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Spatial Panel Model and Kernel Estimation: A Case Study of Interactions in Money Growth

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Abstract

This paper examines the spatial interaction of monetary policy among the EU and OECD countries from 2007 to 2017, by focusing mainly on money growth rates of the economies. The effects of economic relationships on money growth have been analyzed using spatial panel models via alternative weight matrices designed to reflect geographic, economic, or institutional proximity. Our spatial analysis of the data revealed the existence of spatial interactions. The results show that there is a spatial interaction between countries in terms of money growth. Any change in money growth within this group of countries has a positive effect on the other countries according to their economic integration or geographical proximity. Moreover, the interaction between trading partners is larger than between geographically or institutionally close partners. On the other hand, we used nonparametric kernel regression to determine the response of money growth to money growth. It turns out that the interaction of money growth with export partners corresponds to an inverse parabolic function.

Keywords: Monetary Policy, Spatial Model, Spatial Impact, Kernel Estimation

Mekansal Panel Model ve Kernel Tahmini: Para Büyümesi Etkileşimleri Örneği

Öz

Bu çalışmada, Avrupa Birliği (AB) ve/veya Ekonomik İşbirliği ve Kalkınma Teşkilatı (OECD) üyesi ülkelerin para büyüme oranları arasındaki mekânsal etkileşim 2007-2017 dönemi için ele alınmaktadır. Ekonomik ilişkilerin para büyümesi üzerindeki etkileri, coğrafi, ekonomik veya kurumsal yakınlığı yansıtmak için tasarlanmış alternatif ağırlık matrisleri aracılığıyla mekânsal panel modelleri kullanılarak analiz edilmiştir. Elde edilen sonuçlar, para büyümesi açısından ülkeler arasında mekânsal bir etkileşim olduğunu göstermektedir. Bu ülke grubundaki para arzında meydana gelecek pozitif yönlü herhangi bir değişiklik, ekonomik entegrasyonlarına veya coğrafi yakınlıklarına göre diğer ülkeler üzerinde olumlu bir etki yaratmaktadır sonucu tespit edilmiştir. Ayrıca, ticaret partnerleri arasındaki etkileşim özellikle de ihracat partnerleri arasındaki etkileşim, coğrafi veya kurumsal olarak yakın ortaklar arasındaki etkileşimden daha büyük sonucuna da ulaşılmıştır. Ayrıca çalışmada para büyümesinin para büyümelerine tepkisini belirlemek ve şeklini ortaya koymak adına parametrik olmayan kernel regresyon modeli kullanılmıştır. Kernel regresyon modeli tahmini sonuçları ise, parasal büyümenin ihracat ortaklarıyla etkileşiminin ters bir parabolik fonksiyona karşılık geldiği ortaya koymaktadır.

Anahtar Kelimeler: Para Politikası, Mekânsal Model, Mekânsal Etki, Kernel Tahmini

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Introduction

The knowledge of the interactions between countries' monetary policies is not new. As in the monetary theory of exchange rates, this knowledge has already been crystalized in the popularly used textbooks. In our time, we also observe day to day that the inflation targeting central banks keep an eye on each other's policy decisions. This is not surprising given the intertwined economic relationships of our globalized economic world. Global economic integration has led to substantial effects on monetary policy decision-making processes of many central banks. Since a central bank's monetary policy instruments mainly affect consumption and investment decisions, it would be natural to expect an interaction among different countries' policy tools given that consumption and investment are no longer domestic-only variables.

In some cases, like the post-Lehman crisis environment of 2008-2012 and in the very recent experience of the world's policymakers having faced the Covid-19 pandemic's globally adverse impacts, the interactions between monetary policies even turn into cooperation, going beyond simple cross-surveillance. After the Global Financial Crisis, a number of unconventional monetary policy tools were used by many central banks, in close cooperation or under strong information sharing. All these observations make the web of relationships between countries' monetary policies constantly deserve some professional research attention. In that, there are ample studies in the literature on both monetary policy and impact of globalization on economies. Although studies on interaction between monetary policy implications have different perspectives, they often do not directly consider the degree of closeness of countries as a measure of globalization. In this study, we reconsider the linkages between monetary policies chiefly from a spatial econometric perspective to fill this gap. Taking into account some actual and quasi- measures of closeness, we investigate the impacts of closeness of countries on their policies. Among the several monetary policy-related variables, owing to its simplicity and commonness, we focus on nominal money growth.

Monetary policy refers to the decisions, which affect the availability and the cost of money to enable economic growth, employment growth and price stability. Consequently, investigating monetary policy is a topic that does not lose popularity in the literature. Many studies examined the monetary policy efficiency in the literature via different econometric methods. A remarkable portion of these studies discusses the growth of either the money supply or the demand for money. The literature about money growth can be divided into 2 groups. Whereas the first one includes single country examples, the second one includes multi-country examples. The most common econometric methods in the literature for the first group are VAR

(Vector Autoregressive Regression) based techniques such as VAR, iterative VAR or structural VAR, FAVAR (Factor Augmented Vector Auto Regression). The most popular econometric methods in the second group are panel-based techniques like panel models, panel VAR or panel cointegration. By these methods, researchers have investigated different aspects of monetary policy. Lately, studies have also pointed out the spillover effect of a single country's monetary policy on other economies. However, little attention has been paid to the whole spillover effects of country group interactions and how global financial and trade networks structure affect these interactions. Furthermore, the quantification relationship between foreign monetary conditions and domestic monetary policy is neglected in the literature.

Over the last few decades, spatial econometrics methods are widely used among regional scientists, economists and researchers in many areas. Many studies applied spatial econometrics methods about economic growth, international trade flows, migration, and housing prices. However, there are very limited literature examples about spatial effects of monetary policy. Giacinti (2003) has investigated the regional effects on monetary policy in the US by applying SVAR (Structural Vector Autoregression) as well as spatial techniques. According to the results, there is spatial interaction between regions in terms of monetary policy. Ozdaglı and Weber (2017) have examined monetary policy impacts on financial markets for the US economy by using spatial autoregression to decompose the overall effect of policy shocks. The results show that production networks have a significant spillover mechanism of monetary policy to the real economy. Wu and Liu (2017) have examined the China–ASEAN bilateral trade balances by using a time-space simultaneous gravity model to get time-varying spatial effects. They have concluded that carrying out an appropriate monetary policy can cut down on the extended spatial effect generated from economic crises. Montecino (2018) have investigated the effects of foreign policies on domestic monetary policy by applying spatial models for 33 advanced and emerging market economies. He used gross bilateral bank financial positions and bilateral foreign asset positions as weight matrices. He found that there is a spatial interaction in terms of monetary policy. The significant spillover effect of monetary policy depends on the network structure of the global economy. Effects of monetary policy of the European Central Bank on the economic activities of Eurozone countries have been analyzed by Dominguez-Torres and Hierro (2019) for three different periods in the 2001-2017 timeline. They have analyzed a set of the economic variables to shaper monetary policy cluster and then they applied ANOVA (Analysis of Variance) to find cluster differences. According to their findings, there is a spatial asymmetric transmission of monetary policy for the October 2008 –

December 2014 period. By applying spatial panel models, Lu and Lou (2019) have examined the international transmission of the US monetary policy shocks on international stock and bond markets. The total effects were decomposed into indirect, network and simultaneous effects. According to findings, there are significant direct, network, and simultaneous effects of bonds on stocks. Moreover, positive monetary policy shocks make bond yields increase whereas stock prices decrease. Pizzuto (2020) has investigated US monetary policy's regional effects by estimating a single equation spatial model. The results indicate that contractionary monetary policy causes a permanent decline in regional personal income and employment. There is also an asymmetric spatial spillover across the regions which depends on the direction of monetary policy shock.

Although there are various studies on this subject in the literature, it is striking that no studies analyzed for a large country group. In this study, we investigate the interaction effect of money growth in OECD and EU[1] countries since they hold a large part of the global money wealth in the world and they have contributed to the global monetary policy direction. To direct monetary policy each country can use common tools as well as country-specific tools. The most common measure is the money supply or equally money demand as the monetary balance in an economy. On the other hand, most of the countries in the study are EU members. When the EU is considered as a single entity, it is hard to observe any significant macroeconomic imbalances. However, serious macroeconomic imbalances can be observed in member countries since the member countries apply different economic growth models (Tunay, 2017). Moreover, it is an expected result to observe spatial interactions since the EU carried out common policies on economies like the European Central Bank which is the single source of policy decisions. However, economic variables are determined not only according to policy decisions but also according to international and domestic dynamics. We base our assumption on the fact that the changes in money growth originate from this perspective. The dynamic increment in financial and economic integration, the liberalization of capital flows and the increased stability of currency fluctuations in Europe have effects on the money supply. The central banks directly control the monetary base rather than the money supply. How much the monetary base increase will change the money supply also depends on the money multiplier value. The value of the money multiplier is determined by the decisions of households and commercial banks as well as the central bank, more precisely by their demand for money (Aydin et al., 2019). As the money demand of households and commercial banks is determined according to market

[1] All the EU countries except Bulgaria, Croatia, Cyprus, Malta and Romania are members of the OECD.

conditions, they are sensitive to both endogenous and exogenous shocks. Since money supply shows the total amount of money circulation, is one of the main important indicators to measure the effectiveness of a monetary policy in any economy. Through the monetary transmission mechanism, it affects many economic variables. Economies have become more sensitive to each other due to the increasing commercial and financial globalization and so money supply can be affected by both interior economic variables and the interactions of the countries and the global dynamics like many other economic variables.

Economic development in one part of the world is increasingly affecting other regions, whether they are in a common economic or financial union or not. As a result of globalization, the analysis of the interactions effects has gained importance especially in recent years and it has become an issue that policymakers attach more importance to. In this manner, this study aims to investigate spatial interactions of money growth among EU and OECD countries by applying spatial panel models, which allow us an opportunity to insert interaction among units. The study covers the period from 2006 to 2017, as dictated by the availability of data. An essential advantage of this analysis allows us to analyze different types of affinities via weight matrices. Several main points differentiate this study from other studies. First, the effect of economic variables on money growth has been examined for the first time through spatial panel models in this study. To examine different spatial interactions several types of spatial matrices are generated. We consider economic relations as well as conventional geographic relations. Also clustering analysis is used to generate a weight matrix as a new approach. The first spatial matrix has been generated conventionally according to geographic position. The other three have been constituted according to the trade affinity of each country part. And to generate the last weight matrix we applied the clustering analysis technique on the Heritage economic freedom index which indicates institutional similarity. In addition, we focus on the implications of weighted money growth using nonparametric kernel estimation.

The paper proceeds as follows: the methodology section introduces spatial econometric estimation. Section 3 provides data, model and our empirical analysis. And the last section concludes the paper and also includes recommendations for policy.

1. Methodology

By the very nature of our research question, our first empirical step utilizes a wealth of spatial econometric specifications. Upon a panel data set and well-known panel data specifications, these models utilize some weight matrices that handle the neighborhood relationships among cross-section entities (here countries). Despite the complex look of the models, assessment of the existence of spatial effects is intuitive. Spatial effects are said to exist as long as the numerical impacts of a weight matrix on estimates are not statistically rejected. So, the placement of spatial specification from a purely econometric perspective is quite understandable. Given these, how appealing any given specification is depending on the quality of work with regard to defining and implementing the neighborhood relationships of concern. The first of the following subsections, then, lay down the statistical basis of our spatial treatment of our question.

The first law of geography by Tobler (1970) states that "everything is related to everything else, but near things are more related than distant things." This law describes the spatial autocorrelation, which can be negative or positive. By this law and the need to measure the effects of nearby things led to the emergence of spatial econometrics. Observations from other locations may have an effect on the dependent variable at one particular location in a spatial econometrics (Kışla and Önder, 2017).

To generate spatial panel models, we can use standard linear panel models. Standard linear panel model can be written as;

$$\mathrm{y_{it}} = \mu_i + \mathrm{X_{it}}\beta + \mathrm{u_{it}} \tag{1}$$

where y_{it} is the dependent variable, *i* shows the individuals, and *t* shows time dimension which is from 2006 to 2017. x_{it} is a matrix of independent variables. β is the vector of coefficients. μ_i denotes individual effects and u_{it} is *i.i.d.* error term that varies with the individual and time. u_{it} has a critical role in panel models. If u_{it} is related to x_{it}, the panel model is a fixed effect model, otherwise it is a random effect model (Fotheringham and Rogerson, 2008). The Hausman specification test is used to identify which model provides a better fit of the data, either fixed or random effects (Hausman, 1978). Hausman specification test by which $H_o\!: h = 0$ hypothesis is tested. In here $h = d'[var(d)]^{-1}$, $d = \hat{\beta}_{FE} - \hat{\beta}_{RE}$, $Var(d) = \sigma_{RE}^2({X^*}'X^*)^{-1} - \sigma_{FE}^2({X^*}'X^*)^{-1}$ and L is the number of explanatory variables. The test statistics distributes asymptotically χ_L^2.

Model (1) can be extended to spatial panel model. Spatial effect can be observed by contributing the spatial effect in the model (1) via *W* spatial weight matrix. The weight matrix is an essential part of the spatial analysis for displaying unit connectivity (Kışla and Onder, 2018). It shows the relationship between individuals, and it is used to examine the effects of neighborhood. Spatial weight matrix elements are not random and they are specified exogenously. A positive spatial weight matrix also is considered to be the presence or absence of the relationship, not the direction (Corrado and Fingleton, 2012). It can be constituted according to not only geographical position or distance between the individuals, but it can also be constituted according to economic, social or any other non-psychical concept (Anselin, 1988). To get neighborhood mean, spatial weight matrix is generally standardized according to row total.

Spatial effects can be inserted into a model in various ways such as endogenous or exogenous variables or errors. A spatial pooled panel model that includes all possible spatial effects can be described as;

$$y_{it} = \rho W y_{it} + \alpha + X_{it}\beta + WX_{it}\theta + u_{it}$$
$$u_{it} = \lambda W u_{it} + \epsilon_{it} \tag{2}$$

where, y_{it} is the dependent variable and X_{it} is the independent variable matrix, for the cross-sectional individuals which are countries in this study (N=38) i, at a time t which is from 2006 to 2017 ($T = 12$). ϵ_{it} is *i.i.d.* error term with zero mean and variance σ^2. W is spatial weight matrix and represents the spatial effects. In this paper, we created binary contiguity matrices that are defined in section 3-b respectively. The spatial autoregressive coefficient ρ, captures the endogenous interaction effect. The spatial autocorrelation coefficient λ, captures correlated effects. θ represents contextual effects with $L\times 1$ dimension vector where L is the number of explanatory variables (Salima et al., 2018; p. 182).

Model (2) includes three different effects and it can be described as three different models. These are (i) Endogenous Effects: It can be captured via Wy_{it}. If any dependent variable value is affected by other units' value of the dependent variable, (ii) Exogenous Effects: It can be captured via WX_{it}. Dependent variable in i^{th} unit is affected by independent variables in other units. (iii) Correlated (interaction) Effects: It can be captured via Wu_{it}. It shows the relationships between the neighborhood units' error terms (Elhorst, 2014).

Since model (2) is not an identifiable form, the parameters β, ρ, λ and θ cannot be estimated at the same time (Floch and Saout, 2018). Therefore, by zero constraining on spatial parameters (*ρ, λ* or *θ)* we can create different types of models which are derived from model (2). Spatial Lag Panel Model (SLM), Spatial Error Panel Model (SEM), and Spatial Durbin

Panel Model (SDM) are three main spatial econometric models that are the most commonly used models in literature[2].

- Spatial lag panel model (SLM) can be generated by assuming that λ and θ are zero in model (2). The SLM form is $y_{it} = \rho W y_{it} + \alpha + X_{it}\beta + \epsilon_{it}$. This model hypothesizes that a spatially weighted average of neighboring dependent variables determines the observed value of the dependent variable.
- Spatial error panel model (SEM) can be generated by assuming that ρ and θ are zero in model (2). The SEM form is $y_{it} = \alpha + X_{it}\beta + \lambda W u_{it} + \epsilon_{it}$. This model hypothesizes that the regional interaction impacts are caused by the excluded factors, which influence both the local and neighboring districts.
- Spatial Durbin panel model (SDM) can be generated by assuming that λ is zero in model (2). The SDM form is $y_{it} = \rho W y_{it} + \alpha + X_{it}\beta + W X_{it}\theta + \epsilon_{it}$. This model is an integration form of SLM and SEM. If the null hypothesis H_0: θ = 0 cannot be rejected then SDM can be simplified to the SLM and if the null hypothesis H_0: θ + ρβ = 0 cannot be rejected SDM can be simplified to the SEM.

Here in this study, y_{it} represents the money growth, X_{it} represent the real gross domestic product, consumer price index, real effective exchange rate and 10-year bond yield. Section 3-a gives detailed information about the data.

Model (2) can be changed whether the spatial panel model has fixed effect (FE) or random effect (RE) like conventional panel models. In the spatial panel model, random effects and fixed effects model comparisons are also performed using Hausman test. Since SLM model includes $\rho W y_t$ as explanatory variable, the test statistics is slightly different. SLM model is calculated by $d = [\hat{\beta}'\ \rho]'_{SE} - [\hat{\beta}'\ \rho]'_{RE}$ and the test statistics distributes asymptotically χ^2_{L+1}.

In order to investigate whether there is spatial effect or not in spatial panel models, the hypothesis ($H_0: \rho = 0$ or $H_0: \lambda = 0$), spatial autocorrelation coefficient or spatial autoregressive coefficient is zero, is tested. LM (Lagrange Multiplier) statistics, developed by Anselin et al. (2006), are widely used in the literature. These statistics are formulized according to spatial model type. If both hypotheses cannot be rejected, the model is estimated by conventional methods. When any hypothesis is rejected, the model for the rejected hypothesis

2 Other forms of the model (2) can be derived, too. However, they are less frequently used or it is possible to observe statistical problems in other forms of model (2) (Floch and Saout, 2018).

is estimated. In case of rejection of both hypotheses, the hypotheses are tested by using robust test statistics. If both hypotheses are rejected according to robust test statistics, the model with larger LM test statistics is estimated (Anselin, 2005).

It is important that deciding which of the estimated spatial panel model is crucial to interpret the results correctly. LeSage and Pace (2009) and Elhorst (2010) suggest that the model selection process should begin by the SDM, which is a more general model and includes all possible spatial effects. LR (Lagrange Ratio) test is used to decide between the SLM and the SDM or between the SEM and the SDM. If the null hypothesis that $\theta = 0$ and $\rho \neq 0$ is not rejected, the SLM model is accepted. If the null hypothesis that $\theta = -\beta\rho$ is not rejected, the SEM model is accepted (Belotti et al. 2017).

2. Model and Empirical Results

In line with the theoretical framework of Section 2, this section unfolds our econometric analyses of spatial interactions in money growth between countries. In what follows, we first reveal statistically significant spatial interactions (subsection b) and then present a refined picture of these interactions (subsection c). In a nutshell, spatial effects do exist in our sample of countries and the size of effects is a good empirically revealed function of neighbors' variables.

a. The Data and Variables

Money circulation in an economy affects both micro and macro trends. While it affects the consumption and investment expenditures of households at the micro level, it affects the indicators such as growth, interest rate, employment and inflation at the macro level. Central banks determine the amount of money in circulation to control these effects by various tools. Having the right amount of money in circulation is important to meet the economic dynamics. The increase or decrease in the amount that will balance the changes in production and trade, in other words, the economic situation, is crucial for a sustainable economy. To associate with economic theory, we base our understanding of money demand on the well-known quantity relationships. These quantity relationship approaches are a guide for us to build an expended money demand equation.

Resorting to the first of these, Fisher's approach, money demand can be written as $MV = PT$, where M is the quantity (volume) of nominal money, V is the velocity of money circulation, P is the general level of prices and T is the volume of transactions performed by money. According to this equation, when the velocity of circulation is constant, the nominal quantity of money and the nominal value of all transactions are in balance. Cambridge approach, on the other hand, expresses a similar relationship as $M = kPY$, where k is used instead of V, often interpreted commonly as $k = 1/V$. So, we utilize an equation expressed in terms of the percentage change of the variables involved as

$$\Delta\ln M = \alpha_0 + \alpha_1 \Delta\ln Y + \alpha_2 \Delta\ln P + \epsilon. \tag{3}$$

It is important that to accept money as an efficient and insightful tool for monetary authorities, a stable relationship between money and the other macroeconomic indicators needs to be initially determined (Mera and Silaghi, 2018). Although there is no common agreement on the stability of the money demand, changes in money demand can be related also to interest rate and exchange rate since they have an impact on money demand instability. Therefore, we have augmented the equation by adding the change of interest rate and percentage change of the real effective exchange rate as regressors[3]. This way, we obtain a single equation specification that is to be handled via the methods maintained here. The reproduced version of the equation (3) is written as

$$\Delta\ln M = \alpha_0 + \alpha_1 \Delta\ln Y + \alpha_2 \Delta\ln P + \alpha_3 \Delta IR + \alpha_4 \Delta\ln ER + \epsilon. \tag{4}$$

where $\alpha_1$represents the income elasticity, α_2 represents the price elasticity, α_3 represents the opportunity cost of holding money and α_4 represents the exchange rate elasticity. While operationalizing our model framework, we use nominal broad money ($M2$) as the dependent variable. Real gross domestic product (GDP at constant local currency prices), consumer price index (CPI with 2010=100), the real effective exchange rate (CPI-based $REER$ with 2010=100) and 10-year bond yield (IR) are used as regressors. Whereas IR is used in the first difference form, other variables are used in percentage change forms. Instability in all of these variables can lead to an unpredictable effect of money demand, which can reduce the impact of monetary policy measures based on monetary assessments.

The data are collected annually from 2006 to 2017 for 38 countries, which are members of at least one of the European Union (EU) or the Organization for Economic Cooperation and Development (OECD), from the International Monetary Fund's International

[3] There are various examples that use these variables in Money demand function like Capasso and Napolitano (2012), Kumar and Webber (2013), Dabrowski et al.(2015), Farazmand et al. (2016), Mera and Silaghi (2018), Asongu et al. (2018), Bahmani-Oskooee et al. (2019), Bahmani-Oskooee et al. (2020).

Financial Statistics database or from individual central banks and statistical offices when necessary.[4] Table 1 presents the descriptive statistics of our variables.

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
$\Delta\ln M2$	0.062	0.077	-0.175	0.759
$\Delta\ln GDP$	0.018	0.048	-0.262	0.350
$\Delta\ln CPI$	0.022	0.024	-0.045	0.154
ΔIR	-0.271	1.416	-12.443	8.397
$\Delta\ln REER$	-0.002	0.047	-0.219	0.149

Notes: (1) The sample consists of observations for 38 countries over 11 years, yielding 418 observations. (2) The descriptive statistics are given for the versions of our variables as used in econometric estimations.

b. Measurement of Spatial Interactions

As the economic situation and money supply depend on both internal and external dynamics, we extent model (4) to spatial panel model. The spatial dimension of our data has been established through six non-random weight matrices that are described in Table 2. We consider the natural benchmark of geographical proximity first before we turn our attention to trade affinity (three alternative matrices) and institutional similarity (two alternative matrices). So, our treatment of neighborhood or closeness as summarized in Table 2 allow us to investigate a rich-enough spectrum of relationships.

Table 2. Neighborhood Measures

Geographical proximity
W_1=1 if the neighbor is a geographical neighbor; 0 otherwise (1): A shared land or maritime border
Trade affinity
$W_{2,3,4}$=1 if the neighbor is in the first 50% trade partners; 0 otherwise (2): Trade volume, (3): Export volume, (4): Import volume

[4] As we could not reach all their data, Chile, Cyprus and Israel could not be covered in our sample of Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Mexico, The Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States of America.

Institutional similarity
$W_{5,6}$=1 if the neighbor is in the same Economic Freedom Index category; 0 otherwise (5): Based on the Heritage Foundation's original assessments, (6): Based on authors' clustering analysis. The distances between the average economic independence index values for the 2007-2017 period is used for clustering analysis. The number of clusters has been calculated as 4.36 via $\mathrm{k} = (\mathrm{n}/2)^{1/2}$, rounded up to 5 to ensure inclusion of all sample countries.

As noted earlier, the neighborhood or closeness in our analysis is in its actual/physical sense only in W_1 and we employ some quasi-neighborhood measures in the remaining five matrices. Having come up with the weighting schemes embodied in these six matrices, both fixed effects and random effects spatial panel models (Spatial Durbin Model, Spatial Lag Model, and Spatial Error Model) have been estimated for all weight matrices, covering a sequence of 36 different spatial models. Then we applied the Hausmann test to determine whether the model is FE or RE. Table 3 presents the best models for six weight matrices, chosen on the basis of model selection tests, model selection criteria AIC and SBC as well as our theoretical expectations.

Each column shows the best model results for the relevant weight matrix in Table 3. The results can be categorized into two main groups. Whereas the first one includes conventional results, the other one includes innovative results.

As conventional results, we obtained the signs of the coefficients of the model parameters as expected in the literature. There is a positive relationship between the GDP and the money growth which is similar to the results of Hossain (2010), Bhattarai (2011), Urbanovsky (2016), Li and Mohan-Neill (2017), Yu and Niu (2019), and Bahmani-Oskooee et al. (2020). Inflation rate coefficients show that inflation has a serious pressure on the money growth in all matrices model estimation. The positive relationship between the money growth and inflation is parallel to Oomes and Ohnsorge (2005), Pelipas (2006), Hossain (2010), Berument et al. (2012), Ishaq and Mohsin (2015), Nguyen (2015), Urbanovsky (2016) and Ellington and Milas (2018) results. The interest rate effect on the money supply is negative but statistically insignificant. This negative relationship between money growth and interest rate is similar to Monnet and Weber (2001), Ariff et al. (2012), Urbanovsky (2016) and Ellington and Milas (2018) studies. The exchange rate variable is negative, thus statistically insignificant in all models, except the W1 weight matrix. The REER coefficient sign is parallel to Berument et al. (2012), Su (2012), Usman and Adajare (2014), Li and Mohan-Neill (2017), Ojede and Lam (2017) and Yu and Niu (2019) studies.

Table 3. Spatial Panel Model Estimates (Dependent Variable: M2, % change)

Variable	W_1 SLM-FE	W_2 SDM-RE	W_3 SDM-RE	W_4 SLM-RE	W_5 SEM-RE	W_6 SLM-RE
GDP (% change)	0.486*** (6.900)	0.569*** (6.610)	0.585*** (6.880)	0.573*** (8.070)	0.513*** (6.190)	0.586*** (8.050)
CPI (% change)	0.533*** (3.200)	1.057*** (6.540)	1.022*** (6.440)	0.832*** (6.010)	0.483** (2.430)	0.844*** (5.860)
IR (change)	-0.000 (-0.090)	-0.003 (-1.010)	-0.003 (-1.070)	-0.002 (-0.710)	-0.002 (-0.760)	-0.002 (-0.710)
REER (% change)	-0.138** (-2.040)	-0.097 (-1.380)	-0.098 (-1.390)	-0.108 (-1.570)	-0.103 (-1.490)	-0.112 (-1.600)
Constant term		0.027*** (3.580)	0.026*** (3.640)	0.001** (2.240)		0.020*** (3.620)
W*GDP		-0.083 (-0.480)	-0.179 (-1.090)			
W*CPI		-1.039*** (-3.060)	-0.896** (-2.880)			
W*IR		0.013* (1.920)	0.013* (1.950)			
W*REER		-0.162 (-1.300)	-0.097 (-0.800)			
ρ	0.296*** (4.960)	0.413*** (4.790)	0.426*** (5.090)	0.342*** (3.950)		0.204*** (3.050)
λ					0.277*** (3.300)	
Mean of fixed effect	0.023					
$\boldsymbol{\sigma_\varepsilon^2}$	0.038	0.004	0.004	0.004	0.004	0.004
R^2 Within	0.173	0.173	0.174	0.162	0.156	0.172
R^2 Between	0.683	0.704	0.694	0.696	0.694	0.663
R^2 Total	0.244	0.257	0.257	0.239	0.232	0.249
LogL (x10^4)	56.542	55.031	55.051	54.332	55.878	54.075
AIC	-1118.8	-1076.6	-1077.0	-1070.6	-1105.5	-1065.4
SBC	-1094.6	-1028.1	-1028.5	-1038.3	-1081.3	-1033.2
Hausman test	842.990***	5.810	6.250	6.640	9.450*	4.930
LR test (SDM to SLM)	4.630	12.290**	12.440**	9.310*	11.470**	7.360
LR test (SDM to SEM)	8.730*	8.800*	6.310	6.490	16.070***	9.850**

Notes: t-statistics are in parentheses. (*), (**) and (***) indicate statistical significance at 10%, 5% and 1% levels.

The innovative results part seeks to answer the questions of whether money growth is determined by market forces and interactions or controlled by monetary policies, which are controversial in monetary economics. In addition, this part answers to the question of any country’s money growth how much depends on financial or economic conditions within the rest of the world.

According to the results, the most appropriate model is the SLM model for geographically based weight matrix (W_1). The spatial lag coefficient ρ is 0.296 and statistically significant at 1% significance level. Any change in average money growth in geographically neighboring countries affects positively the money growth of countries. The sum of the GDP and CPI coefficients is approximately 1, which indicates that the equation is homogeneous. Based on the Cambridge equation, in case the GDP and CPI factors increase by 1% each, the money growth will also increase by 1%. Geographic position determines not only political relations but it also determines economic and social relations between neighboring countries. The results show that the effects of economic decisions can be observed in neighboring countries too.

The use of acceptable trade weights is an important aspect in empirical studies of trading partner data. Therefore, we formed W_2 weight matrix according to the total trade partnership structure. The spatial Durbin model can quantify the impact of trading partners’ money growth on domestic money growth, which is the best model for W_2. Any change in the money growth in foreign trade partner countries affects the money growth of the countries positively and statistically significant. A 1% increase in the money growth in foreign trade partner countries causes 0.413% in the money growth increase of countries. Statistically significant exogenous effects of trade partner countries (*W.CPI* and *W.IR*) point out that growing economic integration across EU and OECD countries, money growth in a country is significantly influenced by price changes and also interest rate changes. A 1% increase in the inflation rate of foreign trade partner countries will cause a statistically significant and 1.039% decrease in the money growth of the countries. Also, total trade partner countries’ interest rates have a positive and statistically significant effect on countries’ money growth. The outputs point out that the proximity relations based on foreign trade are essentially shaped according to the export markets.

Besides being an important issue that a country does trade with which country/country groups, the direction of foreign trade is also important in terms of monetary balances. To identify the effect of foreign trade direction, we have created two more trade affinity matrices. While the first one contains export partnership, the latter contains import partnership.

The results of W_3 weight matrix formed by export partnership structure are in parallel W_2 (trade volume partnership) weight matrix results in terms of coefficient signs and net effects, although not in terms of numerical quantities. The results show that the best model is the spatial Durbin model. The total of GDP and CPI coefficients are more than 1 which means when GDP and CPI factors increase by 1% each, the money growth will increase more than 1%. The results show that the impact of countries' export markets on their domestic liquidity needs to actualize through the relative price channel, not from the economic activity channel. Any increase in money growth in the export partner countries affects countries positively and significantly (ρ=0.426). Moreover, the average inflation rate of export partners affects the money growth of countries negatively and the average interest rate of export partners affects countries' money growth positively. ($W.CPI = -0.896, W.IR = 0.013$). Statistically significant coefficients of *W.CPI* and *W.IR answer* the question of how much does a country's money growth depends on economic conditions in export partner countries. An inflationary effect in export partner countries has a negative and significant effect on the money growth of local countries. A 1% increase in the inflation rate of partner countries will reduce the money growth of the countries by 0.896%. The price-channel inflationary effects of export partner countries affect the money growth of countries less than their total trade partner. Furthermore, the interest rates of export partners show a similar effect on money growth as observed in the interest rates of foreign trade partner countries.

Increasing money supply boosts economic growth and causes an increase in consumption. This increase in demand leads to an increase in import demand as well as an increase in domestic prices. Increasing import demand contributes to the income of the countries that export to these countries, which creates a monetary expansion in the exporting country. This interaction mechanism is also observed in total trade partner countries model results and export partner countries model results by spatial autoregressive coefficients (ρ). Since investors can evaluate foreign bonds as an alternative investment tool, the money demand literature emphasizes the importance of taking into account foreign exchange substitution and foreign interest rates to investigate the money growth (Chaisrisawatsuk et al., 2004 and Folarin & Asongu, 2017). In fact, the results of the weight matrix created for total trade partner and export partner countries support this argument. A 1% increase of export partner countries' or trade partner countries' the long-term interest rates cause the money growth of the countries increase by 0.013% on average at 10% significant level.

The results of W_4 weight matrix, which is constituted according to import partnership, show that the most suitable model is the spatial lag model. Although the total of GDP and CPI coefficients are more than 1, the total is smaller than other trade affinity matrix results. In addition, money growth changes in import partner countries affect the money growth of countries (ρ=0.342). Import, is a global indicator that plays an essential role in economic activity and prices. Consequently, the results are similar to the weight matrix based on geographic locations. The findings of trade partner affinity indicate that export is much more dominant than import in total foreign trade to identify money growth interaction among EU and OECD countries.

The economic freedom index, which expresses the freedom of individuals to engage in economic activities and to freely use and own the values obtained because of these activities without any external coercion, actually reflects the common characteristics of countries. To identify the interaction mechanism among similar countries, we constituted W_6 spatial weight matrix, generated by clustering analysis using the economic freedom index calculated by the Heritage Foundation for each country. The best model for W_6 spatial weight matrix is spatial lag model. The results indicate that there is a positive and significant spatial interaction between similar countries in terms of economic independence (ρ=0.204). It means that any change in money growth in a country has an impact on countries that have similar economic and financial structures.

Although money growth decisions are determined by a single authority, this study has shown that the role of partner countries, especially trade partners, is essential in money growth. In other words, the results obtained with spatial models support the argument that the money supply does not depend on only domestic but also international dynamics. Money growth of any country depends on other countries' economic and financial conditions as well as trade partnership. The empirical results show that in this paper a country's money growth is positively influenced by other countries' money growth. The most interesting finding of this paper is that economic conditions in partner countries, especially trading partners, trigger money growth in EU and OECD countries. Moreover, the results indicate that although the central banks can control the influence of common global effects, they cannot control the regional and economic trends. As the globalization phenomenon gets stronger, it is observed that exogenous dynamics and their effects on endogenous dynamics gain more importance in open market economies. The regionalization movements are generally carried out to increase the productivity and competitiveness of countries that are geographically close to each other and have economic relations, freeing the flow of goods, services and capital. However, the results include findings that regionalization or neighboring is no longer determined geographically but according to commercial and economic relations. In other words, the results indicate that economic or financial globalization is much more important than any other integration.

c. Further Insights

To gain a deeper understanding, we treat the data of our statistically plausible spatial models using a nonparametric kernel regression/smoothing approach. In these models, we do not impose any specific constructs related to spatial econometrics, yet we define some of our regressors as neighbors' weighted means as presented earlier. The plain reason for using the nonparametric kernel smoothing is that it allows us to obtain estimates (even) in the absence of a functional form. Indeed, at its very origin, this approach reflects the notion of "let the data talk" by facilitating local estimation within 'windows' centered around every single observation of a data set. So, extent and practical meaning of the smoothing process depends mainly on the selection of window width, where a window width of infinity (any number beyond the range of a data set) reduces the estimation problem to well-known least squares. For the purposes of this paper, the nonparametric kernel-based models allow us to further unveil the spatial effects of our step 1 without contaminating the measurements with an additional bunch of functional forms and parameters. Technicalities of kernel smoothing are discussed in the second sub-section below.

In this section, we turn our attention to the shape of the spatial interactions between economies. In that, our main concern is the degree, rather than existence, of these interactions. So, we use a nonparametric kernel regression (or smoothing) relationship as in Equation 5.

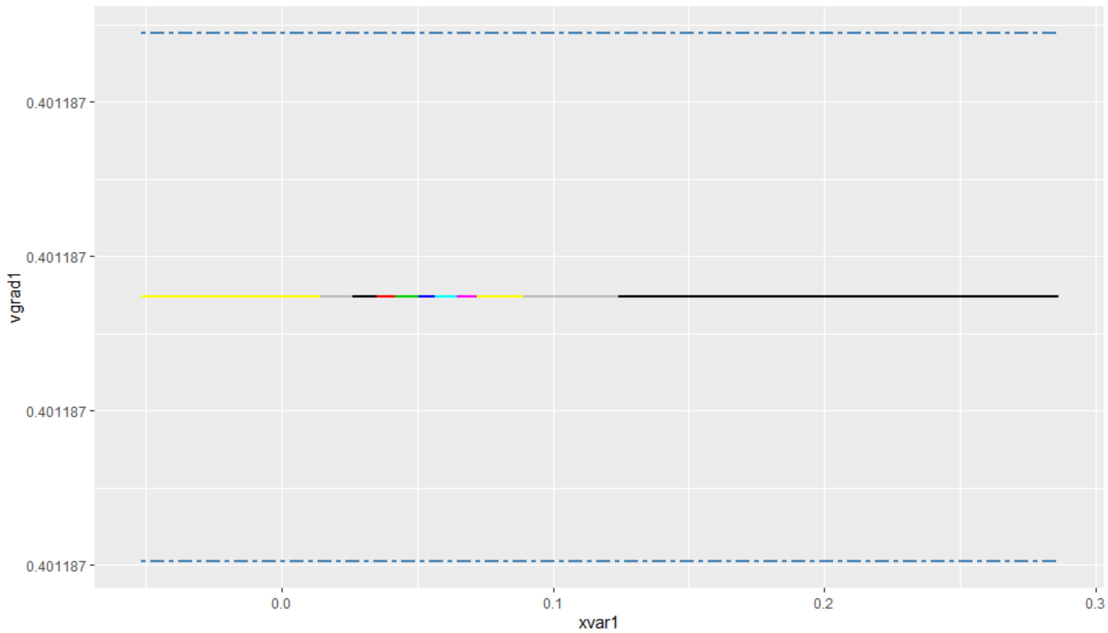
$$y_i = \sum_{j=1, j\neq k}^{J} \hat{\beta}_j x_j + \widehat{m}(x_k) + \epsilon_i \tag{5}$$

Equation 5 expresses the dependent variable ($M2$ growth) in terms of three components. The first of them transfers the estimated effects of the explanatory variables except one (denoted as the k-th variable here) to Equation 5 from the spatial panel estimations of the previous subsection. The second term handles the effects of the k-th variable x_k on y via a nonparametric kernel surface. The last term, ϵ_i, represents the usual statistical error term. Since we carry the spatial panel estimates to Equation 5 without any alteration, Equation 5 can be rearranged to yield Equation 6 which conveys our intuition.

$$y_i - \sum_{j=1, j \neq k}^{J} \hat{\beta}_j x_j = \hat{m}(x_k) + \epsilon_i$$	(6)

According to Equation 6, we perform kernel smoothing of '$M2$ growth net of the effects of other explanatory variables but one' with respect to the selected explanatory variable. In other words, the kernel estimation step solely focuses on the effect of one variable, here the weighted average of $M2$ growth rates of neighbors. So, we blend the parametric estimation information of the previous subsection with the flexibility of nonparametric estimation. Such an approach allows us to obtain the concerned effects in addition to saving our estimation practice from the data-hunger of nonparametric kernel-based methods. In the absence of a wealth of observations, defining part of a regression equation in a parametric manner (as in Equation 6) and focusing on a narrower portion of the statistical relationship is not uncommon.

Neighborhood Based on Geographical Proximity (W_1 basis)



Notes: Dashed blue lines represent a 90% confidence interval for gradient estimates.

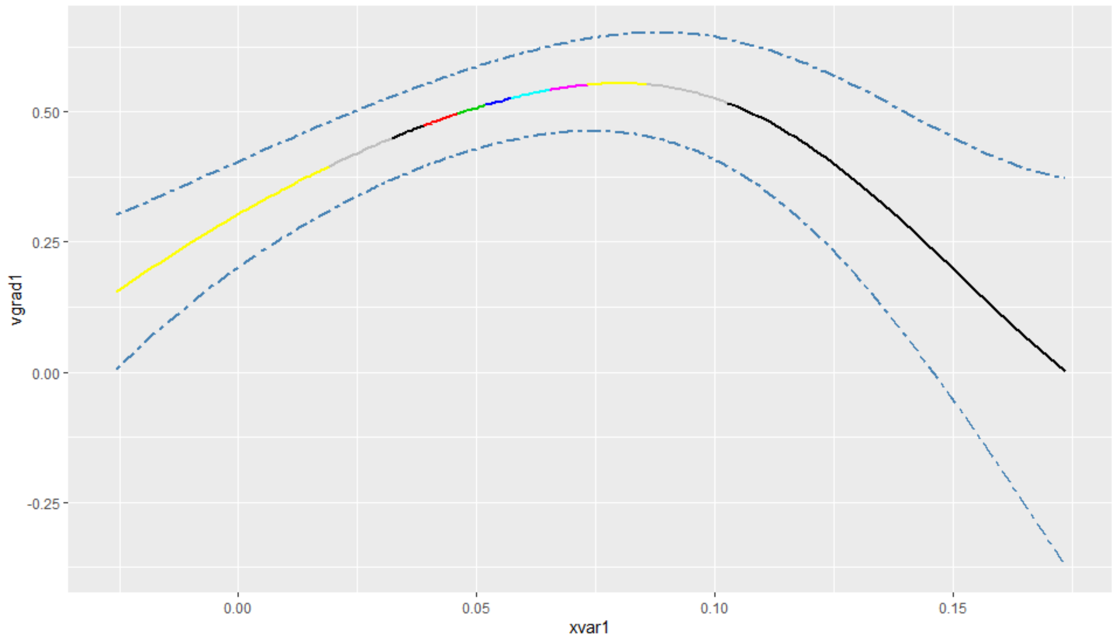
Figure 1. Response of M2 Growth at Home to M2 Growth of Neighbors

As described up to this point, we obtain the local linear estimates of y_i in Equation 6, calculating an optimal window width with respect to a second order Gaussian kernel. The gradients of y_i with respect to x_{ki} have been calculated from the estimated nonparametric regression surface and presented in Figure 1 and Figure 2. In Figure 1, we present the gradient estimates of Equation 6 according to spatial panel estimates of Table 3 with W_1, i.e. considering the geographical proximity, where in Figure 2 we repeat the same exercise for W_3, i.e. trade affinity measured via export volumes. Explicitly, Figure 1 and Figure 2 display the impacts of neighbors' money growth on home country's money growth at varying magnitudes of the former. Once the existence of spatial effects has been statistically revealed in Subsection 3.b, this exercise gives us a sense of the size of these effects.

A necessary change in the format of data while moving from spatial panel estimation to nonparametric kernel estimation must be noted/explained here: while it was feasible to use the full neighborhood weight matrices in spatial panel estimation (by the very structure implied by this method), we are not able to use the weight matrices directly in the nonparametric kernel smoothing procedures. During the switch between methodologies, we mainly calculate the neighbors' weighted average money growth rate to be used as a regressor in this section. While y_i of Equation 6 is the money growth rate at home, x_{ki} show the weighted average money growth rate of neighbors using the corresponding W matrix.

Figure 2. Response of M2 Growth at Home to M2 Growth of Neighbors

Neighborhood Based on Trade Affinity (W_3 basis)



Notes: Dashed blue lines represent a 90% confidence interval for gradient estimates.

Despite the cumbersome appearance of model and data preparation, the results out of the nonparametric kernel regression gradients are fairly simple and intuitive. In Figure 1, the empirical gradient ($\partial\widehat{m}(.)/\partial x_{ki}$) of home country money growth rate with respect to neighbors' weighted money growth rate is graphed against the neighbors' weighted money growth rate (x_{ki}). As the graph suggests, the gradients are not of a varying nature, i.e. the specification of $m(.)$ reduces to least squares, or a nonparametric kernel surface with infinite window width.

This simply suggests the absence of a changing reaction coefficient for the case of geographical neighborhood.

When the exercise of Figure 1 is repeated with neighborhood based on trade affinity (i.e. considering the web of relationships as summarized in W_3), the empirical gradients display an inverted U-shaped behavior. In that, response of money growth to neighbors' money growth is revealed as an inverse parabola-like function. For the values of neighbors' money growth rate ranging from 0 to approximately 0.076, impact on home country money growth is increasing, where it is decreasing thereafter. Around approximately 0.14 on the horizontal axis, the gradient estimates lose their statistical significance as suggested by the configuration of the related confidence interval shown by dashed blue lines.

d. A Consolidated View of Estimates

As mentioned earlier, the overall relationship we are investigating is of the form $MV = PT$ or $M = kPY$, both of which can be expressed as $\Delta \ln M = \alpha_0 + \alpha_1 \Delta \ln Y + \alpha_2 \Delta \ln P + \epsilon$ as a regression model, despite their landmark differences noted in the history of economic thought. We further augment this equation by adding the change of interest rate and percentage change of the real effective exchange rate as regressors. This way, this single equation specification allowed us to handle the several factors related to growth of nominal money growth.

Based on one main (spatial panel) and one auxiliary (nonparametric kernel) approaches implemented sequentially on our empirical problem of finding spatial interactions between countries in money growth, first we were able to reveal a statistically significant spatial relationship between countries and second we came up with an empirical characterization of how the magnitude of this revealed relationship has changed. Here, the linkage between countries' nominal money growth rates based on neighborhood is indicative of a connected world, as economists often put forth. More importantly, this connectedness is not only in the long term, but also it is there in the short term, as implied by our specifications with short term model characteristics.

The reader might be curious about whether a similar relationship obtains under alternative definitions of money growth. The answer has turned out to be negative in our preliminary analyses that are not reported in the paper to save some space. When we estimated alternative specifications with broad money in relation to income ($M2/GDP$) and real volume of broad money (proxied by $M2/CPI$), no strong-enough spatial effects manifested. As a matter of fact, such an empirical regularity, i.e. not having spatial connections in real terms but in nominal terms, may deserve attention as a further research question.

3. Concluding Remarks

Despite its relatively altered importance in today's complex financial world, "money" still accounts for a good proportion of our understanding of economic dynamics. As a common denominator of all other financial assets and being the simplest economic bridge between countries, it seems to continue doing so. In addition, creation of money, directly/exogenously as a policy instrument or indirectly/endogenously as a policy consequence, preserves its indicative role under a variety of monetary policy strategies. In that, the literature is rich in studies that analyze the money growth process. However, the same wealth is not observed as far as the effects of neighborhood/closeness between countries on their money growth processes are concerned, indicating a gap in literature that we intend to fill in this paper. At our departure point, we naively put forth the question that whether closeness between economies is a determinant of their money creation patterns.

Nevertheless, this naïve question does not have a naïve answer/solution, first, as the closeness can be defined in many arbitrary ways among which one has to pick the economically relevant ones, second, as the chosen measure of closeness has to be treated via a reliable methodology. In this paper, we employ spatial panel models to the second end and examine the interactions among 38 countries being the member of at least one of the EU and OECD over the years from 2006 to 2017. To the first end, we consider actual geographical proximity, trade affinity and institutional similarity between the countries picked.

While we use common land and maritime borders as a measure of geographical proximity, we use size in income of international trade linkages (exports, imports and trade volume separately) between countries as measures of trade affinity, and finally the Heritage Foundation's Economic Freedom Index in two alternative treatments as measures of institutional similarity. These closeness measures are handled through weight matrices to be used in a series of panel estimations.

A critical point for the general reader from a conceptual angle is that the terms closeness and neighborhood are used in the dictionary sense only when we consider the geographical proximity. In the other measures employed there is a perspective of quasi-neighborhood or quasi-closeness as any two countries with a sizable trade-related or institutional closeness need not to share a common border in today's globalized world. So, the term “spatial” here does not indicate actual physical space, but rather underlines a conceptual mapping.

Within the framework defined, our estimated models indicate that there exists a spatial interaction among the sample countries in terms of their nominal money growths. Nonetheless, the spatial effect is higher in the export partnership and the total trade partnership than any other relations. Furthermore, export partner countries’ inflation rates and interest rates have an impact on home country’s money growth. Therefore, good estimates of nominal liquidity require a solid consideration of spatial linkages. Based on our estimates, as not only domestic factors but also international ones determine money growth, it must be evident that countries taking into account only domestic dynamics while making monetary policy decisions will be inadequate in the globalized world, our findings prescribe not to rule out a spatial perspective in monetary policy design and implementation. Additionally, as we revealed that spatial effects due to geographical closeness are invariant with respect to the regressor (i.e. neighbors’ money growth), whereas they display an inverted-U type of behavior in the case of export-based closeness, we suggest that a good monetary policy making practice is to weigh neighbors’ proximities well.

From a solely technical perspective, we kept the two econometric techniques disjoint through our analyses, where we only substituted the coefficients obtained in spatial panel stage into the nonparametric kernel smoothing exercise. A genuine blend of the two techniques to jointly assess the existence and size of spatial interactions might be an interesting future reiteration of the research question.

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Appendix: Nonparametric Kernel Estimation

For a sample of n observations $\{(X_i, Y_i)\}_{i=1}^{n}$ where independent X_i and dependent Y_i are defined in R^d and R, respectively, a regression relationship can be written as (Hardle, 1990):

$Y_i = m(X_i) + \epsilon_i$	(7)

where m is the unknown regression (mean) function and ϵ_i are the independent error terms with zero mean.

The local constant kernel regression, the local means of the dependent variable yield $\widehat{m}$ (Equation 8) by solving the problem in Equation 9 (Li and Racine, 2007).

$\widehat{m}(x) = \frac{\sum_{i=1}^{n} Y_i K(\frac{x - X_i}{h})}{\sum_{i=1}^{n} K(\frac{x - X_i}{h})}$	(8)
$\min_{a} \sum_{i=1}^{n} (Y_i - a)^2 K(\frac{x - X_i}{h})$	(9)

K is the kernel (weight) function which is symmetric around zero with $\lim_{x \to \infty} |x| K(x) = 0$. The parameter h is known as window width (band width) and controls the smoothness of $\widehat{m}$ (Schimek, 2000). Intuitively, the problem is nothing but to obtain the averages of the dependent variables as fitted values. However, this problem entails two risks: a totally insufficient degree of smoothing, i.e. a window width of zero yields the observed values of the dependent variable as the fitted values and reflects full variance. The other extreme involves an infinite window width and so yield a constant fitted value at each observation, which is the case of full bias. Given a kernel function, the nonparametric kernel estimation is to find the fine line between variance and bias. This is achieved by solving for Equation 8 and 9. In many circumstances, local linear estimator in Equation 10 yield superior empirical outcomes:

$\widehat{m}(x) = \frac{\sum_{i=1}^{n} Y_i K(\frac{x - X_i}{h})(s_{n,2} - (x - X_i)s_{n,1})}{n^{-2} + \sum_{i=1}^{n} K(\frac{x - X_i}{h})(s_{n,2} - (x - X_i)s_{n,1})}$	(10)
$s_{n,l} = \sum_{i=1}^{n} K(\frac{x - X_i}{h})(x - X_i)^l, l = 0,1,2, \ldots$	
$\min_{a,b} \sum_{i=1}^{n} (Y_i - a - b(x - X_i)')^2 K(\frac{x - X_i}{h})$	(11)

This version of kernel regression has a slightly different intuition: one may imagine a least squares line segment within the window surrounding every single point of observation. A window of width h is located at each observation (call this observation of interest as center) and weights are assigned to full set of observations with respect to kernel function K, where weights are lower for observations more distant to center. Then a fitted value is computed for the center (see Hardle, 1990; Li and Racine, 2007; and Hardle et al., 2004).

Having obtained an estimate of the regression surface ($\widehat{m}$), the researcher can use it directly to make inferences about the variable of concern. Though, a richer set of findings can be achieved by calculating the empirical gradients, i.e. the response of $\widehat{m}$ to unit changes in its regressors:

$$\hat{\delta}(x_i) = \partial\widehat{m}(X)/\partial x_i \tag{12}$$

where $\widehat{m}(X)$ is the regression surface conditional on X and x_i is the regressor of concern. By design, the gradients are essentially the same thing as the coefficients in a typical (linear or nonlinear) least squares regression setup. For instance, when the regression surface and the regressors are both in percentages or percent changes, the gradients turn out to be elasticities. A major difference as to gradient estimates of the nonparametric kernel regression is that they are byproducts of surface estimation problem rather than being directly estimable objects.