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Space-time dynamics of fertility and commuting

The study contributes in analytical description of spatial diffusion of fertility, in particular, influenced by labour movements of people between places of residence and work. It is assumed that the labour market has externality on the marriage market due to commuting, which, in turn, affects fertility. A model of spatial diffusion of fertility is based on assumption of global and local spillover effects. The global spillover effect, as shifts in fertility norms, is motivated by increasing variance of social interactions of an individual, when places of work and residence are different. One local spillover effect is in response to flows of earnings across space. Another mechanism is related to expected changes in probabilities to find a partner affected by differences in day and night population. The analytical model, in which the effects on fertility of the cited spillovers are decomposed, is constructed in the paper on the base of a model of the demand for children, spatial stock-flow model of a market, and a matching model with a sex imbalance or spatial mismatch as the probability of matching. Three sex imbalances, namely of night-, day-time population and an adjusted to sex imbalance of commuters to residents are empirically tested. Empirical evidence on municipal Swedish data for the period 1994–2008 does not provide any strong evidence of spatial diffusion of fertility. However, there are externalities of labour mobility on fertility due to changes of gender structure of population.

Keywords: commuting; demand for children; effect of flows of earnings; effect of matching; local spillover effect; spatial diffusion of fertility.

JEL classification: C23; J11; J13; J61.

1. Introduction

The purpose of the paper is to describe spatiotemporal dynamics of fertility with focus on commuting as a factor influencing fertility. Three different mechanisms by which commuting may interact with fertility are studied: the spatial diffusion of fertility, the effect of earnings on fertility through differences in wages in the place of residence and work, and the effect of matching through the process of search in the marriage market. This paper extends a previous study (Kotyrlo, 2014), where fertility spatiotemporal dynamics is described.

The first mechanism, studied in relation to commuting, is a global spillover influence on fertility. Spillover effects may be motivated by social interactions and, therefore, be related to changes in individual preferences to have children. Social interactions may reduce the uncertainty inherent in a chosen life style by imitating others' life styles or family norms such as the timing of childbearing (Balbo, Barban, 2012). The spatial diffusion of fertility can also be caused by learning from others (Montgomery, Casterline, 1996). Due to rivalry in pro-natalist policy that might affect fertility in a regional context, spillover effects may also arise in the relation

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to public goods provision (e. g. Besley, Case, 1995; Brueckner, 2003; Lundberg, 2006). Previous empirical studies of spatial diffusion of fertility in developed countries (in Italy by Waldorf and Franklin (2002)) have found that the global spillover effect of fertility change is positive. The concept of the diffusion of fertility decline, presented in meta-analysis by de Castro (2007), can also be interpreted as a positive spatial autocorrelation.

The possibility of commuting to a distant place of work affects potential earnings of individuals. The second mechanism, studied in this paper, relates to the potential benefit of commuting in terms of earnings and its consequences on the demand for children. The change in income, associated with increased commuting, is assumed to shift the family budget constraint and, consequently, this can be reflected in birth rate changes. Direct evidence of a trade-off between commuting time and income gain is demonstrated by trends in the process of 'suburbanization'. Increasing levels of income and car ownership have made residence in family friendly suburbs more attractive compared to living in cities (Brueckner, 2003). Bunker et al. (1992), Camstra (1996) and Winfield (1985) have described the stratification of industrial society in spatial terms, whereby high-earning families tend to reside in suburbs and less skilled workers (i. e. lower-paid) tend to live in central parts of cities country. There are no paper found where, suburbanization is considered to be related to a certain shifts in fertility. High-earning families are likely to invest more in children and substitute «quantity by quality» (Becker, Lewis, 1974). Empirical results on Swedish data (Klevmarken, Lindgren, 2008) reveal an opposite tendency in suburbanization. In particular, out-migration from Stockholm relates to childbearing, however, this effect is stronger for low-income than high-income families. There appears to be no decisive evidence regarding the influence of earnings in the spatial dimension. The spatial effect of earnings is found insignificant by Kotyrlo (2015). This may depend on the fact that earnings measure both income and substitution effects, which under normal conditions go in opposite directions.

The third mechanism is related to changes in the size and pattern of the marriage market, when people have the opportunity to commute. There is no straightforward evidence in the literature that the stock of commuters coming to a city changes the overall probability of marriage. However, some theoretical models of the marriage market suggest that increasing returns to scale come into effect (Botticini, Siow, 2008; Choo, Siow, 2006; Coles, Smith, 1998). Commuter destinations are usually asymmetric: workers are usually attracted by large labour markets. The job, itself, might be not the only reason of commuting. The assumption of labour mobility for seeking a partner is the base for models in several papers (Botticini, Siow, 2008; Compton, Pollack, 2007; Drewianka, 2003; Edlund, 2005; Gautier et al., 2010; Stark, 1988). If commuting is assumed to expand the marriage market in a defined area in terms of increasing the numbers of potentially matching men and women, the concept of increasing returns to scale can be relevant. Due to commuting, opportunities of finding a partner increases both in the place of residence and in the place of work. There are studies, where tendency of single women to commute more often than married or women with children is linked to searching for a partner (Camstra, 1996; Hjorthol, 2000; Law, 1999; Madden, White, 1980; McLafferty, 1997; Sandow, 2008; Winfield, 1985). This can influence fertility through the change in sex ratio (the ratio of the number of men to the number of women in their fertility ages), which is usually found to give a positive impact on childbearing (Burdett, Coles, 1998, 1999; Edlund, 2005).

The main contribution of this paper is a description of an analytical model decomposing spatial interaction between commuting and fertility in three different mechanisms. Becker and Barro (1988) model of the demand for children is employed to describe the effect of earnings. The spatial stock-flow model of a market (Beenstock, Felsenstein, 2010) gives an understanding of the spatial effect

of earnings. Matching models with constant and increasing returns to scale (Coles, Smith, 1998; Pissarides, 1979) are employed to describe effect of the change in the day-population on childbearing.

The three mechanisms by which commuting and fertility can interact are incorporated into a spatial time-lag model of total fertility rates. The model is estimated on empirical data for the Stockholm area in Sweden over the period 1994 to 2008. The robustness of the results is investigated by several specifications of weight matrices, based on contiguity of spatial units, spherical distances between them and gravity between labour markets, described in weights by sizes of labour markets and by proportions of commuters in the labour force of different spatial units. Any spatial interaction in the model is assumed to be serially lagged by natural reasons. This justifies methods of empirical estimation on dynamic panel data. To deal with potential endogeneity, related to causality of a choice of residential area and commuting, and a marital search and commuting, general method of moments (Blundell, Bond, 1998) is applied. Invariance of weight matrices to the studied process is provided by 5-year smoothed values of the indicators employed in their constructing.

The rest of the paper is structured as follows. Firstly, the analytically model, where the main focus is on spatial interactions between commuting and fertility is constructed. Secondly, issues of estimation of the empirical model, description of the data for the period 1994–2008, and the empirical results are discussed. We conclude with a summary of results.

2. The model

Motivation of the model specification

The demand for children is modelled as a process with space and time dynamics. Fertility dynamics in industrialized economies is usually described as a cyclical process, in particular, second-order time series (Kotyrlo, 2014; Lee, 1974; Wilkinson, 1973). The specification of the spatial time-lag model is discussed in the papers of Anselin (2002), Beenstock and Felsenstein (2010), Brueckner (2003), Elhorst (2010), and Manski (1993), among others. The processes of social and economic interaction across space imply either a model with a global form of spatial spillover, as a spatial multiplier, or a local form of spillover as an autoregressive term, or a mix of them (Anselin, 2002; Brueckner, 2003; Elhorst, 2010). Manski (1993) classifies spatial interactions into three types. Global spillover respects to endogenous interaction effects, local spillover corresponds to exogenous interaction effects and their correlated effects correspond to a spatially autocorrelated error term. LeSage and Pace (2010) showed that a model with both global and local spillover effects produces unbiased coefficient estimates if the true data-generating process is either a spatial lag or a spatial error model. This justifies the choice of a model with global and local spatial interactions and a time lag, so called time-space recursive model (Anselin et al., 2008). According to LeSage and Pace (2010) models of this kind can be estimated with different weight matrices for different terms. However, Manski (1993) points out that interpretation of parameter estimates is problematic since endogenous and exogenous effects cannot be distinguished from each other.

Weight matrix has to be specified in advance (Lee, 2004). This is considered as a weakness of a spatial econometric modelling (Elhorst, 2010). In constructing a weights matrix, asymmetry of flows of commuters can be described by gravity of labour markets of metropolis areas (Alonso, 1971; LeSage, Pace, 2008; Rincke, 2010) or by difference in wages (Beenstock, Felsenstein, 2010). Constructing of such a matrix includes the fundamental difficulty of identification of the

covariance matrix; the choice of distance criteria; and the requirement of exogeneity of the spatial weights matrix (Anselin, 2002).

The modelled demand for children, see (1) below, is assumed to be an additive form of separable global and local fertility spillovers. The total variation in the number of newborn children per individual n_{it} in a given spatial unit i in a period t includes serially lagged dependent variables n_{it-1} and n_{it-2} with parameters τ_1 and τ_2 . The lagged both in space and time dependent variable terms $\mathbf{W}n_{it-1}$ and $\mathbf{W}n_{it-2}$, where $\mathbf{W}$ denotes the weight matrix, respect to the global spillover effect. Income y and changes in the residing population (pop) and the number of commuters (m) in their fertility ages are assumed to be potential variables of spatial interaction related to commuting. A description of these interactions, denoted as functions $f(y_{it})$ and $g(pop_{it})$, affecting childbearing, their parameterization, and estimation of the parameters are discussed below. Other potential explanatory variables $\mathbf{X}$ as a matrix of size $K \times N$ are included in the regression with a vector of parameters β_k , $k = 1, \dots, K$ at explanatory variables:

$$\ln n_{it} = \tau_1 \ln n_{i,t-1} + \tau_2 \ln n_{i,t-2} + \rho_1 \sum_{j \neq i} w_{ij} \ln n_{j,t-1} + \rho_2 \sum_{j \neq i} w_{ij} \ln n_{j,t-2} + \eta \sum_{j \neq i} f(y_{j,t-1}) + \delta \sum_{j \neq i} g(pop_{j,t-1}) + \sum_k \beta_k x_{k,i,t-1} + \varepsilon_{it}, \quad (1)$$

where $i, j = 1, \dots, N$ denote of spatial units and $t = 1, \dots, T$ is a period of time; ρ_1, ρ_2, η , and δ are the parameters of interest. Disturbances ε_{it} are assumed to be identically distributed error terms with zero mean and variance σ^2 , spatially independent but not necessarily independent over time since some explanatory variables may be endogenous. The parameters ρ_1 and ρ_2 depict the relative change in the number of newborn children per individual due to the global spillover of fertility, or summarizing interactions not explicitly considered in the model; η shows the relative changes in the demand for children due to the direct mechanism of spatial differences in income; and δ reflects the relative changes in fertility due to the shift in the number of women and men of fertile age caused by commuting.

Spatial effect of earnings on fertility

The spatial effect of earnings on fertility is assumed due to a shift of the family budget constraint when earnings change because of labour mobility. For the sake of simplicity, the optimal allocation of demand for children and other consumption is described on two geographical units or municipalities, i and j , where flows of commuters affect income flows. The population size of fertile age pop_{it} and pop_{jt} is assumed to be equal to the size of the labour force in each spatial unit. The term m_{ijt}^- is the number of commuters, i.e. the people residing in municipality i and working in j at time t . Average wages in the two local labour markets in municipalities i and j are equal to y_{it} and y_{jt} . Let $n_{it}(y_{it})$ be the optimal number of children for a representative non-commuting individual living in municipality i at time t .

If people work in their own municipality and earn y_{it} , on average, the total number of children born in a given period is $pop_{it}n_{it}$. In the case of commuting, the aggregate demand for children n_{it} is given by $(pop_{it} - m_{ijt}^-)n_{it} + m_{ijt}^-n_{jt}$, in which n_{jt} is the number of children per individual in the municipality j . Spatial differences in income are expected to be the main reason for differences in the demand for children. The change in the average number of newborn children per individual in the municipality i is presented in equation:

$$f(y_{it}) = \frac{m_{ijt}^-(n_{jt} - n_{it})}{pop_{it}}. \quad (2)$$

The demand for children n_{jt} , as a function of earnings (Becker, Barro, 1988), can be approximated by two first terms of Taylor series decomposition $n_{jt} = n_{it} + \frac{\partial n_{it}}{\partial y_{it}}(y_{jt} - y_{it})$. This yields in following equation:

$$f(y_{it}) \approx \frac{m_{ijt}^-}{pop_{it}} \frac{\partial n_{it}}{\partial y_{it}} (y_{jt} - y_{it}), \quad (3)$$

which exhibits how interaction between spatial units leads to a change in fertility by flows of earnings. The shift in the demand for children is increasing with the gap in earnings between two units and with the proportion of commuting workers in the population of a certain unit. The described effect can be expressed in general for N units (see (4)) as a sum of effects (3). The measure $h(d_{ij})$ of the geographical distance between i and j is introduced to reflect the effect of distance decay on the relation:

$$f(y_{it}) \approx \mu \sum_{j=1}^N y_{jt} h(d_{ij}) \frac{\tilde{m}_{ij}^-}{pop_i} (1 - \tilde{y}_i / \tilde{y}_j). \quad (4)$$

Here tilde denotes 5-year smoothed values to avoid endogeneity problems, and μ measures the average marginal effect of earnings on the demand for children. The values under the sum reflect local spillover effect generated by difference in earnings. The last factor can be negative. It is transformed to non-negative values by the Bray–Curtis definition of distance (Piras, 2010). The intuition of the local spillover is such that the spatial weights capture gravity into the model. The larger the labour market in certain locality j for people living in place i , the higher will be the weight due to the share of commuters in the population and due to the relative difference in earnings. Non-negative spatial weights matrix $\mathbf{Q}$, related to the local spillover, is described in equation (5). It is asymmetric and not row-standardized, since standardization would diminish the gravity effect.

$$\begin{cases} q_{ij} = \frac{\tilde{m}_{ij}^-}{pop_i} \cdot \frac{|\tilde{y}_j - \tilde{y}_i|}{\tilde{y}_j + \tilde{y}_i} h(d_{ij}), & i \neq j, \quad i, j = 1, \dots, N; \\ q_{ii} = 0, & i = 1, \dots, N. \end{cases} \quad (5)$$

Finally, the difference in the number of newborn children per individual attributable to income flows and invariant to individual preferences is given by the expression:

$$f(y_{it}) \approx \mu \sum_{j \neq i} q_{ij} y_{jt}. \quad (6)$$

In addition to the approach described above, several variations of weights matrices based on different understanding of geographical distance and economic gravity between units are employed to compare the results and test their robustness (see section 3).

Spatial effect of matching on fertility

Labour market movements can be related to movements in family formation or marriage market. Both negative and positive effect can be assumed. This can be related to a «population effect in grooms/brides supply» as an analogy of income effect in labour supply. Labour markets of a big size can give a positive externality in an increased supply of grooms and brides in their fertility

age due to commuting. Negative effect relates to substitution between formal work and housework linked to family formation. Thus, increased time consumption including work itself and commuting as extra time spending would decrease demand in the marriage market and childbearing.

The measurement of the second term in equation (1) is based on a matching function. Following Pissarides (1979) a matching function is described by the Poisson distribution:

$$M(pop_{female,it}, pop_{male,it}) = pop_{female,it} \cdot \left(1 - \left(1 - 1/pop_{female,it}\right)^{pop_{male,it}}\right), \quad (7)$$

where $pop_{male,it}(pop_{female,it})$ is the number of men (women). This is a constant returns to scale matching function employed in Botticini and Siow (2008), Burdett and Coles (1999), Coles and Petrongolo (2008), Diamond (1981), and Mortensen (1982). For the sake of simplicity, groups of men and women are assumed to be homogenous and the net-flow of people, who enter and exit the marriage market, is assumed to be zero. In such a case, the parameter of distribution or resulting matches, as well as the expected value of matches and its variance, are equal to the sex ratio (the ratio of men to women) (Edlund, 2005).

The matching function (7) is asymmetric with respect to sex. Further, it is assumed that the sex ratio of the population living in the municipality expresses the probability of matches for the less represented sex in the night-time population. This is called *the sex imbalance of the night-time population*:

$$\tilde{R}_{night,it} = \min \left\{ \frac{pop_{male,it}}{pop_{female,it}}, \frac{pop_{female,it}}{pop_{male,it}} \right\}. \quad (8)$$

Taking into account the stock of commuters coming into the city, the probability of a match is equal to *the sex imbalance of the day-time population*, as the probability of matches for the less represented sex in the day-time population:

$$\tilde{R}_{day,it} = \min \left\{ \frac{pop_{male,it} + m_{male,it}^+}{pop_{female,it} + m_{female,it}^+}, \frac{pop_{female,it} + m_{female,it}^+}{pop_{male,it} + m_{male,it}^+} \right\}, \quad (9)$$

where $m_{male,it}^+(m_{female,it}^+)$ is the male (female) population coming into the city.

Coles and Smith (1998) suggested a matching function with increasing returns to scale in the number of new buyers and sellers entering the market. Male and female commuters can be associated with new buyers and sellers. Similar to their model, the matching function in the marriage market increasing in the number of incoming commuters to the size of the population yields:

$$\begin{aligned} R_{adj,it} &= \left[1 - \left(1 - \frac{1}{pop_{male,it}}\right)^{pop_{female,it}} \right] \cdot m_{male,it}^+ + \left[1 - \left(1 - \frac{1}{pop_{female,it}}\right)^{pop_{male,it}} \right] \cdot m_{female,it}^+ \approx \\ &\approx \frac{1}{pop_{it}} \left(\frac{pop_{female,it} m_{male,it}^+}{pop_{male,it}} + \frac{pop_{male,it} m_{female,it}^+}{pop_{female,it}} \right) = \frac{1}{pop_{it}} \left(\frac{m_{male,it}^+}{R_{night,it}} + R_{night,it} m_{female,it}^+ \right). \end{aligned} \quad (10)$$

Therefore, there are three ways of estimation of effect of matching function on childbearing, namely, by the sex imbalance of the night-time population (8), the sex imbalance of the day-time population (9), and by the variable constructed and presented in equation (10), called «the adjusted sex imbalance». Three sex imbalances are to be tested in empirical estimation separately.

Positive effect of night-time sex imbalance on childbearing is associated with supporting the hypothesis of non-assortative matching when each person of a minor gender group gets a partner, and following risk of childbearing respects to the coefficient at the variable. Negative effect of the sex imbalance of residing population on childbearing can advocate that demand for children is lower due to lower utility of childbearing when the risk of matching in the marriage market is higher. If childbearing is a «necessity» by Tornqvist's classification of commodities (Fisk, 1958), demand might slow down with growing potential to consume. Positive externality of labour market on marriage market and childbearing through change in the day-time sex imbalance due to commuting can be interpreted as a «population effect» or higher risk of childbearing when day-time population is gender equalized. Finally, the adjusted sex imbalance reflects response to higher proportion of commuters of the opposite sexes in the day-time population. If the substitution effect prevails, demand for children would decrease in raising the adjusted sex imbalance. Otherwise, «population effect» would provide positive response in fertility on growing share of commuters.

3. Empirical estimation of the model

The source for empirical estimation of the model is the aggregate data published by Statistics Sweden² (SCB). In 2008, the population of Sweden was 9 million people, 6 million people in the labour force, and 1.3 million were commuters. The Stockholm area, analysed in the study, is represented by 68 municipalities belonging to 12 labour markets by SCB definition. This was 3.2 million people population, 2.1 million in the labour force, and 665 thousand people of commuters by SCB definition. The pattern of commuting in the Stockholm area is typical for metropolitan areas. More men than women commute, and more women than men work in the place of residence. Stockholm attracts commuters and is the biggest source of commuters to surrounding areas, providing from 25 to 75% of the total number of workers coming into a particular municipality.

Descriptive statistics is presented in Table 1. Average values of the demand for children are expressed by total fertility rates (*TFR*), as the sum of the age-specific fertility rates for women aged 16–49 years living in the municipality. The average income per capita for people aged 20–65 years deflated by the consumer price index is assumed to be strongly positively correlated with the average earnings. Variables of interest such as incomes and the proportion of commuters in the size of population have positive time trends, though the relative annual change is relatively low. This substantiates consideration of their serial lags in the model; 3–5-year lags are tested in estimation.

The total change in the average number of children per individual (equation (1)) due to the spatial diffusion of fertility, as changes in consumption preferences, spatial interaction of incomes (equation (6)) and changes in probabilities of matching can be presented as follows:

$$\begin{aligned} \ln TFR_{i,t} = & \tau_1 \ln TFR_{i,t-1} + \tau_2 \ln TFR_{i,t-2} + \rho_1 \sum_{j \neq i} w_{ij} \ln TFR_{j,t-1} + \rho_2 \sum_{j \neq i} w_{ij} \ln TFR_{j,t-2} + \\ & + \eta \sum_{j \neq i} q_{ij} \ln(y_{j,t-3}) + \delta_1 \left(\frac{m_{mi,t-4}^+}{pop_{i,t-4}} \frac{1}{R_{night,i,t-4}} + R_{night,i,t-4} \frac{m_{fi,t-4}^+}{pop_{i,t-4}} \right) + \\ & + \delta_2 \min \left\{ R_{night,i,t-4}, \frac{1}{R_{night,i,t-4}} \right\} + \delta_3 \min \left\{ R_{day,i,t-4}, \frac{1}{R_{day,i,t-4}} \right\} + \beta \ln(y_{j,t-3}) + \varepsilon_{i,t}. \end{aligned} \quad (11)$$

² <http://www.scb.se>.

Table 1. Descriptive statistics. The Stockholm area (1993–2008). $N = 992$, $n = 62$, $T = 16$

Variable	Mean	Standard deviation	Min	Max
<i>TFR:</i>				
overall	1.878	0.264	1.040	3.020
between		0.134	1.568	2.150
within		0.228	1.079	2.819
The proportion of male coming commuters aged 16–49 yrs, m_{male}^+ / pop :				
overall	0.168	0.135	0.037	1.019
between		0.133	0.051	0.904
within		0.029	0.057	0.283
The proportion of female coming commuters aged 16–49 yrs, m_{female}^+ / pop :				
overall	0.121	0.131	0.024	0.922
between		0.130	0.031	0.838
within		0.021	–0.008	0.205
Income (hundred SEK)				
overall	75.023	15.318	50.329	180.705
between		13.482	60.789	138.296
within		7.458	44.950	117.432
Sex imbalance of night-time population, R_{night}				
overall	0.951	0.033	0.860	1.000
between		0.031	0.885	0.995
within		0.012	0.907	1.000
Sex imbalance of day-time population, R_{day} :				
overall	1.120	0.088	0.778	1.517
between		0.084	0.819	1.451
within		0.026	0.989	1.259
Adjusted sex imbalance, R_{adj} :				
overall	0.287	0.261	0.062	1.939
between		0.259	0.081	1.741
within		0.048	0.067	0.485

Source: Calculated on the base of data published by SCB.

There are two general approaches to deal with endogeneity of commuting to the size of population and wages, namely, employing instrumental variables (IV) and the general method of moments (GMM) in the estimations. Since IV estimates provide option to get fixed effects for labour markets, both approaches are employed in the analysis. However, the main results presented below are based on GMM approach to general method of moments in the estimations. Bond–Blundell system GMM with Windmeijer (2005) finite-sample correction to the reported standard errors in two-step estimation is employed (Blundell, Bond, 1998), since lagged levels of variables in Arellano–Bond difference GMM (Arellano, Bond, 1991) are shown weak instru-

ments when explanatory variables are persistent over time (Alonso-Borrego, Arellano, 1999; Blundell, Bond, 1998). This problem is related to the sex imbalances included in the model estimation, varying relatively little. Post-estimation tests are made to test over-identifying restrictions on the number of instruments (Hansen, 1982; Sargan, 1958) and serial correlations in residuals (Arellano, Bond, 1991). The error term is likely first-order serially correlated (Roodman, 2006); therefore, the null hypothesis of no second-order correlation is tested. Since Sargan test is inefficient when T is larger than 13 (Anderson, Sørensen, 1996; Bowsher, 2002), difference-in-Sargan/Hansen C -statistics (Roodman, 2006) is also employed.

Weight matrices are described in Table A1. There are three pairs of matrices based on different meanings of gravity between the municipal labour markets. Matrices Q_1 and Q_2 are straightforward applications of equation (5) with spherical distances (Q_1) and neighbourhood within 100 km (Q_2). Weight matrices Q_3 and Q_4 include population size as extra source of gravity beside income levels and flows of commuters. Q_5 and Q_6 are based only on population size, and income is not included. Influence of spatially weighted income has likely negative influence on fertility.

Time dummies in order to eliminate time-related shocks from the errors are included in all estimates. Cyclical pattern is assumed both in serial and spatiotemporal terms, therefore having two serial lags. Several weight matrices based on different understanding of geographical distance between units are estimated to test consistency of the results. The best estimates are provided by weight matrix based on spherical distances (W_1) and neighbourhood defined as area 100 km (W_2). Estimates are presented in Tables A2–A5. Table A2 exhibits estimates in the spatially unadjusted model and models where spatially lagged $\log TFR$ is included together with sex imbalances terms. Day-time, night-time and adjusted sex imbalances are added in the estimation separately. The estimates show that coefficients on serially lagged $\log TFR$ are positive and significant, which is credible in assumption of cyclicity of fertility. According to estimates, serial autocorrelation explains 52–78% of variation of total fertility rates. In contrast with the results on the entire Sweden (Kotyrlo, 2014), spatially lagged terms are neither significant nor robust in sign and value for the Stockholm area. Arellano–Bond test rejects second-order autocorrelation in residuals. Sex imbalance coefficients are relatively robust in sign and value. This is positive for sex imbalance of day-time population and negative for night-time and adjusted sex imbalances, though confidence level does not reach 95%.

Income flows are assumed to constitute the second local spillover effect on fertility. The estimates including spatially weighted income are presented in Tables A3–A5. Weight matrix including both income and population size meanings of gravity provides the best estimates. This can be interpreted as a higher fertility in suburbs of densely populated cities and higher income disparities between them. This is not necessarily related to commuting and can be explained by favourable family conditions of suburbs compensating relatively low-income level.

Among components associated with increasing opportunities of matching due to commuting (equation (11)), the fourth-order lagged sex imbalance of night-time population δ_2 has negative effect on fertility. Therefore, in assumption of probability of matching corresponding to the sex imbalance of population residing in a municipality, total fertility rates would decrease with equalizing of population of both sex and this would be higher in areas with greater disparities in female and male population. This, however, is not supported on the 95% confidence level.

The estimate for the parameter at the fourth-order lagged sex imbalance δ_3 of population working in municipality, both commuting and residing, positively respects total fertility rates. This can be interpreted as follows. If matching function was based on the day-time sex imbalance, fertility

would be higher with equalizing of working population of both sexes. This would support positive effect of commuting on fertility; however, estimates do not reach 95% of confidence level. Higher sex imbalance of day-time population seems to be a good indicator of favourable demographic shifts in terms of fertility. The result is consistent to other studies, where sex imbalance of in-migrants is proposed to be an indicator of matching in assumption of constant returns to scale.

Adjusted sex imbalance likely negatively affects fertility. Therefore, greater flows of in-commuters with respect to the residing population negatively influences on total fertility rates. The hypothesis of decreasing returns to scale due to commuting is accepted in the estimates with income spatially weighted by matrix Q_3 . This explains 5.9% of decrease in fertility.

Thus, of the three postulated components in the spatial diffusion of fertility, the empirical evidence advocate neither for the global spillover effect nor for local spillover generated by income flows. It can be concluded that there is no spatiotemporal diffusion of fertility. However, fertility is positively related to the sex imbalance of day-time population and negatively to the proportion of commuters of the opposite sex in the residing population. This reflects effect of changes in structure and size of population in their fertility ages due to commuting on probability of childbearing.

4. Conclusion

The relationship between commuting and fertility in assumption of existence of externalities of growing labour markets on marriage markets has been described analytically in the paper. The main contribution is the integration of different spatial effects in one analytical model. Three spatial effects due to commuting, namely the global spillover and two types of local spillovers generated by income flows and changes in the probability of matching in the marriage market, are considered in the model. Global spillover is included in the model in the form of the second-order spatial and serial term and tested in empirical estimates based on several definitions of gravity between the units.

Local spillover effect of earnings on fertility is analytically constructed on the base of the model of demand for children of Becker and Barro (1988) and spatial stock-flow model of a market, suggested by Beenstock and Felsenstein (2010). The composed weights express gravity between spatial units generated by flows of commuters, population size, and average wages. Lagged and 5-year smoothed values of the variables are employed in construction of weight matrices. To deal with potential endogeneity in explanatory variables, Bond–Blundell GMM estimation is applied.

There is no evidence of global spillover of fertility. As anticipated, the estimates do not support local spillover effect of earnings reflected by the variable chosen, measured as average earnings of residents and commuters leaving the municipality, therefore, already containing spatial interaction. However, this does not disapprove the analytical approach to describe influence of spatial income flows on fertility.

By analysis of theoretical and empirical contributions in the issue studied, three approaches to introduce probability of matching in the model of fertility are described and empirically tested. They are sex imbalances of residing population, day-time population, including coming commuters and workers living in the municipality, and adjusted sex imbalance, linear to proportions of commuters of a certain gender to the residing population of the opposite sex. The latter is constructed to test increasing returns to scale in changes of probability of childbearing due to changes in structure of population. This is negatively related to fertility, which supports that substitution effect between formal work and housework linked to family formation prevails, and demand

for children decreases with growth of the adjusted sex imbalance. The sex imbalance of day-time population working in municipality positively respects total fertility rates, which advocate higher fertility if the population is gender-balanced. However, estimates do not reach 95% of confidence level. The found relation indirectly suggests influence on age-gender structure and the proportion of people anticipating matching in a day-time population. However, the terms related to matching in the marriage market do not contain spatial dimension, since total effect of changes in the structure of population in their fertility ages comes into consideration. Nevertheless, it is analytically and empirically proven that the size and the gender structure of commuters play a role in fertility.

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Appendix

In Table A1:

$d_{spher,ij}$ is a spherical distance between i and j ;

d_{ij} is equal to one if a distance between i and j does not exceed 100 km and zero otherwise;

$\tilde{m}_{ij}$ is 5-year smoothed flows of commuters between i and j ;

$\widetilde{pop}_j$ is 5-year smoothed population size in municipality j ;

$\tilde{y}_j$ is 5-year smoothed values of log incomes in municipality j .

The matrices are row-standardized.

Table A1. Weight matrices description

$$\begin{aligned}
 \mathbf{Q}_1 & \begin{cases} q_{1ij} = \frac{1}{d_{spher,ij}} \cdot \frac{|\tilde{y}_j - \tilde{y}_i|}{\tilde{y}_j + \tilde{y}_i} \tilde{m}_{ij}, i \neq j, \quad i, j = 1, \dots, N; \\ q_{1ii} = 0, \quad i = 1, \dots, N. \end{cases} \\
 \mathbf{Q}_2 & \begin{cases} q_{2ij} = \frac{|\tilde{y}_j - \tilde{y}_i|}{\tilde{y}_j + \tilde{y}_i} \tilde{m}_{ij}, \text{ if } d_{ij} = 1 \text{ and } i \neq j, \quad i, j = 1, \dots, N; \\ q_{2ij} = 0, \text{ otherwise.} \end{cases} \\
 \mathbf{Q}_3 & \begin{cases} q_{3ij} = \frac{1}{d_{spher,ij}} \cdot \frac{|\tilde{y}_j - \tilde{y}_i|}{\tilde{y}_j + \tilde{y}_i} \widetilde{pop}_j \tilde{m}_{ij}, i \neq j, \quad i, j = 1, \dots, N; \\ q_{3ii} = 0, \quad i = 1, \dots, N. \end{cases} \\
 \mathbf{Q}_4 & \begin{cases} q_{4ij} = \frac{|\tilde{y}_j - \tilde{y}_i|}{\tilde{y}_j + \tilde{y}_i} \tilde{m}_{ij} \widetilde{pop}_j, \text{ if } d_{ij} = 1 \text{ and } i \neq j, \quad i, j = 1, \dots, N; \\ q_{4ij} = 0, \text{ otherwise.} \end{cases} \\
 \mathbf{Q}_5 & \begin{cases} q_{5ij} = \frac{1}{d_{spher,ij}} \widetilde{pop}_j \tilde{m}_{ij}, \quad i \neq j, \quad i, j = 1, \dots, N; \\ q_{5ii} = 0, \quad i = 1, \dots, N. \end{cases} \\
 \mathbf{Q}_6 & \begin{cases} q_{6ij} = \widetilde{pop}_j \tilde{m}_{ij}, \text{ if } d_{ij} = 1 \text{ and } i \neq j, \quad i, j = 1, \dots, N; \\ q_{6ij} = 0, \text{ otherwise.} \end{cases}
 \end{aligned}$$

In Tables A2–A5 below all regressions are one-step Bond–Blundell GMM estimates with the robust estimator of the covariance matrix. Period dummies not reported. AR (2) is p -value for Arellano–Bond test for AR (2) in first differences. Hansen test supports null of joint validity of instruments (p -value 0.01%). Sargan test of overidentifying restrictions is rejected in all the cases with p -value 0.1%. Difference-in-Hansen tests of exogeneity of instrument subsets does not reject null hypothesis that instruments added are exogenous in all the cases.

Table A2. Estimates for log total fertility rates.

Variable	Unadjusted	$W_2 TFR$	$W_1 TFR$	$W_2 TFR$	$W_1 TFR$	$W_2 TFR$	$W_1 TFR$	$W_2 TFR$	$W_1 TFR$
$\log TFR_{t-1}$	0.199*** (0.045)	0.172** (0.051)	0.207*** (0.046)	0.188** (0.057)	0.168** (0.062)	0.182** (0.059)	0.216*** (0.053)	0.203*** (0.058)	0.216*** (0.054)
$\log TFR_{t-2}$	0.228*** (0.049)	0.196** (0.058)	0.231*** (0.056)	0.197** (0.062)	0.173* (0.067)	0.180** (0.064)	0.217*** (0.062)	0.214*** (0.061)	0.221*** (0.061)
$W \log TFR_{t-1}$		0.116 (0.141)	-0.06 (0.111)	0.127 (0.130)	0.143 (0.123)	0.104 (0.149)	-0.048 (0.113)	-0.048 (0.110)	-0.055 (0.113)
$W \log TFR_{t-2}$		0.41 (0.286)	-0.011 (0.253)	0.356 (0.286)	0.519 (0.306)	0.565 (0.351)	0.047 (0.254)	-0.008 (0.264)	0.012 (0.253)
$Income_{t-3}$	-0.044 (0.058)	-0.033 (0.057)	-0.049 (0.058)	-0.05 (0.072)	0.023 (0.086)	-0.047 (0.061)	-0.045 (0.080)	-0.023 (0.089)	-0.076 (0.073)
$R_{adj, t-4}$				-0.044 (0.031)			-0.05 (0.031)		
$R_{night, t-4}$					-0.184 (0.296)			-0.181 (0.322)	
$R_{day, t-4}$						0.013 (0.094)			0.025 (0.117)
Intercept	-0.649** (0.216)	-0.371 (0.232)	-0.692** (0.242)	-0.097 (0.306)	0.214 (0.297)	0.247 (0.314)	-0.43 (0.294)	-0.358 (0.229)	-0.367 (0.277)
Observations	806	793	806	732	732	732	744	744	744
Instruments	117	118	118	115	115	115	115	115	115
AR(2)	0.423	0.342	0.389	0.848	0.982	0.939	0.845	0.968	0.852

Notes. *, **, *** — significance at the level 5, 1 and 0.1% respectively; standard deviations are below the regression coefficients.

Table A3. Estimates for log total fertility rates

Variable	$\mathbf{W}_2 TFR$	$\mathbf{W}_2 TFR$	$\mathbf{Q}_1$	$\mathbf{W}_2 TFR$	$\mathbf{Q}_1$	$\mathbf{W}_1 TFR$	$\mathbf{Q}_1$	$\mathbf{W}_1 TFR$	$\mathbf{Q}_1$	$\mathbf{W}_2 TFR$	$\mathbf{Q}_2$	$\mathbf{W}_2 TFR$	$\mathbf{Q}_2$	$\mathbf{W}_1 TFR$	$\mathbf{Q}_2$	$\mathbf{W}_1 TFR$	$\mathbf{Q}_2$
$\log TFR_{t-1}$	0.165* (0.068)	0.156* (0.067)	0.177** (0.065)	0.203** (0.063)	0.195** (0.064)	0.219*** (0.060)	0.181** (0.061)	0.169** (0.062)	0.186** (0.061)	0.213*** (0.058)	0.205** (0.062)	0.221*** (0.059)	0.221*** (0.059)				
$\log TFR_{t-2}$	0.165** (0.057)	0.167** (0.059)	0.175** (0.059)	0.218*** (0.062)	0.222*** (0.063)	0.229*** (0.063)	0.184** (0.058)	0.184** (0.065)	0.189** (0.061)	0.223*** (0.062)	0.227*** (0.064)	0.232*** (0.064)	0.232*** (0.064)				
$\mathbf{W} \log TFR_{t-1}$	0.048 (0.148)	0.148 (0.115)	0.069 (0.136)	-0.102 (0.118)	-0.089 (0.116)	-0.091 (0.121)	0.081 (0.149)	0.175 (0.117)	0.105 (0.153)	-0.077 (0.110)	-0.083 (0.111)	-0.088 (0.113)	-0.088 (0.113)				
$\mathbf{W} \log TFR_{t-2}$	0.509 (0.317)	0.421 (0.233)	0.521 (0.287)	-0.030 (0.244)	-0.086 (0.254)	0.000 (0.233)	0.410 (0.321)	0.355 (0.243)	0.428 (0.295)	0.007 (0.241)	-0.043 (0.272)	-0.005 (0.245)	-0.005 (0.245)				
$Income_{t-3}$	0.308 (0.218)	0.207 (0.212)	0.135 (0.169)	0.244 (0.230)	0.160 (0.227)	0.062 (0.191)	0.066 (0.115)	-0.017 (0.096)	-0.026 (0.105)	0.031 (0.108)	-0.033 (0.099)	-0.06 (0.110)	-0.06 (0.110)				
$\mathbf{Q} Income_{t-3}$	-0.443 (0.253)	-0.244 (0.250)	-0.272 (0.205)	-0.372 (0.278)	-0.199 (0.269)	-0.183 (0.245)	-0.241 (0.197)	0.035 (0.157)	-0.093 (0.208)	-0.168 (0.194)	0.049 (0.154)	-0.040 (0.220)	-0.040 (0.220)				
$R_{adj, t-4}$	-0.057 (0.036)			-0.056 (0.034)			-0.027 (0.030)			-0.036 (0.030)							
$R_{night, t-4}$		-0.104 (0.302)			-0.197 (0.311)			-0.191 (0.357)			-0.280 (0.375)						
$R_{day, t-4}$			0.100 (0.111)			0.065 (0.121)			0.071 (0.152)			0.037 (0.157)	0.037 (0.157)				
Intercept	0.128 (0.352)	-0.019 (0.239)	0.110 (0.263)	-0.328 (0.317)	-0.415 (0.234)	-0.222 (0.301)	0.256 (0.422)	-0.087 (0.222)	0.077 (0.329)	-0.229 (0.422)	-0.452 (0.251)	-0.361 (0.416)	-0.361 (0.416)				
Observations	732	732	732	732	732	732	732	732	732	732	732	732	732				
Instruments	115	115	115	115	115	115	115	115	115	115	115	115	115				
AR(2)	0.85	0.903	0.959	0.802	0.859	0.662	0.98	0.932	0.914	0.7	0.736	0.632	0.632				

Notes. *, **, *** — significance at the level 5, 1 and 0.1% respectively; standard deviations are below the regression coefficients.

Table A4. Estimates for log total fertility rates

Variable	$\mathbf{W}_2TFR$	$\mathbf{Q}_3$	$\mathbf{W}_2TFR$	$\mathbf{Q}_3$	$\mathbf{W}_1TFR$	$\mathbf{Q}_3$	$\mathbf{W}_2TFR$	$\mathbf{Q}_4$	$\mathbf{W}_2TFR$	$\mathbf{Q}_4$	$\mathbf{W}_1TFR$	$\mathbf{Q}_4$	$\mathbf{W}_1TFR$	$\mathbf{Q}_4$	$\mathbf{W}_1TFR$	$\mathbf{Q}_4$
$\log TFR_{t-1}$	0.165* (0.070)	0.160* (0.066)	0.176* (0.067)	0.200** (0.065)	0.197** (0.063)	0.215** (0.063)	0.160* (0.065)	0.153* (0.065)	0.173** (0.064)	0.196** (0.061)	0.191** (0.063)	0.214*** (0.061)				
$\log TFR_{t-2}$	0.169** (0.058)	0.170** (0.059)	0.174** (0.060)	0.214*** (0.062)	0.222*** (0.063)	0.230*** (0.064)	0.159** (0.056)	0.163** (0.059)	0.170** (0.058)	0.215** (0.062)	0.221*** (0.063)	0.230*** (0.063)				
$\mathbf{W}\log TFR_{t-1}$	0.069 (0.141)	0.133 (0.116)	0.056 (0.148)	-0.094 (0.114)	-0.091 (0.114)	-0.109 (0.118)	0.027 (0.158)	0.129 (0.117)	0.055 (0.148)	-0.114 (0.119)	-0.097 (0.118)	-0.113 (0.121)				
$\mathbf{W}\log TFR_{t-2}$	0.443 (0.296)	0.416 (0.235)	0.512 (0.299)	-0.018 (0.249)	-0.079 (0.257)	-0.051 (0.244)	0.497 (0.310)	0.431 (0.234)	0.520 (0.291)	-0.068 (0.234)	-0.112 (0.243)	-0.062 (0.227)				
$Income_{t-3}$	0.212 (0.140)	0.144 (0.121)	0.105 (0.117)	0.181 (0.134)	0.113 (0.120)	0.065 (0.117)	0.276 (0.165)	0.182 (0.159)	0.111 (0.129)	0.242 (0.172)	0.156 (0.170)	0.066 (0.141)				
$\mathbf{Q}Income_{t-3}$	-0.804* (0.401)	-0.509 (0.417)	-0.647 (0.397)	-0.721 (0.409)	-0.431 (0.433)	-0.556 (0.433)	-0.470* (0.220)	-0.265 (0.219)	-0.289 (0.197)	-0.437 (0.244)	-0.239 (0.238)	-0.243 (0.226)				
$R_{adj, t-4}$	-0.059* (0.028)			-0.059* (0.029)			-0.069 (0.037)			-0.066 (0.037)						
$R_{night, t-4}$		-0.061 (0.304)			-0.157 (0.313)			-0.096 (0.312)			-0.192 (0.312)					
$R_{day, t-4}$			0.087 (0.098)			0.074 (0.112)			0.084 (0.101)			0.070 (0.110)				
Intercept	1.497 (0.860)	0.928 (0.857)	1.328 (0.878)	0.936 (0.848)	0.400 (0.874)	0.728 (0.920)	0.264 (0.401)	0.096 (0.291)	0.229 (0.325)	-0.172 (0.386)	-0.314 (0.292)	-0.231 (0.345)				
Observations	732	732	732	732	732	732	732	732	732	732	732	732				
Instruments	115	115	115	115	115	115	115	115	115	115	115	115				
AR(2)	0.881	0.93	0.945	0.807	0.831	0.71	0.776	0.859	0.91	0.894	0.908	0.735				

Notes. *, **, *** — significance at the level 5, 1 and 0.1% respectively; standard deviations are below the regression coefficients.

Table A5. Estimates for log total fertility rates

Variable	$\mathbf{W_2TFR}$	$\mathbf{W_2TFR}$	$\mathbf{W_2TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_2TFR}$	$\mathbf{W_2TFR}$	$\mathbf{W_2TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$	$\mathbf{W_1TFR}$
	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_5}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$	$\mathbf{Q_6}$
$\log TFR_{t-1}$	0.166* (0.069)	0.161* (0.065)	0.177* (0.067)	0.201** (0.064)	0.198** (0.063)	0.216** (0.063)	0.154* (0.065)	0.174** (0.063)	0.198** (0.060)	0.193** (0.063)	0.215*** (0.061)				
$\log TFR_{t-2}$	0.171** (0.058)	0.172** (0.059)	0.175** (0.060)	0.215*** (0.062)	0.223*** (0.063)	0.231*** (0.064)	0.164** (0.058)	0.164** (0.059)	0.214*** (0.062)	0.221*** (0.063)	0.229*** (0.063)				
$\mathbf{W}\log TFR_{t-1}$	0.069 (0.140)	0.136 (0.113)	0.059 (0.145)	-0.092 (0.114)	-0.089 (0.114)	-0.106 (0.118)	0.133 (0.117)	0.042 (0.162)	-0.108 (0.118)	-0.093 (0.117)	-0.108 (0.120)				
$\mathbf{W}\log TFR_{t-2}$	0.436 (0.295)	0.408 (0.232)	0.503 (0.296)	-0.015 (0.247)	-0.074 (0.255)	-0.046 (0.241)	0.426 (0.232)	0.652 (0.350)	-0.043 (0.232)	-0.095 (0.244)	-0.045 (0.228)				
$Income_{t-3}$	0.213 (0.147)	0.137 (0.125)	0.102 (0.123)	0.181 (0.143)	0.105 (0.126)	0.061 (0.125)	0.178 (0.162)	0.106 (0.133)	0.230 (0.174)	0.141 (0.171)	0.051 (0.144)				
$\mathbf{Q}Income_{t-3}$	-0.691 (0.365)	-0.412 (0.381)	-0.540 (0.360)	-0.617 (0.374)	-0.341 (0.398)	-0.458 (0.396)	-0.254 (0.223)	-0.248 (0.197)	-0.414 (0.247)	-0.213 (0.241)	-0.216 (0.227)				
$R_{adj, t-4}$	-0.059* (0.028)			-0.059* (0.029)			-0.068 (0.037)		-0.065 (0.036)						
$R_{night, t-4}$		-0.065 (0.308)			-0.161 (0.320)		-0.100 (0.311)			-0.195 (0.313)					
$R_{day, t-4}$			0.086 (0.100)			0.072 (0.114)		0.074 (0.101)							
Intercept	1.148 (0.732)	0.659 (0.718)	1.0140 (0.745)	0.624 (0.724)	0.163 (0.743)	0.451 (0.790)	0.083 (0.288)	0.435 (0.366)	-0.182 (0.385)	-0.327 (0.291)	-0.251 (0.344)				
Observations	732	732	732	732	732	732	732	732	732	732	732				
Instruments	115	115	115	115	115	115	115	115	115	115	115				
AR (2)	0.892	0.944	0.958	0.8	0.821	0.703	0.871	0.883	0.863	0.883	0.712				

Notes. *, **, *** — significance at the level 5, 1 and 0.1% respectively; standard deviations are below the regression coefficients.