Spillover effects of economic complexity on the per capita GDP growth rates of Mexican states, 1993-2013*

Efectos derrame de la complejidad económica en las tasas de crecimiento del PIB per cápita de los estados Mexicanos, 1993-2013

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Abstract

The opening up of the Mexican economy completely transformed the growth dynamics of the per capita Gross Domestic Product (GDP) of the country's various states, with a clear tendency towards growth being concentrated in specific regions. In this study, we quantify the indirect or spillover effect of economic complexity on growth based on the following two facts: i) economic complexity is an important factor in explaining GDP growth rates, and ii) there is a clear regional pattern in the states' economic complexity, i.e., the economic complexity variable shows a positive spatial autocorrelation. Our results provide two insights: first, that the estimated positive spillover effect of complexity on growth is not negligible, particularly for states in the north of the country, whose own economic complexity is as important as that of their neighbors. In contrast, the spillover effect in southern states is negative. Being located next to states with low levels of economic complexity has a significant negative externality that almost overrides the positive effect of a state's own level of complexity. Our findings lead us to conclude that spillover effects may

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have played a more important role in explaining the diverse pattern of growth between northern and southern Mexico than previously thought.

Key words: Economic complexity, spillover effects, spatial econometrics.

JEL Classification: O10, O14, O47.

Resumen

La apertura de la economía mexicana transformó por completo la dinámica de crecimiento del Producto Interno Bruto (PIB) per cápita de los diversos estados del país, con una clara tendencia a concentrar el crecimiento en regiones específicas. En este estudio, cuantificamos el efecto derrame o indirecto de la complejidad económica sobre el crecimiento con base en los siguientes dos hechos: i) la complejidad económica es un factor importante para explicar las tasas de crecimiento del PIB, y ii) hay un patrón regional claro en la complejidad económica de los estados, i.e., la variable complejidad económica muestra una autocorrelación espacial positiva. Nuestros resultados muestran: i) que el efecto derrame o indirecto estimado de la complejidad en el crecimiento es positivo y no insignificante, particularmente para los estados del norte del país, cuva propia complejidad económica es tan importante como la de sus vecinos. Por el contrario, el efecto indirecto en los estados del sur es negativo. Estar ubicado al lado de estados con bajos niveles de complejidad económica tiene una externalidad negativa significativa que casi anula el efecto positivo del propio nivel de complejidad de un estado. Nuestros hallazgos nos llevan a concluir que los efectos indirectos pueden haber jugado un papel más importante para explicar el patrón diverso de crecimiento entre el norte y el sur de México de lo que se pensaba anteriormente.

Palabras clave: Complejidad económica, efectos contagio, econometría espacial.

Clasificación JEL: 010, 014, 047.

1. INTRODUCTION

The structure of the Mexican economy has undergone a significant transformation since the economic liberalization period, with the impact on the various states being remarkably heterogeneous.¹ This fact has inspired a growing

¹ The opening-up period is generally considered to have begun in the mid-1980s with Mexico's joining the General Agreement on Tariffs and Trade (GATT). However, most studies analyze the effects after its signing of the North America Free Trade Agreement

literature, which attempts to document the changes brought about by the economic reforms, including: i) studies that analyze the changes in the localization of specific industries or the specialization of specific states as a result of the trade reforms; ii) studies that seek to determine the key factors in explaining the diverse economic growth performance of Mexican states in this period, and; iii) studies that document the increase in the concentration of economic activity, primarily manufacturing, just as traditional trade models, new trade theories or new economic geography models predict.² Therefore, studies that endeavor to establish the causes of growth during this period should take into account the agglomeration of economic activity, since spatiality represents an important component of the regional growth process in Mexico following the reforms.

Hidalgo and Hausmann (2009) (henceforth HH) propose a measure of the amount of *productive knowledge* that economies have, which they call *economic* complexity. Traditional approaches to performing this task seek to gauge the latter by taking into account all of the productive elements (inputs) that economies possess, e.g., abundance of resources, human and physical capital, infrastructure (communications, transportation, etc.), technology, quality of institutions, to mention just a few. In contrast, HH's method looks at the products that are already being produced by economies or the economic activities they already undertake.³ They show that their measure of productive knowledge can account for the per capita GDP differences among countries and, furthermore, that it can be used to predict their future growth rates.⁴ They do this by estimating growth regressions, using the growth rate as the dependent variable explained by the economic complexity. They argue that economic complexity alone is much more predictive than other development indicators combined, such as, aggregate measures of human capital, various measures of physical capital, and measures of social capital and of the health of their institutions (institutional quality, measures of enforcement of the rule of law, etc.).

⁽NAFTA) in 1994, as this is regarded as a more influential event and, more importantly, there is little or no reliable data for the 1980s or before.

² Theoretical models predict that trade will lead to greater concentration and only differ in regard to the explanation of the factors that cause it. For example, Ricardo's model predicts that trade will lead to regional specialization and to a higher level of industrial localization due to the productivity differences among economies, whereas in the Heckscher-Ohlin model, economies specialize in economic activities that are intensive in those factors of production in which they are relatively abundant. Models from the literature known as "new economic geography" explain that trade costs, increasing returns to scale, input-output linkages (among companies in the same or different industrial sectors), and so on can lead to increased agglomeration of economic activity [see Krugman (1991), Krugman and Venables (1995, 1996), among others].

³ We believe this makes perfect sense, since it is easier to measure the goods being produced by an economy than the inputs needed to produce them, e.g., the quality of institutions, etc.

⁴ Hartmann *et al.* (2017) state that: "These measures of economic complexity have received wide attention because they are highly predictive of future economic growth."

Chávez *et al.* (2017) apply the ideas of HH to the Mexican case and use information on the productive structure of each of the country's 32 states to calculate a measure of economic complexity, then show that this variable goes a long way to explaining the different growth patterns of Mexican states during the period 1998-2013. However, they do not consider the spatial dimension of economic complexity. As theoretical models predict and various empirical studies illustrate, increased trade tends to lead to a concentration of economic complexity as a predictor of growth rates, since they ignore the spillover effects. In this study, we find empirical evidence to affirm that the growth rates of the states during this period depend not only on their own economic complexity measure but also on that of their neighboring states.

The present study follows on from the work of Chávez et al. (2017) and expands upon it in various ways: i) we extend the sample period by adding data from the 1993 economic census to the analysis of the 1998, 2003, 2008, and 2013 census data that they employed, thus covering more of the post-liberalization period; ii) we provide evidence to affirm that the automotive industry also helps to explain the different growth rates of the states during this period, with states specializing in the economic activities associated with the latter experiencing growth rates that were above the national average, and, more importantly: iii) we confirm that economic complexity is an important factor in explaining the observed growth rates of Mexican states in the post-liberalization period. Indeed, the level of economic complexity has a direct impact, with more complex states growing faster than their less complex counterparts; furthermore, we document an indirect or spillover effect that can be generated in different ways (the existence of technology dissemination, agglomeration effects, economies of scale, network effects, etc.). States whose neighbors have more complex economies tend to grow faster than those with less complex neighbors. Moreover, this spillover effect is not homogeneous among the states: northern states (the most complex) have a positive influence on their neighbors' growth rates, whereas southern states (the least complex) have a negative impact. Compared to the direct effect, the magnitude of the estimated indirect effect is not negligible.

Panel data studies looking to measure the relationship between growth and its determinants –using growth regressions à la Barro– find it very straightforward to investigate if those determinants have both direct and indirect (spillover) effects on economic growth. As defined by Halleck-Vega and Elhorst (2017), a direct effect measures the marginal impact of a change in one explanatory variable in a particular cross-sectional unit on the dependent variable of that unit itself. Meanwhile, an indirect (or spillover) effect is defined as the marginal impact of a change in the explanatory variable in a particular unit *i* on the dependent variable values in another unit *j* (\neq *i*). Spatial econometrics literature includes a range of models to estimate different types of interaction effects among units: i) endogenous interaction effects among the dependent variables, (ii) exogenous interaction effects among the explanatory variables, and (iii) interaction effects among the error terms. The General Nesting Spatial (GNS) model is the most

general specification, containing all three of the types of interactions previously mentioned, while the Spatial Autoregressive Combined (SAC), Spatial Durbin (SDM), and Spatial Durbin Error (SDEM) models contain only two. The Spatial Autoregressive (SAR), Spatial Lag of X (SLX), and Spatial Error (SEM) models contain only one of the three interactions.⁵

Our study employs the simplest model, the SLX, to estimate the spillover effect of economic complexity on growth. As SLX only considers exogenous interaction among the explanatory variables, it can be estimated using OLS. Therefore, our growth regressions incorporate economic complexity as independent variable in two distinct ways: i) as the specific economic complexity of each state to estimate the direct effect of that particular variable, and; ii) as the average economic complexity of the neighbors of each state to estimate the indirect effect of complexity, *i.e.*, to estimate the effect that the complexity of a state's neighbors has on its own growth.⁶

The remainder of the article is organized as follows. In Section 2, we present a brief review of studies that document the main changes in the Mexican economy in the post-liberalization period. In Section 3, we present the data to be used in the empirical analysis and explain the method for calculating the measure of economic complexity that we will use to explain the states' growth rates. Appendices 1 and 2 show the computed values of the complexity variable for all the economic censuses considered, along with the evidence for the need to include a spatial dimension when attempting to explain per capita GDP growth rates based on complexity. In Section 4, we present and discuss the main results. Section 5 presents the final remarks.

2. Related Studies

The change in Mexico's development strategy –from import substitution to economic liberalization and trade promotion– resulted in a significant change in the growth performance of its individual states. Esquivel (1999) finds evidence in favor of the per capita output convergence hypothesis for Mexican states during the period 1940-1995, *i.e.*, that poor states tended to grow faster than rich states during this period. In general, rich states tend to be located in the north of the country, with the notable exception of Mexico City, while poor states tend to be located in the south.⁷ This would imply that the gap between rich and poor states decreased during this period. In line with these findings, Chiquiar (2005) uses

⁵ Excellent references for spatial econometrics include Elhorst (2013), LeSage and Pace (2009), LeSage (2014), Halleck-Vega and Elhorst (2015), and Elhorst and Halleck-Vega (2017)

⁶ To estimate the spatially lagged level of complexity, we employ the simplest contiguity matrix: the queen matrix.

⁷ An analysis of subperiods reveals a clear pattern in the rates at which states converge. The convergence rate from 1940 to 1960 is higher than that for the period 1960-1980, while

a similar methodology to that of Esquivel (growth regressions), though finds that the trade reforms led to a divergent pattern in the per capita output levels of states during the period 1985-2001. Other studies also affirm that the gap between rich and poor states has been widening since the mid-1980s.⁸

What can explain these changes in the states' growth rates? Hanson (1998) describes how there was an important reallocation of manufacturing industry within the country after the enactment of NAFTA, from the country's center (Mexico City and Mexico State) to states in the north, mainly those sharing a border with the U.S. (Baja California, Chihuahua, Coahuila, Nuevo León, Tamaulipas, and Sonora).⁹ He argues that this reallocation of industry sought, in part, to reduce transportation costs to what would become the most important market after the signing of the agreement: the U.S. Mosqueda et al. (2017) state that the sectors that contributed most to the increase in manufacturing concentration in the first ten years of NAFTA were: transportation equipment, chemicals, food products, and primary metal industries. In 1993, these four manufacturing subsectors accounted for 32% of the concentration of all manufacturing production; ten years later, the figure was 52%. Chiquiar (2005) reports that states more favorably endowed in terms of human and physical capital and better levels of transport and communications infrastructure (*i.e.*, states in the north) have grown faster since the signing of NAFTA. Rodríguez-Oreggia (2005) also finds that human capital plays a decisive role in explaining the difference in growth rates, as well as evidence to affirm that public investment causes greater growth. Jordaan and Rodríguez-Oreggia (2012) argue that Foreign Direct Investment (FDI) and agglomeration have acted as important drivers of state growth since the trade reforms. Moreover, they affirm that there is a spatial dimension to the structural change in the Mexican economy, since many economic activities have agglomerated in the states that share a border with the U.S., fostered by FDI, which also tends to localize in certain economic activities. Cabral and Varella-Mollick (2012) document that trade, FDI, and international migration contributed significantly to the growth of the output per capita of Mexican states during the period 1993-2006. The role of migration in explaining growth rates is more important for states located on the northern border, in the center, and in the northern-central region. Cabral, Varella-Mollick, and Saucedo (2016) study the effect of violence on the evolution of the productivity (GDP per worker) of

both are greater than that for 1940-1995 and 1960-1995. For the period 1980-1995, the rate is estimated to be statistically not different from zero.

⁸ See Aguayo-Téllez (2006), Gómez-Zaldívar and Ventosa-Santaulària (2010, 2012), Rodríguez-Oreggia (2005), and Rodríguez-Pose and Sánchez-Reaza (2002), among others.

⁹ Mosqueda *et al.* (2017) affirm that during the first ten years of NAFTA: the contribution of Mexico City and Mexico State to domestic manufacturing value added decreased from 37.3 to 18.3 percent; that of the six states along the northern border rose from 23.8 percent to 33.4 percent, and that of Aguascalientes, Durango, Guanajuato, Querétaro, San Luis Potosí, and Zacatecas (states in the North-Center of the country) rose from 8.7 percent to 14.8.

Mexican states during the period 2003-2013 and find that crime has negative and statistically significant effects on labor productivity, particularly across those categories of crime prosecuted by local authorities.

Using municipal-level data, Garduño (2014) shows that output per worker grew faster in regions located closer to the U.S.-Mexico border and slower in regions located further away from it. According to him, the trade agreement increased inequality and the localization of economic activity. Finally, Chávez *et al.* (2016) find empirical evidence of a positive relationship between the average GDP growth rate of Mexican states and a measure of efficiency of the judicial system in the states; in particular –for the period 2006-2013–, the time it takes to solve commercial disputes brought before local courts.¹⁰ They explain that their goal was to find evidence of a positive correlation between the rule of law and economic growth; however, constructing a rule of law measure for Mexican states –a multidimensional concept that should be constructed from indicators of property rights, the efficiency and independence of the judicial system, crime rates, efforts to combat corruption, political stability, and so on– is a difficult task, since there is not enough data available.

More recently, Chávez *et al.* (2017) show evidence to affirm that *economic complexity* (or *productive knowledge*) is an important factor in explaining the disparities in the growth rates of Mexican states in the period 1998-2013.¹¹ They conclude that the states that have reaped most benefit from the trade reforms are those with a more complex structure, *i.e.*, those specializing in more economic activities (are more diverse) or in economic activities that are more complex or sophisticated (are less ubiquitous). As in HH, they find evidence that using one variable, economic complexity, to explain state growth rates is at least as good as the traditional approach, where a numerous of variables are necessary to explain these rates.

Several variables have been found to be relevant in explaining the states' growth rates after trade liberalization (including human and physical capital, various measures of infrastructure and agglomeration, FDI, and the efficiency of the judicial system, among others); however, economic complexity seems to provide the most parsimonious explanation. Nevertheless, a flaw of Chávez *et al.* (2017) is their failure to take into account the spatial dimension of economic complexity.

As classical models of trade, new trade theories, and new economic geography models predict,¹² and previous studies applied to Mexico have documented,

¹⁰ The data on the ease of enforcing contracts come from the World Bank's *Doing Business* reports.

¹¹ Economic complexity as a predictor of economic growth is illustrated empirically at the international level by HH and at the subnational level for Mexico by Chávez *et al.* (2017).

¹² These models expect more integration or trade to lead to an increase in economic concentration, either in the form of industrial localization or in the level of specialization of the states. Diverse studies have evaluated the predictions of these models by examining the changes in the patterns of localization and specialization and found evidence in favor

the concentration of production has increased since the signing of NAFTA; therefore, economic complexity must be useful in explaining the growth rate of any given state and that of its neighboring states. To show this, we use spatial growth panel regressions.

3. Data and Methodology for Calculating the Economic Complexity Index (ECI) and its Spatial Lag

In this section, we describe the variables used in the spatial growth panel regressions that we will calculate to show the connection between growth rates and ECI. This includes an explanation of the methodology used to compute the two main independent variables: ECI and ECI spatial lag.

The dependent variable, average state per capita GDP growth rate, is computed using data from the Economic Information Bank of Mexico's National Institute of Statistics and Geography (INEGI) and the National Population Council (CONAPO).

The main independent variable, the ECI, is computed using data on the number of people employed (PE) in each state and each economic activity from INEGI's economic censuses.¹³ We employ the Method of Reflections (MR) proposed by HH to calculate the ECI for each state. The ECI measures the productive knowledge embedded in each state economy or the sophistication of its productive structure. It is calculated by combining information on the diversity of each state (*i.e.*, the number of economic activities in which each state specializes) and the ubiquity of economic activities (*i.e.*, the number of states that specialize in each economic activity). Intuitively, more complex economies are, in general, diverse and specialize in less ubiquitous economic activities.

of this hypothesis. The studies that analyze specific countries focus principally on the E.U. [see, Amiti (1999), Storper *et al.* (2001), Ezcurra *et al.* (2006), and Krenz and Rübel (2010), among others]. At the regional level, they primarily discuss the experience of developed economies, for example, the U.S. [see Kim (1995), Kim (1999), and Mulligan and Schmidt (2005), among others]; France (Maurel and Sédillot, 1999), and Spain (Paluzie *et al.*, 2001), to mention just a few.

¹³ The economic census years are 1993, 1998, 2003, 2008, and 2013. The 1993 census classifies economic activities according to the Mexican Classification of Activities and Products (CMAP) system. From 1998 onwards, the censuses use the North American Industry Classification System (NAICS). The 1994 data were adapted to make them consistent with the NAICS system. We use the data at the six-digit level of aggregation and the total number of economic activities are, 620, 797, 866, 882, and 883, respectively. GZ only considers the last four censuses, *i.e.*, 1998, 2003, 2008, and 2013.

First, using the definition of Location Quotient (LQ) commonly employed in regional science literature,¹⁴ we construct a binary matrix, $M_{s,a}$, for each year for which we have data:¹⁵

$$lq_{s,a} = \frac{\frac{p_{s,a}}{\sum_{a=1}^{n} p_{s,a}}}{\frac{\sum_{s=1}^{32} p_{s,a}}{\sum_{s=1,a=1}^{s=32,a=n} p_{s,a}}}$$
(1)

where $p_{s,a}$ is the number of people employed by state *s* in economic activity *a*; $\sum_{a=1}^{n} p_{s,a}$ is the total number of people employed by state *s*; $\sum_{s=1}^{32} p_{s,a}$ is the total number of people employed in economic activity *a* throughout the country; $\sum_{s=1}^{32} \sum_{a=1}^{n} p_{s,a}$ is the total number of people employed in the entire country. The matrix, $M_{s,a}$, is defined as follows:

$$m_{s,a} = \begin{cases} 1 & \text{if} \quad lq_{s,a} \ge lq^* = 1 \\ 0 & \text{in any other case} \end{cases}$$

Intuitively, state s is considered to be specialized in economic activity a if the percentage of PE in that activity with respect to the total PE in state s is greater than or equal to the analogous percentage nationwide.

Secondly, from matrix $M_{s,a}$ we define the two dimensions needed to calculate the ECI, which describe the economic structure of states and economic activities:

Diversity of states
$$\kappa_{s,0} = \sum_{a=1}^{m} m_{s,a}$$
 (2)

 $\sum n$

Ubiquity of economic activities $\kappa_{a,0} = \sum_{s=1}^{32} m_{s,a}$ (3)

The diversity vector is obtained by summing each of the rows of matrix $M_{s,a}$; each entry of this vector indicates the number of economic activities in which a given state is specialized. Diversity is the first approximation of a state's ECI; this measure is refined later with the information that provides the ubiquity. The ubiquity vector is obtained by summing each of the columns of matrix $M_{s,a}$; each entry of this vector indicates the number of states that specialize in each economic activity. The iterative process that combines these two dimensions is:

¹⁴ Analogous to the definition of Revealed Comparative Advantage employed by HH.

¹⁵ The dimensions of the matrix M are 32*n; the number of rows (32) is the number of states in Mexico and the number of columns (n) represents the number of economic activities to be considered.

$$\kappa_{s,N} = \frac{1}{\kappa_{s,0}} \sum_{a=1}^{n} m_{s,a} \cdot \kappa_{a,N-1} \tag{4}$$

$$\kappa_{a,N} = \frac{1}{\kappa_{a,0}} \sum_{s=1}^{32} m_{s,a} \cdot \kappa_{s,N-1}$$
(5)

where *N* is the number of iterations, which continue until the process reaches a fixpoint that occurs when the relative ranking of the $k_{s,N}$ remains unchanged for three consecutive iterations.¹⁶ We will refer to the complexity variable, $CX_{s,r}$.

To quantify the spillover effect of economic complexity, we compute the spatial lag of the ECI variable. To do this, we use a row-standardized "queen contiguity" spatial weight matrix, W.¹⁷ Therefore, the variable $(W \cdot CX_{s,t})$ represents the average complexity of the neighbors of each state.¹⁸

To complement the complexity measure, we first consider a control variable that captures the growth derived from natural resource endowment, since this source of growth cannot be explained by the ECI. In some Mexican states, the exploitation of natural resources (petroleum) accounts for an important portion of their GDP. This variable is constructed with data from INEGI.

Similarly, the automotive industry has always made a very important contribution to the country's output, and its impact has increased since the signing of NAFTA. By 2016, the industry represented 3 percent of overall GDP and 18 percent of manufacturing GDP, and accounted for almost 900,000 direct jobs. Motor vehicle production has increased so much that Mexico is now the seventh largest automobile producer in the world. However, the localization of this industry is limited to just a few of the country's states. Only certain states manufacture motor vehicles, whereas all 32 manufacture motor vehicle parts, though there are huge disparities among them.¹⁹ Whilst Chihuahua has 122,704 persons employed in motor vehicle parts manufacturing, Coahuila has 115,758, Nuevo León has 49,939, and Tamaulipas 56,507; there are eleven states (Baja

¹⁶ Appendix 1 shows the estimation of the ECI of each state in each census year. These results will be used in the empirical application.

¹⁷ A queen-contiguity spatial weight matrix considers a state to be the neighbor of another if they share a common border. Each entry of this matrix takes the value of one if states share a border and zero otherwise.

¹⁸ In Appendix 2, we offer empirical evidence of the nature of the spatial autocorrelation of the economic complexity variable (ECI). Moran's I test statistics and scatterplots do not support the null hypothesis that states are randomly distributed; instead, the results suggest that there is a positive and statistically significant autocorrelation. States with high ECI values are surrounded by high ECI states (these tend to be located in the north of the country), while states with low ECIs are surrounded by low ECI states (which tend to be located in the south) in each census year.

¹⁹ This industry comprises three different industrial groups: motor vehicle manufacturing, motor vehicle parts manufacturing, and motor vehicle body and trailer manufacturing, representing around 52%, 46%, and 2% of the total value added of the industry, respectively.

California Sur, Campeche, Chiapas, Guerrero, Hidalgo, Michoacán, Nayarit, Quintana Roo, Tabasco, Veracruz, and Yucatán), mainly in the south of the country, that have fewer than 1,000 persons employed in this activity. Since state growth rates during this period may also be explained, in part, by the performance of this industry, we believe it necessary to control for it.

4. RESULTS

To illustrate the spatial effects of economic complexity on growth, we use three different panel estimation methods: Pooled, Random effects, and Panel Corrected Standard Errors (PCSE). The Hausman test suggests that using random effects is more appropriate than fixed effects.²⁰ The Breusch-Pagan (BP) test based on the Lagrange Multiplier (LM) for random effects suggests that Pooled OLS estimation is preferred over random effects.²¹ In addition, we report the PCSE estimations, as this method provides a more efficient estimation, according to Beck and Katz (1995). As can be seen in Table 1, the estimations obtained by Pooled OLS and PCSE are identical, the only difference being the estimated standard errors.²²

We begin by showing that economic complexity is related to future economic growth or that a state's future growth rates are correlated with its initial level of complexity, exactly as Chavez *et al.* (2017) did, the only difference being that our estimations include an additional five-year period.

We do this by estimating a panel growth regression model [Equation (6)] that has as a dependent variable the average annual growth rate of per capita GDP, $\gamma_{s,t}$. As independent variables, we have the logarithm of initial per capita GDP, $\log(y_0)$;²³ a dummy variable, *Oil*, which identifies the oil mining states;²⁴ a dummy variable, *Aut*, which identifies states specializing in the automotive

²⁰ The random effects models appears to be more appropriate than the fixed because: i) the Hausman test indicated it was, as reported in Table 1, and more importantly; ii) as Barro (2015) mentions, "...with country fixed effects, it is challenging to estimate statistically significant coefficients on X variables that do not have a lot of independent variation over time within economies," as is the case with our independent variable, economic complexity.

²¹ This test is also reported in Table 1.

²² We applied three different tests of cross-sectional correlation: the Frees, the Friedman, and the Pesaran (see De Hoyos and Sarafidis, 2006). In none of these were we able to reject the null hypothesis of cross-sectional independence.

²³ This variable is always included in growth regressions because of the convergence hypothesis, which implies that, *ceteris paribus*, poor economies tend to grow faster than rich ones.

²⁴ This variable is included to complement the economic complexity variable, given that the measure of complexity (ECI) cannot explain the income that comes from the exploitation of natural resources. It takes the value of 1 for states where oil mining represents more than 5 percent of the state's GDP (Campeche, Tabasco, Tamaulipas, Chiapas, and Veracruz), and 0 in all other cases.

industry;²⁵ and the states' economic complexity in the initial year of the period, $(CX_{s,t})$. In addition, we include time-fixed effects dummies, (p_i) , one for each five-year period analyzed, which captures the common factors that affect all states in each period.²⁶

$$\gamma_{s,t} = \delta + \sum_{i=1}^{3} \alpha_i \cdot p_i + \beta_0 \cdot \log(y_{s,t_0}) + \beta_1 \cdot Oil + \beta_2 \cdot Aut + \beta_3 \cdot CX_{s,t} + \varepsilon_{s,t}$$
(6)

where *s* identifies the states, *s* = 1,2,...32; *t* identifies the periods, *t* = 1993-1998, 1998-2003, 2003-2008, and 2008-2013.

Columns (1), (4), and (7) in Table (1) show the results of estimating Equation (6), which are comparable to those presented in Chávez *et al.* (2017). All parameters have the expected sign. The results confirm the positive correlation between growth rates and economic complexity, with more complex states growing faster. The estimated parameter associated with this variable is always statistically significant at the one per cent level and slightly greater in value to that estimated in Chávez *et al.* (2017). The parameters associated with the dummy variable that identifies states that specialize in the automotive industry show that, in general, these had higher growth rates than the rest of the states in the country, and they are also highly significant. Similar to the estimations presented in Chávez *et al.* (2017), the parameter associated with the variable that identifies the oil-mining states is always estimated to be statistically insignificant.

Once we have shown that future growth is related to the initial level of economic complexity of a state, our aim is then to show how that future growth is also correlated to the initial economic complexity of its neighboring states. To do so, we need to include a term that incorporates the spatial effects of the ECI variable into the previous model.

Equation (7) includes a term to calculate the spillover effect of the ECI variable, $(W \cdot CX_{s,t})$. W represents the row-standardized queen contiguity matrix to compute the spatially lagged economic complexity, *i.e.* the average economic complexity of the states' neighbors. This specification is known in spatial econometrics literature as the spatial externality model (SLX). It includes the spatial lag $CX_{s,t}$ as independent variable (LeSage and Pace, 2009); it is the simplest specification for measuring spillover effects (Halleck-Vega and Elhorst, 2015), yet the most appropriate based on the spatial distribution of the ECI variable, as

²⁵ Takes the value of 1 for states with car assembly plants (Aguascalientes, Coahuila, Guanajuato, Morelos, Puebla, San Luis Potosí, and Sonora) and 0 in all other cases.

²⁶ This model was estimated using few variables, just as HH (2009) presented it, their argument being that if complexity and all the other variables normally included in growth regressions to capture the different capacities of economies (*i.e.*, human capital, various measures of physical capital, institutional quality measures, measures of enforcement of the rule of law, etc.) are controlled for, this last group of variables proves to be redundant.

shown in Appendix 2.²⁷ We expect the estimate of parameter β_4 to be positive and significant, *i.e.*, we expect that states whose neighbors have a high ECI will tend to grow faster than those whose neighbors have, on average, a low ECI. This would imply that growth depends not only on a state's own ECI but also on the ECI of its neighbors, due to the spillover effects.

$$\gamma_{s,t} = \delta + \sum_{i=1}^{3} \alpha_i \cdot p_i + \beta_0 \cdot \log(y_{s,t_0}) + \beta_1 \cdot Oil + \beta_2 \cdot Aut + \beta_3 \cdot CX_{s,t} + \beta_4 \cdot (W \cdot CX_{s,t}) + \varepsilon_{s,t}$$
(7)

As can be seen in columns (2), (5), and (8), the estimated values of the parameters that Equations (6) and (7) have in common $-\delta$, β_0 , β_1 , β_2 , and β_3 - are fairly similar. The parameter of interest, β_4 –the one associated with the spatial lag of the ECI–, is always estimated to have the expected sign, regardless of the estimation method, though is nevertheless marginally statistically insignificant in all cases. These results are quite unexpected given the strong evidence in favor of the positive spatial association of the ECI. We presume that this may be occurring because the spillover effect is not homogeneous among all states (or regions) and depends instead on the ECI level of neighboring states. As shown by the maps in Appendix 2, in general, states located in the north of the country have higher levels of economic complexity, while states located on the south have lower levels of economic complexity.

To find evidence of the heterogeneity of the spillover effect, we estimate a slightly modified Equation (7), one in which the spillover effect of highly complex states is different from the spillover effect of less complex states. Equation (8) is design to quantify the difference in the spillover effects of the ECI between states with high and low ECIs. Equation (8) is similar to (7) except for its last term, which includes a dummy variable, φ , which takes the value of 1 if the state has neighbors with a higher than average mean ECI, and 0 otherwise. Therefore, $\beta_4 + \beta_5$ estimate the spillover effect among the most complex states (as shown in Appendix 2, these tend to be located in the northern part of the country).

²⁷ There is a plethora of alternative model specifications to study spatial spillover effects, not only the SLX model. We also considered the estimation of other models: the SAR (Spatial Autoregressive) and the SDM (Spatial Durbin) models [as LeSage (2014) pointed out, the nature of spillover effects in an SLX specification is *local*; in contrast, the SAR and SDM models allow us to study *global* spillover phenomena]. However, the autoregressive coefficients in all these other cases were not different from zero; hence, following Elhorst (2014), we discarded these models as an option for measuring spatial spillover effects, which in our case, are local in nature.

Variable (Parameter) Pooled OLS Random Effects Panel Corrected Standard Errors (1) (2) (3) (4) (5) (6) (7) (8) (9) $(v_0), (\beta_0)$ -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1044^* -1022^* 0455^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* 0655^* <t< th=""><th>Panel Corrected Standard En (6) (7) (8) $-1.237 * * *$ $-1.041 * *$ $-1.041 * * *$ $-1.237 * * * *$ $-1.041 * * * *$ $-1.041 * * * * * * * * * * * * * * * * * * *$</th><th>Panel Corrected Standard El (8) (8) (8) (4**) (-1.041**) (-2.24) (-2.24) (-2.24) (-2.24) (-2.24) (-4.22) (-4.22) (-4.22) (-4.22) (-1.09) (-1.2) (-1.09) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) (-1.2) 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$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c} C_{x_r}(\beta_3) & (-1) (-1) (-1) (-1) (-1) (-1) (-1) (-1)$	$\log(y_0), (\beta_0)$	-1.044*	-1.041*	-1.239**	-1.078^{***}	-1.078^{***}	-1.237^{***}	-1.044**	-1.041^{**}	-1.239^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} CX_{x,r}\left(\beta_{3}\right) & 0.473^{****} & 0.472^{****} & 0.665^{****} & 0.479^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.472^{****} & 0.0338 \\ W \cdot CX_{x,r}\left(\beta_{4}\right) & - & 0.0338 & -0.525 & (3.03) & (3.26) & -0.0398^{***} & - & - \\ 0.13) & (-1.66) & - & 0.143 & (-1.68) & - & 0.0398^{***} & - & - \\ 0.13) & (-1.66) & - & 0.0398^{***} & 0.639^{***} & 0.639^{***} & 0.639^{***} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.639^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{*****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{****} & 0.632^{*****} & 0.632^{*******} & 0.632^{*******} & 0.642^{******} & 0.632^{****$		(-1.92)	(-1.91)	(-2.14)	(-3.75)	(-3.77)	(-5.02)	(-2.25)	(-2.24)	(-2.58)
$ \begin{array}{rccccc} (3.02) & (2.98) & (3.25) & (3.03) & (3.00) & (3.56) & (3.29) & (3.26) \\ \hline & & & & & & & & & & & & & & & & & &$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{split} W \cdot C X_{s,r} \left(\beta_4 \right) & (3.25) & (3.25) & (3.25) & (3.25) & (3.25) & (3.26) & (3.26) & (3.26) & (0.19) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) & (1.6) $	$CX_{\epsilon,\mu}(\beta_{1})$	0.473^{***}	0.472^{***}	0.605^{***}	0.479^{***}	0.478^{***}	0.596^{***}	0.473^{***}	0.472^{***}	0.605 * * *
$ \begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{split} W \cdot CX_{x_1}(\beta_1) & -CX_{x_1}(\beta_1) & -0.0398 & -0.552^* & -0.514^* & -0.0398 & -0.532^* & -0.0398 & -0.532^* & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0398 & -0.0388 & -0.0388 & 0.0398 & -0.0398 & -0.0388 & -0.0388 & -0.0388 & 0.0398 & -0.0398 & -0.0388 & -0$		(3.02)	(2.98)	(3.25)	(3.03)	(3.00)	(3.56)	(3.29)	(3.26)	(3.73)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$W \cdot CX_{s,n}(\beta_A)$	I	0.0398	-0.552*	I	0.0275	-0.514*	I	0.0398	-0.552*
$ \begin{array}{cccccc} - & - & 1.082^{**} & - & - & 0.98^{**} & - & - & 0.98^{**} & - & - & - & 0.038^{**} & - & - & - & - & 0.038^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.630^{**} & 0.009 & 0.0112 & -0.009 & 0.009 & 0.0112 & -0.009 & 0.009 & 0.0112 & 0.000 & 0.009 & 0.0112 & 0.000 & 0.020 & -& 0.000 & 0.020 & -& 0.000 & 0.001 & -& & -& - & - & - & - & 0.006 & 0.006 & 0.006 & 0.20 & -& 0.012 & 0.031 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & 0.387 & $	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	+ + +'o		(0.13)	(-1.66)		(0.14)	(-1.68)		(0.19)	(-1.71)
$ \begin{array}{cccccc} 0.630^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Au, (β_2) (2.51) 0.630^{***} 0.633^{***} 0.633^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.630^{***} 0.240^{****} 0.7230^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.020^{***} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{***} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{****} 0.030^{*****} 0.030^{*****} 0.030^{*****} 0.030^{*****} 0.030^{*****} $0.030^{**********}$ $0.030^{***********************************$	$(\varphi 1 \cdot W \cdot CX_{\epsilon}), (\beta_{\epsilon})$	I	I	1.082 **	I	I	0.998 **	I		1.082 **
$ \begin{array}{ccccccc} 0.630^{\#\#} & 0.632^{\#\#} & 0.633^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.630^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.642^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} & 0.632^{\#} &$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Aut. (β_1) 0.630*** 0.632*** 0.663*** 0.663*** 0.630*** 0.630*** 0.630*** 0.632*** 0.032*** 0.012 0.289 0.299 0.078 0.099 0.078 0.009 0.078 0.009 0.078 0.009 0.078 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.078 0.079 0.009 0.070 0.025 0.025 0.025 0.0229 0.029 0.078 0.070 0.070 0.090 0.0112 0.0299 0.079 0.009 0.078 0.070 0.090 0.0112 0.0299 0.070 0.059 0.070 0.050 0.070 0.029 0.029 0.070 0.050 0.070 0.070 0.090 0.0112 0.025 0.0229 0.070 0.090 0.0112 0.025 0.0229 0.070 0.090 0.0112 0.025 0.0229 0.0299 0.070 0.050 0.090 0.091 0.0112 0.0299 0.070 0.090 0.091 0.0112 0.0299 0.070 0.090 0.091 0.01 0.021 0.028 0.090 0.091 0.01 0.021 0.028 0.090 0.091 0.01 0.021 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.01 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.090 0.091 0.028 0.038 0.090 0.091 0.028 0.038 0.000 0.020 0.020 0.028 0.028 0.028 0.090 0.031 0.0387 0.04111 0.028 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.0387 0.038				(2.06)			(2.51)			(2.203)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Aut, (β_{γ})	0.630^{***}	0.632^{***}	0.663^{***}	0.628^{**}	0.630^{**}	0.659^{**}	0.630^{***}	0.632^{***}	0.663^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	a ,	(2.87)	(2.88)	(2.95)	(2.49)	(2.50)	(2.46)	(2.97)	(2.99)	(3.07)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Constant. (a) (-0.25) (-0.22) (0.19) (-0.16) (-0.14) (0.18) (-0.25) (-0.22) (-0.22) (-0.22) (-0.22) (-0.22) (-0.22) (-0.22) (-0.21) (-0.22) (-0.22) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.22) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) (-0.21) $(-$	$Oil, (\beta_1)$	-0.112	-0.099	0.078	-0.089	-0.079	0.069	-0.112	-0.099	0.078
$ \begin{array}{ccccccc} 6.576^{**} & 6.557^{**} & 7.366^{***} & 6.741^{***} & 6.740^{***} & 7.370^{***} & 6.556^{****} & 6.557^{****} & 6.557^{****} & 6.557^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & 5.57^{****} & $	7.370*** 6.576*** 6.557*** 7.377*** 7.370*** 6.557*** 7.66.02) (6.02) (2.903) (2.897) (2.897) (2.897) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812) (2.812)	Constant, (δ) (5.77^{**} (5.57^{**} 7.366 ^{***} (5.71^{***} 5.74 ^{***} (5.77^{***} 6.576 ^{***} (5.57^{***} 7.370 ^{***} (5.897) (7.387^{***} 7.370 ^{***} (5.897) (7.387^{***} 7.370 ^{***} (5.897) (7.387^{***} 7.370 ^{***} (5.897^{***} 7.370 ^{**} (5.897^{***} 7.370 ^{***} (5.897^{***} 7.370 ^{***} (5.897^{***} 7.370 ^{***} (5.977^{****} 7.370 ^{****} (5.897^{***} 7.370 ^{***} (5.997^{***} (5.997^{***} 7.370 ^{***} (5.997^{***} 7.370 ^{***} (5.997^{***} 7.370 ^{***} (5		(-0.25)	(-0.22)	(0.19)	(-0.16)	(-0.14)	(0.18)	(-0.25)	(-0.22)	(0.19)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	(6.02) (2.903) (2.897) 0.91 0.20 - 2 128 128 128 YES YES YES - 0.387 0.387 ercent, respectively.	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Constant, (δ)	6.576^{**}	6.557**	7.366^{***}	6.741^{***}	6.740^{***}	7.370^{***}	6.576^{***}	6.557^{***}	7.366^{***}
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	0.91 0.20 128 128 128 YES YES YES - 0.387 0.387 0	Hausman test*0.980.990.91BP-LM test for random effectsh0.060.060.20Dbservations128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128128<		(2.46)	(2.45)	(2.63)	(4.67)	(4.71)	(6.02)	(2.903)	(2.897)	(3.173)
or random effects ^b - - - 0.06 0.06 0.20 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - <th<< td=""><td>0.20 0.28 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.38</td><td>BP-LM test for random effects^b 0.06 0.06 0.20 $-$</td><td>Hausman test^a</td><td>I</td><td>I</td><td>1</td><td>0.98</td><td>0.99</td><td>0.91</td><td>1</td><td></td><td></td></th<<>	0.20 0.28 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.3887 0.38	BP-LM test for random effects ^b $ 0.06$ 0.06 0.20 $ -$	Hausman test ^a	I	I	1	0.98	0.99	0.91	1		
128 128 128 128 128 128 128 128 128 128	128 128 128 128 YES YES YES YES - 0.387 0.387 (ercent, respectively.	Observations 128 128 128 128 128 128 128 128 128 128 Year FE YES YES YES YES YES YES YES YES R-squared 0.387 0.387 0.387 0.387 0.387 0.387 0.387 R-squared 0.387 0.387 0.387 0.387 0.387 0.387 Robust t-statistics in parentheses. The symbols ***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively. 0.387 0.387 0.387 The null hypothesis of random freets cancely reflected. Instease significance at the 1, 5, and 10 percent, respectively. 0.387 0.387 0.387	BP-LM test for random effects ^b	I	I	I	0.06	0.06	0.20	I		
d YES	YES YES YES YES - 0.387 0.387 (ercent, respectively.	Year FE YES YES YES YES YES YES YES YES YES YE	Observations	128	128	128	128	128	128	128	128	128
0.387 0.387 0.411 0.387 0.387 0.387 0	- 0.387 0.387 0.	R-squared 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.387 0.50 transfer the second constraints of the statistical significance at the 1, 5, and 10 percent, respectively.	Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
	Robust t-statistics in parentheses. The symbols ***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively.	Robust t-statistics in parentheses. The symbols ***, **, and * denote statistical significance at the 1, 5, and 10 percent, respectively. The null hypothesis of random effects cannot be rejected. Its test statistic is asymptotically distributed as χ_{10}^{2} .	R-squared	0.387	0.387	0.411	I	I	I	0.387	0.387	0.411

Following the suggestion of one of the referees, we estimate these models, excluding the last 5-year period, this as a robustness check to evaluate the impact of the global financial crisis. The estimated values of the parameters are similar, the only difference being the estimated standard errors, which increase slightly.

asymptotically distributed as a $\chi^2_{(i)}$. Its result suggests that the null cannot be rejected.

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$$\gamma_{s,t} = \delta + \sum_{i=1}^{3} \alpha_i \cdot p_i + \beta_0 \cdot \log(y_{s,t_0}) + \beta_1 \cdot Oil + \beta_2 \cdot Aut + \beta_3 \cdot CX_{s,t} + \beta_4 \cdot (W \cdot CX_{s,t}) + \beta_5 \cdot (\varphi \cdot W \cdot CX_{s,t}) + \varepsilon_{s,t}$$
(8)

The results in columns (3), (6), and (9) show that there is a positive spillover effect among states with the highest levels of ECI, which is estimated to be of a similar magnitude regardless of the estimation method: -0.552+1.082=0.530, -0.514+0.998=0.484, and -0.594+0.936=0.342. This implies that the growth rates of the most complex states (in general, those closer to the U.S.) were higher not only because of their own level of complexity, but also due to the positive impact of the higher level of complexity of their neighbors.

The same results for states whose neighbors have lower than average ECIs show the spillover effects to be negative, their magnitudes being: 0.531-1.082 = -0.551, 0.484-0.998 = -0.514, and 0.342-0.936 = -0.594. In both cases, it is important to note that the magnitude of the indirect effect is high (whether positive or negative) compared to the direct effect of ECI, β_3 .

The results can be summarized as follows: future growth rates are positively related to the initial level of economic complexity of a state, *i.e.*, the higher the initial level of complexity of a state, the higher its future growth rate. Furthermore, future growth rates are also correlated with the average level of complexity of a state's neighbors, *i.e.*, complexity has a spillover effect. Nevertheless, the level of economic complexity of a state's neighbors can affect growth rates either positively or negatively. States with highly complex neighbors are affected positively, *i.e.*, their future growth rates rise, whereas states with less complex neighbors are negatively affected by being geographically close to states with low levels of development.

The existence of important externality effects suggests that regional development policies require greater coordination among the various levels of government: federal, state, and municipal. The efforts of one state to improve its economic, social or demographic conditions may not be successful if the states surrounding it do not take similar actions to reach the same goal, in which case the failure to harmonize their policies would result in a waste of valuable economic resources.

Regional development would be enhanced by policies aimed at developing specific productive capabilities. A successful policy in one region might not necessarily be the best policy for other regions, *i.e.*, there is no *universal* strategy that is perfect for every region, since each region has a different economic structure, with dissimilar strengths and weaknesses. Therefore, policies should be designed carefully so as to boost the economic activities in which regions have a relative comparative advantage, where the participation of local stakeholders in the design, implementation, and management of these strategies is essential. In the literature, policy interventions aimed at spurring regional development that take into account regional diversity and are conditional on the specific characteristics of the target region are usually referred to as bottom-up policies.

5. FINAL COMMENTS

The amount of productive knowledge available in any given Mexican state measured by its economic complexity index (ECI) is strongly related to its per capita GDP growth rate. Nevertheless, a state's ECI is not only related to its own rate of growth, but also to that of its neighboring states, *i.e.*, it has a spillover effect. This indirect effect is estimated to be just as important as the direct effect and is not homogeneous among all states in the country, since northern and southern states differ markedly in terms of their productive structure.

Although previous studies have mentioned the existence of spillover effects, none found them to be as significant. We believe that the spatial dimension of the adjustments experienced by the Mexican economy occurred because northern states are alike in terms of their endowment of human capital, infrastructure (transportation, communications, industry, health, etc.), inflows of foreign direct investment, distance to the most relevant market (the U.S. is the main market for Mexican exports), and so on, and decidedly different from those in the south. This is also why northern states have proved more capable of taking advantage of the new sources of growth brought by liberalization.

We consider the southern half of the country to be a region immersed in a sequence of cause-and-effect events that mutually intensify and exacerbate one another, leading to an inexorable worsening of the economic performance of the states there relative to those in the north.

One way to break this vicious circle is to implement regional development policies to trigger short-, medium-, and long-term economic growth in the south of the country.

In an effort to increase productive opportunities in three of the most economically and socio-demographically disadvantaged regions of the country,²⁹ the administration of President Peña Nieto (2012–2018) proposed the implementation of a Special Economic Zones (SEZ) program, inspired by the success of China's SEZ created in the 1980s (in Shenzhen, Zhuhai, and Shantou). By promoting local and foreign direct investment through tax benefits, customs and business facilitation measures, and so on, the program sought to develop the economic activities in which these regions had a comparative advantage. The administration of President López Obrador has proposed an alternative yet similar program in its National Development Plan 2019–2014. The specific project for the country's southern regions includes different incentives: modernizing the Tehuantepec Isthmus railway; improving the ports of Coatzacoalcos in Veracruz and Salina Cruz in Oaxaca; developing road infrastructure and the airport network; constructing a gas pipeline to supply domestic businesses

²⁹ Puerto Chiapas in the state of Chiapas, the port of Lázaro Cárdenas–La Unión (shared by the states of Michoacán and Guerrero), and the Isthmus of Tehuantepec region that includes the ports of Salina Cruz in the state of Oaxaca and the port of Coatzacoalcos in the state of Veracruz.

and consumers in 76 municipalities in the two states; and tax incentives (*i.e.*, a reduction in valued-added tax and income tax).

The expected benefits of these types of projects for southern states, which seek to strengthen their economy, may be augmented by the recent new trade agreement between the U.S., Mexico, and Canada (USMCA). If expectations are actually met and these regions succeed in developing new competitive economic activities, the southern regions may take advantage of the new sources of growth that international trade offers, just as the north of the country did more than two and a half decades ago with NAFTA. Without a doubt, access to the greatest market in the world is a huge opportunity that could help them overcome their historical lag.

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Appendix 1

ESTIMATED VALUES OF THE ECONOMIC COMPLEXITY INDEX (ECI)

Table A1 shows the estimated ECI values. The state rankings according to their complexity show very little variation; this is because economies can only accumulate productive capacities gradually over time. The results are robust if the computations are done with different levels of aggregation of economic activities (*i.e.*, 4 or 5-digits).

Estados	1993	1998	2003	2008	2013
Nuevo León	2.04 (1)	2.09 (1)	1.94 (1)	1.84 (1)	2.05 (1)
México	1.85 (2)	1.34 (4)	1.01 (7)	0.74 (8)	0.65 (9)
Chihuahua	1.48 (3)	1.51 (3)	1.77 (2)	1.68 (2)	1.43 (5)
Coahuila	1.33 (4)	1.25 (5)	1.41 (4)	1.46 (5)	1.61 (2)
Distrito Federal	1.18 (5)	1.75 (2)	1.69 (3)	1.34 (6)	1.25 (6)
Baja California	1.15 (6)	1.24 (6)	1.35 (5)	1.48 (4)	1.53 (4)
Querétaro	1.05 (7)	1.09(7)	1.06 (6)	1.58 (3)	1.56 (3)
Tlaxcala	0.69 (8)	0.05 (15)	-0.36 (18)	-0.55 (21)	-0.39 (17)
Tamaulipas	0.63 (9)	0.63 (10)	0.88 (8)	1.10(7)	1.04 (7)
Jalisco	0.53 (10)	0.82 (8)	0.76 (9)	0.66 (10)	0.70 (8)
Aguascalientes	0.50(11)	0.78 (9)	0.47 (10)	0.50(11)	0.50(11)
Guanajuato	0.44 (12)	0.49 (11)	0.31 (13)	0.33 (12)	0.56 (10)
Sonora	0.28 (13)	0.43 (12)	0.33 (11)	0.71 (9)	0.43 (13)
Durango	0.21 (14)	-0.09 (16)	0.31 (12)	0.02 (14)	0.10(14)
Hidalgo	0.12 (15)	-0.35 (18)	-0.50 (20)	-0.36 (16)	-0.43 (18)
San Luis Potosí	0.12 (16)	0.13 (14)	0.15 (14)	0.25 (13)	0.44 (12)
Puebla	0.11 (17)	0.13 (13)	-0.12 (16)	-0.46 (18)	-0.36 (16)
Morelos	-0.45 (18)	-0.50 (19)	-0.67 (22)	-0.69 (23)	-0.72 (23)
Yucatán	-0.48 (19)	-0.29 (17)	0.01 (15)	-0.36 (17)	-0.46 (19)
Michoacán	-0.57 (20)	-0.74 (22)	-0.79 (26)	-0.81 (27)	-0.76 (26)
Sinaloa	-0.59 (21)	-0.70 (21)	-0.27 (17)	-0.19 (15)	-0.29 (15)
Zacatecas	-0.65 (22)	-0.89 (26)	-0.96 (27)	-0.78 (26)	-0.23 (25)
Baja California Sur	-0.83 (23)	-0.83 (23)	-0.54 (21)	-0.50 (20)	-0.64 (20)
Veracruz	-0.90 (24)	-0.87 (25)	-1.01 (28)	-0.75 (25)	-0.79 (27)
Colima	-0.93 (25)	-0.85 (24)	-0.70 (23)	-0.65 (22)	-0.65 (22)
Tabasco	-1.02 (26)	-0.91 (27)	-0.76 (25)	-0.89 (28)	-0.75 (24)
Quintana Roo	-1.03 (27)	-0.69 (20)	-0.48 (19)	-0.49 (19)	-0.64 (21)
Campeche	-1.18 (28)	-1.01 (28)	-0.76 (24)	-0.71 (24)	-0.81 (28)
Guerrero	-1.25 (29)	-1.28 (31)	-1.40 (30)	-1.59 (31)	-1.56 (32)
Oaxaca	-1.26 (30)	-1.20 (30)	-1.50 (32)	-1.60 (32)	-1.36 (31)
Nayarit	-1.27 (31)	-1.18 (29)	-1.21 (29)	-1.09 (29)	-1.21 (29)
Chiapas	-1.31 (32)	-1.35 (32)	-1.43 (31)	-1.23 (30)	-1.27 (30)

 TABLE A1

 STANDARDIZED ECONOMIC COMPLEXITY INDEX (ECI)*

* The number in parenthesis indicates the state position in the ranking.

APPENDIX 2

SPATIAL AUTOCORRELATION OF THE ECI VARIABLE.

The scatterplots (and their corresponding Moran's I statistic) and maps show evidence of a very strong positive spatial dependence on the ECI variable.**





^{**} For the sake of brevity, we show the two years for which the evidence of positive spatial dependence is more conclusive. Moran's I statistic allows us to reject the null of no spatial dependence in favor of positive spatial dependence at the 1 percent level for 1993 and 2008; at 3 percent for 2013; at 5 percent for 2003, and; at 11 percent for 1998.



The maps below show the distribution of states according to their estimated ECI. There is a clear regional pattern, with more complex states being located, in general, in the northern part of the country. For 1993, we divide all the states into 4 different groups and for 2008 into 2 groups.



MAP 1 LEVEL OF ECONOMIC COMPLEXITY (ECI) OF THE STATES, 1993

MAP 2 LEVEL OF ECONOMIC COMPLEXITY (ECI) OF THE STATES, 2008

