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JEL Codes: C33; D33; O10; R11.

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1. Introduction

Whether and how a change in the functional distribution of income between profits and wages causes a change in the level of macroeconomic activity as measured by output, capacity utilization or output growth is a key issue that has been long debated theoretically and more recently frequently explored empirically. In effect, the related and equally important issue of whether and how a causality involving those variables operates in both directions has been so debated and explored as well, though to a lesser extent.

The possible existence of a unidirectional or bidirectional causal relationship between the functional distribution of income and macroeconomic activity is an important issue that has become even

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more timely and pressing in recent times. The evident reason is that two salient stylized facts observed in several developed and developing countries are the declining trend of the wage share in income in the last two or three decades and the slow pace of macroeconomic activity especially in the wake of the Great Recession of 2008-2009.[4]

In regard to the US economy, there is evidence suggesting that it has experienced a slowdown in its long-term output growth and job creation that predates the recent Great Recession. In effect, the salient fall in the wage share after 2000 is associated with a slowdown in average output growth, which suggests that such a change in the US functional distribution of income could be an essential contributing factor toward a more persistent stagnation in the US economy (Blecker, 2016b; Charpe et al., 2020; Blecker et al., 2022). Nikiforos (2017) draws attention to a decline in the US wage share accompanying the increase in capacity utilization during the recovery from the 2001 recession, a shift in the relationship between the considered variables during the recent Great Recession, and another fall in the wage share during the initial stages of recovery from the Great Recession. Meanwhile, Barrales and von Arnim (2017) use wavelet analysis and find that various measures of US macroecomic activity and the wage share Granger cause each other. Yet in a novel contribution testing for Granger causality also in the conditional distribution and not only in the conditional mean, Marques and Lima (2022) detect that capacity utilization positively Granger causes the wage share in all conditional quantiles in the US, whereas capacity utilization is negatively impacted by lagged values of the wage share only in a few conditional quantiles.

The main theoretical framework that has been employed to underpin empirical estimations of the impact of a change in the functional distribution of income on macroeconomic activity is the Neo-Kaleckian approach broadly conceived. In this approach, the level of macroeconomic activity varies positively with aggregate demand in the short run as well the long run, and aggregate demand in turn varies (among other factors) with the functional distribution of income. Meanwhile, dynamic macroeconomic models in the Neo-Kaleckian tradition (and a few other non-mainstream traditions) very often treat the wage share as endogenously time-varying, and predictions about the impact of macroeconomic activity on the functional distribution offered by these models have been empirically tested. In these models, the real wage as a component of the wage share is sometimes endogenously time-varying often as driven by class conflicting claims on available income, with the employment rate and/or capacity utilization crucially affecting the real wage dynamics. Labor productivity as another component of the wage share is also often treated as endogenously time-varying, with its growth rate varying positively with output growth (in a Kaldor-Verdoorn fashion); positively with R&D spending and positively or negatively with market concentration (in a Schumpeterian manner); and/or positively with the real wage or wage share (in a fashion associated with Marx-Hicks, cost-push or induced technical change).[5]

We estimate a modified demand-and-distribution system for the 48 contiguous US states and the District of Columbia (DC) using dynamic spatial panel data for the period 1980–2019.[6] Our estimation strategy involves utilizing endogenous regressors and, as required by the regional nature of the

[4]See Karabarbounis and Neiman (2014), ILO (2015), Stockhammer (2017), and Guerriero (2019) for the observed decline trend of the wage share, and Summers (2015), Blecker (2016b), Onaran (2016), and World Bank (2018) for different interpretations of the observed slow pace of macroeconomic activity.

[5]These non-mainstream theoretical approaches to the relationship between the functional distribution of income and the level of macroeconomic activity are aptly surveyed and discussed in Dutt (2017), Tavani and Zamparelli (2017), and Blecker and Setterfield (2019).

[6]In a convenient and facilitating abuse of language, we will thereafter refer to those 49 regional units simply as states.

data being used, also properly testing for spatial spillovers. Our methodology accounts for endogeneity, omitted variable bias and spatial autocorrelation, yielding estimates that are consistent, insensitive to initial conditions, and does not require testing for or making assumptions about instrumental variables. Although the existing literature testing for unidirectional or bidirectional causality between the functional distribution of income and macroeconomic activity is large and growing, to the best of our knowledge, there is no study in such an important literature testing for the presence and significance of spatial dependence and spillover effects across countries or across either regions or states in a specific country. Against this backdrop, the purpose of the current paper is to fill such an important existing gap in the empirical literature on the relationship between the functional distribution of income between wages and profits and the level of economic activity. Our methodology usefully permits us to explore the interactions between the considered economic variables across *states* within the US, across *space* and over *time*, measuring their magnitude and testing for their statistical significance. In effect, given the existence of free (or almost free) movement of goods, services, labor, and capital between states of a given country, the estimation of the relationship between the wage share and the level of economic activity within a certain country using state-level data does require testing for the presence and significance of spatial dependence and spillover effects across the sample states.

As elaborated in the following section, the existing empirical studies of the considered relationship for the US economy, when employing aggregate time series data, do not fully exploit all the relevant information contained in the cross-sectional dimension of the data. Meanwhile, when utilizing panel data methods, the respective empirical studies do not tackle some complications involved in utilizing panel models, for example, by not considering the possibility of existence of spatial dependence in the data and therefore of the presence of direct and indirect spatial spillover effects. Moreover, the existing empirical literature on the relationship between the wage share and the level of macroeconomic activity at large (and not only for the US economy) does not feature estimates of persistence parameters allowing the separate evaluation of the significance, sign and magnitude of the cumulative as opposed to the immediate effects of the wage share on macroeconomic activity, and vice versa. Therefore, a further contribution of this paper lies in its consistent estimation of the persistence parameter associated with the effect of the wage share on economic activity, and vice versa.

Drawing on the empirical methods introduced by Arellano and Bond (1991) and Lancaster (2002), we employ a dynamic spatial panel model that allows for endogeneity of regressors and unobserved heterogeneity, accounts for spatial autocorrelation, and permits us to test for the presence of spatial spillovers across the sample US states and also estimate their magnitude. Drawing also on LeSage (2014), Vega and Elhorst (2015), and Baltagi and Rokicki (2014), we contribute to the existing empirical literature on the dynamic relationship between the wage share and the level of economic activity in a novel and original way by taking into account the spatial dimension of that relationship, which is a strict requirement owing to our use of state-level data. In addition to the popular generalized method of moments (GMM) estimator, we adopt the orthogonal reparametrization approach proposed by Lancaster (2002), to which we refer as OPM (for orthogonalized panel model), to generate a likelihood-based estimator that is independent from initial conditions, exact, and consistent as $N \to \infty$ for $T \geq 2$, even in the presence of correlation between explanatory variables and the error term.[7] The OPM approach proceeds by *integrating* instead of *maximizing* the likelihood concerning a uniform prior distribution. This procedure generates a joint posterior distribution that yields a consis-

[7] The degree of correlation between the error term and covariates expresses the endogeneity bias found in the parameter estimates. The source of this correlation can be simultaneous determination between dependent and explanatory variables, measurement error in variables, and relevant omitted variables not included in the regression model.

tent estimator for the structural parameters of interest. More importantly for our purposes in this paper, this method can account for spatial dependence, is insensitive to initial conditions (while the choice of initial conditions strongly affects maximum likelihood estimators), and does not require making assumptions about or running specification tests for instrumental variables, as it is the case with GMM estimators.[8] Interestingly, empirical studies of important issues related to the US economy employing state-level data and spatial panel models have become quite common more or less recently. For example, Korniotis (2010) estimates a spatial panel data model to explore the pattern of consumption in 48 US continental states, while Burnett et al. (2013) use several spatial panel data models to estimate the relationship between US state-level carbon dioxide (CO2) emissions, economic activity, and other factors.

Our main results are as follows. Without testing for spatial dependence and spillovers, the sample US states feature output growth and capacity utilization varying in the same direction as their own wage share. However, when testing for spatial dependence and spillovers as required by the state-level nature of the sample data, we estimate that a higher state wage share lowers output growth and capacity utilization in the own state, but raises both output growth and capacity utilization averaged over neighboring states. The former direct effect is larger (smaller) in absolute magnitude than the latter indirect effect in the case of capacity utilization (output growth). These results for the effect of a change in the wage share on the level of economic activity at the state level are somewhat expected, as regional economies in a given country are typically more (and usually much more) open to each other than national economies are open to each other. Meanwhile, a higher state output growth or capacity utilization is estimated to reduce the wage share in the own state, but to raise the wage share averaged over neighboring states. The former direct effect is larger in absolute magnitude than the latter indirect effect. In addition, we estimate that the response of the state-level economic activity and wage share to changes in each other exhibits persistence, with the above-summarized direct and indirect effects being qualitatively the same both immediately and cumulatively over time.

The remainder of this paper is structured as follows. In Section 2, to suitably contextualize the contribution of this paper, we outline the contours of the related empirical literature. Section 3 presents the econometric models to be estimated and describes the data to be employed for such a purpose. Section 4 reports the main results and discusses their substance, while Section 5 concludes. Finally, Appendix A features descriptive statistics and diagnostic tests of the endogenous variables utilized in the estimations and Appendix B reports further estimation results of interest.

2. Related empirical literature

The relationship between the functional distribution of income and macroeconomic activity has been explored empirically in an extensive literature. Existing studies have employed different econometric methodologies and focused on individual countries or groups of countries over various time periods. In fact, several of the empirical studies mentioned below cover countries other than the US, but for necessary brevity and focus on the country case study under consideration, we report only the results found for the US economy.

In our review of studies for the US economy, for consistency and comparability we use a common

[8] While Caselli et al. (1996) use the GMM estimator of Arellano and Bond (1991) and Lancaster and Aiyar (2000) use the OPM approach to estimate the parameters of the *same* economic growth model as alternative methods, we see such empirical methods as complementary, given that the OPM estimator uses less restrictive assumptions than the GMM estimators.

terminology that sometimes differs from that employed by the authors of the studies being reviewed. We will utilize this same terminology in the presentation and discussion of our novel results to facilitate comparability with the related evidence for the US economy. More specifically, by *wage-led* (*profit-led*) *demand* we mean a situation where a change in the wage share leads to a change in the same (opposite) direction in output or capacity utilization. Analogously, we dub *wage-led* (*profit-led*) *growth* a situation where a change in the wage share leads to a change in the same (opposite) direction in output growth. Meanwhile, by *wage-squeeze* (*profit-squeeze*) *in distribution* we mean a situation in which a change in output, capacity utilization or output growth generates a change in the opposite direction in the wage share (profit share).

As well known in the related theoretical literature, depending on the specification of the investment function, it is possible that a given change in the wage share leads to a change in the same direction in capacity utilization and in the opposite direction in output growth. In the case of the so-called Marglin-Bhaduri specification (Marglin and Bhaduri, 1990), in which investment as a proportion of the capital stock varies separately and positively with the profit share and capacity utilization, the resulting capacity utilization and output growth can vary either positively or negatively with the profit share depending on the relative strength of the several effects at play. However, with a linear Marglin-Bhaduri investment function the profit share effect can never be strong enough to lead capacity utilization to vary negatively with the wage share. Blecker (2002) demonstrates that with a kind of 'Cobb-Douglas' functional form (but with degree of homogeneity strictly greater than one, we would add) for the Marglin-Bhaduri investment function, capacity utilization responds negatively to an increase in the wage share only in the extreme case where the elasticity of investment with respect to the profit share is strictly greater than one (in a model with no workers' saving, no government, and no foreign trade). In this case, as an expected result, the rates of profit and output growth are necessarily profit led. Meanwhile, other model specifications also with consumption and investment as the only components of aggregate demand but with investment varying non-linearly with the wage share in a quadratic manner results in capacity utilization (output growth) varying positively (either negatively or positively) with the wage share (see, e.g., Lima, 2004; Lima, 2009).

The vast majority of the empirical literature on the relationship between the functional distribution of income and aggregate demand and hence macroeconomic activity (output, capacity utilization or output growth) in the US and several other countries has been employing two alternative methodologies, usually finding different results. Studies using a structural or single equation approach separately estimate the effects of the wage share on each component of aggregate demand and some measure(s) of macroeconomic activity, while treating the wage share as exogenously given. Such studies usually find evidence of wage-led demand and growth for economies which are larger and less open, and often find profit-led demand and growth for economies which are smaller and more open. Meanwhile, studies following an aggregative approach (a modified version of it we adopt in this paper) directly estimate a one-way or (less often, as carried out here) the two-way relationship between the wage share and some measure(s) of macroeconomic activity, usually finding evidence of profit-led demand and profit-squeeze in distribution. Comprehensive presentations of these two alternative approaches which also include an authoritative evaluation of their strengths and weaknesses are provided in Blecker (2016a) and Blecker and Setterfield (2019).

Recall that we will report only the empirical results for the US economy. Following a structural or single equation approach, Bowles and Boyer (1995) find that demand is wage-led and Hein and Vogel (2008) find evidence of wage-led output growth, while Naastepad and Storm (2006) detect that demand and output growth are profit-led. However, Onaran et al. (2011), Onaran and Galanis (2012), and Stockhammer and Wildauer (2016) provide evidence that both demand and output growth are wage-led (although only moderately so in the former empirical study). Also adopting a structural modeling approach, but nicely innovating by employing GMM estimation to properly correct for simultaneity bias, Blecker et al. (2022) detect that private-sector aggregate demand is wage-led. In fact, the authors' GMM estimates implies a higher, rather than lower, degree of wage-ledness (or in some cases, less profit-ledness) compared with OLS estimates of identically specified models. Interestingly, the paper by Blecker et al. (2022) is also the first that distinguishes the effect of different sources of changes in the wage share (namely, unit labor costs and monopoly power by firms) in an empirical exploration of distributional impacts on several components of aggregate demand.

Employing a system or aggregative approach, which in turn relies on estimation of a reduced form solution for some measure(s) of macroeconomic activity, Stockhammer and Onaran (2004) find that shocks to the profit share have no significant overall effects on capacity utilization, but find only weak evidence for wage-led demand. Barbosa-Filho and Taylor (2006) find that capacity utilization varies negatively with the wage share, while the latter is normally an increasing function of the former, which means profit-led demand and profit-squeeze in distribution. Later studies along similar lines tend to obtain the same qualitative results found in Barbosa-Filho and Taylor (2006). In fact, Kiefer and Rada (2015) provide evidence of profit-led demand and profit-squeeze in distribution during the expansion phase of a business cycle. In addition to also obtaining the result that capacity utilization varies negatively with the wage share, Carvalho and Rezai (2016) detect that with the rise in income inequality (as measured by the Gini coefficient) demand became more profit-led. Nikiforos and Foley (2012) also find that demand is profit-led, but detect a U-shaped impact of capacity utilization on the wage share, with a rise in the former lowering (raising) the latter at lower (higher) levels of capacity utilization, which means wage-squeeze (profit-squeeze) in distribution. Tavani et al. (2011) likewise find both that demand is profit-led and that the impact of capacity utilization on the wage share is non-linear, but with profit-squeeze (wage-squeeze) in distribution arising at lower and higher (intermediate) levels of capacity utilization. The results in Araujo et al. (2019) indicate that positive shocks to the employment rate impacts positively on the wage share and positive shocks to wage share impacts negatively on the employment rate. Basu and Gautham (2019) detect that positive shocks to the wage share have long-lasting negative impacts on demand and output growth, while the results in Oyvat et al. (2020) indicate that demand and ouput are wage-led in the long run. In fact, using time frequency (wavelet) analysis, Charpe et al. (2020) find that the impact of the wage share on output growth changes sign with the time frequency under consideration from negative at high frequencies to positive at low frequencies: the wage share leads output growth negatively over shorter cycles (2–4 and 4–8 years), but positively over longer cycles (16–32 and 32+ years), with the positive coefficient associated with the wage share at low frequencies increasing over time. The results in Costa Santos and Araujo (2020), likewise using wavelet methods, similarly find profit-led demand and output growth in the short run and wage-led demand and output growth in the long run. Thus, the latter two studies somehow confirm the hypothesis advanced in Blecker (2016a) that demand is more likely to be profit-led in the short run (if at all) and more likely to be wage-led in the long run, at least in the US case (recall again that all the results reported in this section are for the US). However, Barrales and von Arnim (2017), also using wavelet analysis, find that cycles up to the medium run are characterized by profit-led macroeconomic activity (measured in three different ways) and profit-squeeze in distribution, but obtain inconclusive results for the long run.[9] Meanwhile, employing wavelet and vector autoregression methods, Barrales

[9]Barrales and von Arnim (2017) find evidence of profit-led/profit-squeeze cycles up to the medium run between 1955 and 1980. In the post-1980 period, however, there is an initial rise in macroeconomic activity with little or no accompanying increase in the wage share, with both variables then declining sharply from the late 1990s onwards. For Setterfield

et al. (2021) detect that the wage share varies positively with lagged values of capacity utilization and the latter varies negatively with lagged values of the former at business cycle frequency, with long-run macroeconomic activity varying positively with the wage share.

Our paper is mostly related to the interesting and pioneering contribution by Petach (2020) employing data for the 50 US states and Washington DC for the years 1974–2014 to estimate a demand-and-distribution system. In order to identify the effect of changes in the state wage share on capacity utilization and output growth in the own state through a demand equation, the author relies on variations in the statutory minimum wage across states as an instrumental variable to account for the endogeneity of the regressors. Yet claiming to lack such an instrument for capacity utilization (and presumably for output growth as well), Petach (2020) estimates a distributive equation non-parametrically. The author finds that both demand and growth are wage-led at the state level in the US economy, with the country in turn exhibiting profit-squeeze dynamics at low levels of capacity utilization and wage-squeeze dynamics at high levels.

As suggested by Roberts and Setterfield (2010), the sources of output growth are geographically confined, so that the output growth process at the regional level has an inherently spatial dimension. We would further suggest that the determinants of the functional distribution of income between wages and profits are also geographically confined, so that the functional distribution process at the regional level has an inherently spatial dimension as well. Consequently, given the prevalence of free (or almost free) movement of goods, services, labor, and capital between states of a national economy, we would argue that the proper estimation of the two-way relationship between the wage share and the level of economic activity using state-level data necessarily requires testing for the presence and significance of spatial dependence and spillover effects across states. It follows that an accurate understanding of such two-way relationship at the state-level requires taking into due consideration own-state as well as neighbouring states characteristics, the spatial connectivity structure of the states, and the strength of spatial dependence. This inevitably requires using spatial econometric methods that account for spatial dependence as well as own and neighbouring states characteristics. And an essential advantage of the data used both in Petach (2020) and in this paper is the fitting ability of regional data to exploit variations across *states* within the US, over *time*, and also across *space*, although the panel data analysis in Petach (2020) exploits only the two former dimensions of variation. In fact, the same under-exploitation also features in the existing studies of the relationship between the functional distribution of income and the level of economic activity employing national data for different panels of countries (e.g., Hartwig, 2014; Kiefer and Rada, 2015; Stockhammer and Wildauer, 2016).

This paper contributes to the empirical literature on the relationship between wage or profit share and the level of economic activity in several ways. First, our panel data investigation using regional data for the US exploits the above-mentioned three dimensions of variation, which considerably improves the reliability of the parameter estimates. Second, the econometric methods that we employ do not depend on the availability of external instruments, avoid the overestimation bias associated with the omission of relevant variables, and account for spatial autocorrelation in the disturbances. When spatial spillovers are not accounted for, the effect of a change in the wage share on the level of economic activity (and vice versa) so obtained overestimates the actual value. Third, our panel data analysis delivers estimates of persistence parameters allowing the separate evaluation of the significance, sign and magnitude of the cumulative as opposed to the immediate effect of a change in the

(2021), what has been so recently witnessed in the US is a decoupling of wage-share dynamics from the level of macroeconomic activity, the author's suggestive interpretation being that it results from the consolidation of an 'incomes policy based on fear' as an essential component of the economic policy regime that has prevailed in the last few decades.

wage share on the level of economic activity, and vice versa. In this way we are able to consistently estimate how a change in the wage share (level of economic activity) of a given US state affects the level of economic activity (wage share) in the own state and neighboring states immediately as well as cumulatively over time.

3. Econometric Methodology

3.1. Econometric models

The preceding sections compiled sound theoretical and empirical support for the need to conceive of the functional distribution of income between wages and profits and the level of economic activity as endogenously time-varying in a coupled and mutually influencing way. In effect, neglecting such a mutual endogeneity of the considered variables potentially leads to obtaining inconsistent estimates. This simultaneity bias can be corrected for by employing methods such as the two-stage least squares, instrumental variables, the GMM estimator or the OPM estimator in each estimated equation.[10] The dynamic spatial panel data model to be estimated in this paper, which is fully specified in Equations (1)–(4), is a modified and generalized version of the demand-and-distribution system specified in Nikiforos and Foley (2012), Kiefer and Rada (2015), and especially Petach (2020). For a given US state, the functional distribution of income is measured by the state wage share, while economic activity is measured by both the growth rate of the state output (or state gross domestic product, GDP) and the state capacity utilization. Given that the state-level economic activity can be a self-perpetuating process by exhibiting persistence over time, the demand equation is specified as the following dynamic model with fixed effects:

$$g_{i,t} = \rho g_{i,t-1} + \beta \psi_{i,t} + \gamma \ln T_{i,t} + \theta W \psi_{i,t} + \delta W \ln T_{i,t} + \eta_i + \tau_t + \xi_t, \tag{1}$$

$$\xi_t = \lambda_1 W \xi + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim NID(0, \sigma^2) \tag{2}$$

with $i = 1, \ldots, 49$ and $t = 1980, \ldots, 2019$, and where $g_{i,t}$ and $g_{i,t-1}$ denote the output growth rate between time t and $t+1$ and its one-lagged value for state i at time t, ρ is the autoregressive parameter that measures the degree of persistence in the state-level output growth rate, while $\psi_{i,t}$ and $lnT_{i,t}$ are non-lagged dependent explanatory variables (the wage share and the natural logarithm of the real per-capita personal taxes paid to the state government, both for state i at time t), with the respective slope coefficients represented by β and γ. The coefficient λ_1 is the scalar spatial autoregressive coefficient measuring the strength of the spatial dependence in the disturbances. While the coefficient β represents the own-state partial derivative of interest, the coefficient θ can be interpreted as the (cumulative) cross-partial derivative (or indirect effect). Following LeSage (2014), by cumulative we mean that the coefficient θ represents the sum of spillovers falling on all neighbors, thus reflecting

[10] If the number of observations is not large enough but there is no correlation between the explanatory variables and the error terms, one can then estimate all equations of interest simultaneously, thus accounting for correlation of the errors of those equations, using the seemingly unrelated regression method. This is not the case here because N is large enough and there are two sources of endogeneity: the lagged dependent variable is an explanatory variable and aggregate demand and functional distribution are simultaneously determined. Both features induce a correlation between the error terms and the covariates. Another possibility would be to estimate all equations simultaneously using the full information estimator, which typically yields lower standard errors for the estimated parameters. The downside of this alternative method is that if one equation is misspecified, it can contaminate and induce bias in all estimated parameters of the other equations.

average or typical spillovers. The state tax collection is expected to vary positively and contemporaneously with the own-state output growth rate, whereas the coefficient β is suggested by the related theoretical and empirical literature to be ambiguous in sign. Meanwhile, the W matrix is an n by n non-stochastic, non-negative spatial weight matrix, the substance of which will be properly explained shortly. Given our purpose in this paper, we employ two convenient spatial regression models allowing for *local spatial spillovers*, namely, the Spatial Lag of X (SLX) model and the Spatial Durbin Error Model (SDEM). The latter accounts simultaneously for such spillover effects and also, using the spatial autoregressive process represented by $\xi_t = \lambda_1 W\xi + \varepsilon_{i,t}$, spatial dependence in the disturbances. When $\lambda_1 = 0$ the SDEM specification reduces to the SLX model (LeSage and Pace, 2009). Given our main purpose in this paper, the main parameters of interest in Equation (1) are β and θ, the latter also being suggested by the related theoretical and empirical literature to be ambiguous in sign. An econometric point to be mentioned is that regression estimates of β and θ from the SLX model should be unbiased even when the true model is SDEM, the reason being that spatial dependence in the disturbances represents only an efficiency problem (LeSage, 2014). The time dummy parameter represented by τ_t is intended to capture national and global shocks that may affect state-level demand conditions. Note that η_i is time-invariant and plausibly correlated with regressors, accounting for any state-specific effect that is not included in the regression. When dependence exists between the effects and regressors, the assumption of strict exogeneity of the regressors is not valid (Hsiao, 2014). In this case, adding the time-invariant state-specific effects represented by η_i eliminates a potential source of omitted variable bias (Baltagi, 2013). Drawing on LeSage and Pace (2009) and LeSage (2014), further controls for omitted variable bias featuring in Equation (1) include the spatial lagged explanatory variables represented by $W\psi_{i,t}$ and $W\ln T_{i,t}$.

The W matrix is an n by n non-stochastic, non-negative spatial weight matrix whose elements represent the strength of the spatial dependence among the sample states. If state i is spatially related to state j, then $w_{ij} > 0$. Otherwise, $w_{ij} = 0$, and the diagonal elements of W are set to zero as a normalization standard. Because the row sums equal one, the variable $W\psi_{i,t}$ contains a linear combination of wage shares from related states. This variable captures the spatial dependence in $\psi_{i,t}$ and the variable $WlnT_{i,t}$ captures the spatial dependence in the real per-capita personal taxes paid in neighboring states. Given that our model includes the spatial lag of the explanatory variables, a change in a single explanatory variable in state i has both a *direct* impact (represented by β) on the own state i and an *indirect* impact (represented by θ) on other, neighboring states ($j \neq i$).

Equation (2) specifies that the unobserved composite error term $\xi_{i,t}$ can be separated into an unobserved time-invariant state-specific effect η_i, whose values correlate with explanatory variables of the model, the time dummy parameter τ_t, and an idiosyncratic remainder component $\varepsilon_{i,t}$. The correlation between covariates and the error term accounts for some potential endogeneity in order to ensure the obtaining of consistent estimates of the structural parameters ρ, β, γ, θ, δ, and σ^2 for large N and a smaller T.

Considering that the functional distribution of income between wages and profits at the US state level can also behave as a self-perpetuating process by exhibiting persistence over time, the distribution equation is specified as the following dynamic model with fixed effects:

$$\psi_{i,t} = \alpha\psi_{i,t-1} + \kappa g_{i,t} + \phi \ln T_{i,t} + \pi W g_{i,t} + \omega W \ln T_{i,t} + \mu_i + \zeta_t + \nu_t, \tag{3}$$

$$\nu_t = \lambda_2 W\nu + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim NID(0, \sigma^2) \tag{4}$$

with $i = 1, \dots, 49$ and $t = 1980, \dots, 2019$, and where $\psi_{i,t}$ and $\psi_{i,t-1}$ denote the wage share and its one lagged value for state i at time t, α is an autoregressive parameter measuring the degree of persistence in the state-level wage share, while $g_{i,t}$ and $lnT_{i,t}$ are non-lagged dependent explanatory variables (the state-level output growth rate and the natural logarithm of the real per-capita personal taxes collected by the state government, both for state i at time t), with the respective slope coefficients being represented by κ and ϕ. The coefficient λ_2 is the scalar spatial autoregressive coefficient measuring the strength of the spatial dependence in the disturbances. How the state-level wage share varies with tax revenues in the own state is likely to depend, inter alia, on the degree of regressivity of the state tax system, whereas the sign of the coefficient κ is suggested by the related theoretical and empirical literature to be ambiguous. Similarly to Equation (1), the W matrix in Equation (3) denotes an n by n non-stochastic, non-negative spatial weight matrix whose elements represent the strength of the spatial dependence among the sample states. When $\lambda_2 = 0$ the Spatial Durbin Error Model (SDEM) reduces to the Spatial Lag of X (SLX) model, with the former accounting for spatial dependence in the disturbances by means of the spatial autoregressive process represented by $v_t = \lambda_2 W v + \varepsilon_{i,t}$. Therefore, the main parameters of interest in Equation (3) are κ and π, which represent the direct impact of a change in the state output growth rate on the wage share in the own state and the indirect impact of a change in the output growth rate in neighboring states on the wage share in the considered state. Our interpretation of the related theoretical and empirical literature suggests us to conjecture that the sign of the parameter π is likely to be strictly positive. Meanwhile, the time dummy parameter represented by ζ_t is intended to capture national and global conditions that may affect the functional distribution of income in the own state. Analogously to η_i in Equation (2), the time-invariant state-specific effects μ_i are included in Equation (4) to eliminate a potential source of omitted variable bias.

An appealing feature of the structural model specification adopted in this paper, in which an endogenous variable appears as explanatory in the right-hand side of Equations (1) and (3), is that it avoids the use of a long list of exogenous variables as regressors (Hall and Jones, 1999), which leads to more efficient parameter estimates (LeSage and Pace, 2009). Therefore, our approach is quite different from the literature on growth convergence across countries or across states in a given country, which uses reduced forms and needs to incorporate a long list of regressors all assumed to be exogenous, thus raising the dispersion of parameter estimates and creating uncertainty and inefficiency, as in the case for example of Sachs and Warner (1997).

The reparametrization approach recommended by Lancaster (2002) generates a conditional likelihood estimator which is exact and consistent, yielding unbiased and efficient estimates of the structural parameters α, κ, ϕ, π, ω, and σ^2. A key property of the OPM estimator is that even when the autoregressive parameter is close or even equal to one (i.e., a non-stationary dynamic linear model in which $\alpha = 1$ or $\rho = 1$ in Equations (1) and (3)), it still yields consistent and unbiased parameter estimates. This important advantage results in the OPM estimator outperforming both the maximum likelihood and the GMM estimators.

In the dynamic panel model specification in Equation (1), the coefficients β and θ indicate the immediate effect of a change in the wage share on the output growth rate. Yet the ultimate effect of a change in the wage share on the output growth rate also depends on the extent to which future values of the output growth rate are causally affected by the current value of the own output growth rate, as indicated by the persistence parameter ρ. It follows that the ultimate effect of a change in the wage share on the output growth rate when the latter is stationary ($\rho < 1$) is given by $\beta/(1-\rho)$ and $\theta/(1-\rho)$, which constitute the *cumulative* effect of the wage share on the output growth rate. Similarly, the coefficients κ and π in Equation (3) for the functional distribution of income specify the immediate effect of a change in the output growth rate on the wage share. But the ultimate effect of a change in the output growth rate on the wage share is also determined by the extent to which future values of the wage share are causally affected by the current value of the own wage share, as indicated by the persistence parameter α. Therefore, the ultimate effect of a change in the output growth rate on the wage share when the latter is stationary ($\alpha < 1$) is represented by $\kappa/(1-\alpha)$ and $\pi/(1-\alpha)$, which express the *cumulative* effect of the output growth rate on the wage share.

Another appealing feature of our dynamic panel model specification in Equations (1)-(4) is its ability to simultaneously control for unobserved heterogeneities that are constant over time (through η_i and μ_i) and for unobserved factors that are time-varying and idiosyncratic (through $\varepsilon_{i,t}$). In the present case it seems reasonable to expect that unobserved characteristics of the states (as captured by η_i and μ_i) are correlated with their ability to collect taxes (as captured by $lnT_{i,t}$). Better institutional design and more skilled officials, for instance, are likely to improve tax collection. Such unobserved and observed factors are likely to affect both economic activity and the wage share at the state level, even when individually they are subject to time-varying and idiosyncratic random shocks (as captured by $\varepsilon_{i,t}$). Furthermore, the term η_i in Equation (2) can also capture the unobserved level of technology of a given state (Caselli et al., 1996), which may be correlated with the state wage share. Similarly, the term μ_i in Equation (4) can also capture unobserved technological factors of a given state, which may be correlated with the state economic activity as measured by the output growth rate. In addition, national and even global trends likely impact on the dependent variables at the state level, as captured by the term τ_t in Equation (2) and the term ζ_t in Equation (4). We employ the spatial Hausman test statistic to verify whether the unobserved effects η_i and μ_i correlate with the respective explanatory variables. When such a correlation is absent, the random-effects model should be preferred; otherwise, a fixed-effects model is adopted.

3.2. Data description

The panel of data employed in this paper was compiled from three sources. Data on state-level output, wage share, and tax revenue were all obtained from the Bureau of Economic Analysis (BEA) Regional Economic Accounts (`www.bea.gov`). The wage share is computed as the ratio of wage and salary compensation to the sum of wage and salary compensation and the gross operating surplus of the business sector at the state level. We employ two measures of state-level economic activity. The first is the state-level output growth rate between time t and $t+1$. As mentioned in the preceding sections, there is theoretical and empirical support for conceiving of the wage share and the output growth rate as endogenously time-varying in a coupled and mutually influencing fashion. Also, the output growth rate is conveniently not a measure obtained through some statistical transformation, which is typically the case in regard to the different measures of capacity utilization. Nonetheless, following the related literature, the other measure of state-level economic activity used in our empirical analysis is the actual capacity utilization, which is calculated as the ratio of real output to trend output, the latter computed by applying the Hamilton (2018) filter.

The second source of data is the Bureau of Labor Statistics (`www.bls.gov`), from which we obtained the Consumer Price Index for all urban consumers that we used to convert to real terms all nominal variables. The third source of data is the US Census Bureau (`www.census.gov/geographies/mapping-files`), from which we drew the shapefiles with complete geographical information for the sample states (this sample is listed on Table 4 in Appendix A). As in the studies using spatial panel data for the US states in Korniotis (2010) and Burnett et al. (2013), we considered only the adjoining US states (that is, not including Alaska, Hawaii, and Puerto Rico). However, as data are also available for the Distric of Columbia, we differ from those studies by also including the latter, so that our sample includes all the regional units comprising what is known as the conterminous (or contiguous) US. Therefore, we have panel data with 49 cross-sectional units observed over the years between 1980 and 2019, which results in 1960 observations ($N * T = 49 * 40 = 1960$) varying across our sample US states, and also across time. In order to more clearly illustrate the change in the spatial pattern of the endogenous variables of interest between the endpoints of our sample data, in Appendix A we depict the densities of the wage share and output growth rate estimated for the years 1980 and 2019 (Figure 1) and state-level choropleth maps of the wage share for the same years (Figure 2).

Meanwhile, some illustrative descriptive statistics for the endogenous variables are presented in Table 5 in Appendix A, from which we can draw a number of interesting observations. First, between the endpoints of our data for the sample states, the mean output growth and capacity utilization rates increased (with the former actually increasing considerably, from 0.04% to 1.93%), whereas the mean wage share decreased about 7 percentage points. Second, the mean output growth rate (wage share) below the sample median rose (fell) from -2.41% (54.53%) in 1980 to 1.05% (49.65%) in 2019, while the respective figures for above the sample median were 2.39% (64.73%) and 2.76% (55.59%). Third, as indicated by the figures for the first quartile of the sample distributions (Q1, the point at which 25% of the sample states show lower figures for the respective endogenous variable and 75% show higher), the output growth rate (wage share) in (around) 13 states was at most -1.68% (55.78%) in 1980 and at most 1.04% (50.19%) in 2019. Meanwhile, the respective figures for the third quartile of the sample distributions (Q3, the point at which 75% of the sample states show lower figures for the respective endogenous variable and 25% show higher) were 2.13% (63.32%) in 1980 and 2.72% (54.98%) in 2019. Fourth, the dispersion of the distribution each endogenous variable across the sample states fell between the endpoints of our data, as indicated by the decline in both the interquartile range and the coefficient of variation (see also Figures 1 and 2 in Appendix A).

4. Results and Discussion

As an initial exploratory analysis, we proceed similarly to Petach (2020) by setting $\theta = \delta = 0$ in Equation (1). Our purpose is to propely examine how important is the issue of endogeneity in our data sample. In the context of the present paper, such parametric assumptions imply that we are not controlling for spatial dependence and spillovers across the sample states. Nonetheless, we employ two standard measures of state-level economic activity as dependent variables: the output growth rate between time t and $t+1$, denoted by $g_{i,t}$, and the current full value (instead of the cyclical component) of capacity utilization, denoted by $u_{i,t}$.

This initial exploratory analysis allows us both to appropriately address and deal with the important issue of the potential endogeneity involved in our estimations and to compare our results with those obtained in mostly related studies. In effect, in order to make reliable inferences from the state-level panel data employed in our estimations, we need to consider the following issues: (*i*) the potential endogeneity of the regressors and the additional potential endogeneity caused by including the dependent variable as predictor; (*ii*) the likely correlation between the unobserved effects and the explanatory variables; and (*iii*) the likely existence of spatial dependence in the data, meaning simply that the value of a variable in a given state is likely related to its value in nearby or neighboring states, with the strength of such a dependence decreasing with distance. We deal with issue (*i*) by employing methods provided in Arellano and Bond (1991) and Lancaster (2002), and with issue (*ii*) by making use of the spatial Hausman statistic to test for the hypothesis of independence between the unobserved effects and the explanatory variables proposed by Mutl and Pfaffermayr (2011). The spatial Hausman test statistic extends the original Hausman test proposed by Hausman (1978) to a spatial setting. Meanwhile, we employ the Lagrange Multiplier (LM) test statistic provided in Anselin et al. (2008) to address issue (*iii*).

In order to control for the potential simultaneity bias involved in the dynamic relationship between the state-level values of economic activity and the wage share, we use the efficient instrumental-variable (IV) estimator devised by Breusch et al. (1989), which accounts for the correlation between the error term and the covariates, thus controlling for endogeneity. We then evaluate how much the parameter estimates change when we apply the OLS estimator, which assumes the absence of correlation between the error term and the covariates, without control for endogenous regressors.

As reported in Table 1 in boldface, the estimate of the parameter β in Equation (1) differs in both sign and magnitude between the OLS and the IV estimations, suggesting the existence of endogeneity caused by simultaneity between the wage share and output growth in the data. Assuming that the state wage share and tax revenues collected by the state are exogenous, the OLS estimation yielding that the estimate of β is negative and significant indicates that (at a regional level) the US features profit-led demand and output growth. However, when we account for the simultaneity between the state-level economic activity (measured by either output growth or capacity utilization) and wage share with the IV estimation yielding that the estimate of β is positive instead and significant, the US features wage-led demand and output growth at a regional level. In effect, the spatial Hausman test statistic (p-values equal to 0.0000 and 0.0003) significantly rejects the assumption of independence between unobserved effects and regressors at the 1% level for the rates of output growth and capacity utilization. Thus, the pooling ordinary least squares (POLS) parameter estimates are inconsistent and biased, and we need a model with correlated fixed effects for obtaining consistent estimates. Note that the value of the estimate of β (0.408) in the last column of Table 1 roughly corresponds to the estimate of the same parameter displayed in Table 3 in Petach (2020), according to which demand is strongly wage-led at the US state level: a 10 percentage-point increase in the wage share would correspond to a 4.7 percentage-point increase in capacity utilization. The two results are comparable because we use the same dependent and explanatory variables and the same estimation methods used by Petach (2020), with differences in the sample states and time periods explaining the difference between the estimates (recall that our sample does not include Hawaii and Alaska). The key issue here is that, in many empirical applications, neglecting spatial spillovers when they are present in the data may in fact yield an overestimated effect in the parameter estimates (Baltagi and Rokicki, 2014; LeSage and Pace, 2009).

Table 1. OLS and IV parameter estimates for a **restricted demand equation** (Equation (1) with $\theta = \delta = 0$).

Estimates	***POLS*** $(g_{i,t})$	***IV*** $(g_{i,t})$	***POLS*** $(u_{i,t})$	***IV*** $(u_{i,t})$
$\hat{\rho}$	0.348***	0.846***	0.488***	0.229***
	(16.423)	(8.628)	(24.643)	(4.498)
$\hat{\beta}$	**-0.042*****	**0.097*****	**-0.042*****	**0.408*****
	(-3.736)	(2.276)	(-2.968)	(8.556)
$\hat{\gamma}$	0.006***	-0.049***	0.007***	-0.039***
	(3.190)	(-4.397)	(2.986)	(-2.996)
N	1911	1862	1911	1862
State FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Spatial Hausman test statistic	**86.010*****	—	**52.703*****	—
	[0.0000]	—	[0.0003]	—
Robust LM statistic (W_q)	**36.735*****	—	**10.995*****	—
	[0.0000]	—	[0.0000]	—

Notes: (***), (**), (*) denote significant at the 1%, 5%, and 10% levels, respectively. Following Anselin et al. (2008), we employ geographic contiguity as criterion to specify the matrix W. The matrix W_q is the queen contiguity (LeSage and Pace, 2009; Anselin et al., 2008). Using the geographic contiguity criterion, the average number of links across states is four, the minimum is one, and the maximum is eight. The values of the t-statistic are within parentheses. The p-values are in square brackets. Based on Baltagi and Rokicki (2014), for each of the following variables we use its value in the previous year as instrument: $g_{i,t-1}$, $u_{i,t-1}$, $\psi_{i,t}$, and $ln(T_{i,t})$. The null hypothesis of the locally robust LM test is the absence of spatial autocorrelation in the disturbances.

Drawing on Anselin et al. (2008), Table 1 also displays in boldface the locally robust LM test for spatial error dependence. In the spatial econometrics literature, the spatial weights matrix W is used to measure the cross-sectional dependence across spatial units (Anselin et al., 2008).[11] Note that the p-value of the LM statistic for both measures of economic activity (output growth and capacity utilization) indicate strong evidence of spatial autocorrelation at the 1% level. This then implies that a suitable spatial model should be employed to make our demand-and-distribution inferences of interest from the sample data.[12]

The Instrumental Variable (IV) methodology predominates in non-experimental contexts employing not strictly exogenous regressors. However, its main drawbacks include heteroscedasticity and the frequent unavailability of suitably exogenous external instruments. Although heteroscedasticity does not compromise the consistency of the IV coefficient estimates, the standard errors become inconsistent, thus preventing valid inference (Baum et al., 2003). A commonly used procedure when facing heteroscedasticity of unknown form, and without relying on external instruments for dealing with potentially endogenous regressors, is to employ the generalized method of moments (GMM) (Hansen, 1982; Arellano and Bond, 1991; Baum et al., 2003).

We use the one-step GMM estimator proposed by Arellano and Bond (1991). This estimation procedure delivers consistent estimates with stationary dynamic panel data featuring endogenous regressors and has been less sensitive to the problem of instrument proliferation that plagues the alternative

[11] Contiguity means that two spatial units share a common border of non-zero length. In analogy to the moves allowed for one of or even the most powerful piece on a chessboard, the queen criterion defines neighbors as spatial units sharing a common edge or vertex. Figure 3 in Appendix A provides an example of the neighbor structure represented by the queen contiguity criterion.

[12] In fact, we also apply the spatial Hausman test and perform the spatial autocorrelation test in the residuals of the distribution equation (3) with $\pi = \omega = 0$. The respective results are reported in Table 6 in Appendix A. As in the case of the restricted demand equation with results reported in Table 1, the spatial Hausman test statistic indicates that a model with correlated fixed effects is needed, while the conditional LM test provides strong evidence of spatial autocorrelation.

system GMM estimation (Roodman, 2009).[13] The one-step GMM estimator proposed by Arellano and Bond (1991) also presents a better performance in finite samples when compared to the two-step GMM estimator (Arellano and Bond, 1991; Bond, 2002; Windmeijer, 2005). Meanwhile, our chosen dynamic spatial lag of X (SLX) model, a regression model extended to include explanatory variables observed on neighboring cross-sectional units, yields consistent and unbiased parameter estimates even when the regressors are endogenous (Vega and Elhorst, 2015; Baltagi and Rokicki, 2014). Our main motivation for choosing the dynamic SLX regression model lies in the theoretical considerations advanced by LeSage (2014) and especially Vega and Elhorst (2015), who consider the SLX model as a quite reliable procedure to estimate spatial effects, apply significance tests, and interpret the direct and indirect (spillover) effects. In fact, when spatial spillovers are significant, neglecting such indirect effects in regression models leads to estimates that suffer from omitted variable bias (LeSage and Pace, 2009; LeSage, 2014). As elaborated in Vega and Elhorst (2015), the SLX model is the simplest spatial econometric model yielding flexible spatial spillover effects and the easiest one to parameterize the spatial weights matrix W representing the spatial disposition of the cross-sectional units in the sample data. According to Vega and Elhorst (2015), a strong positive feature of the SLX model is that it does not require the imposition of a priori restrictions on the ratio between the direct effects and spillover effects, which is a limitation of other alternative spatial econometric models.

In both the demand and distribution equations (1) and (3), we use the output growth rate between time t and $t+1$ as the main measure of economic activity insofar as such a variable is not computed through some form of statistical transformation or filtering. Besides, as mentioned earlier, there is theoretical and empirical support for conceiving of the wage share and the output growth rate as endogenously time-varying in a coupled and mutually influencing way. But in Appendix B we report the results for the demand and distribution equations (1) and (3) using the full value of capacity utilization, for which calculation we employ the Hamilton (2018) filter to extract the trend output. According to Baltagi (2013), in studies using macro panels of countries or regions with long time series data the stationarity prerequisite must be satisfied. Meanwhile, the issue of cross-sectional dependence in the data becomes essential in that it affects inference in unit root tests for panels. The OPM estimator does not depend on the stationarity of the data to yield consistent estimates, but the GMM estimator does (Bond, 2002). Therefore, we apply a test for unit root which is robust to cross-sectional dependence proposed by Chang (2002), the results of which are reported in Table 7 in Appendix A. This unit root test for panels with cross-sectional dependency rejects the unit root hypothesis at 1%, which suggest that the data can be considered stationary overall. While frequentist methods yield point estimates for parameters of interest for the conditional mean, the method employed by the OPM estimator, instead of providing a 'single true' effect, yields a distribution of possible values for the structural parameters. More precisely, instead of providing single estimates of the 'true effect', this Bayesian inference approach computes the probability of different effects given the observed data, thus yielding a distribution of possible values for the parameters, which is called the posterior distribution. We use the median of the posterior distribution of the parameters for inference. When employing median of the posterior drawns for inferencing, Makowski et al. (2019) recommends a large sample size to compute the equal-tailed credible intervals of 95% to measure the uncertainty associated with the estimation. The Bayesian framework considerably improves the reliability and interpretability of confidence intervals: given the observed data, the effect has 95% probability of falling within such a range. Table

[13] The one-step GMM estimator proposed by Arellano and Bond (1991) employs only lagged levels of the variables of interest as instruments. In contrast, the alternative system GMM estimator uses both lagged levels and lagged differences of the variables of interest as instruments, thus potentially giving rise to instrument proliferation.

2 displays the parameter estimates for the unrestricted demand specification in Equation (1) using the dynamic SLX model, with salient results shown in boldface. Such parameter estimates were generated by applying the methods proposed by Arellano and Bond (1991) and Lancaster (2002), accounting for correlated fixed effects and spatial autocorrelation. We performed parameter estimations for both one-way and two-way correlated fixed effects models (Baltagi, 2013).

We present the results for the POLS estimator only for comparison purposes, given that the spatial Hausman test statistic indicates that the respective estimates are biased and inconsistent. As regards specification checks, note that the stationarity condition ($\rho < 1$) is satisfied in all specifications, while the Sargan test statistic ($\chi^2 = 49$) for overidentification does not reject the validity of the instruments (p-value is 1.000). Besides, we cannot reject the null of the absence of second-order serial correlation in the first-difference residuals (p-value of the m_2 statistic is 0.4574), which indicates that the parameter estimates are consistent (Arellano and Bond, 1991). And the p-values of the Wald test for time and state fixed effects being both equal to 0.0000 confirm that we have to estimate the complete model with two-way fixed effects owing to the rejection of the null of pooling and absence of time effects at the 1% level.

In order to carry out a more thorough evaluation of both the spillover effects and the spatial pattern of propagation of shocks across the sample US states, the last column of Table 2 presents estimation results of the Spatial Durbin Error Model (SDEM). This model specification subsumes the SLX and the Spatial Error models as special cases. The SDEM reduces to the to SLX when $\lambda_1 = 0$, the substance of which is that there is no evidence of spatial dependence in the disturbances. The SDEM delivers consistent and more efficient estimates than all the other model specifications employed in the present paper because the sample data significantly reject the assumptions that $\lambda_1 = 0$ and $\lambda_2 = 0$ in all dynamic spatial panel model specifications. The M-estimation method for dynamic spatial panel models proposed by Yang (2018) is free from the specification of the distribution of the initial observations and robust against the nonnormality of the errors. Regarding the different model specifications in Table 2, in all cases the static SLX model does not describe the considered sample data because the latter significantly reject the assumption that $\rho = 0$ for all model specifications at the 1% and 5% levels. More importantly, considering that the sample data significantly reject the assumption that $\lambda_1 = 0$ at the 1% level, it follows that the best model specification is the SDEM, given that it accounts simultaneously for spatial effects in the explanatory variables and disturbances. The other model specifications in Table 2 are simpler versions accounting only for spatial dependence in the explanatory variables.

Table 2. Parameter estimates for the **unrestricted demand equation** (Equation (1) with $\theta \neq \delta \neq 0$) using the dynamic SLX model and the dynamic Spatial Durbin Error model - dependent variable: $g_{i,t}$; distribution explanatory variable: $\psi_{i,t}$.

Estimates	***POLS***	***GMM***	***OPM***	***OPM***	***SDEM***
$\hat{\rho}$	0.346***	0.145***	0.286**	0.291**	0.167***
	(16.290)	(3.623)	[0.240;0.332]	[0.244;0.338]	(3.888)
$\hat{\beta}$	-0.042***	**-0.212*****	**-0.137****	**-0.131****	**-0.167*****
	(-3.371)	(-3.129)	[-0.203; -0.073]	[-0.196;-0.066]	(-4.602)
$\hat{\gamma}$	0.008***	0.103***	0.049**	0.051**	0.068***
	(3.621)	(5.381)	[0.031;0.067]	[0.032;0.069]	(4.978)
$\hat{\theta}$	0.010	**0.446*****	**0.236****	**0.212****	**0.185*****
	(0.443)	(4.158)	[0.152;0.323]	[0.124;0.298]	(2.944)
$\hat{\delta}$	-0.006*	0.012	-0.051**	-0.052**	-0.004
	(-1.790)	(0.511)	[-0.070;-0.032]	[-0.071;-0.033]	(-0.288)
$\widehat{\lambda_1}$	—	—	—	—	**0.330*****
					(9.726)
LR_β	—	**-0.248**	**-0.192****	**-0.185****	**-0.200**
		—	[-0.284;-0.102]	[-0.277;-0.093]	—
LR_θ	—	**0.521**	**0.331****	**0.299****	**0.222**
	—	—	[0.216; 0.449]	[0.177;0.417]	—
Deviance information criterion	—	—	-36233.89	**-36246.53**	—
Wald test for coefficients	—	**[0.0000]**	—	—	—
Wald test for time dummies	—	**[0.0000]**	—	—	—
N	1911	1960	1960	1960	1960
State FE	**No**	**Yes**	**Yes**	**Yes**	**Yes**
Time FE	Yes	Yes	**No**	**Yes**	**Yes**
Sargan test (χ^2-statistic)		49	—	—	—
Sargan test (p-value)		[1.000]	—	—	—
m_2 (p-value)	—	**[0.4574]**	—	—	—

Notes: (***), (**), (*) denote significant at the 1%, 5%, and 10% levels, respectively. The t- and z-statistic are within parentheses. The p-values and the lower and upper bounds of credible intervals are within square brackets. We use the one-step GMM estimator proposed by Arellano and Bond (1991) treating $g_{i,t}$, $\psi_{i,t}$ and $ln(T_{i,t})$ as endogenous. In order to control for the problem of proliferation of instruments, we follow the advice in Roodman (2009) in using only lagged values from two to nine of the same explanatory variables as valid GMM instruments. The Sargan test statistic has χ^2 distribution regardless of heteroscedasticity. We use robust standard errors from Windmeijer (2005) for GMM estimates. The equal-tailed 95% credible intervals for the OPM estimates are based on 10000 Monte Carlo samples. Statistical significance is achieved when the 95% credible intervals exclude the value of zero. We use the queen contiguity matrix to obtain the spatial lag of $\psi_{i,t}$ and $ln(T_{i,t})$ (LeSage and Pace, 2009; Anselin et al., 2008). The deviance information criterion (DIC) is a generalization of the Akaike information criterion (AIC), and the smaller the DIC, the better the model fit. And LR_β and LR_θ measure the cumulative direct effect and the cumulative spillover effect of the own-state wage share on the own-state output growth rate and the output growth rate averaged over neighboring states, respectively.

Our results in Table 2 are directly comparable to those obtained in the related study carried out in Petach (2020). In the latter, as reported in the last column of its Table 4, the impact of changes in the state-level wage share in time t on the growth rate of output in the own state between t and $t+1$ is significant at the 1% level and positive and equal to 0.531 (considering the highest p-value of the Sargan test statistic, which is the one for the more inclusive specification estimated in the paper). However, our GMM parameter estimates suggest that the direct effect is significant at the 1% level but negative and equal to -0.212. This estimated magnitude of the parameter β in Equation (1) suggests that a 10 percentage-point increase in the wage share would correspond to a 2.1 percentage-point average decline in the growth rate of output at the state level. We also found that the indirect (spillover) effect from changes in the state-level wage share in time t to the growth rate of output in the neighbouring states between t and $t+1$ is significant at the 1% level and positive with a value equal to 0.446. This estimated magnitude of the parameter θ in Equation (1) suggests that a 10 percentage-point increase in the wage share in a given state, despite corresponding to a 2.1 percentage-point average decline in the growth rate of output in the own state, would correspond to a 4.5 percentage-point average increase in the growth rate of output in the neighbouring states. Therefore, although a change in the own-state wage share impacts negatively on the own-state output growth rate, it also impacts positively on the output growth rate in the neighbouring states, with the former direct effect being lower in absolute magnitude than the latter indirect effect. This interpretation of the indirect impact estimate corresponds to what LeSage and Pace (2009) label as the *average total impact from an observation*. The alternative interpretation, to which LeSage and Pace (2009) refer as the *average total impact to an observation*, reflects how a change in the wage share in all the neighbouring states by some constant amount impacts on the output growth rate in a typical state. It follows that the GMM estimated parameter θ in Equation (1) also suggests that a 10 percentage-point average increase in the wage share in the neighbouring states would correspond to a 4.5 percentage-point average increase in the growth rate of output in a typical state. Meanwhile, as expected, the per-capita tax collection variable is positively related to the output growth rate at the state level, with an estimated magnitude of the parameter γ in Equation (1) equal to 0.103 and significant at the 1% level.

Considering now the fourth and fifth columns of Table 2, similarly to the GMM estimator, the OPM estimator with two-way fixed effects in the fifth column also better describe the sample data, given that it features the smallest vale of the DIC (-36246.53). Employing 95% credible intervals, the estimates yielded by the OPM estimator in the fifth column for the parameters of interest (β, γ, and θ) are qualitatively the same as those obtained with the GMM estimator. Indeed, the OPM estimator interestingly allows estimating the magnitude and significance of both the immediate and the cumulative direct and indirect effects of changes in the wage share on the growth rate of output (and using the two interpretations of the indirect impact estimate proposed in LeSage and Pace (2009)). This is a further analyticallly informative differentiation that has not been explored in the related empirical literature that also uses a dynamic panel model specification, as it is the case for example in Kiefer and Rada (2015) and Petach (2020).

Note from the fifth column of Table 2 that the magnitude of the positive cumulative spillover effect ($LR_\theta = 0.299$) is greater than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\beta = -0.185$), and both are significant at the 5% level and higher (in absolute value) than their counterparts measuring the respective immediate effects ($\hat{\theta} = 0.212$ and $\hat{\beta} = -0.131$). Thus, a 10 percentage-point increase in the wage share in a given state, despite corresponding to a median cumulative decline in the growth rate of output in the own state of about 1.8 percentage-point, would correspond to a median cumulative increase in the output growth rate in the neighbouring states of about 3.0 percentage-point. Or, using the alternative interpretation of the indirect impact estimate proposed in LeSage and Pace (2009), a 10 percentage-point median increase in the wage share in the neighbouring states would correspond to a median cumulative increase in the output growth rate in a typical state of about 3.0 percentage-point. Notice that the same conclusions apply to the estimates obtained with the GMM estimator, as the magnitudes of the cumulative direct and indirect effects yielded by that estimator are $LR_\beta = -0.248$ and $LR_\theta = 0.521$, respectively. More importantly, given that the sample data significantly reject the assumption that $\lambda_1 = 0$ at the 1% level, the key qualitative results reported in Table 2 that were discussed above are also supported by the more complete SDEM model, the respective results for which appear in the last column of the same table. In fact, the SDEM parameter estimates suggest that a 10 percentage-point increase in the wage share in a typical state would correspond to roughly a 1.7 percentage-point average fall in the output growth rate in the own state, but to roughly a 1.8 percentage-point average rise in the rate of output growth in the neighbouring states. Besides, the magnitude of the positive cumulative spillover effect ($LR_\theta = 0.22$) is slightly higher than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\beta = -0.2$), and both have the same sign as and are higher (in absolute value) than their counterparts measuring the respective effects ($\hat{\theta} = 0.185$ and $\hat{\beta} = -0.167$)

As noted earlier, we also use the full value of the rate of capacity utilization to measure the state-level economic activity, and the respective results are displayed in Table 8 in Appendix B. We present the results for the POLS estimator only for comparison purposes, given that the Hausman test statistic indicates that the respective estimates are biased and inconsistent, as reported in Table 1. Concerning specification checks, the stationarity condition ($\rho < 1$) is satisfied in all specifications, while the Sargan test statistic for overidentification does not reject the validity of the instruments (p-value is 1.000). However, data significantly reject the null of the absence of second-order serial correlation (p-value of the m_2 statistic is 0.0000), so that the GMM estimates are not consistent and we are left with the OPM estimates. Meanwhile, the p-values of the Wald test for time and state fixed effects being both equal to 0.0000 confirm that we have to estimate the complete model with two-way fixed effects owing to the rejection of the null of pooling and absence of time effects at the 1% level.

The OPM estimates for the main parameters of interest in Table 8 can also be directly compared to those obtained in Petach (2020) with the author's preferred identification strategy (which employs state minimum-wage instruments and a lagged value of the state wage share as an additional instrument). In Petach (2020), as reported in its Table 3, a 10 percentage-point increase in the wage share is found to correspond to a 2.3 percentage-point (average) increase in capacity utilization, which means that the latter is wage-led at the state level for the US. However, the OPM parameter estimates suggest that the same direct effect is negative: a 10 percentage-point increase in the wage share would correspond to roughly a 1.7 percentage-point (median) decline in capacity utilization at the state level. Meanwhile, we also found that the indirect (spillover) effect from changes in the state-level wage share to capacity utilization in the neighbouring states is positive: a 10 percentage-point increase in the wage share in a given state, despite corresponding to about a 1.7 percentage-point (median) decline in capacity utilization in the own state, would correspond to roughly a 1.3 percentage-point (median) increase in capacity utilization in the neighbouring states. Therefore, although a change in the own-state wage share impacts negatively on the own-state capacity utilization, it also impacts positively on capacity utilization in the neighbouring states, with the former direct effect being greater in absolute magnitude than the latter indirect effect. As in the case of Table 2, the OPM estimated parameter θ in Table 8 also suggests that a 10 percentage-point increase in the wage share in the neighbouring states would correspond to a 1.3 percentage-point (median) increase in capacity utilization in a typical state. Meanwhile, as expected, the per-capita tax collection variable is positively related to capacity utilization at the state level, with an estimated magnitude of the parameter γ in Table 8 equal to 0.038 and significant at the 5% level.

Note from the fourth column of Table 8 that the magnitude of the positive cumulative spillover effect ($LR_\theta = 0.251$) is lower than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\beta = -0.340$), and both are significant at the 5% level and higher (in absolute value) than their counterparts measuring the respective immediate effects ($\hat{\theta} = 0.128$ and $\hat{\beta} = -0.172$). It follows that a 10 percentage-point increase in the wage share in a given state, despite corresponding to a median cumulative decline in capacity utilization in the own state of about 3.4 percentage-point, would correspond to a median cumulative increase in capacity utilization in the neighbouring states of about 2.5 percentage-point. Or, using once again the alternative interpretation of the indirect effect proposed in LeSage and Pace (2009), a 10 percentage-point increase in the wage share in the neighbouring states would correspond to a median cumulative increase in capacity utilization in a typical state of about 2.5 percentage-point. The above qualitative conclusions equally apply to the estimates obtained with the SDEM model, the results for which appear in the last column of Table 8 with all immediate effects being significant at the 1% level. The SDEM estimates suggest that a 10 percentage-point increase in the wage share in a typical state would correspond to roughly a 2.0 percentage-point average fall in capacity utilization in the own state, but to roughly a 1.4 percentage-point average increase in capacity utilization in the neighbouring states. Moreover, the magnitude of the positive cumulative spillover effect ($LR_\theta = 0.254$) is lower than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\beta = -0.353$), and both have the same sign as and are higher (in absolute value) than their counterparts measuring the respective immediate effects ($\hat{\theta} = 0.141$ and $\hat{\beta} = -0.196$)

Table 3 displays the parameter estimates for the unrestricted distribution specification in Equation (3) using the dynamic SLX and SDEM models, with salient results shown in boldface. Such parameter estimates were also obtained by applying the methods proposed by Arellano and Bond (1991) and Lancaster (2002), which properly account for correlated fixed effects and spatial autocorrelation. We performed parameter estimations for both one-way and two-way correlated fixed effects models (Baltagi, 2013). We present the results for the POLS estimator only for comparison purposes, given that the Hausman test statistic indicates that the respective estimates are biased and inconsistent, as reported in Table 6 in Appendix A. As regards specification checks, the stationarity condition ($\alpha < 1$) is satisfied in all specifications, while the Sargan test statistic ($\chi^2 = 49$) for overidentification does not reject the validity of the instruments (p-value is 1.000). We cannot reject the null of the absence of second-order serial correlation at the 1% level (p-value of the m_2 statistic is 0.010), so that the GMM estimates are not consistent. As a result, we are left with the OPM and the SDEM parameter estimates in the last three columns. As discussed shortly, consistent GMM estimates for the unrestricted distribution specification in Equation (3) employing the dynamic SLX model are obtained when the full value of capacity utilization is used as the economic activity explanatory variable, as reported in Table 9 in Appendix B. In any case, note that the p-values of the Wald test for time and state fixed effects being both equal to 0.0000 in Table 3 confirm that we have to estimate the complete model with two-way fixed effects owing to the rejection of the null of pooling and absence of time effects at the 1% level. Meanwhile, the OPM estimator with two-way fixed effects in the penultimate column is the one better describing the sample data, given that it features the smallest DIC (-48167.47).

As regards the different model specifications in Table 3, data significantly reject the assumption that $\alpha = 0$ for all model specifications at the 1% and 5% levels. This result indicates the need for a dynamic SLX model. More importantly, considering that the sample data significantly reject the assumption that $\lambda_2 = 0$ at the 1% level, it follows that the best model specification is again the SDEM, given that it accounts simultaneously for significant spatial effects in the explanatory variables and disturbances. While accounting for spatial dependence in the explanatory variables, the other model specifications in Table 3 ignore statistically significant spatial autocorrelation in the disturbances.

Table 3. Parameter estimates for the **unrestricted distribution equation** (Equation (3) with $\pi \neq \omega \neq 0$) using the dynamic SLX model and the dynamic Spatial Durbin Error model - dependent variable: $\psi_{i,t}$; economic activity explanatory variable: $g_{i,t}$.

Estimates	***POLS***	***GMM***	***OPM***	***OPM***	***SDEM***
$\hat{\alpha}$	0.959***	0.868***	0.992**	0.993**	0.917***
	(202.274)	(45.404)	[0.977; 0.995]	[0.983;0.995]	(54.243)
$\hat{\kappa}$	**-0.259*****	**-0.277*****	**-0.286****	**-0.284****	**-0.294*****
	(-26.228)	(-13.706)	[-0.310; -0.263]	[-0.307; -0.261]	(-18.993)
$\hat{\phi}$	0.003***	0.033***	0.024**	0.024**	0.024***
	(3.396)	(3.750)	[0.017; 0.031]	[0.018;0.031]	(6.556)
$\hat{\pi}$	**0.111*****	**0.118*****	**0.193****	**0.189****	**0.082*****
	(6.967)	(4.709)	[0.164; 0.222]	[0.160;0.217]	(3.266)
$\hat{\omega}$	-0.003**	-0.019*	-0.010**	-0.012**	-0.003
	(-2.383)	(-1.696)	[-0.018; -0.003]	[-0.019;-0.005]	(-0.421)
$\widehat{\lambda_2}$	—	—	—	—	**0.378*****
					(8.524)
LR_{κ}	—	**-2.090**	**-34.354****	**-40.722****	**-3.534**
		—	[-59.723;-12.375]	[-59.940;-16.359]	—
LR_{π}	—	**0.892**	**22.900****	**26.992****	**0.988**
	—	—	[8.368; 41.158]	[10.950;41.436]	—
Deviance information criterion	—	—	-48028.17	**-48167.47**	—
Wald test (coefficients)	—	**[0.0000]**	—	—	—
Wald test (time dummies)	—	**[0.0000]**	—	—	—
N	1960	1960	1960	1960	1960
State FE	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	**No**	Yes	Yes
Sargan test (p-value)	—	[1.000]	—	—	—
m_2 (p-value)	—	[0.010]	—	—	—

Notes: (***), (**), (*) denote significant at the 1%, 5%, and 10% levels, respectively. The t- and z-statistic are within parentheses. The p-values and the lower and upper bounds of credible intervals are within square brackets. We use the one-step GMM estimator proposed by Arellano and Bond (1991) treating $g_{i,t}$, $\psi_{i,t}$ and $ln(T_{i,t})$ as endogenous. The Sargan test statistic has χ^2 distribution regardless of heteroscedasticity. We use robust standard errors from Windmeijer (2005) for GMM estimates. In order to control for the problem of proliferation of instruments, we follow the advice in Roodman (2009) in employing only lagged values from two to nine of the same explanatory variables as valid GMM instruments. The equal-tailed 95% credible intervals for the OPM estimates based on 10000 Monte Carlo samples. Statistical significance is reached when the 95% credible intervals exclude the value of zero. We use the queen contiguity matrix to obtain the spatial lag of $\psi_{i,t}$ and $ln(T_{i,t})$ (LeSage and Pace, 2009; Anselin et al., 2008). The deviance information criterion (DIC) is a generalization of the Akaike information criterion (AIC), and the smaller the DIC, the better the model fit. And LR_{κ} and LR_{π} measure the cumulative direct effect and the cumulative spillover effect of the own-state output growth rate on the own-state wage share and the wage share averaged over neighboring states, respectively.

According to the OPM results featuring in the penultimate column of Table 3, for which the value of the DIC is the smallest one (-48167.47), the estimated coefficient of the direct effect of the economic activity variable $g_{i,t}$ (output growth rate) on the distribution variable $\psi_{i,t}$ (wage share) is significant at the 5% level and negative with a value equal to -0.284. The respective estimated magnitude of the parameter κ in Equation (3) suggests that a 10 percentage-point increase in the output growth rate would correspond to about a 2.8 percentage-point median decrease in the wage share at the state level. Yet we also found that the indirect (spillover) effect from changes in the state-level output growth rate to the wage share in the neighbouring states is significant at the 5% level and positive with a value equal to 0.189. This estimated magnitude of the respective parameter π in Equation (3) then suggests that a 10 percentage-point increase in the output growth rate in a given state, despite corresponding to about a 2.8 percentage-point median decline in the wage share in the own state, would nonetheless correspond to about a 1.9 percentage-point median increase in the wage share in the neighbouring states. This result implies that a 10 percentage-point increase in the output growth rate in the neighbouring states would correspond to about a 1.9 percentage-point (median) increase in the wage share in a typical state. Meanwhile, the per-capita tax collection variable is positively related to the wage share at the state level, with an estimated magnitude of the OPM estimated parameter ϕ in Equation (3) equal to 0.024 and significant at the 5% level. Note from the ultimate column of Table 3 that the estimation of such parameters κ, π, and ϕ with the SDEM model yielded the same qualitative results and actually at a higher significance level (1% instead of 5%). In fact, the SDEM estimation found that the magnitude of the positive cumulative indirect (spillover) effect ($LR_\pi = 0.988$) is lower than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\kappa = -3.534$), and both have the same sign as and are higher (in absolute value in the case of the latter) than their counterparts measuring the respective immediate effects ($\hat{\pi} = 0.082$ and $\hat{\kappa} = -0.294$). As shown in the penultimate column of Table 3, the OPM estimates of such cumulative effects are qualitatively the same as the SDEM estimates but much larger in magnitude (recall from Section 3.1 that the cumulative direct and indirect effects of a change in the output growth rate on the wage share when the latter is stationary ($\alpha < 1$) is given by $\kappa/(1-\alpha)$ and $\pi/(1-\alpha)$, respectively).

As intimated earlier, in addition to consistent OPM and SDEM estimates, we also present consistent GMM estimates for the specification in Equation (3) using the dynamic SLX model when the full value of capacity utilization features as the economic activity explanatory variable. As shown in Table 9 in Appendix B, the ensuing results are qualitatively the same as those obtained when the output growth rate is used as the measure of state-level economic activity. The estimated GMM and SDEM coefficients of the direct effect of capacity utilization on the wage share are significant at the 1% level and negative with values equal to -0.078 and -0.108, respectively. Such estimated magnitudes of the parameter κ in Equation (3) suggest that a 10 percentage-point increase in capacity utilization would correspond respectively to about a 0.8 and 1.1 percentage-point decrease in the wage share at the state level (or about a 1.0 percentage-point in the case of the OPM estimate, which is significant at the 5% level). Yet we also found that the indirect (spillover) effect from changes in the state-level capacity utilization to the wage share in the neighbouring states is significant at the 1% level and positive with estimated values equal to 0.054 (GMM) and 0.046 (SDEM). These estimated magnitudes of the respective parameter π in Equation (3) suggest that a 10 percentage-point increase in capacity utilization in a typical state, despite corresponding to about a 0.8 and 1.1 percentage-point decline in the wage share in the own state, would correspond to about a 0.5 percentage-point average increase in the wage share in the neighbouring states in the case of either the GMM or the SDEM estimator (or about a 0.7 percentage-point median increase in the case of the OPM estimate, which is significant at the 5% level). Using again the alternative interpretation of the indirect impact, which LeSage and Pace (2009) dub the *average total impact to an observation*, the GMM and SDEM estimates for the parameter π in Table 9 can also be interpreted as suggesting that a 10 percentage-point average increase in capacity utilization in the neighbouring states would correspond to about a 0.5 percentage-point average increase in the wage share in a typical state in the case of both the GMM or the SDEM estimator (or about a 0.7 percentage-point median increase in the case of the OPM estimate). Meanwhile, the per-capita tax collection variable is positively related to the wage share at the state level, with an estimated magnitude of the respective parameter ϕ in Equation (3) equal to 0.008 (0.009) and significant at the 1% (5%) level in the SDEM (OPM) estimation. As regarding persistence, the SDEM estimation found that the magnitude of the positive cumulative indirect (spillover) effect ($LR_\pi = 0.354$) is lower than the absolute value of the magnitude of the negative cumulative direct effect ($LR_\kappa = -0.831$), and both have the same sign as and are higher (in absolute value) than their counterparts measuring the respective immediate effects ($\hat{\pi} = 0.046$ and $\hat{\kappa} = -0.108$).

Therefore, using the terminology specified in Section 2 to review the related empirical literature, our finding that a higher wage share in a given US state reduces capacity utilization and output growth in the own state, while increasing these variables in neighboring states, could be taken to mean that the *direct* (*indirect*) *demand* and *growth* effects are both *profit-led* (*wage-led*). This finding is somehow intuitive since regional economies in a given country are typically more (and often much more) open to each other than national economies are open to each other. Meanwhile, our other main result that a higher capacity utilization or output growth in a typical US state lowers the wage share in the own state, while pushing up the wage share in neighboring states, could be taken as meaning that the *direct* (*indirect*) *distribution* effect is of *wage-squeeze* (*profit-squeeze*). We also estimated that the response of the state-level economic activity and wage share to changes in each other exhibits persistence, so that the above-mentioned direct and indirect effects are qualitatively the same both *immediately* and *cumulatively* over time.

5. Conclusions

There is a long theoretical tradition in economics of consistently positing that the functional distribution of income between wages and profits, by influencing aggregate demand formation, causally affect the level of macroeconomic activity. In effect, there are as well sound theoretical and empirical reasons to consider the causality involving these economic variables as running in both directions. Meanwile, the determinants of the functional distribution of income and the level of economic activity are arguably geographically confined, the implication of which is that the coupled dynamics of these variables at the regional level has an inherently spatial dimension. Thus, when such coupled dynamics is estimated using state-level data, both own- and neighboring-state variables or characteristics matter. Against this conceptual backdrop, we estimated a modified demand-and-distribution system for the 48 contiguous US states and the District of Columbia (DC) employing dynamic spatial panel data for the period 1980–2019. The econometric methodology that we adopted allowed for endogenous regressors and accounted for omitted variable bias and spatial autocorrelation, thus permitting testing for the presence, significance, sign, and magnitude of spatial spillovers across the regional units in our sample data.

In regard to the relationship between the level of economic activity and the functional distribution of income at the state level in a given country, spatial spillovers have important possible policy implications when they become known among the involved states (which should not be taken for granted). One reason is that these spatial spillovers are likely to engender either a convergence or a divergence of incentives among the respective state officials or even between these (or some of these) state officials and those of supra-regional entities (e.g. national officials). Consider for example our finding that a higher capacity utilization or output growth in a typical US state (possibly resulting from an expansionary state fiscal policy) lowers the wage share in the own state, while raising the wage share in neighboring states. Or consider our other main finding that a higher wage share in a typical US state (possibly resulting from a redistributive state fiscal policy) lowers capacity utilization and output growth in the own state, while raising these economic variables in neighboring states. In effect, the likely existence of different demand, growth and distribution regimes across both time and space makes the national policy pursuit of objectives in terms of output growth and distribution much more challenging and complicated.

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Appendix A: List of sample US states, descriptive statistics, and unit root tests

Table 4. List of sample US states.

State	*State*
1. ME (Maine)	26. UT (Utah)
2. AZ (Arizona)	27. IN (Indiana)
3. AR (Arkansas)	28. MA (Massachusetts)
4. DE (Delaware)	29. MS (Mississippi)
5. GA (Georgia)	30. NE (Nebraska)
6. MN (Minnesota)	31. NM (New Mexico)
7. CA (California)	32. NC (North Carolina)
8. DC (District of Columbia)	33. RI (Rhode Island)
9. FL (Florida)	34. OH (Ohio)
10. ID (Idaho)	35. OK (Oklahoma)
11. IL (Illinois)	36. SC (South Carolina)
12. IA (Iowa)	37. CO (Colorado)
13. KY (Kentucky)	38. KS (Kansas)
14. LA (Louisiana)	39. CT (Connecticut)
15. MD (Maryland)	40. NV (Nevada)
16. MI (Michigan)	41. WA (Washington)
17. MO (Missouri)	42. WV (West Virginia)
18. MT (Montana)	43. WY (Wyoming)
19. NY (New York)	44. AL (Alabama)
20. OR (Oregon)	45. NH (New Hampshire)
21. TN (Tennessee)	46. NJ (New Jersey)
22. TX (Texas)	47. ND (North Dakota)
23. VA (Virginia)	48. PA (Pennsylvania)
24. WI (Wisconsin)	49. VT (Vermont)
25. SD (South Dakota)	—-

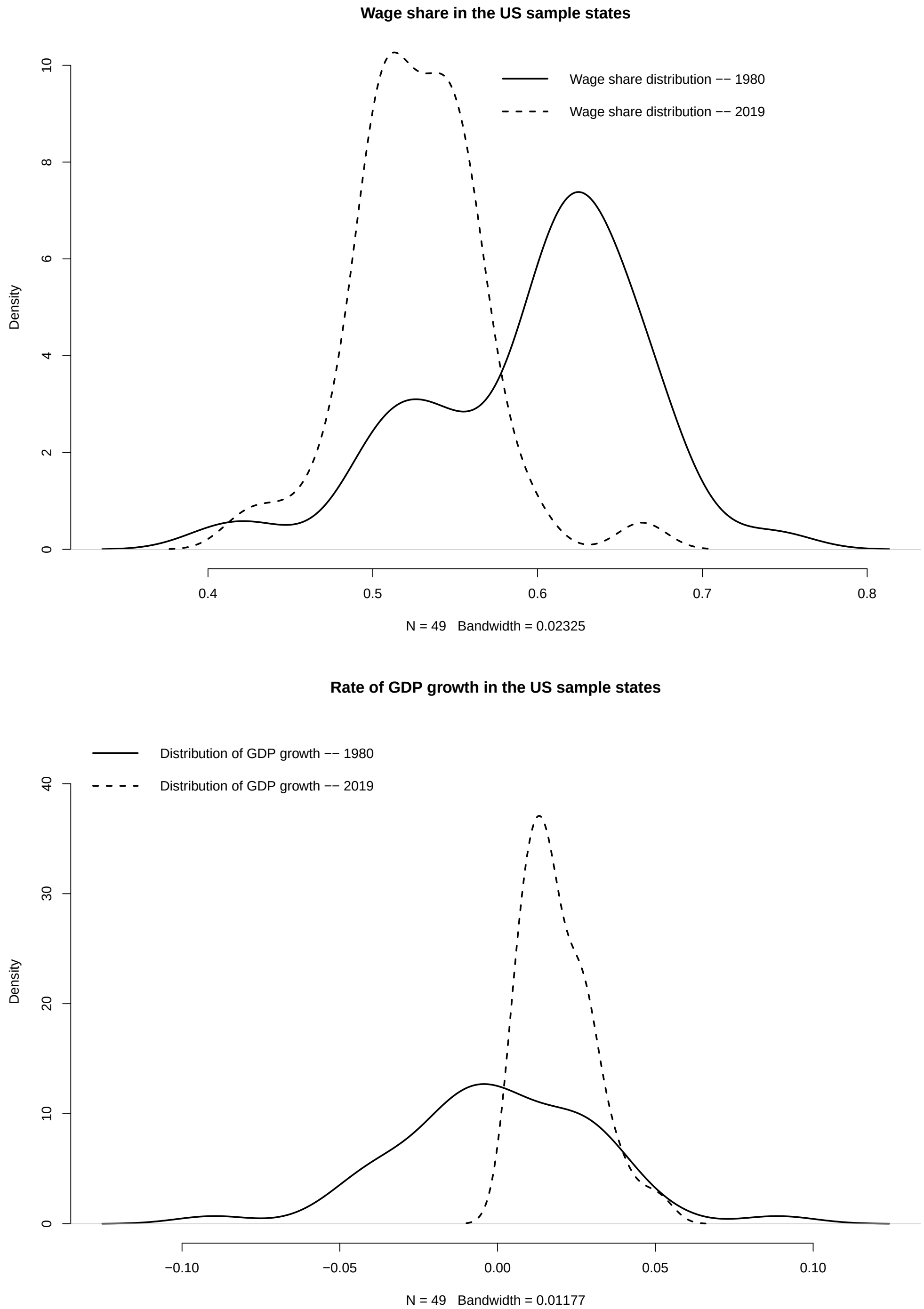

Figure 1: US sample states – output (GDP) growth and wage share patterns, 1980 and 2019.

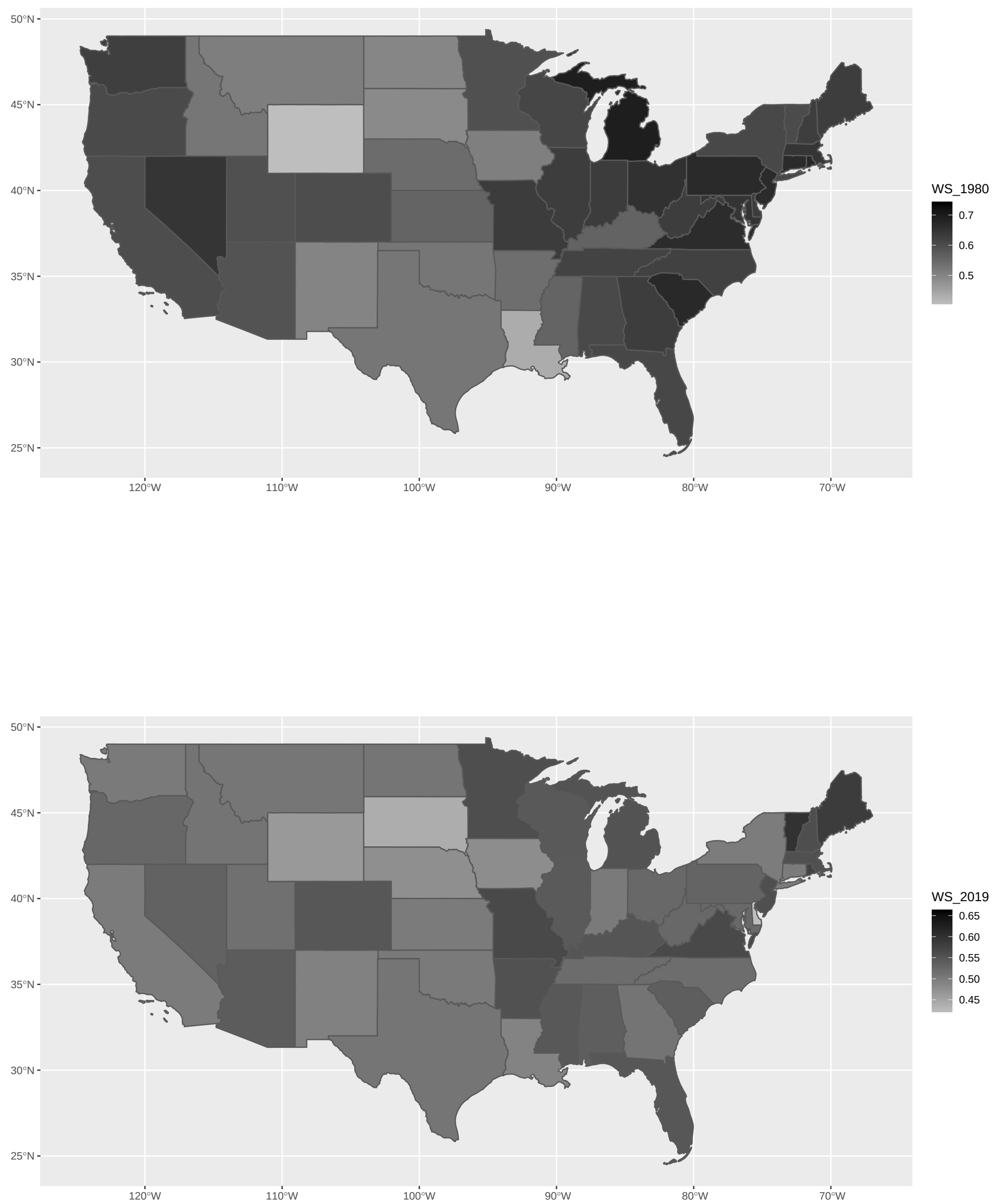

Figure 2: Wage share in the sample US states (in levels), 1980 and 2019.

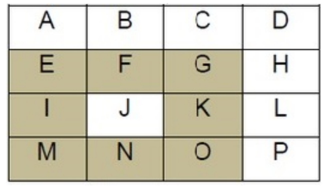

Figure 3: When using the contiguity queen criterion to define neighbors structure, all shaded areas refer to the first-order neighbors of the J observation.

Table 5. Descriptive statistics: state-level output growth rate, g_i, wage share, ψ_i, and capacity utilization, u_i.

Statistic	$g_{i,1980}$	$g_{i,2019}$	$\psi_{i,1980}$	$\psi_{i,2019}$	$u_{i,1980}$	$u_{i,2019}$
Mean	0.0004	0.0193	0.5973	0.5268	0.9464	1.0111
Third Quartile (Q3)	0.0213	0.0272	0.6332	0.5498	0.9661	1.0175
First Quartile (Q1)	-0.0168	0.0104	0.5578	0.5019	0.9255	1.0046
Mean above the median	0.0239	0.0276	0.6473	0.5559	0.9711	1.0203
Mean below the median	-0.0241	0.0105	0.5453	0.4965	0.9207	1.0016
CV	83.1786	0.5758	0.1129	0.0760	0.0369	0.0123

Note: The coefficient of variation (CV) is a measure of the level of dispersion around the mean given by the ratio of the standard deviation to the sample mean.

Table 6. Residual test statistic for a **restricted distribution equation** (Equation (3) with $\pi = \omega = 0$).

Statistic	***POLS*** **($g_{i,t}$)**	***POLS*** **($u_{i,t}$)**
Spatial Hausman test statistic	**26.301***	**69.867***
	[0.0000]	[0.0000]
Robust LM statistic (W_q)	**60.309***	**41.818***
	[0.0000]	[0.0000]

Notes: (***), (**), (*) denote significance at the 1%, 5%, and 10% levels, respectively. Following Anselin et al. (2008), we employ geographic contiguity as criterion to specify the matrix W. The matrix W_q is the queen contiguity (LeSage and Pace, 2009; Anselin et al., 2008). Using the geographic contiguity criterion, the average number of links across states is four, the minimum is one, and the maximum is eight. The values of the t-statistic are within parentheses. The p-values are within square brackets. Based on Baltagi and Rokicki (2014), for each of the following variables we use its value in the previous year as instrument: $\psi_{i,t-1}$, $g_{i,t}$, $u_{i,t}$, and $ln(T_{i,t})$. The null hypothesis of the Lagrange Multiplier (LM) test is that there is no spatial error correlation allowing the existence of serial correlation and random regional effects.

Table 7. Unit root test for models with constant and both constant and trend – results.

Model: constant	$u_{i,t}$	$\psi_{i,t}$	$\ln T_{i,t}$	$g_{i,t}$
S_n statistic	-18.0496***	-8.9196***	-8.6258***	-22.4098***
Optimal lag length	4	1	1	1
Model: constant and trend	$u_{i,t}$	$\psi_{i,t}$	$\ln T_{i,t}$	$g_{i,t}$
S_n statistic	-18.0502***	-8.9575***	-8.6530***	-22.4183***
Optimal lag length	4	1	1	1

Notes: In each test, the time series has a unit root under the null hypothesis, with (***) denoting significance at the 1% level. We follow Chang (2002) in using the Bayesian Information Criterion (BIC) for selecting the optimal lag length with the maximum number of lags equal to 4 for annual data frequency. For both models, the test for panels with cross-sectional dependency rejects the unit root hypothesis at 1%, suggesting that the data can be considered stationary overall.

Appendix B: Additional estimation results

Tables 8 and 9 display parameter estimates for the unrestricted versions of the demand equation (1) and the distribution equation (3) using the dynamic SLX and SDEM models with the full value of capacity utilization measuring the level of economic activity at the state level and the queen contiguity W matrix reflecting the strength of the spatial dependence.

Table 8. Parameter estimates for the **unrestricted demand equation** (Equation (1) with $\theta \neq \delta \neq 0$)) using the dynamic SLX model and the dynamic Spatial Durbin Error model - dependent variable: $u_{i,t}$; distribution explanatory variable: $\psi_{i,t}$.

Estimates	*POLS*	*GMM*	*OPM*	*SDEM*
$\hat{\rho}$	0.488***	0.312***	0.491**	0.445***
	(24.611)	(18.474)	[0.447;0.536]	(22.923)
$\hat{\beta}$	**-0.050*****	**-0.309*****	**-0.172****	**-0.196*****
	(-3.216)	(-3.951)	[-0.258;-0.087]	(-5.362)
$\hat{\gamma}$	0.006**	0.115***	0.038**	0.052***
	(2.230)	(4.670)	[0.014;0.062]	(3.732)
$\hat{\theta}$	**0.033**	**0.564*****	**0.128****	**0.141*****
	(1.177)	(4.572)	[0.014;0.239]	(2.372)
$\hat{\delta}$	-6.678e-05	0.031	-0.025	0.014
	(-0.016)	(0.942)	[-0.051;0.0004]	(0.959)
$\widehat{\lambda_1}$	—	—	—	**0.283*****
	—	—	—	(9.077)
LR_β	—	**-0.450**	**-0.340****	**-0.353**
	—	—	[-0.508;-0.171]	—
LR_θ	—	**0.820**	**0.251****	**0.254**
	—	—	[0.029; 0.467]	—
Deviance information criterion	—	—	**-33295.98**	—
Wald test (coefficients)	—	[0.0000]	—	—
Wald test (time dummies)	—	[0.0000]	—	—
N	1911	1960	1960	1960
State FE	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Sargan test (p-value)	—	[1.000]	—	—
m_2 (p-value)	—	[0.0000]	—	—

Notes: (***), (**), (*) denote significance at the 1%, 5%, and 10% levels, respectively. The values of the t-statistic are within parentheses. The p-values and the lower and upper bounds of credible intervals are within square brackets. We use the one-step GMM estimator proposed by Arellano and Bond (1991) treating $u_{i,t}$, $\psi_{i,t}$ and $ln(T_{i,t})$ as endogenous and adopting lagged values of the same variables as valid GMM instruments. The Sargan test statistic has χ^2 distribution regardless of heteroscedasticity. We use robust standard errors from Windmeijer (2005) for GMM estimates. In order to control for the problem of proliferation of instruments, we follow the advice of Roodman (2009) in using only lagged values from two to nine of the same explanatory variables as valid GMM instruments. The equal-tailed 95% credible intervals for the OPM estimates are based on 10000 Monte Carlo samples. Statistical significance is achieved when the 95% credible intervals exclude the value of zero. We use the queen contiguity matrix to obtain the spatial lag of $\psi_{i,t}$ and $ln(T_{i,t})$ (LeSage and Pace, 2009; Anselin et al., 2008). The deviance information criterion (DIC) is a generalization of the Akaike information criterion (AIC), and the smaller the DIC, the better the model fit. And LR_β and LR_θ measure the cumulative direct effect and the cumulative spillover effect of the own-state wage share on the own-state capacity utilization and capacity utilization averaged over neighboring states, respectively.

Table 9. Parameter estimates for the **unrestricted distribution equation** (Equation (3) with $\pi \neq \omega \neq 0$) using the dynamic SLX model and the dynamic Spatial Durbin Error model - dependent variable: $\psi_{i,t}$; economic activity explanatory variable: $u_{i,t}$.

Estimates	***POLS***	***GMM***	***OPM***	***SDEM***
$\hat{\alpha}$	0.955***	0.800***	0.986**	0.870***
	(178.102)	(35.932)	[0.959;0.995]	(59.589)
$\hat{\kappa}$	**-0.099*****	**-0.078*****	**-0.098****	**-0.108*****
	(-12.046)	(-5.790)	[-0.115;-0.080]	(-9.782)
$\hat{\phi}$	0.002	0.002	0.009**	0.008***
	(1.528)	(0.266)	[0.002;0.017]	(2.50)
$\hat{\pi}$	**0.054*****	**0.054*****	**0.067****	**0.046*****
	(4.023)	(2.707)	[0.045;0.090]	(2.562)
$\hat{\omega}$	-0.001	-9.61e-05	0.004	0.003
	(-0.356)	(-0.008)	[-0.004;0.012]	(0.516)
$\widehat{\lambda_2}$	—	—	—	**0.308*****
	—	—	—	(7.455)
LR_{κ}	—	**-0.390**	**-7.000****	**-0.831**
	—	—	[-19.969;-2.343]	—
LR_{π}	—	**0.207**	**4.786****	**0.354**
	—	—	[1.551; 14.312]	—
Deviance information criterion	—	—	**-46869.26**	—
	—	—	—	—
Wald test for coefficients	—	[0.0000]	—	—
Wald test for time dummies	—	[0.0000]	—	—
N	1911	1960	1960	1960
State FE	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Sargan test (p-value)	—	[1.000]	—	—
m_2 (p-value)	—	[0.5364]	—	—

Notes: (***), (**), (*) denote significance at the 1%, 5%, and 10% levels, respectively. The values of the t-statistic are within parentheses. The p-values and the lower and upper bounds of credible intervals are within square brackets. We use the one-step GMM estimator proposed by Arellano and Bond (1991) treating $\psi_{i,t}$, $u_{i,t}$, and $ln(T_{i,t})$ as endogenous and adopting lagged values of the same variables as valid GMM instruments. The Sargan test statistic has χ^2 distribution regardless of heteroscedasticity. We use robust standard errors from Windmeijer (2005) for GMM estimates. In order to control for the problem of proliferation of instruments, we follow the advice of Roodman (2009) in using only lagged values from two to nine of the same explanatory variables as valid GMM instruments. The equal-tailed 95% credible intervals for the OPM estimates based on 10000 Monte Carlo samples. Statistical significance is reached when the 95% credible intervals exclude the value of zero. We use the queen contiguity matrix to obtain the spatial lag of $u_{i,t}$ and $ln(T_{i,t})$ (LeSage and Pace, 2009; Anselin et al., 2008). The deviance information criterion (DIC) is a generalization of the Akaike information criterion (AIC), and the smaller the DIC, the better the model fit. And LR_{κ} and LR_{π} measure the cumulative direct effect and the cumulative spillover effect of the own-state capacity utilization on the own-state wage share and the wage share averaged over neighboring states, respectively.