	99	96	82	84	63	68
15	15	102	NA	101	NA	99	NA	98	NA
	20	110	111	101	108	94	103	88	99
	30	107	109	104	105	91	95	74	80
	40	112	113	102	103	87	90	67	72
20	20	101	NA	100	NA	99	NA	98	NA
	25	105	109	101	107	96	105	88	100
	30	113	113	102	108	93	100	83	96
	40	114	112	101	101	89	92	74	82

Notes: The spatial weighting matrix (W) was estimated using the OLS residuals. This matrix cannot be estimated unless T > N. S-OLS includes a spatial lag of the residuals on the right-hand-side (W*E). These results are based on 1,000 trials.

Monte Carlos from Franzese and Hays (2004)

We use a reduced form of the spatial-lag model to generate the data for our experiments:

$$\mathbf{y} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1}\varepsilon$$

Our **X** matrix (of non-diffusion elements) has three parts: $\boldsymbol{\xi}$, $\boldsymbol{\eta}$, and $\boldsymbol{\xi\eta}$. The vector $\boldsymbol{\xi}$ is an NTx1 stack of *i.i.d.* draws from a standard normal distribution. These observations, unique to each spatial unit in each time period, represent purely domestic variables. Analytically, these $\boldsymbol{\xi}$ represent the set of domestic institutions, structures, and conditions that exist in each unit *i* at each time *t*. The vector $\boldsymbol{\eta}$ is an NTx1 stack of T vectors, each Nx1 in size, and each element of which is identical. That is, each of the T vectors has N elements that are all the same, but each of the T vectors can differ from the others. Thus, $\boldsymbol{\eta}$ represents a set of globally common shocks, one occurring in each of the T periods. These shocks are also drawn *i.i.d.* from a standard normal distribution. The interaction term, $\boldsymbol{\xi\eta}$, captures the idea that the effects of common external shocks are mediated by domestic variables. Additionally, however, the model will involve diffusion, with average magnitude ρ and with specific connections from unit j to unit i of magnitudes w_{ij}.

Drawing the data for $\boldsymbol{\xi}$, $\boldsymbol{\eta}$, and $\boldsymbol{\xi\eta}$—i.e., for $\mathbf{X}$—in this manner, and drawing $\boldsymbol{\varepsilon}$ also independently from standard normal distributions, we generate the data for **Y** using two different sets of coefficients, $(\beta_1, \beta_2, \beta_3, \rho)$. For coefficients, we use $(\beta_1, \beta_2, \beta_3, \rho) = (1,1,1,0.1)$ and $(\beta_1, \beta_2, \beta_3, \rho) = (1,1,1,0.5)$. Note that one set of coefficients has smaller ρ than the other, and recall that the spatial weighting matrix determines the relative importance of each unit to each of the others in the pattern of spatial diffusion while ρ determines the average strength of diffusion. Thus, the second set of coefficients represents a stronger diffusion process. We assume the spatial weights are time-invariant so all the elements along the diagonals of the TxT off-diagonal blocks of **W** are the same. That is, only one w_{ij} connecting j to i persists for all T periods; this connectivity does not change from period to period. We set all of these w_{ij} equal to 1/(N-1). In this case, every unit affects every other unit equally, and the appropriate right-hand-side spatial lag for each unit-year to reflect this proposition would be an unweighted average of the dependent variable for the other units in that year.

We evaluate the non-spatial OLS, S-OLS, S-2SLS, and S-ML estimators, the first two with and without panel-corrected standard-errors (i.e., estimates of the variance-covariance matrix of the coefficient estimates that are "robust to", i.e., consistent in the presence of, spatial correlation). We report results for samples with dimensions N = 5, 40 and T = 20, 40.

We report the mean coefficient estimates, the mean conventional standard-error estimates, the mean PCSE estimates, the actual standard deviation of the coefficient estimates, and the root mean-squared error (RMSE) of the coefficient estimates. Comparing the mean of the coefficient estimates to the true value of that parameter in that experiment gives the bias. We chose coefficients of 1 (and ρ of .1 or .5) so the percentage bias may be seen directly. By comparing the mean of the estimated standard errors to the actual standard deviation of coefficient estimates, we can observe the potential over-confidence of conventional standard errors and whether and how well PCSE's may redress any such over-confidence. Finally, the RMSE's, being the square root of the sum of the bias-squared and the actual variance of the coefficient estimates, offer summary evaluation combining both bias/consistency and efficiency considerations.

Table A3. Comparing Estimators (N=5, $\rho = 0.1$, w_{ij} = (1/N-1), 1,000 trials)

		OLS			S-OLS			S-2SLS			ML (100 Trials)		
		Mean	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*
	β_1	.998	.104	.103	.993	.105	.105	.992	.106	.106	0.972	0.121	0.124
	s.e.(β_1)	.105	.012		.106	.012		.107	.014		0.107	0.012	
	pcse(β_1)	.103	.012		.103	.013							
	β_2	1.112	.124	.167	1.027	.215	.216	1.003	.236	.235	1.046	0.219	0.222
	s.e.(β_2)	.108	.020		.175	.037		.2127	.081		0.181	0.036	
T=20	*pcse*(β_2)	.111	.026		.163	.042							
	β_3	1.005	.115	.115	1.002	.117	.117	1.001	.119	.119	0.977	0.139	0.14
	s.e.(β_3)	.111	.024		.111	.024		.113	.026		0.115	0.024	
	pcse(β_3)	.108	.025		.108	.025							
	ρ				.078	.154	.155	.097	.177	.177	0.074	0.141	0.143
	s.e.(ρ)				.119	.024		.158	.068		0.074	0.006	
	pcse(ρ)				.112	.028							
	β_1	1.008	.072	.072	1.004	.071	.071	1.003	.072	.071	1.003	0.072	0.072
	s.e.(β_1)	.073	.005		.072	.005		.073	.005		0.071	0.006	
	pcse(β_1)	.072	.005		.072	.005							
	β_2	1.112	.081	.139	.991	.125	.125	1.001	.139	.139	1.025	0.120	0.122
	s.e.(β_2)	.074	.009		.116	.016		.135	.026		0.103	0.012	
T=40	*pcse*(β_2)	.079	.013		.110	.018							
	β_3	1.002	.075	.075	1.000	.075	.075	.999	.075	.075	0.995	0.086	0.085
	s.e.(β_3)	.075	.011		.075	.011		.075	.011		0.073	0.011	
	pcse(β_3)	.0738	.011		.074	.011							
	ρ				.108	.092	.093	.099	.103	.103	0.072	0.066	0.072
	s.e.(ρ)				.079	.011		.100	.023		0.049	0.003	
	pcse(ρ)				.076	.012							

Table A4. Comparing Estimators (N=40, ρ = 0.1, w_{ij} = (1/N-1), 1,000 trials)

		OLS			S-OLS			S-2SLS			ML (100 Trials)		
		Mean	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*
	β_1	1.000	.036	.036	.999	.036	.036	.999	.036	.036	1.001	0.037	0.037
	$s.e.(\beta_1)$	.036	.002		.037	.002		.037	.002		0.036	0.002	
	$pcse(\beta_1)$	.036	.002		.036	.002							
	β_2	1.112	.041	.119	1.049	.209	.215	.994	.211	.211	1.042	0.172	0.176
	$s.e.(\beta_2)$	.038	.007		.152	.035		.199	.083		0.127	0.026	
T=20	$pcse(\beta_2)$	.039	.010		.144	.046							
	β_3	1.000	.038	.038	.999	.038	.038	1.000	.038	.038	0.999	0.032	0.032
	$s.e.(\beta_3)$	.038	.007		.038	.007		.038	.007		0.039	0.007	
	$pcse(\beta_3)$	.038	.007		.037	.007							
	ρ				.055	.186	.191	.105	.188	.188	0.062	0.143	0.147
	$s.e.(\rho)$				.133	.030		.175	.074		0.025	0.001	
	$pcse(\rho)$				.126	.040							
	β_1	1.001	0.026	0.026	1.001	0.026	0.026	1.001	0.026	0.026			
	$s.e.(\beta_1)$	0.025	0.001		0.025	0.001		0.025	0.001				
	$pcse(\beta_1)$	0.025	0.001		0.025	0.001							
	β_2	1.112	0.03	0.116	0.999	0.119	0.119	1.003	0.136	0.136			
	$s.e.(\beta_2)$	0.026	0.003		0.101	0.016		0.126	0.032				
T=40	$pcse(\beta_2)$	0.028	0.005		0.096	0.02							
	β_3	1	0.026	0.026	1	0.026	0.026	1	0.026	0.026			
	$s.e.(\beta_3)$	0.026	0.003		0.026	0.003		0.026	0.003				
	$pcse(\beta_3)$	0.026	0.003		0.026	0.003							
	ρ				0.101	0.105	0.105	0.098	0.12	0.12			
	$s.e.(\rho)$				0.087	0.014		0.111	0.028				
	$pcse(\rho)$				0.083	0.017							

Table A5. Comparing Estimators (N=5, $\rho = 0.5$, w_{ij} = (1/N-1), 1,000 trials)

		OLS			S-OLS			S-2SLS			ML (100 Trials)		
		Mean	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*
	β_1	1.092	0.145	0.171	0.988	0.106	0.107	0.997	0.107	0.107	1.010	0.116	0.116
	$s.e.(\beta_1)$	0.138	0.019		0.106	0.012		0.108	0.014		0.106	0.012	
	$pcse(\beta_1)$	0.131	0.021		0.104	0.013							
	β_2	1.999	0.289	1.04	0.837	0.178	0.242	0.998	0.253	0.253	1.019	0.175	0.176
	$s.e.(\beta_2)$	0.142	0.027		0.184	0.04		0.228	0.109		0.162	0.030	
T=20	$pcse(\beta_2)$	0.231	0.051		0.148	0.035							
	β_3	1.076	0.173	0.189	0.997	0.117	0.117	1.002	0.117	0.117	0.983	0.117	0.118
	$s.e.(\beta_3)$	0.146	0.032		0.112	0.024		0.115	0.026		0.110	0.022	
	$pcse(\beta_3)$	0.135	0.034		0.111	0.025							
	ρ				0.579	0.076	0.11	0.499	0.108	0.108	0.482	0.064	0.067
	$s.e.(\rho)$				0.073	0.015		0.098	0.049		0.070	0.005	
	$pcse(\rho)$				0.059	0.013							
	β_1	1.101	0.106	0.146	0.981	0.074	0.076	0.996	0.075	0.075	0.996	0.073	0.073
	$s.e.(\beta_1)$	0.097	0.009		0.073	0.006		0.074	0.006		0.072	0.005	
	$pcse(\beta_1)$	0.095	0.01		0.073	0.006							
	β_2	2.001	0.202	1.021	0.826	0.119	0.211	1	0.146	0.146	1.034	0.118	0.122
	$s.e.(\beta_2)$	0.098	0.013		0.121	0.018		0.145	0.031		0.112	0.014	
T=40	$pcse(\beta_2)$	0.166	0.025		0.102	0.016							
	β_3	1.102	0.122	0.159	0.988	0.075	0.076	1.002	0.075	0.075	1.009	0.077	0.077
	$s.e.(\beta_3)$	0.099	0.015		0.075	0.012		0.076	0.012		0.075	0.011	
	$pcse(\beta_3)$	0.096	0.017		0.075	0.012							
	ρ				0.587	0.049	0.1	0.5	0.061	0.061	0.486	0.045	0.046
	$s.e.(\rho)$				0.048	0.007		0.062	0.014		0.050	0.003	
	$pcse(\rho)$				0.041	0.006							

Table A6. Comparing Estimators (N=40, $\rho = 0.5$, w_{ij} = (1/N-1), 1,000 trials)

		OLS			S-OLS			S-2SLS			ML (100 Trials)		
		Mean	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*	*Mean*	*Std. Dev.*	*RMSE*
	β_1	1.011	0.038	0.04	0.999	0.036	0.036	0.999	0.036	0.036	1.001	0.042	0.041
	$s.e.(\beta_1)$	0.038	0.002		0.036	0.002		0.037	0.003		0.036	0.002	
	$pcse(\beta_1)$	0.038	0.003		0.036	0.003							
	β_2	2.004	0.11	1.01	0.861	0.165	0.216	1.008	0.27	0.27	1.054	0.141	0.151
	$s.e.(\beta_2)$	0.04	0.007		0.154	0.037		0.208	0.206		0.130	0.022	
T=20	$pcse(\beta_2)$	0.086	0.02		0.123	0.036							
	β_3	1.007	0.041	0.042	0.998	0.039	0.039	0.998	0.039	0.039	1.001	0.037	0.036
	$s.e.(\beta_3)$	0.04	0.007		0.038	0.007		0.038	0.007		0.038	0.006	
	$pcse(\beta_3)$	0.039	0.007		0.038	0.007							
	ρ				0.57	0.081	0.107	0.497	0.131	0.131	0.477	0.063	0.067
	$s.e.(\rho)$				0.074	0.018		0.102	0.097		0.025	0.001	
	$pcse(\rho)$				0.059	0.018							
	β_1	1.011	0.026	0.029	0.998	0.025	0.025	0.999	0.025	0.025			
	$s.e.(\beta_1)$	0.026	0.001		0.025	0.001		0.025	0.001				
	$pcse(\beta_1)$	0.026	0.001		0.025	0.001							
	β_2	2	0.073	1.002	0.844	0.1	0.185	1.002	0.135	0.135			
	$s.e.(\beta_2)$	0.027	0.003		0.101	0.016		0.127	0.032				
T=40	$pcse(\beta_2)$	0.061	0.009		0.084	0.015							
	β_3	1.009	0.029	0.031	0.997	0.027	0.027	0.999	0.027	0.027			
	$s.e.(\beta_3)$	0.027	0.003		0.026	0.003		0.026	0.003				
	$pcse(\beta_3)$	0.027	0.003		0.026	0.003							
	ρ				0.578	0.049	0.092	0.499	0.065	0.065			
	$s.e.(\rho)$				0.049	0.008		0.062	0.016				
	$pcse(\rho)$				0.041	0.007							