Multidimensional Spatial Econometrics, Infrastructure and the Efficiency Wage

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Multidimensional Spatial Econometrics, Infrastructure and the Efficiency Wage[1]

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Abstract

The paper begins by putting together a critical evaluation of existing academic literature on the topic of spatial meritocracy and then outlines the use of panel models in overcoming issues related to consistent and robust regression estimation. This is followed by an outline of the theoretical microfoundations found in the literature on the topic of rational choices made by agents in the Overlapping Generations (OLG) model and the Neoclassical Growth model (NGM) with respect to spatial variables and the efficiency wage. The author then notates a Lagrangian Multiplier constrained optimisation problem. The objective function of the constrained problem is set up to optimise multidimensional consumption smoothing across an infinite time period, where firm location, wage growth and worker transportation costs are all endogenous variables. Further meritocratic issues are mentioned and interpreted through the prism of Actor Network Theory (ANT). The paper concludes by suggesting topics for further research.

[1] JEL Classification: D19, D21, J24, J31, J53, J61, J62, J64

1. Contents

2. Introduction

Labour economists have long studied the data that exist between *spatial* variables, such as the locational differences with respect to perfectly competitive profits, consumer demand, and wages, using advanced means of estimation (Zenou and Smith, 1995). In this working paper, I will focus on *multidimensional* spatial econometric methods, particularly the panel data fixed- effects model (Wang, *et. al.*, 2023), the Cliff-Ord model and the Durbin model with autocorrelated spatial residuals. These models are used as tools for interpreting a relatively under utilised area of study in the field, that is, the area of spatial meritocracy. In general, by spatial meritocracy, I mean to define a wholly pluralistic topic and as such I treat it with the utmost respect. In the context of this paper, I will use the term "*multidimensional*" to mean *time*-dependent and *space*-dependent variables, that is - variables that are spatio-temporal (Ferreira *et.al.*, 2020). This paper outlines spatial econometrics as a means for channeling applied and empirical research focused on spatial meritocracy, and its cause.

Spatial meritocracy concerns itself with meritocratic outcomes. But not just these outcomes, it also concerns itself with viable solutions, solutions that address the problem of inequitable distribution, both of income around city centers *and* of the knowledge base. But moreover, the cause concerns itself with ensuring equitably designed infrastructure in towns within an economy, minimising the influence of factors such as race and income on life chance. This is why economics is being used to better understand firm-worker proximity. As I press on towards achieving this goal, I will make use of the value of Bruno Latour's Actor Network Theory (ANT). ANT is a necessary part to the working paper's view on the efficiency wage because of its grounding in heterogeneous networking. Latour's work on ANT is typically seen in light of Michael Foucault's work on the subject, power and observation. Finally, what Econometrics can do well is to help us better understand the experience of people who use infrastructure and the experience of city dwellers in overcoming barriers to communal equity.

3. Knowledge Diffusion and Firm-Worker Proximity

Take this nuanced but pertinent example. This instance is as pivotal to the interpretation and initial application of the topic in this paper, as the critique that I will embark on shortly. Take the agglomeration effects of income distributed around a metropolitan city and consider the assumption that there can only be either skilled or unskilled labour in an economy. I have explained generally how this may be possible using the policy implications of a folk theorem (Mayaki. 2015). Now, many in the literature claim that spatial meritocracy is a firm-worker proximity problem. In other words, they claim that there is a positive correlation between the abundance of skilled labour and the size of the city's economy (Behrens and Robert-Nicoud, 2015:34). Why is this particular observation important? It is important because it again suggests that there are firm-worker *proximity* issues. Others make the argument that over time, the agglomeration of the knowledge base towards specific *centralised* hubs within specific parts of an economy or (business district) skews the concept of truly equal distribution of opportunity (Yang, *et.al.*, 2019). Hence, spatial meritocracy can be seen through the lens of labour, skillfulness, mobility, and firm knowledge diffusion. I have, needless to say, witnessed the point argued in reverse. That is to imply, internal migration and knowledge diffusion are concepts that can alleviate this problem[2].

4. Measuring Spatial Data - The Main Problems with Panel Models

We already know that literature on spatial meritocracy relies somewhat heavily on the utilisation of Econometric methods to conclude on interdisciplinary arguments. The main chapters in the literature on Econometrics that explain the capability of statistical packages are found in Wooldridge (2002) and Greene (2012). These chapters are

[2] See Sakabe (2023) https://academiccommons.columbia.edu/doi/10.7916/gckw-ft91

typically used in postgraduate advanced level courses. But many other resources are available. For the purposes of this seminal paper, I will refer to the work of Mans Soderbom (2011).

According to Soderbom, in his first chapter on Econometrics and Panel Data, he describes panel data as unique. So unique that it is worthwhile to treat them separately to data we regress on using the standard OLS estimator. In raw form, panel data are incompatible with the OLS estimator approach. Why is this? As Soderbom explains, this is because of the inherent bias that will result from the outcome of an estimation. Panel datasets are first and foremost described by Soderbom as existing in order to *follow a random set of individuals, firms or households over time*. Soderbom proceeds by stating that, with panel data, researchers can control for *individual-specific, time-invariant, unobserved* heterogeneity. He explains that for panel data to be relevant in a standard OLS regression, it should ideally take a certain form. In the following subsection I outline how one panel data regression can ideally take form.

According to Soderbom[3] in the chart accompanying his chapter, "id" is *the variable identifying the individual that is followed over time* whereas *yr92, yr 93* and *yr93* are *time dummy variables derived from the year variable.* X1 is time varying (for example, this could be income, or firm profits) while x2 is time invariant (likewise, this could reflect gender, race, ethnicity or level of education). The latter are known commonly as fixed or individual effects[4]. We will come to see why fixed effects are important shortly.

As Soderbom explains, when panel data is *balanced*, it can derive more useful results. Balanced data can occur in both *microeconomic* (where the id column or Ω can be substantially large, and the number of years the dataset covers is typically small) and *aggregate* form (where the time variable is proportionally measured as longer than microeconomic data). In instances where the reverse is true, that is - where the id

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[3] See https://soderbom.net/metrix2/lec6_7.pdf
[4] See https://www.fsb.miamioh.edu/lij14/411_note_panel.pdf

column or Ω, may contain as little as 5 observations, and the time variable (in years) may be large, Soderbom defines this instance as *multiple time series.*

Likewise, panel data should not be confused with *repeated* cross-sections. If you recall, from Soderbom's notes on pp.3 and pp.4 of this Chapter on Panel Data, respectively, he hammers home the point that cross-sectional data are designed to span two different points in time are *not* considered to be the equivalent of panel data - importantly, because no attempt is made to *monitor* the individual observation (in this case the *id*) across time.

Before proceeding to explore *spatial* panel models, it may be worthwhile highlighting why panel data is useful in the process of addressing endogeneity. Essentially, panel data regressions are useful in solving the following problem. Consider the Soderbom model from pp.5:

(3.0) $y_{it} = x_{it}\theta + (\alpha_i + \mu_{it})$

Such that

$\mathrm{COV}\,(x_{it}, \alpha_i) \neq 0$

If α at time t is *correlated* with x_{it} then allowing the residual to capture the unobserved α_i can cause serious problems. Soderbom refers to this as the *omitted variable problem*. Why is this problem important? It is important because the objective of this regression is to estimate the θ variable. If there is an unobserved variable in the model's equation, in this case α[5], where the variable is constant over time, varying for each individual in the model, then using OLS to estimate the relationship in the model will cause α to be captured in the residual value.

[5] The variables in parenthesis are unobserved.

We will now explore the value of Soderbom's Fixed Effects ("*FE*" or "*Within*") Estimator. The model considered by Soderbom is (3.1) on pp.7 is given by:

(3.1) $$y_{it} = x_{it}\theta + (\alpha_i + \mu_{it})$$

$$t = 1, 2, \ldots, T; \; i = 1, 2, \ldots, \Omega$$

Soderbom proposes the following assumptions about the unobserved terms (in parenthesisx_{it}). Firstly, the assumption that α_i is *freely correlated* with x_{it}, and secondly he puts forward the assumption that:

(3.2) $$E(x_{it}\mu_{is}) = 0 \text{ for } s = 1, 2, \ldots, T$$

With these two assumptions in place, researchers can use either the Fixed Effects ("FE") or First Difference ("FD") estimator to arrive at a consistent estimate for all θ variables. To demonstrate how FE can assist in estimating panel data, Soderbom takes the average of the equation (3.3) for *each individual*.

(3.3) $$\overline{y}_i = \overline{x}_i\theta + (\alpha_i + \overline{\mu}_i) \qquad i = 1, 2, \ldots, \Omega$$

$$\text{Where } y_i = \left(\sum_{t=1}^{T} y_{it}\right) / \; T$$

Subtracting (3.3) from (3.1) gives:

$$y_{it} - \overline{y}_i = (x_{it} - \overline{x}_i)\theta + (\alpha_i - \alpha_i + \mu_{it} - \overline{\mu}_i)$$

$$y_{it} - \overline{y}_i = (x_{it} - \overline{x}_i)\theta + (\mu_{it} - \overline{\mu}_i)$$

Rewritten as:

(3.5) $\widehat{y}_{it} = \widehat{x}_{it}\theta + \widehat{\mu}_{it}$ $for\ all$ $t = 1, 2, \ldots, T;$ $i = 1, 2, \ldots, \Omega$

Soderbom arrives at the conclusion that we can estimate θ *consistently* by using OLS on the time-demeaned data in (3.5) above. This is because, as we have just demonstrated, the transformation of the original equation, according to Soderbom, has eliminated the unobserved variable α_i from the equ

ation.

5. Introducing Spatial Panel Models

In deciding the level of detail and impact that a panel model may retain, two references in the literature are of immense value. The first is the breakdown of literature on spatial and dynamic models (Elhorst, 2011) and the second is the step-by-step procedure for estimating spatial panel models (Kopczewska, 2019).

In the second of these reference texts, the author, Katarzyna Kopczewska, a Polish Academic, suggests a thought process or procedure that includes six important steps that surround the use of panel model estimations. In the following subsection, I will comment on this process in more detail.

Preliminarily, Kopczewska suggests researchers engage in the transform demeaning process I have just outlined, derived from Soderbom (2011). This process indeed eliminates the constant, any constant effects, and variables with time constant values.

The first step Kopczewska suggests is the choice of a **specific effect**. By this, the author is referring to the decision to use either fixed effects or random effects models. Fixed effects models are estimated using least squares (or maximum likelihood) and random effects are estimated with shrinkage. Random effects are estimated with partial pooling, while fixed effects are not. *Spatial* fixed effects are similar to other types of fixed effects in that these models control for unobserved heterogeneity. However, spatial models take things one step further, by accounting for spatial dependence between observations. This is easily done by including spatially lagged dependent variables as regressors in the model.

The second step Kopczewska mentions in her text is the choice of **model type**. Now, according to the author, there are two model types which each contain *spatial* lags; one is the Cliff-Ord model and the other is the Durbin model. The Cliff-Ord model contains spatial lag y and/or ε, whereas th Durbin model contains spatial lags x and if necessary spatial lags y and/or ε. Indeed, as noted in Elhorst (2011:8), the spatial Durbin can be estimated as a spatial lag model with explanatory variables.

The third step, after selecting between Cliff-Ord and Durbin, according to the author's procedure, is to select an appropriate *type* of **lag variable(s)**. This may include one of four lagged variable types (Kopczewska, 2019:275) which include time and space lagged explanatory or dependent variables.

The fourth step is to define the **error structure** of the model. Now, as the Durbin model excludes the need for an error term, the author suggests a model that takes into account the spatial error found in Cliff-Ord (Baltagi, *et.al*. 2003; Kapoor, *et.al.*, 2007). The fifth is the choice of the *spatial* **weights matrix**, denoted as W of which there are several. According to the author, there is a common neighbourhood matrix, inverse distance and inverse square distance. She highlights the importance of the contiguity matrix.

The sixth and final step is a choice to select a **method of estimation** and model form. Noting that the spatial panel model should control for spatial correlation and heterogeneity, the author suggests the Breusch-Pagan LM test as a means of controlling for spatial autocorrelation and random individual effects.

6. Outlining and Explaining the Baseline Model

The baseline model of this paper will briefly investigate and elaborate on two claims. The first is the theoretical assumption that underpins both the infinitely-lived Ramsey-Cass-Koopmans (RCK) or workhorse neoclassical growth model (NGM) *and* the two-period Overlapping Generations (OLG) models found in the literature

(Aiyagari, 1988; Campante, 2021). In one of these models, the OLG, there is the assumption that rational agents have additively separated preferences over consumption c. I will argue convincingly that in the OLG model, if rational agents make smoothing decisions for c, and what we shall term as optimal labour mobility β at time $t-n$, under normal dynamic stochastic general equilibrium conditions, optimal c and β are a function of a constrained optimisation Lagrangian problem where utility U is optimised after deriving third order conditions of optimality.

The premise here is that the firm and the agent are not necessarily positioned in an approximate vicinity. We refer to this as firm-worker proximity. Thus, what can be said is that the agglomeration of firm activity spatially around a metropolitan business district creates at the very least the need for transportation mechanisms that may carry significant cost to the earning and consumption cycle experienced by the agent. The greater this observed transportation cost is, the greater the leakage the agent experiences.

Take also the microfoundations which internalise the assumption of constant returns-to-scale found in the Cobb-Douglas assumption and the endogenous production function (Krugman, 1991). These lmnts are important to the theoretical framing of factors of economic well-being when considering spatial meritocracy (Combes, *et.al.*, 2008). All too often, production functions include productivity as a variable that is indeed given as exogenous, thereby underrepresenting the valued contribution which labour has on economic development.

While Post-Keynesian models certainly do not lack the relevant foundations concerned with optimising spatial meritocracy (Dymski and Kaltenbrunner, 2021), literature on this topic from a DSGE perspective is almost defunct of any reference to *spatial* microfoundations.

In this paper, I would also like to draw attention to very recent evidence with respect to the field of wages and labour (Overman and Xu, 2022). Many authors have highlighted the proof that equilibrium wage determination[6] $w*$ is a factor that is strictly increasing, intuitively, with respect to two key endogenous variables: agent utility and mobility of labour, respectively.

7. Interpreting Spatial Meritocracy through Actor Network Theory

Moving away from the economic interpretations I have just outlined, spatial meritocracy arguably positions itself as a much more complex topic when as researchers, beginning with the work of Bruno Latour (1987), we overtly attempt to capture and iterate the movement and network relations of heterogeneous agents in a way that does not dehumanise the subject (Law, 1992:387). Until now, in this paper I have considered agents as models and data-sets, but many authors contend with this viewpoint. For instance, in John Law's incisive deconstruction of the heterogeneous nature of Actor Network Theory (ANT), Law claims rational agents experience the effect of Foucauldian power-relations. Yet, despite this, many authors concerned with spatial meritocracy have overlooked this dynamic (Dutta, *et.al.* 2022). As some authors have suggested, ANT is quintessential to interpreting spatiality (Amin, 2002). Indeed, if *durability* is about ordering through time, then *mobility* is about ordering through space (Law, 1992). The concise premise of ANT is here described and alluded to Latour's concept of c*enters of translation* which is brought to the fore by amongst others, Guggenheim (2016[7]).

Importantly, Foucauldian power in respect to Latour and Guggenheim is largely seen to be a sort of strategy rather than an explicit possession at the disposal of one specific person or group of persons. Yet nevertheless, the idea that network power is something that computational agents are subject to is an incessant feature of ANT.

[6] By "determination" we mean to refer to the dynamic and stable outcome of individual and collective bargaining decisions
[7] Guggenheim (2016) mentions spatial neighbourliness as a valued theme of his critique of ANT.

8. Aspects of the Model: Demand and Knowledge

Consider F number of perfectly-competitive firms, independent and identically distributed, and evenly positioned along a spatial plane Z, with market profit given by π at time t, output decisions given by Q, and price given by P. Efficiency wages are denoted by w. Knowledge endowments are given by σ, such that:

(7.1) $$\pi_t = F(Q, P, w, \sigma)^{1-Z}$$

(7.2) $$Q = \pi_t(logF, P, w, \sigma) / F$$

What can be said is that for the variables illustrating a *spatial* observation in F, that is to say F_1 to F_Ω, there is the assumption that each firm faces an increasing demand curve over time. This Cournot demand function in (7.2), is dependent on a number of factors including competitive downstream prices to consumers, agent disposable income, and agent preferences. The logarithm of the exponent $1 - Z$ expresses the significance of rural or urban location decisions faced by F. Hence, the problem here is intuitive. It should hold that if F_t is not an increasing function in π_t then we can argue that Pareto-optimal outcomes have not been sufficiently met. Put simply, the observation of π along the spatial plane Z at time t for each F may be suboptimal for every F where location decisions are a determining factor. Hence the proposition that: if F_N are spatially dispersed evenly, clusters may form based on knowledge intensity as concluded by Ferreira (2016). Knowledge diffusion is not an altogether optimal component to consider (Greve, and Seidel, 2015). Not only are we assuming that a significant determinant of demand is knowledge i.e., which is a fair assumption to make but we are also assuming factors such as the rise in globalization (Amin, 2002), government policy and interest rates are not a feature. Does the model of this economy choose to recognise free-trade zones or low business rates in specific regions? Is the knowledge growth variable representative of innovation? Is it applicable to consumer preference? A number of unanswered questions.

9. Spatial Disparities and Structural Inequality

The following working paper concerns the how and why behind the rise in inequality associated with unevenly distributed variables traditionally denoted as exogenous at general equilibrium (Di Comite, 2017). I attempt to model the relevant variables in a constrained optimisation problem at (11.1) and later I attempt to explain how, with the use of spatial econometrics, we can improve our understanding of this phenomena by observing results found in previous literature comparatively. The phenomena itself can be referred to as what we shall term structural inequality. This inequality is defined broadly throughout the literature on spatial economics.

Academic theory has brought management and spatial meritocracy together to better understand how we can view the consequence of structural inequality on work conducted in more well off parts of developed cities. It has been argued that minute differences in access to infrastructure can affect journey routes, and hence the interconnectedness of nearby living areas within a city, which can in turn drastically affect life opportunities, and economic prospects of the lived agent[8] (Dutta, *et.al.* 2022). However, no conclusions are made on the *success* of economic activity arising from interconnected behaviour in this respect.

Furthermore, I find additional value in the framing of this inequality through the lens of spatial meritocracy (Bissett, 2015[9]) and *Rawlrasian* utilitarianism (Gandy and Armanios, 2023) but I shall argue that the legacy concept[10] of Actor Network Theory (ANT) has a greater level of applicable impact on this topic and opens up areas of further research.

[8] An interesting view is found in Chapter 8.3 (Campante *et.al.*, 2021) where in the absence of a transversality condition, the author suggests a continuous OLG with the condition that agents pre-sell their assets before the next period begins.
[9] See figure 1: Proposed framework for components of spatial meritocracy
[10] Latour has reportedly since developed a new theoretical project that has made ANT redundant.

The distribution of income reverberated around relevant physical infrastructure, such as airports (Bahar *et.al.*, 2023), bridges (Brooks and Donovan, 2020), railways (Zhang *et. al.,* 2020), and other physical transportation methods (Chen and Vickerman, 2017; Faoziyah, 2016) supports the view that spatial heterogeneity is a strong determining factor for the level of income a lived agent may accumulate.

There are, as the literature explains on this topic of research, crossovers that exist between both the type of infrastructure asset class that selected authors have found insightful in exploring and global research spillovers. A large number of authors have found value in exploring the role that equitable access to bridges play in overcoming this type of structural inequality. Researchers in the United States have been concerned with rapid economic development in Asia-Pacific, namely the People's Republic of China (Armanios *et.al.*, 2016). All the while, researchers in Asia-Pacific have studied the entrepreneurial relationships that are a key component to the heterogeneity of data related to firms in the United States (Cheng and Li, 2011).

I argue that, on this basis, it is not only possible to observe firm-wide and government investment behaviour in relation to heterogenous price-setting (Anthonisen, 2010; Migliardo, 2012) and product innovation (Isaksen, 2001) but it is also possible to observe demand-side choices along the spatial plane (Jann, 2016) through the use of applied methods such as spatial concentration analysis based on the theory of inequality put forward by Henry Theil over half a century ago (Postiglione and Panzera, 2015).

10. Aspects of the Model: Search and Matching

Other similar research has been elaborated upon to better understand a variety of topics, including mass migration (Hatton and Williamson, 1998), rural-to urban migration (Stark and Fan, 2008), demographic shifts (Wu and KC, 2022), urbanisation (Lynam, 2023; Zhou, *et.al.*, 2016), and wage disparities across inner city locations (Combes, *et.al.* 2008). Importantly, I note that the seminal work on spatial econometrics (Anselin, 1988), and subsequent renditions on spatial regression analysis

(Chi and Zhu, 2019) may be relied upon to help to comparatively assess how advances in regional transportation infrastructure have affected the distribution of spatially observable income demographics over time, but also in light of the advent of spatially applied search and matching (Lucas and Prescott, 1974), which itself relies on a set of assumptions about preference, utility, and rational choice, particularly with respect to the well-known Mortensen-Diamond-Pissarides aggregate matching function[11] (Pissarides, 1994; Wasmer and Zenou, 2002).

11. Inter-Temporal Smoothing

Now, consider for a moment an economy that can best be explained by two variables. The first of these variables is one I shall rephrase as the *intertemporal efficiency of household utility.* In describing this variable, intertemporal utility, I note that as a lived agent seeks to sell labour and earn income associated with a specific job vacancy v, agents do so with different decisions based on unique preferences (Behrens and Robert-Nicoud, 2015:36; Pickles and Rogerson, 1984). Rational agents optimise a strictly increasing household utility function, increasing levels of income, greater employment choices and the intrinsic ability to relocate throughout a lifetime of work (spatial location decisions - denoted as $\beta(t)$). The problem here is not that the agent's income is not increasing with time (because it is[12]), the problem is that one household's income along a spatial plane (z-axis) of $z(t) > x(t) = y(t) = 0$, where x is utility U and y is labour mobility β may be increasing faster than another household's income can compete, hence creating and introducing what the literature explains as the concept of Lorenz dominance[13] (Biongiorno and Goia, 2019; Gastwirth, 1971). Lorenz dominance is the applied concept that, in the context of wages, one wage distribution's Lorenz curve has greater comparative inequality than that of another. This has been explored *unidimensionally* (Mosler, 2020), in adjacent

[11] See two charts which explain the quarterly data behind how skilled migration into the UK has affected labour outcomes. This has been monitored by the Oxford Migration Observatory.
[12] See http://www.stats.gov.cn/english/PressRelease/202301/t20230118_1892303.html
[13] Here, the Lorenz Curve was introduced as a tool for investigating and quantifying the land use structure changes from 1987 to 2007 in Xiamen, a coastal city found in Fujian, China.

literature on temporal-spatial change (Song, *et.al*., 2010) and also with respect to the *multidimensional* Lorenz dominance relationship (Banerjee, 2014).

This problem I have described as found in the published literature is simple to resolve to many academics, to some extent. We can assume that equal and sufficient spatially separated Pigou-Dalton regressive wealth transfers (Bosmans *et. al*, 2009) and secondly, out-of-work welfare payments (Mazzocco, 2007) as being a resolution to symptoms of the overall problem. But the problem may exacerbate what we can refer to as the *spatially dynamic* utility gap (Zhang, 2007). In essence, it is the role of the government to ensure welfare smoothing to reduce Lorenz dominance spatially. This may mean welfare programmes that have significant uplift in areas with more income disparity.

Consider for instance, a simple decision of a household H in the infinitely-lived agents model taken at a discrete time period $t - n$, and assume that it be treated as a sub-game perfect Nash equilibrium, with utility maximising payoffs against future endowments of wealth and future household expenditure $H\,(\beta(t)i(t) - 1 + \alpha)$ where income i is earned at the net present discount rate α. Equation (11.1) thus expresses how these expenditure decisions are taken well in advance of an intertemporal income derived at time t from participation in the labour market. A valid criticism of equation (11.1) is however that it holds non-empirically as a mathematical expression, focusing its efforts on deriving an understanding that equates itself to the rigour of regression analysis with empirical data (Cheron and Langot, 2004).

Now also consider $\beta(t)\ *$ or the optimal growth path of labour mobility along the temporal spatial plane $z(t) > x(t) = y(t) = 0$ (Stark and Bloom, 1985). This intuition implies that an infinitely-lived agent can, given the level at which the government sets regulations to control who can participate in the labour market and when participation can take place (Mayaki, 2015), position her labour along a path which smooths her consumption in future periods.

A lived agent is in control of what that can be controlled by her rationality towards variables explained by the following equations, and likewise indebted to the factors that can affect and control these variables, inextricably. In a continuous time model with rational expectations, H may engage at time $t - n$ in an intertemporal smoothing exercise. In contrast to the permanent income hypothesis' assumption that the average propensity to consume is constant (Fridman, 1957) what becomes fascinating about intertemporal smoothing is the effect it can have on future expenditure decisions. Below, the objective of the constrained optimisation problem is to discover the dynamic stability of U *, the utility level of H, for a given level of w * which is the optimal wage given a function of the difference between the wage expected from an *intertemporal efficiency of household utility* and the efficiency wage for that market.

12. The Baseline Model (Revisited)

Consider, within the confines of an economy that hosts an infinitely-lived agent, that there exists this concept of a "*augmented*" workforce[14] (Mayaki, 2015). That is to say, within the scope of wage renegotiations, collective bargaining and what we might refer to as a normal distribution, there is, within the infinitely-lived model, an idea that the employer pays a premium on the going rate of pay in order to motivate its worker. The literature assumes that standard life-cycle of utility is derived from a model with zero tax base (Garriga, 2019) and only a brief level of welfare at the marginal level (Batyra and Sneessons, 2006), but utility remains continuously increasing in w[15] (this includes workers who are re-entering the market after observing existing contracts). The disparity between w * and efficiency wage w_e is an area I would like to understand further.

[14] See https://www2.deloitte.com/bd/en/pages/human-capital/articles/fow-augmented-workforce.html

[15] This is because according to Samiri and Millard (2022) lower taxes generally implies "more investment and therefore higher labour productivity." See https://www.niesr.ac.uk/blog/why-uk-productivity-low-and-how-can-it-improve

(11.1) $$f(U(t), w(t), c(t)) = \beta(U(t))\, v(t)c(t) \,/\, 1 - (1 + \alpha)$$

s.t.

$$w(\beta(t)\, v(t) + c(t))^{1-U} = 1$$

13. Conclusion & Further Research

This paper concludes by recommending areas for continued research on spatial meritocracy using relevant *spatial* econometric methods. The efficiency wage has been studied thoroughly and comprehensively within the literature on spatial components (Zenou and Smith, 1995). However, I conclude that there needs to be more work done on the topic of knowledge diffusion and asset prices.

14. References

1. Aiyagari, S.R. (1988) “Nonmonetary steady states in stationary overlapping generations models with long lived agents and discounting: Multiplicity, optimality and consumption smoothing”, *Journal of Economic Theory*, 45(1), pp. 102-127

2. Amin, A. (2002) “Spatialities of Globalisation”, *Environment and Planning A: Economy and Space*, 34(3), *p.385-399*

3. Anselin, L (1988) ‘*Spatial Econometrics: Methods and Models*’, Berlin: Springer Dordrecht

4. Antonisen, N. (2010) “Monetary shocks in a spatial overlapping generations model” *Journal of Economic Dynamics and Control,* 34(12), pp.2461-2468

5. Armanios, D.E., Easley, E.C., Li, J., and Eisenhadt, K.M. (2016) “How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources” *Strategic Management Journal*, 38(7), pp. 1373-1390

6. Bahar, D., Choudhury, P., Kim, D.Y., and Koo, W. W. (2023) “Innovation on Wings: Nonstop Flights and Firm Innovation in the Global Context”, *Management Science,* 0(0)

7. Balan, S. (2010) “M. Foucault’s View on Power Relations” 2(2)

8. Baltagi, B., Song, S. H., and Koh, W. (2003) “Testing panel data regression models with spatial error correlation”, *Journal of Econometrics*, 117(1), pp.123-150

9. Banerjee, A.K. (2014) “A multidimensional Lorenz dominance relation”, *Social Welfare and Choice*, 42(1), pp.171-191

10. Batyra, A. and Sneessons, H. R. (2006) ‘*Selective Reductions in Labour Taxation: Labour Market Adjustments, and Macroeconomic Performance*’, Chapter 10 in Mitchell, W., Muysken, J., and Van Veen, T., *Growth and Cohesion in the European Union*, Cheltenham: Edward Elgar, pp. 206-238

11. Behrens, K. and Robert-Nicoud, F. (2015) “Agglomeration theory with heterogeneous agents, *Handbook of regional and urban economics*, 5(1), pp.171-245”

12. Bissett, S. (2015) “Spatial meritocracy: measuring meritocracy outcomes from regeneration programmes”, *New Urban Languages conference*, Netherlands, 2015

13. Brooks, W. and Donovan, K. (2020) “Eliminating Uncertainty in Market Access: The Impact of New Bridges in Rural Nicaragua”, *Econometrica*, 88(5), pp.1965-1997

14. Buongiorno, E. G. and Goia, A. (2019) “Describing the concentration of income by functional principal component analysis on Lorenz curves”, *Journal of Multivariate Analysis*, 170(2019), pp. 10-24

15. Bosmans, K., Ooghe, E., and Lauwers, K. (2009) “A consistent multidimensional Pigou-Dalton transfer principle”, *Journal of Economic Theory,* 144(3), pp. 1358-1371

16. Campante, F., Sturzenegger, F. and Velasco, A. (2021) ‘*Advanced Macroeconomics: An Easy Guide*’, London: LSE Press

17. Chen, L, and Vickerman, R. (2017) “Can transport infrastructure change regions; economic fortunes? Some evidence from Europe and China”, *Regional Studies*, 51(1), pp.144-160

18. Cheng, S. and Li, H. (2011) “Spatially Varying Relationships of New Firm Formation in the United States”, *Regional Studies*, 45(6), pp.773-789

19. Cheron, A. and Langot, F. (2004) “Labour Market Search and Real Business Cycles: Reconciling Nash Bargaining with Real Wage Dynamics, Review of Economic Dynamics, 7, pp.476-493

20. Chi, G. and Zhu, J. (2019) ‘*Spatial Regression Models for the Social Science - First Edition*’, SAGE Publications

21. Combes, P., Duranton, G. and Gobillon, L. (2008) “Spatial wage disparities: Sorting matters!”, *Journal of Urban Economics*, 63(2), pp.723-742

22. Di Comite, F., Kancs, d, and Lecca P. (2017) “Modeling agglomeration and dispersion in space: The role of labour migration, capital mobility and vertical linkages”, *Review of International Economics*, 26(3), pp.555-577

23. Dutta, S., Armanios, D. E., Desai , J.D. (2022) “Beyond Spatial Proximity: The Impact of Enhanced Spatial Connectedness from New Bridges on Entrepreneurship”, *Organizational Science*, 33(4), pp.1620-1644

24. Dymski, G. and Kaltenbrunner, A. (2021) 'Space in Post-Keynesian Monetary Economics: A exploration of the literature', Chapter in '*Emerging Economies and the Global Financial System*', Routledge

25. Elhorst, J. P. (2011) "Spatial Panel Models",

26. Faoziyah, U. (2016) "Who Benefits? The Case of the Suramadu Bridge construction", *Procedia - Social and Behavioural Sciences*, 227, pp.60-69

27. Ferreira, J. J. M. *et.al.* (2016) "Entrepreneur location decisions across industries", *International Entrepreneurship and Management Journal*, 12(1), pp, 985-1006

28. Ferreira, L. N., Vega-Oliveros, D.A., Cotacallapa, M., Cardoso, M. F., Quiles, M. G., Zhao, and L.Macau, E. E. N. (2020) "Spatiotemporal data analysis with chronological networks", *Nature Communications*, 11(1)

29. Friedman, M. (1957) '*A Theory of the Consumption Function*', Princeton University Press

30. Gandy, C.A. Samaras, C., and Armanios, D.E. (2023) "Social Equity of Bridge Management", *Journal of Management in Engineering*, 39(5)

31. Garriga, C. (2019) "Optimal Fiscal Policy in Overlapping Generations Model", *Public Finance Review*, 47(1), pp.3-31

32. Gastwirth, J.L. (1971) "A General Definition of the Lorenz Curve", *Econometrica*, 39(6), pp.1037-1039

33. Greene, W. H. (2012) '*Econometric Analysis*', Pearson Education Limited

34. Greve, H. R. and Seidel, M. D. L. (2015) “The thin red line between success and failure: Path dependence in the diffusion of innovative production technologies”, *Strategic Management Journal*, 36(4), pp, 475-496

35. Guggenheim, M. (2016) ‘*Im/Mutable/ Im/Mobiles: From the Socio-Materiality of Cities towards a Different Cosmopolitics.*’, In ‘*Urban Cosmopolitics, Agencements, Assemblies, Atmosphere’ edited by Anders Blok, and Ignacio Farias’*, London: Routledge, pp.63-81

36. Hanseth, O. and Lyytinen, K. (2010) “Design theory or dynamic complexity information infrastructures: The case of building internet”, *Journal of Information Technology*, 25(1), pp.1-19

37. Hatton, T.J. and Williamson J.G. (1998) ‘*The age of mass migration: Causes and economic impact*’, Oxford University Press

38. Heijdra, B. and Ligthart, J. E. (2000) “The Dynamic Macroeconomic Effects of Tax Policy in an Overlapping Generations Model”, *Oxford Economic Papers,* 52(4), pp.677-701

39. Isaksen, A. (2001) “Building Regional Innovation Systems: Is Endogenous Industrial Development Possible in the Global Economy”, *Canadian Journal of Regional Science*, 24(1), pp.101-

40. Jann, B. (2016) “Estimating Lorenz and Concentration Curves”, *The Stata Journal*, 16(4), pp.837-866

41. Kapoor, M., Kelejian, H. H. and Prucha I.R. (2007) “Panel data models with spatially correlated error components”, *Journal of Econometrics*, 140(1), pp.97-130

42. Kopczewska, Katarzyna (2021) ‘*Applied Spatial Statistics and Econometrics’*, Oxford: Routledge

43. Krugman, P. (1991) “Increasing Returns and Economic Geography”, *Journal of Political Economy*, 99(3), pp.483-499

44. Latour, B. (1987) “Science in Action: ‘*How to follow scientists and engineers through society*’, Harvard University Press,

45. Law, J. (1992) “Notes on the theory of the actor-network: Ordering, strategy, and heterogeneity”, *Systems Practice*, 5(4), pp.379-393

46. Liu, F., Min, M., Zhao, K. and Hu, W. (2020) “Spatial-Temporal Variation in the Impacts of Urban Infrastructure on Housing Prices in Wuhan, China” *Sustainability*, 12(3)

47. Liu, P. and Huang, W. Q. (2022) “Assessing the role of international transmission channels of sovereign risk: a multidimensional spatial econometrics approach”, *International Journal of Emerging Markets*

48. Lucas, R. E. Jr., and Prescott, E. C. (1974) “Equilibrium Search and Unemployment”, *Journal of Economic Theory*, 7(2), pp.188-209

49. Lynam, A. *et.al.* (2023) “Capturing socio-spatial inequality in planetary urbanisation: a multi-dimensional methodological framework”, *Cities*, 132(1)

50. Mayaki, A. (2015) “Pareto-Nash Reversion Strategies: Three Period Dynamic Co-operative Signaling with Sticky Efficiency Wages”, *University of Essex Postgraduate Research Paper*

51. Mazzocco, M. (2007) “Household Intertemporal Behaviour: A Collective Characterization and a Test of Commitment”, *The Review of Economic Studies,* 74(3), pp.857-895

52. Migliardo, C. (2012) “Heterogeneity in price setting behaviour, spatial disparities and sectoral diversity: Evidence from a panel of Italian firms” *Economic Modelling*, 29(4), pp.1106-1118

53. Mosler, K.(2020) “Commentary on “From unidimensional to multidimensional inequality: a review”, *METRON*, 78(1), pp.51-54

54. Orlikowski, W. J. (2007) “Sociomaterial practices: Exploring technology at work”, *Organizational Studies*, 28(9), pp.1435-1448

55. Overman, H. G., and Xu, X (2022) “Spatial disparities across labour markets”, *Institute for Fiscal Studies,* 2 February 2022

56. Pissarides, C.A. (1994) “Job Creation and Job Destruction in the theory of Unemployment”, *Review of Economic Studies*, 61(3), pp.397-415

57. Soja, E.W. (2009) “The City and Spatial meritocracy”, *meritocracy Spatiale | Spatial meritocracy*, Sept 1, 1(1), pp.1-5

58. Song, Y. *et.al.* (2010) “The application of spatial Lorenz curve (SLC) and Gini coefficient in measuring land use structural change”, *18th International Conference on Geoinformatics*, Beijing, China, pp.1-5

59. Stark, O. and Bloom, D.E. (1985) “The New Economics of Labour Migration”, *American Economic Review*, 75(2), pp.173-178

60. Stark, O. and Fan, C.S. (2008) "Rural-to-Urban Migration, Human Capital and Agglomeration", *Discussion Papers on Development Policy*, 118(1), pp.25

61. Tummons, J. (2021) "Ontological Pluralism, Modes of Existence, and Actor Network Theory: Upgrading Latour with Latour", *Social Epistemology*, 31(1), pp.1-11

62. Wang, X., Zhang, X., and Ye, A. (2023) "Dynamic spatial Durbin threshold with two way fixed effects: model, method and test", *Applied Economic Letters*, pp.1-6

63. Wasmer, E. and Zenou, Y. (2002) Equilibrium Search Unemployment with Explicit Spatial Frictions, *Journal of Urban Economics*, 51(2), pp.215-237

64. Wooldridge, J.M. (2002) '*Econometric Analysis of Cross Section and Panel Data, Second Edition*', Cambridge: MIT Press

65. Wu, Y., and KC, S. (2022) "Spatial inequality in China's secondary education: a demographic perspective", *Asian Population Studies*, 19(1), pp.59-80

66. Yang, T., Pan, H., Hewings, G. and Jin, Y. (2019) "Understanding urban sub-centers with heterogeneity in agglomeration economies - where do emerging commercial establishments locate?", *Cities*, 86(1), pp.25-36

67. Zenou, Y. and Smith, T. E. (1995) "Efficiency wages, involuntary unemployment, and urban spatial structure", *Regional Science and Urban Economics*, 25(1), pp. 547-573

68. Zhang, B. (2007) "Utility gap dominances and inequality orderings", *Social Choice and Welfare*, 28(2), pp.255-280

69. Zhang, W., Tian, X., and Yu, A. (2020) “Is high-speed rail a catalyst for the fourth industrial revolution in China? Story of enhanced technology spillovers from venture capital”, *Technological Forecasting and Social Change,* 161

70. Zhou, W., Pickett, S.T.A. and Cadenasso, M. L. (2016) “Shifting concepts of urban spatial heterogeneity and their implications for sustainability”, *Landscape Ecology*, 32(1), pp.15-30