Do Motorways Induce Wider Economic Benefits? Evidence from the Slovak Republic[1]

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Abstract

This paper analyses wider economic and social impacts of motorways. It analyses the development of socioeconomic variables in the Slovak LAU 1 regions in the period 1997 – 2016. Difference in differences, panel regression with fixed effects, and synthetic control methods (SCM) are applied so as to identify potential long-run effects of motorways on regional economies and societies. The paper finds positive effects of motorways on wages, the number of firms, and internal migration. An SCM is the best procedure for measuring wider economic benefits of motorways when the number of treated units is low or there is only one treated unit.

Keywords: *large transport infrastructures, regional development, impact assessment, quasi experimental designs, synthetic control method*

JEL Classification: C52, H41, H43, H54

1. Impact Assessment of Large Transport Infrastructure

1.1. Theoretical Framework

The New Economic Geography (Fujita, Krugman and Venables, 1999; Fujita and Thisse, 2002) suggests that growth in real wages determines the price of an urban location and, thus, the real wage which can be earned from jobs accessible within that location (Vickerman, 2008). New transport infrastructure essentially

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increases the spatial size and competiveness of labour markets, and enables productivity gains. A worker can move from a region/industry with lower to higher productivity. An increase in real household income therefore should be one of the major outcomes of motorway construction. Development of transport infrastructure promotes regional specialisation in the production of certain goods and increases productivity and development of spatial relationships between companies. The development of the automotive industry in Slovakia is a good example of regional specialisation (Michniak, 2015, p. 31). There also is a strong correlation between the expenditures on the road infrastructure and GDP growth (Ivanová and Masárová, 2013, p. 273).

Some authors object that the size of wider economic benefits is overestimated. If an increase in agglomeration for one city is accompanied by decreases for other cities, the overall effect can be a zero-sum game (Kanemoto, 2013). There is substantial evidence that while the expansion of a motorway network boosts overall economic growth, it also may result in internal reallocation of economic activities, i.e. a 'distributive effect'. Spatial distributive effects were found for China (Yu et al., 2016), the Netherlands (Meijers, Hoekstra and Leijten, 2012), the USA (Funderburg et al., 2010) and Finland (Kotvaara, Antikainen and Rusanen, 2011). There is currently no established consensus on the magnitude and relevance of wider economic impacts of large transport infrastructure projects, or on how and which of these impacts should be taken into account in transport appraisals (Wangsness, Rødseth and Hansen, 2017).

Regional economies benefit from improved transport infrastructure in several ways. Some direct economic effects are realised during the period of a motorway's construction. Effects of fixed investments, services and labour costs associated with motorway construction are often assessed by Computable General Equilibrium (CGE) models or input-output analysis.

The other types of social and economic effects materialise immediately after a motorway is opened to the public and persist over lifetime use of the infrastructure. Better travel infrastructure shortens travel time, improves travel safety and decreases vehicle operating costs. These effects sometimes are difficult to associate with specific regions. Improvements in long-distance travel need not necessarily improve the economic and social milieu of all regions traversed by the new infrastructure. Transit travel, for example, benefits major transport hubs, but some traversed regions can actually be worse off, because of higher density of travel-related noise and pollution.

The third types of economic and social effects include benefits which are not captured within direct user benefits in terms of better travel. They usually are labelled 'wider economic benefits' and refer to improvements in regional economies and quality of life. These benefits essentially result from better accessibility of regions. Time savings and lower transport costs effectively increase the size of firms' markets and enhance scale economies. Firms enjoy 'localisation economies', in which they benefit from mutual proximity, better-connected supply chains, and access to specialised labour pools (Vickerman 2007, p. 12). Improved accessibility, decreases in transport costs, and the emergence of agglomeration effects improve the attractiveness of the region for investors, tourists and households. More firms are established, more jobs created and more houses constructed in regions with better connection to major agglomerations. Good-quality transport infrastructure promotes competitiveness of local firms and increases their productivity. Increased density of firms should result in higher productivity, as firms and workers can find more matches in respect of their supply of skills.

The wider economic benefits for regions with improved transport infrastructure are generally recognised in the literature on transport economics and regional developments. Numerical specification of the benefits, however, is subject to discussions. There is considerable variation by industry in the magnitude of the elasticities between agglomeration and urbanisation effects and productivity increases. A review of the studies on urbanisation economies for manufacturing industries indicates that a doubling of a city size is typically associated with an increase in productivity of somewhere between 1% and 10% (Graham, 2007).

1.2. Research Hypotheses, Methods and Data

This paper analyses wider economic benefits of motorways on the LAU 1 level in the Slovak Republic. In the absence of good-quality data on productivity by industry, we use the surrogate measures of regional development. We test the hypothesis from the New Economic Geography that wider economic benefits of new transport infrastructure transfer to growth in real wages, density of firm population, employment opportunities, migration balance, and residential construction.

The paper has three objectives:

- It analyses whether construction of motorways creates some wider economic benefits for traversed regions and, if so, which ones and how long it takes for the benefits to materialise.
- It tests alternative methods for identifying potential long-run effects of motorways on regional economies and societies, and discusses their advantages and limitations.
- It LAU 1 level in Slovakia; furthermore, it reviews the validity of data for capturing wider economic benefits of transport infrastructure in Slovak regions.

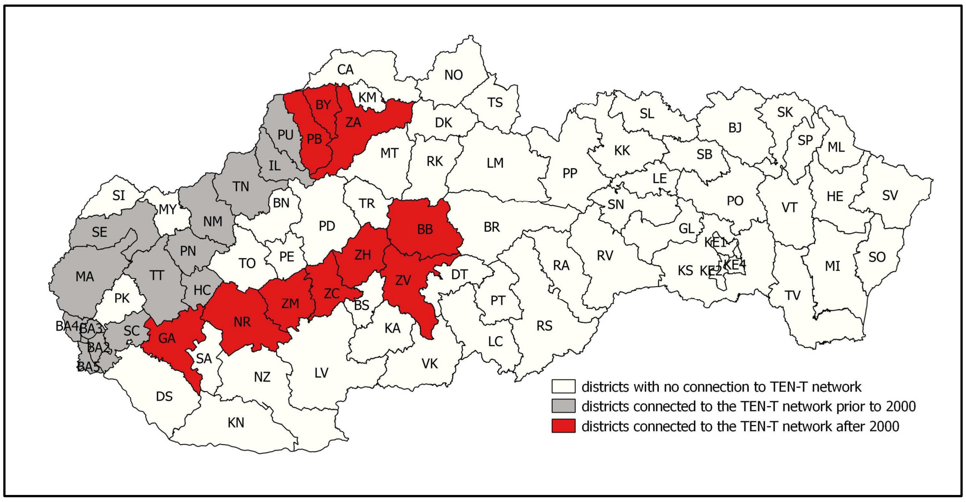
1.3. Data Sources

As for the choice of motorway projects, we follow Rephann-Isserman's hypothesis (Rephann and Isserman, 1994): '*Urban spillover regions are located in close proximity to large metropolitan regions and are stimulated by residential and employment decentralization.*' The key dependent variable – the presence of a motorway in a Slovak district – is stated as '1' if the district is connected to the Trans-European Transport Network (TEN-T) and '0' if otherwise. Isolated parts of motorways were discarded from this analysis.

We assume that potential of the motorway link can fully materialise only if the motorway is connected to the TEN-T. Connection to the TEN-T is of particular importance for Slovakia. The Slovak Republic has a small and very open economy, with exports of goods and services nearing 100% GDP. Key Slovak industries (automotive, consumer electronics) are dominated by multinational companies and dependent on long-distance road transport. TEN-T Priority Project 25 (PP25) is a prolongation of former pan-European transport corridor VI. It runs from Gdańsk via Katowice to Žilina (Slovakia) and through a western branch via Brno to Vienna. An analysis of the potential spatial spillover effects demonstrated substantial internal benefits for the Trenčín – Žilina section of PP25 (Gutiérrez et al., 2011). Another analysis of Polish motorways indicated that improved international accessibility improved territorial cohesion (Stępniak and Rosik, 2013).

F i g u r e 1

Slovak Districts Connected to the TEN-T Network



Source: <www.historiadialnic.sk>.

The data for this paper were provided by the Statistical Office of the Slovak Republic (SO SR, 2017). The data for 1997 – 2016 were available for the following outcome variables on the LAU 1 level: (1) number of firms, (2) number of foreign-owned firms, (3) flats finished in current year, (4) balance of internal migration, (5) unemployment rates, and (6) average wages.[2] Data for variables (1) – (4) were normalised per 1 000 population. Data on wages were recomputed to 1996 constant prices. Time series for variables (1), (2), and (6) are non-stationary. All other time series are stationary.

2. Difference in Differences

Difference in Differences (DiD) is a traditional quasi-experimental design for evaluating the wider economic benefits of motorways. It estimates causal effects of certain policy interventions in pre- and post-intervention periods. DiD compares four different groups of regions: treated versus untreated regions in pre-test versus post-test time periods. The regions firstly are matched in respect of their covariates before the pre-test period. The main purpose of the matching is to reduce bias in the estimation of the treatment effect. The pre-test compares the development of treated and untreated regions during a trial period before a motorway is put into operation. The pre-test tests the null hypothesis that there are no significant differences between treated and untreated regions before the construction of a motorway. The post-test compares growth trajectories in treated and untreated regions from the onset of motorway operation to the final year of analysis. If there are statistically significant differences in growth trajectories by treated and untreated regions, they are attributed to the effect of policy intervention.

If a motorway is part of a large-scale development project, investors and developers may move to the region before the completion of the motorway. Most of the wider economic and social effects of large transport infrastructure, however, emerge after the completion of a motorway. A meta-analysis of 33 studies on output elasticity of transport infrastructure found that long-run output elasticities of transport (over five years) are higher than short-run ones (Melo, Graham and Brage-Ardao, 2013). Some studies found that wages in motorway-traversed regions may take as much as 13 years to differ significantly from earnings in regions with no motorways (Chandra and Thompson, 2000). It is advised to have sufficiently long pre-test and post-test periods when evaluating wider economic

[2] We have also considered effects of motorways on development of tourism infrastructure. The Statistical Office of the Slovak Republic provides district-level data on numbers of beds in accommodation establishments. Numbers of beds show substantial annual variations in many districts. Data was not available at all for some districts due to individual data protection. We found data on beds unreliable and dropped them from the analysis.

benefits of motorways. Rephann and Isserman (1994) used a period of nine years for matching, three years for the pre-test period, and 22 years for the post-test period. Chandra and Thompson (2000) used five-year pre-intervention and 24-year post-intervention periods. The impact evaluation manuals and guidebooks from the national transport agencies of OECD countries tend to consider post-intervention periods of 20 – 35 years (Forkenbrock and Weisbrod, 2001; NPRA, 2006).

The choice of periods was driven by theory, empirical findings from previous studies, and data limitations in this paper. Detailed socioeconomic data for 79 Slovak districts are mostly available from 1996; 1996 was the matching period. Ten districts in Western Slovakia (including Bratislava) already had motorway by 1989.[3] Four districts were connected to the TEN-T in 1998 – 1999. The abovementioned 14 districts were excluded from the analysis. As for the remaining 65 districts, 10 were connected to the TEN-T and 55 remained unconnected in 2000 – 2016 (Figure 1). We therefore compare 10 connected and 55 unconnected districts in periods 1997 – 1999 (pre-test) and 2000 – 2016 (post-test).

The selection of covariates is the first step in the matching procedure. The number of covariates may depend on the sample size. A limited number of covariates is preferred in small samples. A review of quasi-experimental designs in social science indicated that the majority of studies add one to five covariates to the analysis (Aussems, Boomsma and Snijders, 2011). The choice of covariates was driven by theory on regional development. Regional income and employment usually are strongly dependent on the regional stock of human capital. Urban regions with high shares of tertiary graduates tend to have higher income and employment levels than do sparsely populated rural regions. We considered (i) population density, (ii) shares of urban population, (iii) shares of tertiary graduates, and (iv) average wage levels to be the key indicators of the regions' endowment with human capital in 1996 (before the construction of a motorway). All predictor variables, i.e. (i) – (iv), were strongly inter-correlated. The correlation coefficient for an urban population and a population with tertiary education, for example, was 0.818. As to avoid multi-collinearity problems, variables (i) – (iv) were examined by factor analysis. One factor was established, which we further refer to as 'regional endowment with human capital'. Factor scores were used as inputs for covariate 1. Covariate 2 was road distance (in km) from Bratislava to the regional capital in 1996. Distance to the capital is extremely important in Slovakia. The Bratislava Region is a notable outlier in terms of regional development. Bratislava's 2015 regional GDP accounted for 188% of the

[3] The Bratislava City comprises five and the Košice City four districts. We further consider Bratislava Košice cities single entities.

EU average and rendered Bratislava the fifth-richest region of the EU-28.[4] The per capita GDP of the second-richest Slovak region (Western Slovakia) comprised only 71% of the EU average in the same year (Eurostat, 2017).

The next step in matching procedures is the choice of distance method. Some older studies used the Mahalanobis metric (Rephann and Isserman, 1994). Most contemporary studies with a quasi-experimental design apply propensity scores. Propensity scores can be estimated via a number of alternative methods, but application of logistic regression is the most common procedure (Stuart and Rubin, 2007). The two covariates entered the logistic regression and generated Nagelkerke R Square = 0.288.

The distance measure is a key element in sample matching. The most intuitive matching method for estimating the average treatment effect is k: 1 nearest neighbour matching, where k = 1. The method selects for each treated individual *i* the control individual with the smallest distance from individual *i* (Stuart, 2010, p. 10). Some matching designs allow for a higher number of control group members, but in a two-sample comparison of means, the accuracy is largely defined by the smaller group size. The overall power of the test may not actually decrease much, when the size of the treatment group is unchanged, and only the control group decreases in size (Ho et al., 2007).

The validity of matches also depends on the proper value of the caliper – the maximum tolerated difference between matched units. Wider caliper widths allow the inclusion of more subjects and increase the sample size, but may increase bias in estimating the treatment effect. Narrower caliper widths tend to reduce bias, resulting in closer matches. Some units, however, may remain unmatched (Lunt, 2013). Some seminal studies on estimating differences in means recommend matching in respect of the logit of the propensity score using caliper values of width equal to 0.20 – 0.25 of the standard deviation of the logit of the propensity score (Austin, 2011; Wang et al., 2013). We experimented with different caliper vales, but the 0.25 value seemed to work most effectively.

The quasi-experimental design has some limitations related to confounding variables and the sample size. The relation between the treatment and effect may be obscured by confounding variables. Confounding variables may refer to natural disasters, major economic shocks and/or structural changes in regional economies. There were no large-scale natural disasters affecting Slovak districts in the period 1997 – 2016. Economies of the Slovak districts are dependent on manufacturing and service industries, while agriculture, forestry and fishing are of marginal

[4] Key Slovak companies had their headquarters in the Bratislava City. The Bratislava Region has a much small area and population than country capitals in other small European countries. Regional per capita GDP therefore is higher than that in Prague or Budapest.

importance for local employment and output. Slovak regions in the south and east of the country were heavily impacted by the economic and social transition in the early 1990s. Many regional industries collapsed and the economic centre shifted from central to western Slovakia (Smith, 1996). Most transition processes (privatisation, deregulation, liberalisation of foreign trade) happened in the first half of the 1990s. We did not have data on industry restructuring on the LAU level, and could not check for the effect of confounding variables. We further approximate data on industry restructuring via data on internal migration.

Motorways may generate the reallocation of some economic activities among regions. Some effects on regional development are only relocation effects: what is gained by one region is lost by the other (Quinet, 2000). There is a concern over the double counting of such effects (Vickerman, 2000). Spatial reallocation of business activity may generate additional confounding effects. The data limitations do not allow determining how much the increases in real incomes in the TEN-T-connected regions were due to increases in productivity and how much they resulted from reallocation effects.

The quasi-experimental design had to acknowledge a limited sample of districts with treatment effects (presence of the TEN-T-connected motorway, N = 10). Many studies in social science and economics have to work with small samples. There is no fundamental objection to using a regular t-test even with extremely small sample sizes. The t-test can be applied as long as the effect size is expected to be large (de Winter, 2013, p. 8).

We considered two samples: one for matched samples and one for unmatched samples (Table 1). The unmatched samples compared 10 treated districts to 55 untreated ones. The matched samples compared 10 treated districts to 10 districts matched via the propensity score matching (PSM) procedure. Unemployment rates and wage levels became significant in the unmatched sample. As for the matched sample, the pre-test indicated no statistically significant differences between treated and untreated districts in the period 1997 – 1999. The disparities in real wages in treated versus untreated districts increased from 4% in the period 1997 – 1999 to 14.6% in the period 2000 – 2016 (t-test: sig. 0.001). The growth in real wages was the only treatment effect significant on the 0.05 level in the matched sample.

Unemployment rates were lower in treated districts than in the untreated ones in both the pre-test and post-test periods. The disparities in unemployment rates were significant on the 0.01 level in the pre-test period and the 0.05 level in the post-test period.

The construction of a motorway seemed to have little effect on the number of firms per 1 000 population. As for the foreign-owned firms, their numbers actually increased by higher rates in unconnected districts than in connected ones.

This fact, however, relates to cross-border trade and tax optimisation strategies by foreign firms in some districts on the southern border of Slovakia.[5] The increase in migration balance in the TEN-T-connected districts (matched sample) may correspond to the increase in productivity and real wages. The effect, however, was not significant on the 0.05 level.

Table 1
The t-test for Unmatched and Matched Districts

	TENT-T motorway	**N**	**Mean**	**Std. Dev**	**SEM**	**N**	**Mean**	**Std. Dev**	**SEM**
		Unmatched samples				*Samples matched by PSM*			
Firms	No	55	0.74	0.40	0.05	10	0.68	0.21	0.07
1997 – 1999	Yes	10	0.96	0.58	0.18	10	0.96	0.58	0.18
firms	No	55	1.46	0.78	0.11	10	1.50	0.60	0.19
2000 – 2016	Yes	10	1.92	0.88	0.28	10	1.92	0.88	0.28
Foreign firms	No	55	0.40	0.35	0.05	10	0.33	0.21	0.07
1997 – 1999	Yes	10	0.58	0.34	0.11	10	0.58	0.34	0.11
Foreign firms	No	55	1.32	1.54	0.21	10	2.03	2.99	0.94
2000 – 1916	Yes	10	1.43	0.71	0.22	10	1.43	0.71	0.22
Flats per 1 000 pop.	No	55	1.63	0.71	0.10	10	1.74	0.83	0.26
1997 – 1999	Yes	10	1.54	0.60	0.19	10	1.54	0.60	0.19
Flats per 1 000 pop.	No	55	2.04	1.23	0.17	10	2.23	1.28	0.40
2000 – 1916	Yes	10	2.38	0.61	0.19	10	2.38	0.61	0.19
Migration balance	No	55	0.03	2.67	0.36	10	0.10	1.76	0.56
1997 – 1999	Yes	10	0.46	1.39	0.44	10	0.46	1.39	0.44
Migration balance	No	55	–0.38	2.71	0.37	10	–0.45	2.30	0.73
2000 – 2016	Yes	10	0.43	1.46	0.46	10	0.43	1.46	0.46
Unempl. rate (%)	No	55	**19.38***	5.38	0.73	10	**18.88****	3.62	1.14
1997 – 1999	Yes	10	**13.84**	3.59	1.13	10	**13.84**	3.59	1.13
Unempl. rate (%)	No	55	**16.07***	5.71	0.77	10	**15.33***	3.67	1.16
2000-16	Yes	10	**11.78**	3.77	1.19	10	**11.78**	3.77	1.19
Avg. wages, EUR	No	55	251.28	31.66	4.27	10	245.55	18.14	5.74
1997 – 1999	Yes	10	263.08	22.78	7.20	10	263.08	22.78	7.20
Avg. wages, EUR	No	55	291.43	39.48	5.32	10	**275.14*****	21.36	6.76
2000 – 2016	Yes	10	315.19	24.20	7.65	10	**315.19**	24.20	7.65

Notes: SEM – standard error mean; *** significant on the 0.001 level; ** significant on the 0.01 level; * significant on the 0.05 level. Data for firms, foreign firms, flats and balance of internal migration are stated per 1 000 population. Real wages – constant 1996 prices. Wages in Slovak korunas converted to euros via conversion rate 1 EUR = 30.126 SKK for period 1997 – 2008.

Sources: Statistical Office of the Slovak Republic and authors' computations.

The problem with a small sample essentially is that of a matching problem, wherein matched samples should be preferred to unmatched ones (Lechner, 2010). A comparison of means in treated and untreated matched samples also indicates that the districts with motorways improved their regional economies in terms of unemployment rates, housing, and migration balances. These improvements, however, were not significant on the 0.05 level. This finding may be the result of a small sample of treated districts.

[5] The highest numbers of foreign firms per 1 000 inhabitants were found for rural districts on Hungarian border (Komárno 21.8, Nové Zámky 7.0 and Dunajská Streda 5.9) in 2016. Inland-located industrial and metropolitan districts accounted for lower density of foreign firms (Martin 1.5, Trenčín 3.5, Trnava 3.1, Žilina 5.2).

3. Panel Regression with Fixed Effects

The fixed-effect (FE) model is a generalisation of the DiD model when there are more than two groups and periods. Individual-level panel data are embedded in districts for multiple years and the treatment (connection to the TEN-T network) varies over the district – year level. The FE estimation method uses panel data for regions. The treatment effect is denoted as '1' if the region was connected to the TEN-T and '0' if otherwise. As to make the FE model comparable with the DiD, observations with TEN-T = 1 in 1997 – 1999 were excluded from the dataset. This decision, inter alia, excluded the Bratislava City districts (significant outliers). We use a standard framework model

$$y_{it} = a_i + \beta TENT_{it} + \mathbf{Z}\boldsymbol{\gamma} + u_{it}$$

for the identification of treatment effect β on variables of interest y. We explore the effect of treatment on wages, flats, internal migration, the number of enterprises, and unemployment rates. Matrix of control variables **Z,** include population density (DENS), the share of population with higher education (HES) and the share of urban population (UPS) in the regions.

Since we are not primarily interested in time-invariant characteristics of individual regions, we allow them to be soaked up into the a_i. The fixed-effects estimator is then robust to any observed or unobserved time-invariant omitted variables. During the course of estimation, time-fixed unobservable differences between the regions (e.g. geographical or historical characteristics of districts) become effectively eliminated.

One method for model estimation includes cross-sectional (regional) dummies. The dummies capture region-fixed effects. The model specification (i) allows testing the model for joint significance of the period dummies, and (ii) justifies the identification strategy. The analysed period covers both years of high economic growth and downturn. We also include time (year) dummies in the model, so as to account for some time-varying factors, such as business cycles affecting all regions.

The DiD and FE regression rest on some common assumptions. Counterfactual levels for treated and untreated can be different, but their time variation is similar. A constant and additive effect generates a 'control group' that can be substituted for the missing counterfactual. In the absence of treatment, the change in the treated outcome would have been the same as the change in the untreated outcome, i.e. changes in the economy, lifecycle, etc. (unrelated to treatment) affect the two groups in a similar way. The panel data enable controlling for factors that vary across entities, but not over time. The regression cannot include unobserved and unmeasured variables. Omitted variable bias may emerge. The key idea is that if an omitted variable does not change over time it cannot affect time variation in the dependent variable.

We conducted preliminary testing of variables with respect to stationarity. The relevant literature suggests that panel-based unit root tests have higher power than do unit root tests based on individual time series. Two variants of the null hypothesis are possible: the common unit root process suggested by Levin, Lin and Chu (2002) and the individual one explored by Im, Pesaran and Shin (2003), Maddala and Wu (1999), Choi (2001), and Hadri (2000). Lag length and bandwidth selection is automated by the software package. Results of the panel roots test are reported in Appendix 1. The results proved stationarity for all of the time series except for the number of firms and average wages.

Estimates of the treatment effect, along with standard errors, *t*-statistics and respective *p*-values, are reported in Table 2. Statistics for controls also are included. The treatment effect is of primary interest. The significance level for only the TEN-T coefficient is indicated. The FE estimation results suggest that connection to the TEN-T network has a positive and significant impact on the number of firms and flats per 1 000 population. Wages in treated regions were 1.5 percentage points higher than in untreated regions. Coefficients for migration and unemployment are of the expected sign, but not significant at a reasonable significance level.

The FE model indicated positive, albeit much lower, effects of the TEN-T on wages than did the DiD model. DiD operates on the aggregated data. DiD may under- or overestimate the size of the treatment effect if there is a downward or upward trend in the dependent variable. The wage variable, for example, was non-stationary. The FE model provides for more detailed insights into developments in the treated unit over time. DiD has two major advantages over FE. The PSM procedure is easy to apply in the DiD. Application of matching procedure results in more realistic estimates of outcome variables. Application of PSM procedure to the FE model proved more challenging due to data constraints for control variables. Another advantage of DiD over FE is that data averaging in DiD may remove some random effects in the sample.

We complement the FE model estimation results with three sets of tests for period and time dummies. Set 1 (‘Cross-section F’) and set 2 (‘Cross-section Chi-square’) evaluate the joint significance of the cross-section effects. Sets 1 and 2 use sums of squares (F-test) and the likelihood function (Chi-square test) under the null that the cross-section effects are redundant. Set 3 evaluates the significance of period dummies in the unrestricted model against a restricted specification with region effects only. The remaining results evaluate the joint significance of all effects respectively. Redundant fixed-effects test results are reported in Appendix 1.

Table 2

Regression with the Fixed Effects

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Dependent variable firms per 1 000 population				
C	0.629	0.223	2.810	0.005
TEN-T connection	0.184	0.059	3.092	0.002***
Share of population with higher education	0.116	0.012	9.167	0.000
Share of urban population	–0.008	0.001	4.454	0.000
Population density	0.001	0.001	0.570	0.569
Dependent variable foreign firms per 1 000 population				
C	3.353	0.820	4.093	0.000
TEN-T connection	–0.313	0.218	–1.436	0.151
Share of population with higher education	–0.124	0.046	–2.683	0.007
Share of urban population	–0.020	0.007	–2.934	0.003
Population density	0.000	0.004	0.104	0.917
Dependent variable flats per 1 000 population				
C	–0.642	0.657	–0.977	0.329
TEN-T connection	0.449	0.169	2.658	0.008***
Share of population with higher education	0.290	0.037	7.7429	0.000
Share of urban population	–0.014	0.005	–2.684	0.007
Population density	0.004	0.003	1.369	0.171
Dependent variable migration balance per 1 000 population				
C	–4.289	1.094	–3.918	0.000
TEN-T connection	0.406	0.282	1.442	0.150
Share of population with higher education	0.315	0.063	5.053	0.000
Share of urban population	–0.022	0.009	–2.508	0.012
Population density	0.014	0.005	2.721	0.007
Dependent variable unemployment rate				
C	10.120	1.335	7.581	0.000
TEN-T connection	–0.193	0.355	–0.543	0.587
Share of population with higher education	0.287	0.075	3.800	0.000
Share of urban population	–0.005	0.011	–0.436	0.662
Population density	0.021	0.006	3.231	0.001
Dependent variable log wages				
C	5.676	0.034	167.099	0.000
TEN-T connection	0.015	0.009	1.742	0.082*
Share of population with higher education	–0.001	0.002	–0.666	0.505
Share of urban population	–0.000	0.000	–0.823	0.410
Population density	0.000	0.000	–0.224	0.823

Notes: Covariates: (i) population density; (ii) shares of urban population; (iii) shares of tertiary graduates; *** significant on the 0.01 level; * significant on the 0.1 level.

Source: Authors' computations.

4. Synthetic Control Method

The synthetic control method (SCM) creates a weighted average of untreated units ('synthetic cohorts') that best reproduces characteristics of the treated unit over time, prior to treatment (Abadie, Diamond and Hainmueller, 2010; 2015).

The impact of treatment is quantified via a comparison of performance by the treated versus synthetic cohorts after treatment. The synthetic cohort is a counterfactual statistical unit, i.e. a synthetic clone of the treated cohort.

The SCM extends the traditional linear panel data (difference in differences) framework. It has several advantages over the traditional DiD approach. The SCM enables the quantification of causal effects when there are only one or few treatment units. This is an advantage in a situation wherein there is substantial heterogeneity within the population of treated units. The SCM allows the effects of unobserved variables on the outcome to vary with time.

The rapidly growing literature on the SCM includes many evaluations of regional policies. Castillo et al. (2017) evaluated the causal effects of regional industrial policies on tourism employment in Argentina. Gobillon and Maganc (2016) used interactive fixed effects and an SCM to study the effects of enterprise zone policy on local unemployment in France. Percoco (2014) evaluated the effects of road-pricing schemes on curbing pollution and congestion in the city of Milan. Ando (2015) examined the impacts of nuclear power facilities on growth in local per capita income in Japanese municipalities. The SCM has been rarely used to analyse regional impacts of large transport infrastructure projects. Tveter, Welde and Odeck (2017) examined the impacts on settlement patterns for 11 fixed-links projects constructed from 1989 to 2008 in Norway. The SCM, to the authors' best knowledge, has never been used to evaluate wider economic benefits of motorways.

Table 3 summarises the key results of the SCM. The table compares the development of annual average values of actual versus synthetic units in post-treatment periods. The most significant results were detected for wages and unemployment rates. Average real wages increased in seven, the number of firms in eight and the number of flats in three out of 10 districts connected to the TEN-T in 2000 – 2011. Unemployment rates decreased in six out of 10 districts. Detailed results for each district are reported in Appendix 1. Economic theory suggests that many effects of motorways materialise over decades. The impact of treatment increased with the length of the post-test period. The most significant effects were detected for metropolitan and urban regions previously unconnected to the TEN-T. The most significant wage increases were detected in three out of four metropolitan/urban regions (Nitra, Banská Bystrica and Zvolen) compared to their synthetic counterpart after connection to the TEN-T.[6]

[6] No significant wage increase was detected for the Žilina district. The Slovak Government signed agreement with the KIA Motors company in 2004. The KIA planned to start its operations in 2006 and the Slovak Government pledged to connect the Žilina district to the TEN-T in the same year. The KIA actually started car production in 2006, but the motorway was finished in 2010. The big foreign carmaker had significant effect on rise in wages, flats and migration balance prior to Žilina's connection to TEN-T

T a b l e 3

Performance of Actual versus Synthetic Districts (annual averages)

District	TEN-T	Wages (%)	Unemployment (%)	Firms (%)	Flats (%)	Migration
Galanta	2000	+3.0	–3.50	+38.0	+78	+0.26
Nitra	2000	+8.6	–1.60	+5.2	+16	+2.84
Považská Bystrica	2005	–5.6	+1.70	–25.0	–24	–0.11
Bytča	2010	+3.6	+0.55	+9.4	–24	+1.79
Žilina	2010	+2.0	+0.41	+2.0	–31	+0.52
Banská Bystrica	2011	+4.8	–0.53	+2.8	–11	+0.10
Zlaté Moravce	2011	–3.5	–1.30	+5.6	+32	–0.004
Zvolen	2011	+8.0	+0.06	–4.9	–28	+0.47
Žarnovica	2011	–1.0	–2.10	+1.3	–16	+0.47
Žiar nad Hronom	2011	+2.0	–0.96	+1.7	–16	–0.84

Notes: Data for wages, firms and flats are percentage changes between real and synthetic variables to synthetic ones. Unemployment rates and migration balances are differences between values of real and synthetic values.

Source: Authors' computations.

The migration balance variable was impacted by a confounding event – significant immigration to the rural backgrounds of Bratislava and metropolitan districts in the Košice cities. The internal migration balance was significantly higher in the suburban districts of Malacky (3.7) and Pezinok (4.7) than the Slovak average (excluding Bratislava and Košice cities (2.6)). The abovementioned districts were considered outliers and excluded from the donor pool of internal migration. Adjustment of the donor pool had a substantial effect on the migration balance variable. Some actual districts underperformed, compared to synthetic ones, before adjustment, but outperformed after adjustment. The finding points towards the importance of proper composition of the donor pool.

The SCM comes with some limitations. It works most effectively with long-time series for treated and untreated units. The synthetic cohort derives from a donor pool of untreated units The SCM assumes that there are no spillovers from treated regions to the pool of donor regions. Quality of the SCM model essentially depends on the size and structure of the donor pool. If there is a significant outlier in the treated sample, a synthetic unit is difficult or impossible to create (Craig et al., 2017, p. 47). Bratislava City, for example, would be difficult to replicate from the donor pool of other Slovak districts. The SCM further requires that (i) predictor variables be comparable in the donor pool and treated pool units in the pre-test period, and (ii) effects of the predictor variables on the outcome variables be approximately linear. The abovementioned requirements regarding spillovers, outliers and the comparability of predictor variables across regions are not easy to maintain in real life.

Another important limitation of the SCM is that it does not provide clear guidance as to the choice of predictor variables that should be used to estimate the synthetic control weights (Ferman, Pinto and Possebom, 2016, p. 2). The

SCM enables creating counterfactuals for individual units or small groups, but frequentist p-values cannot be used to test the validity of inference. No general agreement has emerged on methods for assessing the goodness of match between the actual and synthetic units thus far (Fremeth, Holburn and Richter, 2016, p. 30). Most authors apply the ‘across-unit’ or ‘in-time’ placebo test to examine the goodness of fit. The latter test, for example, applies hypothetical treatment to a treated unit at different points in time from the actual treatment date (Fremeth, Holburn and Richter, 2016, p. 5). The effect of treatment can be considered causal if actual and synthetic units generate the same or very similar values of outcome variables for treatments falsely applied in different times.

We have implemented the cross-validation technique (‘in-time’ placebo effect) to test whether the SCM was an appropriate method for estimating causal relationships. We firstly used the entire pre-test period to estimate SCM values. Then we divided the pre-test period into two equal parts. When the synthetic units behaved in a similar way in both cases, the SCM was considered an appropriate method for estimating causal relationships. The root mean squared prediction error (RMSPE) test indicated that the results were not impacted by the ‘cherry picking’ for various outcome lags (Ferman, Pinto and Possebom, 2016; McClelland and Gault, 2017). As for the Galanta and Nitra districts, the pre-treatment period was too short to divide it in two parts and apply the in-time placebo effect. We applied the across-unit test for the abovementioned districts. The test confirmed appropriateness of the method. Results of the SCM for different outcome variables and time periods are reported in Appendix 2.[7]

The best results were obtained for wages, unemployment rates, internal migration balance, and the number of firms per 1 000 inhabitants. Results for flats per 1 000 inhabitants were less convincing. The SCM performed poorly for the number of foreign firms and tourism infrastructure. As mentioned before, data on foreign firms were heavily impacted by cross-border tax optimisation. Data on beds in accommodation establishments accounted for significant annual variations.

The SCM estimator requires that the pre-test period be long enough relative to the scale of the treatment size. The SCM does not specify how long the pre-test period must be so as to evaluate the effects of some significant treatments (including connection to the TEN-T network). The choice of the pre-test period must be driven by both theory and empirical findings. The current literature (Chandra and Thompson, 2000; Rephann and Isserman, 1994) recommends a minimal period of 3 – 5 years. The pre-test period in our study ranged from

[7] Results of the across-unit test for the Galanta and Nitra districts are not included in the Appendix 2, but are available upon request.

three to 11 years. The SCM had two major advantages over DiD. The SCM allowed for the evaluation of single treated units (districts) and varying pre-test and post-test periods.

Most studies on SCMs target one outcome variable. There is a question as to how to interpret results when treatment impacts two or more outcome variables. The donor pool of untreated units is always the same for all observed variables in DiD with PSM methods. The synthetic cohort, in contrast, may be constructed from different subsamples of untreated units for each observed variable. The Nitra district, for example, can be constructed from Pezinok and Stará Ľubovňa districts when matching in respect of wages, but from Košice okolie, Košice I and Pezinok when matching in relation to unemployment rates. The scale of the RMSPE value is specific for each outcome variable. The RMSPE values cannot be compared across different outcome variables. Varying composition of synthetic units and different scales of RMSPE for specific outcome variables render the socioeconomic interpretation of the findings rather challenging.

Conclusions

This research applied three impact evaluation techniques so as to identify the wider economic benefits of motorways in the Slovak LAU 1 regions. The research found some support for the hypothesis that connection to the TEN-T network of motorways improves the economic and social milieu of the connected regions. DiD with PSM, FE regression and SCMs identified significant benefits of motorways, i.e. increases in wages and, to a lesser extent, a decrease in unemployment rates and an increase in migration balance and the number of firms and flats. SCM results indicated that the size of effects tended to increase with the length of the post-test period. The results resonate with assumptions by the New Economic Geography (Fujita, Krugman and Venables, 1999; Vickerman, 2007; 2008) and findings by some empirical studies (Rephann and Isserman, 1994; Chandra and Thompson, 2000).

The matching techniques (DiD with PSM, SCM) are the most popular methods regarding the evaluations of policy intervention, when randomisation procedures are not available. DiD is the simplest and most popular impact evaluation method, but also the least exact and powerful one, when the sample size is small. DiD is based on the frequentist inference and requires a relatively large sample. This requirement was difficult to meet for the sample of 10 Slovak districts connected to the TEN-T in 2000 – 2016. The DiD uses only two time periods for evaluation. We had to aggregate treated units for a very long period of 16 years in order to build a minimal sample of 10 districts. Data aggregation over a long period of time skewed values of some non-stationary variables (wages) upwards. The FE regression allowed analysing multiple treatment periods. The power of FE regression, however, also was limited by the small sample of treated districts.

Table 4
Pros and Cons of Specific Methods for Assessing Impacts of Motorways

	Pros	Cons
Difference-in--Difference	'Golden standard' in impact evaluation. Relatively simple method with intuitive interpretation of results. Easy application of matching techniques.	Assumption on parallel trends for treated and non-treated units in pre-test period. Requires, there are no group-specific trends that may affect outcomes of intervention. Works best for large samples of treated units. Treatment effects pooled into one period. Estimates average treatment effects across units and time.
Regression with fixed effects	Allows for multiple treatment periods. Provides for more detailed insights into developments in the treated unit over time.	Potentially higher impact of random effects compared to DiD. Application of matching methods may be more challenging.
Synthetic control method	Higher accuracy = weighs the control group to better match the treatment group before the intervention operates for one or few treatment units. Does not require parallel trends for treated and non-treated units in pre-test period. Allows for multiple treatment periods and provides time varying estimates of individual treatment effects for each treated unit.	Quality of synthetic units depends on size and structure of donor pool. Significant outliers can be difficult/impossible to replicate. No general agreement on methods for measuring quality of model fit. No general agreement on methods for comparing models with different outcome variables. Varying composition of synthetic units for specific outcome variables makes socio-economic interpretation of the findings more difficult.

Source: Authors' conclusions.

The SCM has no limitations in respect of the sample size, but comes with limitations regarding outcome testing and interpreting. The procedure is relatively new and there is no clear guidance on methods for measuring the quality of model fit and/or comparing models with different outcome variables. We, nevertheless, consider an SCM to be the best procedure for measuring wider economic benefits of motorways when the number of treated units is low or there is only one treated unit. A valuable property of the SCM is that it enables identifying time-varying effects of motorways for individual regions. Major pros and cons of the specific assessment methods are summarised in Table 4.

This paper also examined the validity of data for specific outcome variables on the LAU 1 level in Slovakia. Data on wages and unemployment rates account for relatively good coverage and relevance for the impact assessment. Annual variations in wages and unemployment rates are relatively low (except for the crisis year of 2009). As for the theory-based evaluation, we consider wages and unemployment rates to be the best outcome variables for measuring wider economic benefits of motorways. As for the regional relevance, data on wages are more relevant than those on unemployment. Data on wages are reported by place of work, while data on unemployment by place of permanent residence. Regional data on unemployment are impacted by commuting patterns.

Data on internal migration are based on permanent residence and, like data on unemployment, are impacted by regional commuting patterns. Data on the number of firms account for good coverage. Firm data, however, are less relevant for theory-based evaluation, as they offer no information on firm size and economic impact on regional economies. We found data on the number of foreign firms to be heavily skewed by cross-border tax optimisation. Beds in accommodation establishments accounted for problematic coverage and high annual variability.

Numbers of flats show high annual variations, particularly in small districts. Completion of a large residential project can satisfy housing demand for several years. Numbers of flats also are impacted by housing booms and boosts. Numbers of flats and internal migration, however, become more relevant from long--term perspectives. Some workers move to a place of work (or nearby places) over time. The SCM results, for example, indicated significant increases in migration balance in districts connected to the TEN-T in 2000.

The Slovak economy enjoyed impressive growth rates in the period 2000 – 2016. Eurostat data indicate that per capita GDP increased from 50% to 77.3% of the EU-28 average. The western part of Slovakia (Bratislava, Trnava, Trenčín and Žilina NUTS III regions) was connected to the TEN-T network and grew by higher rates than did eastern parts of the country (not connected to the TEN-T). We lacked data on potential internal reallocation of economic activities (distributive effect). Data on internal migration indicate substantial inflows of population from the east to the west of Slovakia. Improved accessibility undoubtedly was an important factor behind economic success and improved migration balance of the western part of the Slovak Republic.

The SCM indicated that the motorway rendered the districts of Považská Bystrica and Žiar nad Hronom worse off in terms of migration balance (after adjustment for Bratislava's suburban districts) (Table 3). The Statistical Office of the Slovak Republic publishes detailed tables on migration flows by district of source and destination (SO SR, 2017). We found that (1) outmigration intensified in the abovementioned districts after connection to the TEN-T, and (2) both districts lost their population to regional capitals connected to the TEN-T (Trenčín and Žilina in the case of Považská Bystrica, and Banská Bystrica in the case of Žiar nad Hronom). This finding may indicate distributive effects of motorways, wherein semi-urban regions lose their population to metropolitan ones.

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Appendices

Appendix 1

Panel Unit Root Tests

Method	Statistic	Prob.	Cross sections	Obs
Series: firms per 1 000 population				
Levin, Lin and Chu t*	25.175	1.000	65	1 216
Im, Pesaran and Shin W-stat	31.940	1.000	65	1 216
ADF – Fisher Chi-square	5.922	1.000	65	1 216
PP – Fisher Chi-square	0.610	1.000	65	1 235
Series: foreign firms per 1 000 population				
Levin, Lin and Chu t*	–0.177	1.000	65	1 192
Im, Pesaran and Shin W-stat	4.900	1.000	65	1 192
ADF – Fisher Chi-square	87.927	1.000	65	1 192
PP – Fisher Chi-square	32.052	1.000	65	1 192
Series: flats per 1 000 population				
Levin, Lin and Chu t*	–21.052	0.000	65	1 150
Im, Pesaran and Shin W-stat	–16.647	0.000	65	1 150
ADF – Fisher Chi-square	570.816	0.000	65	1 150
PP – Fisher Chi-square	741.125	0.000	65	1 170
Series: migration balance per 1 000 population				
Levin, Lin and Chu t*	–13.388	0.000	65	1 148
Im, Pesaran and Shin W-stat	–10.557	0.000	65	1 148
ADF – Fisher Chi-square	361.345	0.000	65	1 148
PP – Fisher Chi-square	374.614	0.000	65	1 170
Series: unemployment rates				
Levin, Lin and Chu t*	–2.619	0.004	65	1 162
Im, Pesaran and Shin W-stat	–4.966	0.000	65	1 162
ADF – Fisher Chi-square	205.799	0.000	65	1 162
PP – Fisher Chi-square	118.672	0.752	65	1 235
Series: wages				
Levin, Lin and Chu t*	9.048	1.000	65	1 130
Im, Pesaran and Shin W-stat	14.239	1.000	65	1 130
ADF – Fisher Chi-square	10.947	1.000	65	1 130
PP – Fisher Chi-square	9.238	1.000	65	1 130
Series: log wages				
Levin, Lin and Chu t*	6.905	1.000	65	1 132
Im, Pesaran and Shin W-stat	12.443	1.000	65	1 132
ADF – Fisher Chi-square	13.211	1.000	65	1 132
PP – Fisher Chi-square	11.099	1.000	65	1 170

Notes: Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.
Automated max lag length selection based on Schwarz information criterion. Barltlett kernel in spectral estimation with automatic Newey-West bandwidth selection.

Source: Authors' computations.

Redundant Fixed Effects Tests: Test Cross-section and Period Fixed Effects

Effects Test	Statistic	d.f.	Prob.
Equation: flats			
Cross-section F	13.39	(78,1400)	0.00
Cross-section Chi-square	836.66	78	0.00
Period F	5.07	(18,1400)	0.00
Period Chi-square	94.84	18	0.00
Cross-Section/Period F	13.31	(96,1400)	0.00
Cross-Section/Period Chi-square	973.55	96	0.00
Equation: log wages			
Cross-section F	67.59	(78,1400)	0.00
Cross-section Chi-square	2343.77	78	0.00
Period F	94.29	(18,1400)	0.00
Period Chi-square	1191.85	18	0.00
Cross-Section/Period F	75.48	(96,1400)	0.00
Cross-Section/Period Chi-square	2732.74	96	0.00
Equation: migration balance			
Cross-section F	35.86	(78,1400)	0.00
Cross-section Chi-square	1648.10	78	0.00
Period F	3.58	(18,1400)	0.00
Period Chi-square	67.48	18	0.00
Cross-Section/Period F	35.24	(96,1400)	0.00
Cross-Section/Period Chi-square	1844.29	96	0.00
Equation: unemployment rate			
Cross-section F	81.93	(78,1478)	0.00
Cross-section Chi-square	2642.02	78	0.00
Period F	144.76	(19,1478)	0.00
Period Chi-square	1660.83	19	0.00
Cross-Section/Period F	92.61	(97,1478)	0.00
Cross-Section/Period Chi-square	3091.96	97	0.00
Equation: firms			
Cross-section F	62.21	(78,1478)	0.00
Cross-section Chi-square	2298.44	78	0.00
Period F	12.86	(19,1478)	0.00
Period Chi-square	241.68	19	0.00
Cross-Section/Period F	51.45	(97,1478)	0.00
Cross-Section/Period Chi-square	2332.42	97	0.00
Equation: foreign firms			
Cross-section F	19.18	(64,1212)	0.00
Cross-section Chi-square	909.38	78	0.00
Period F	4.69	(19,1212)	0.00
Period Chi-square	92.22	19	0.00
Cross-Section/Period F	15.74	(83,1212)	0.00
Cross-Section/Period Chi-square	950.67	97	0.00

Notes: test statistics, degrees of freedom and p-values under the null of no effects.

Source: Authors' computations.

A p p e n d i x 2

Summary of Statistics and Diagrams for the SCM, by District

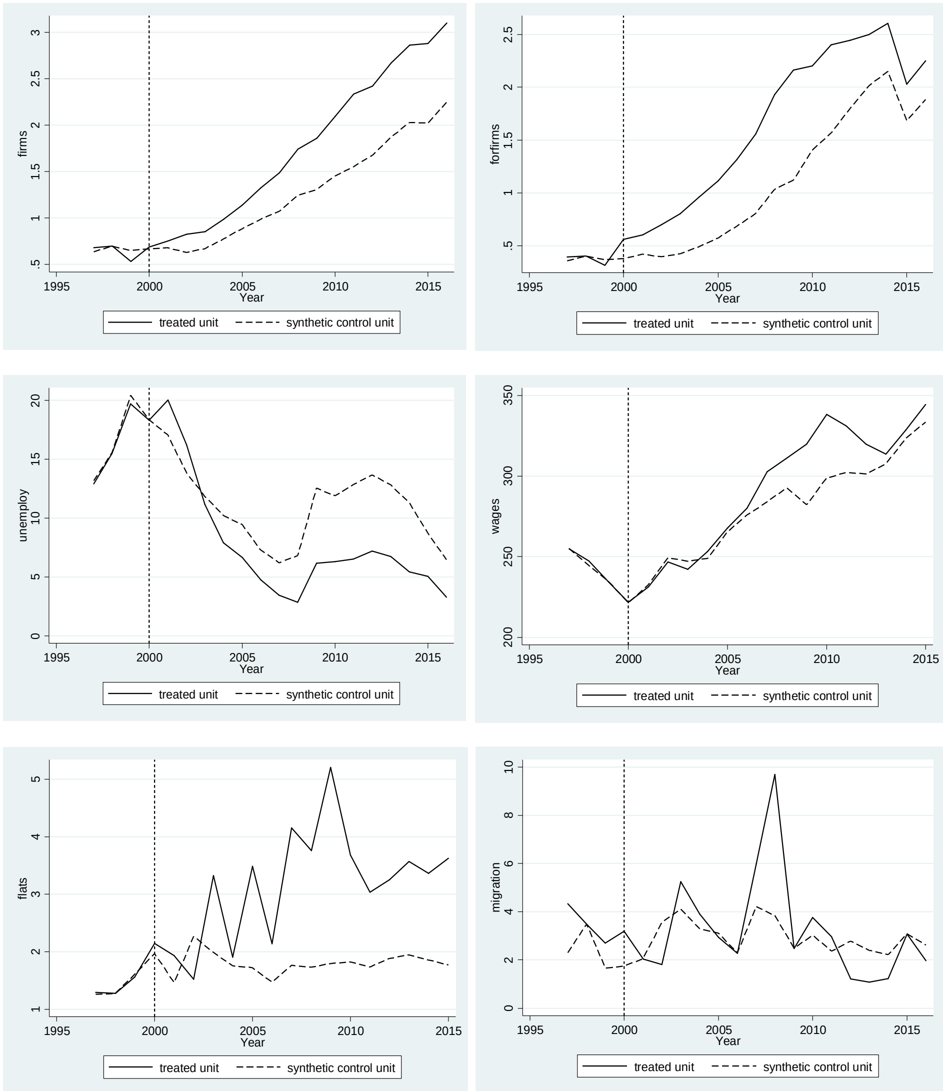
The appendix contains the results of SCM modelling for each district connected to the TEN-T in 2000 – 2011.

Diagrams present developments in outcome variables by actual units (solid lines) and synthetic units (dashed lines) for each district.

Tables provide information on:

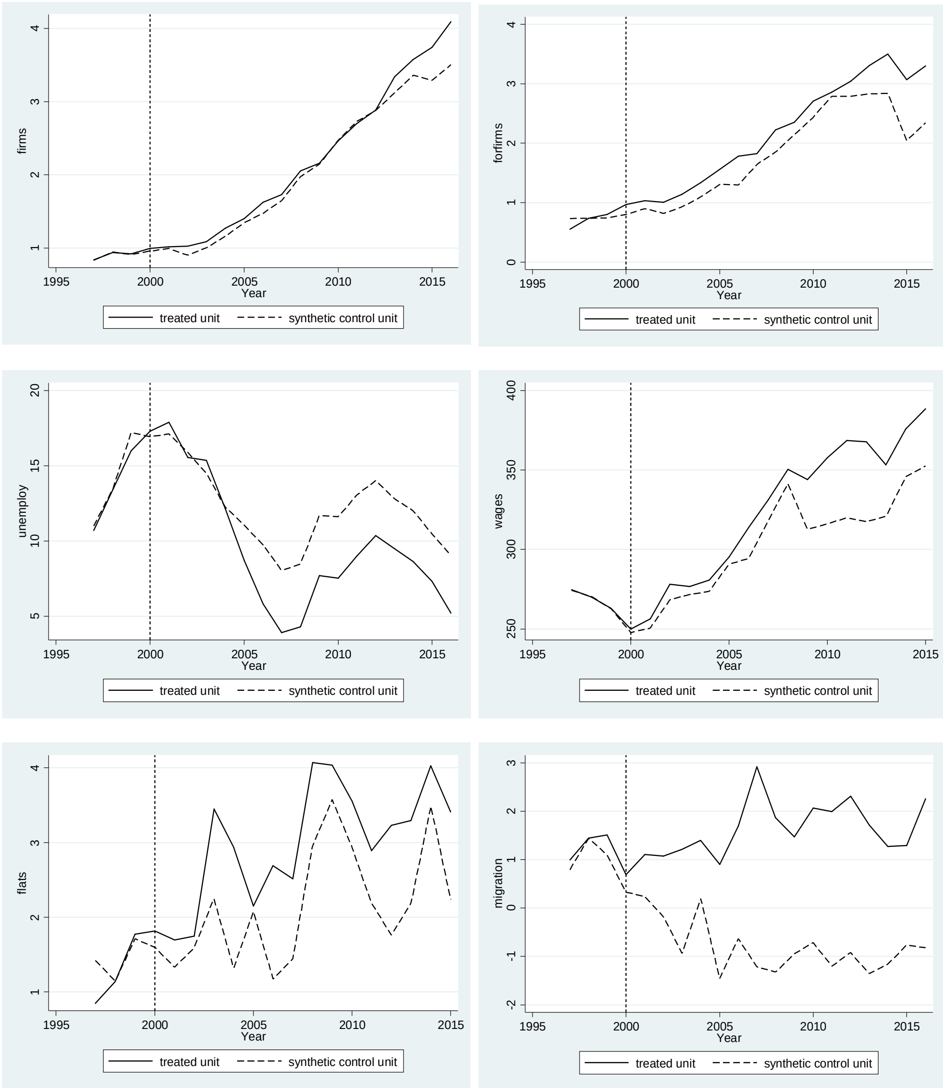
- values of the total root mean squared prediction error (RMSPE);
- composition of synthetic controls in terms of weights and district codes. Up to five synthetic controls (sc1 – sc5) are reported;
- the cross-validation check, the in-time placebo effect for the middle of pre-test period in terms of the RMSPE ratios (ratio of post-intervention to pre--intervention RMSPE values with real and placebo treatment), i.e. values of differences between real and placebo RMSPE ratios. Significant negative difference between real and placebo values denies appropriateness of the method.

Galanta: Connected to TEN-T in 2000



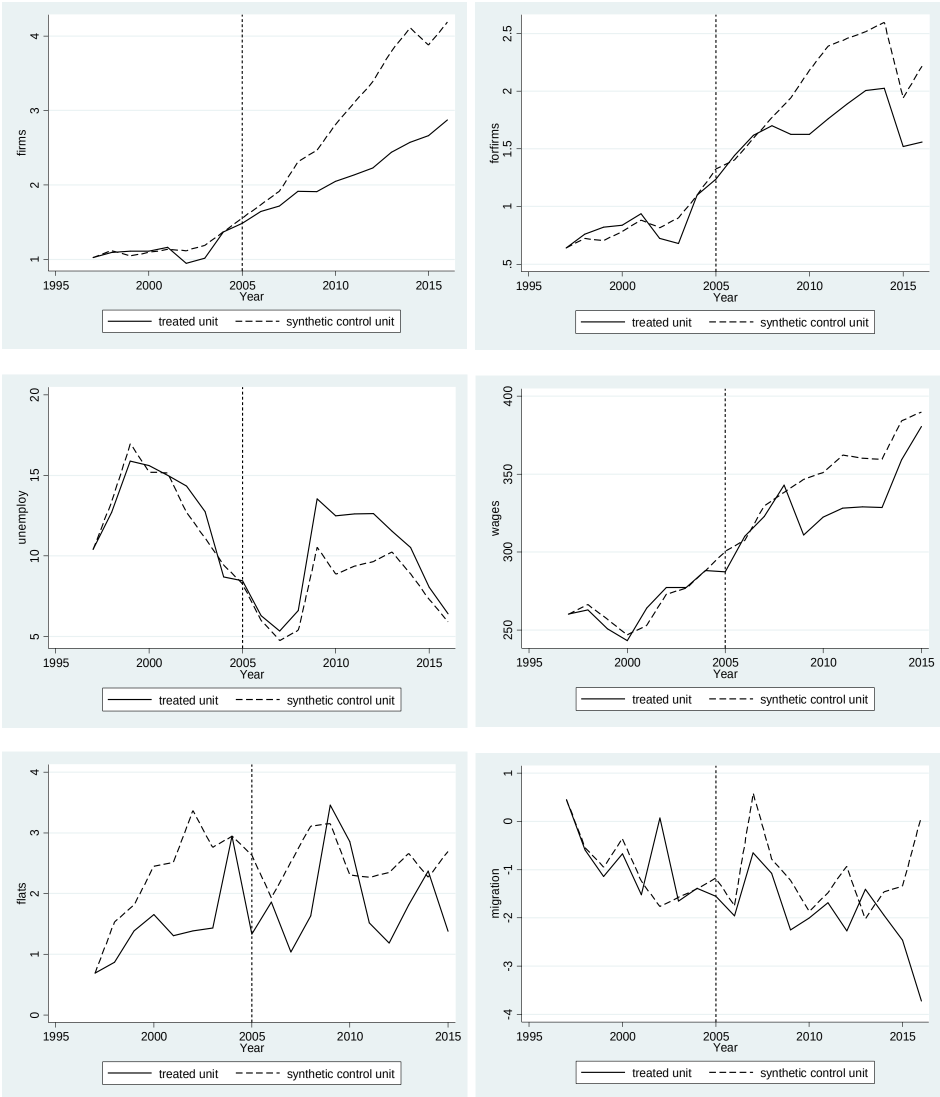
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2000	0.074	0.036	0.399	1.806	0.036	1.33
sc1	0.22 VK	0.17 NO	0.45 NO	0.36 GL	0.20 RV	0.75 DS
sc2	0.12 NO	0.15 CA	0.30 SI	0.08 SK	0.14 KS	0.19 MA
sc3	0.05 KK	0.08 GL	0.16 PD	0.06 DT	x	0.03 NO
sc4	0.04 GL	0.07 KK	x	0.04 KS	x	0.03 KE 3
sc5	x	0.03 RA	x	0.03 CA	x	x
Dif RMSPE ratios (2000 – 1999)	–0.02	–0.06	–3.5	–5.3	–0.065	–2.6

Nitra: Connected to TEN-T in 2000



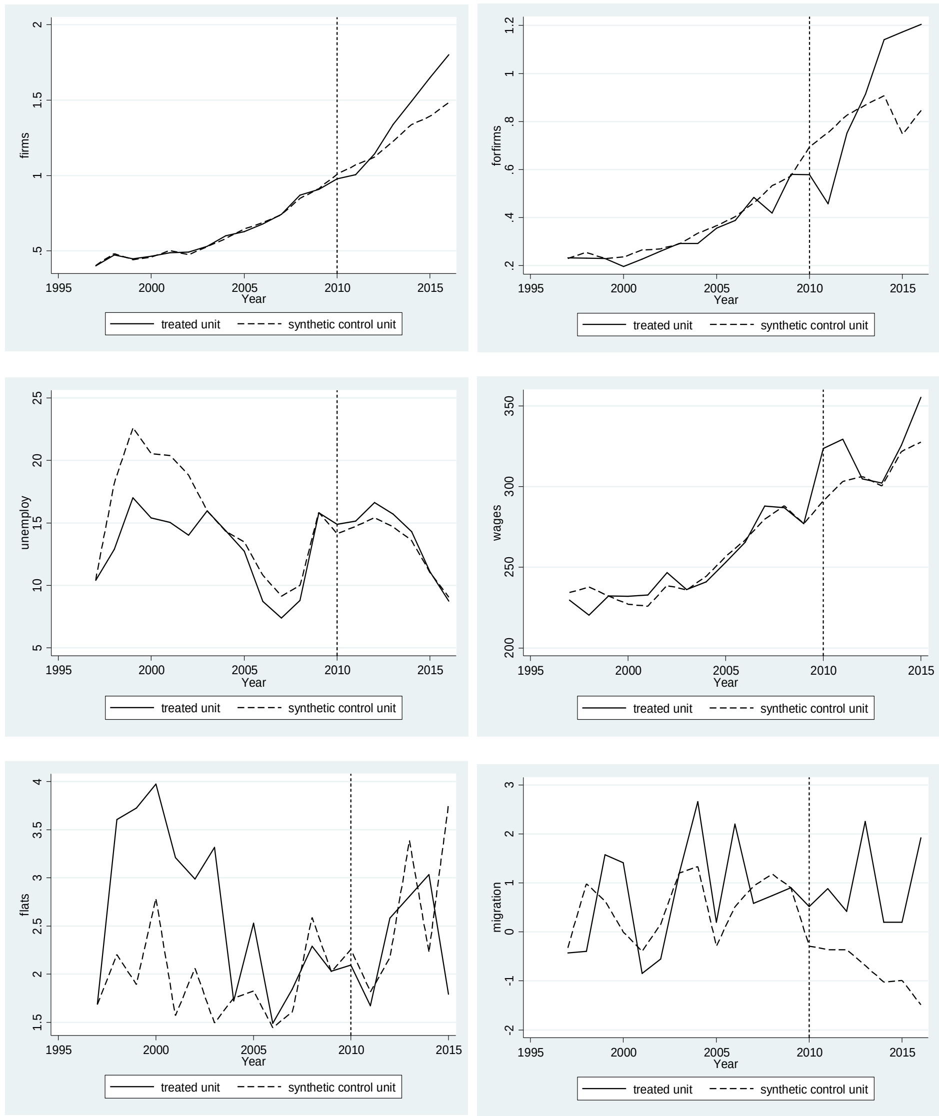
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2000	0.006	0.108	0.715	0.33	0.331	0.267
sc1	0.55 PK	0.56 PK	0.36 PK	0.81 PK	0.92 MT	0.41 BS
sc2	0.36 HE	0.19 BS	0.29 KE 1	0.13 SL	0.07 KE 1	0.25 LM
sc3	0.05 KS	0.14 SA	0.29 KE O	x	x	0.18 BS
sc4	0.04 KE 4	0.08 PT	x	x	x	0.15 KE 2
sc5	x	0.04 KE 3	x	x	x	x
Dif RMSPE ratios (2000 – 1999)	–1.84	–0.22	–1.23	–3.3	–0.17	–1.48

Považská Bystrica: Connected to TEN-T in 2005



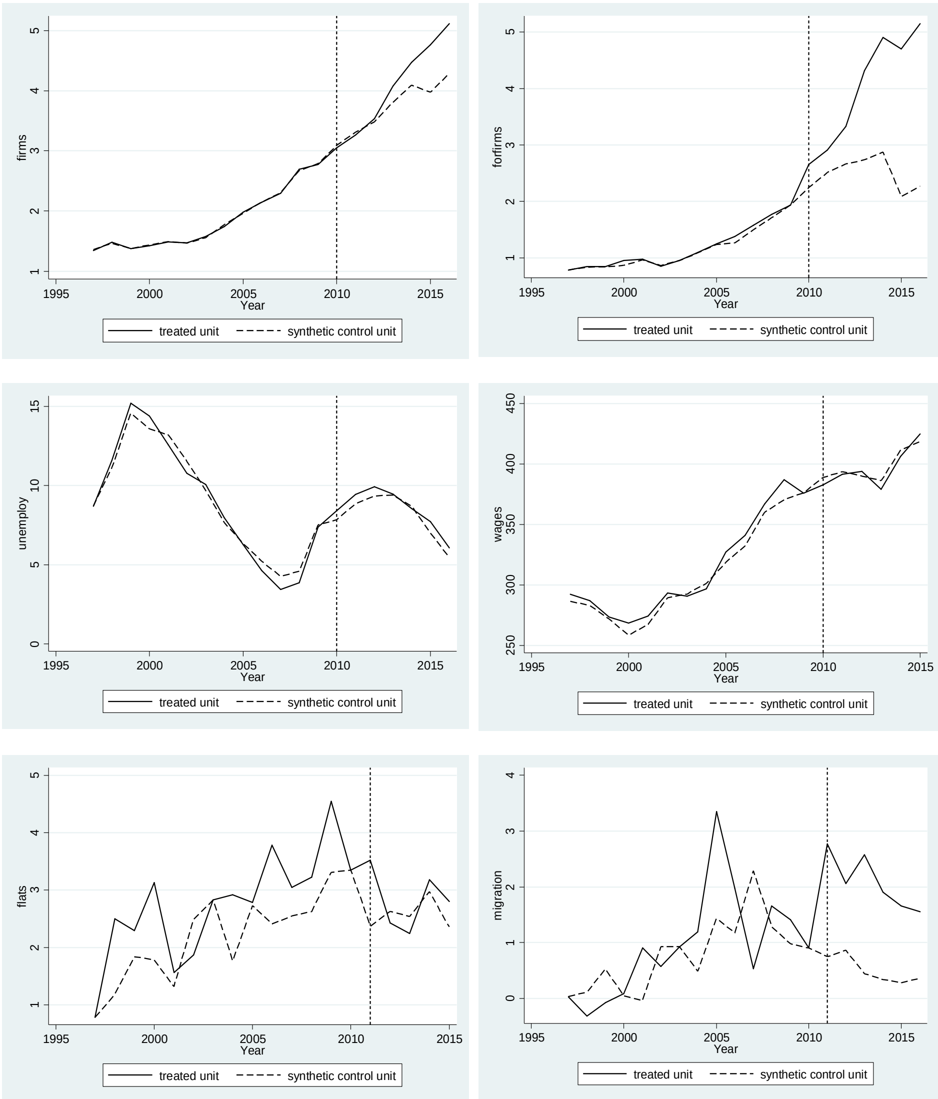
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2005	0.089	0.099	0.98	5.038	1.028	0.673
sc1	0.28 KN	0.27 DT	0.35 SI	0.47 MA	0.36 SI	0.52 MY
sc2	0.19 SI	0.20 PK	0.29 PP	0.40 SV	0.33 TS	0.19 DT
sc3	0.14 PK	0.19 SI	0.18 MY	0.09 KE 1	0.18 KE 3	0.17 MT
sc4	0.14 DT	0.11 BS	0.15 PK	0.04 SI	x	0.04 SI
sc5	0.10 KE 1	x	0.04 KE 1	x	x	0.04 KE 1
Dif RMSPE ratios (2005 – 2001)	0.049	0.062	0.74	4.6	0.78	0.66

Bytča: Connected to TEN-T in 2010



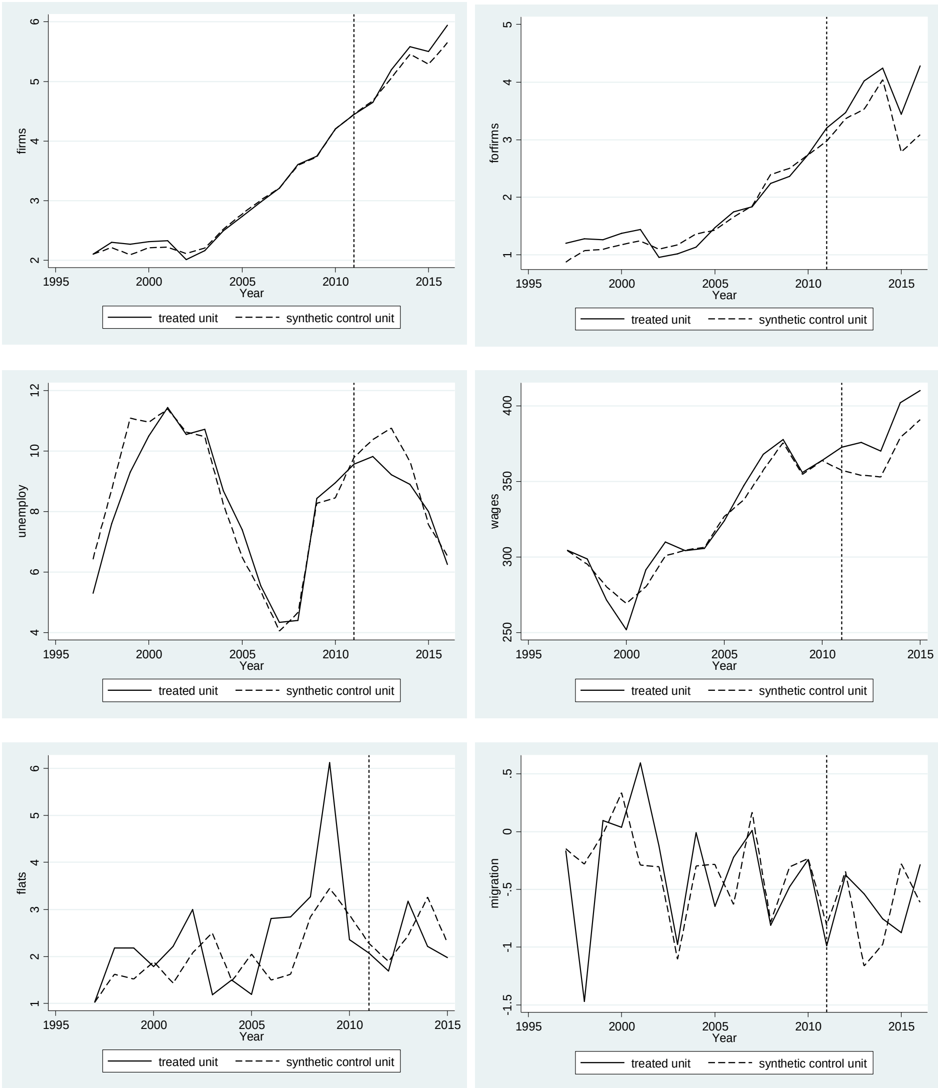
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2010	0.012	0.041	3.363	6.48	1.04	0.906
sc1	0.86 KK	0.41 SB	0.59 SI	0.51 KA	0.62 VK	0.39 VK
sc2	0.10 TR	0.14 NO	0.15 VK	0.24 PE	0.15 DS	0.32 RA
sc3	0.03 MT	0.12 KK	0.11 KK	0.15 NO	0.10 BN	0.18 DS
sc4	x	0.09 KM	0.08 VT	0.10 MA	0.09 CA	x
sc5	x	0.07 RA	0.08 NO	x	x	x
Dif RMSPE ratios (2010 – 2004)	0.02	0.021	–0.5	2.37	0.09	0.08

Žilina: Connected to TEN-T in 2010



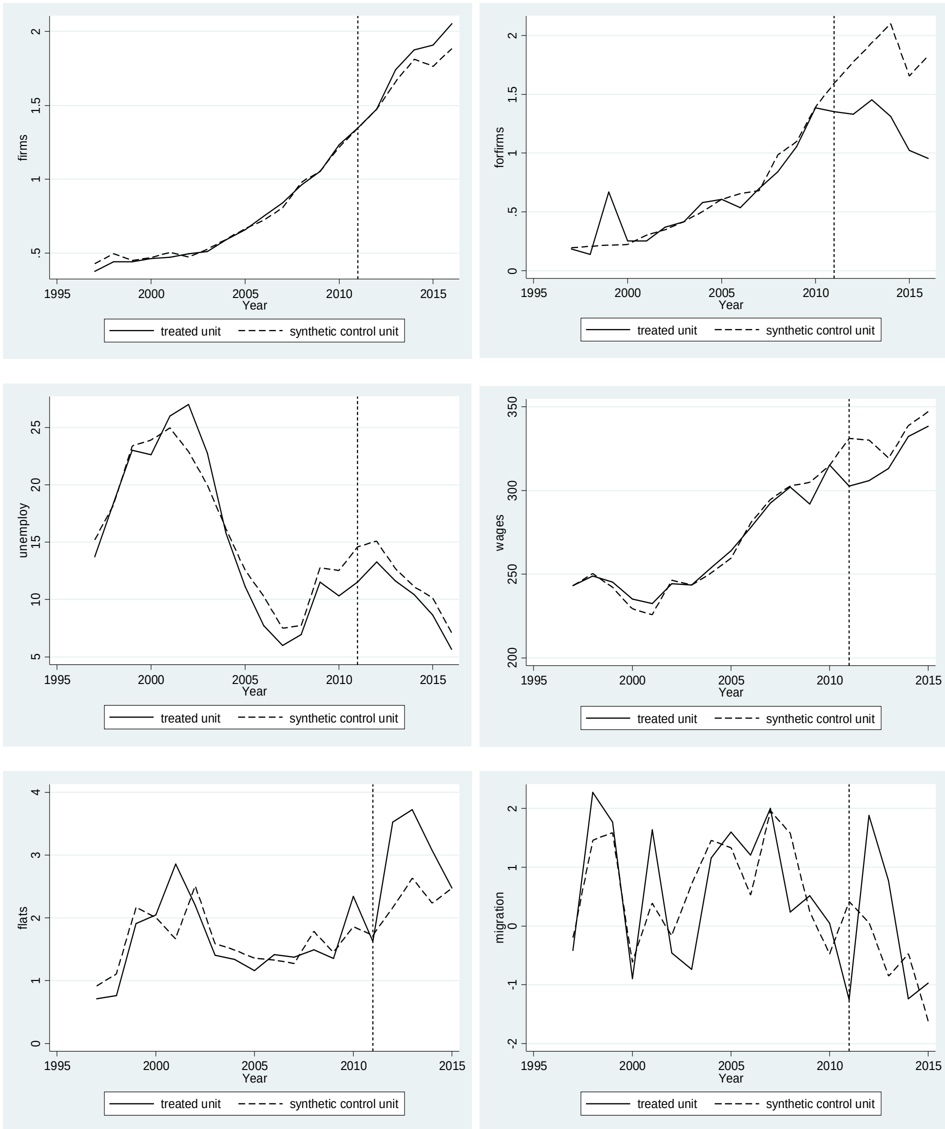
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2010	0.016	0.034	0.554	7.557	0.826	0.835
sc1	0.3 MT	0.37 PK	0.34 KE 4	0.36 MA	0.28 MT	0.44 MT
sc2	0.24 KE 1	0.30 KE 3	0.32 PK	0.28 KE 4	0.24 LM	0.16 TR
sc3	0.22 MA	0.12 MT	0.17 DS	0.18 PK	0.14 SI	0.14 TO
sc4	0.14 DK	0.10 CA	0.15 MA	0.06 KE 1	0.07 KE 4	0.11 DS
sc5	0.11 DS	x	0.03 NO	x	0.22 TO	0.08 KE 4
Dif RMSPE ratios (2010 – 2004)	0.006	0.01	–0.14	4.53	0.25	–0.14

Banská Bystrica: Connected to TEN-T in 2011



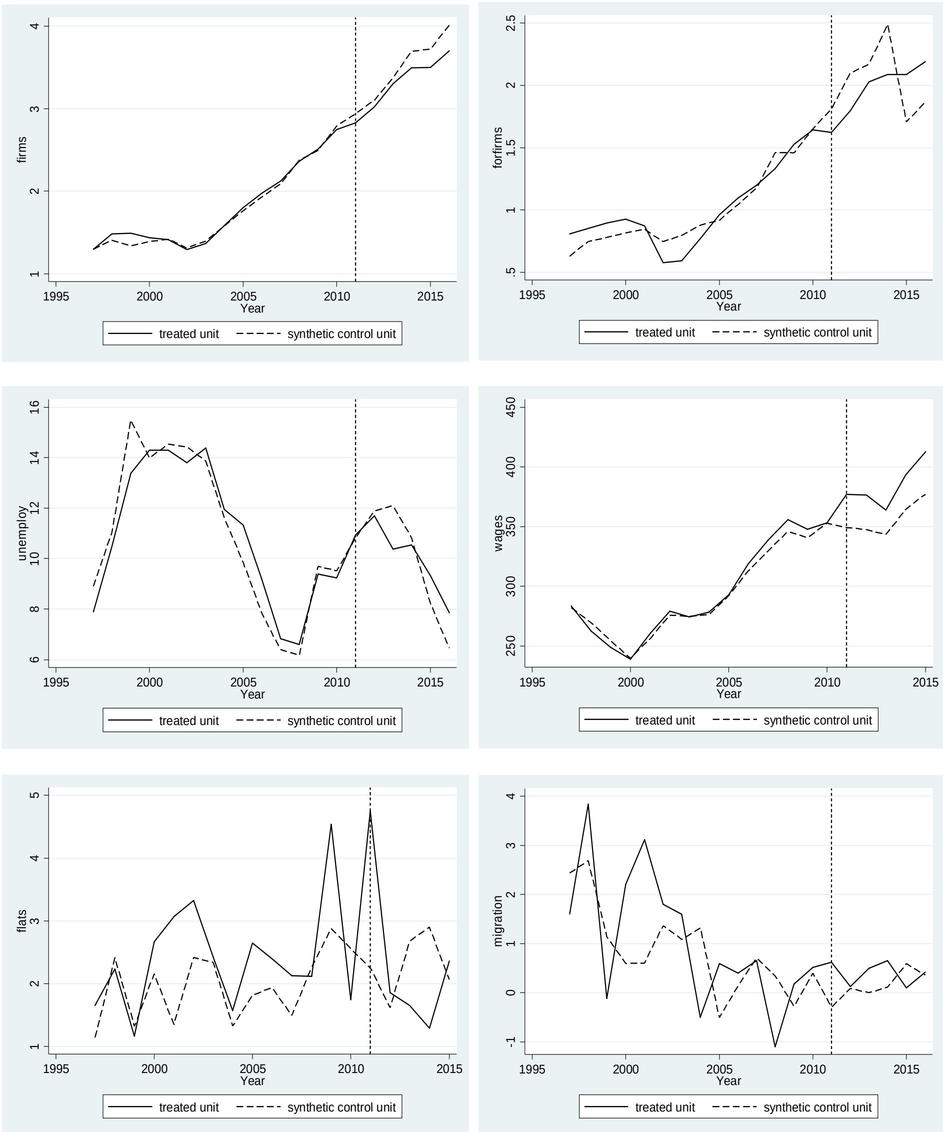
	Firms	**Foreign firms**	**Unemployment**	**Wages**	**Flats**	**Migration**
RMSPE 2011	0.074	0.169	0.731	7.583	1.053	0.446
sc1	0.68 KE 1	0.56 KE 3	0.49 PK	0.56 PK	0.7 MT	0.58 MT
sc2	0.29 KE O	0.26 KE 1	0.46 LM	0.3 KE 1	0.15 DT	0.18 BS
sc3	0.04 PK	0.18 KE 4	0.05 KE 1	0.09 KE 2	0.09 SI	0.14 KE 2
sc4	x	x	x	0.05 SO	x	x
sc5	x	x	x	x	x	x
Dif RMSPE ratios (2011 – 2005)	–0.01	–0.02	–0.09	–0.004	0.6	–0.07

Zlaté Moravce: Connected to TEN-T in 2011



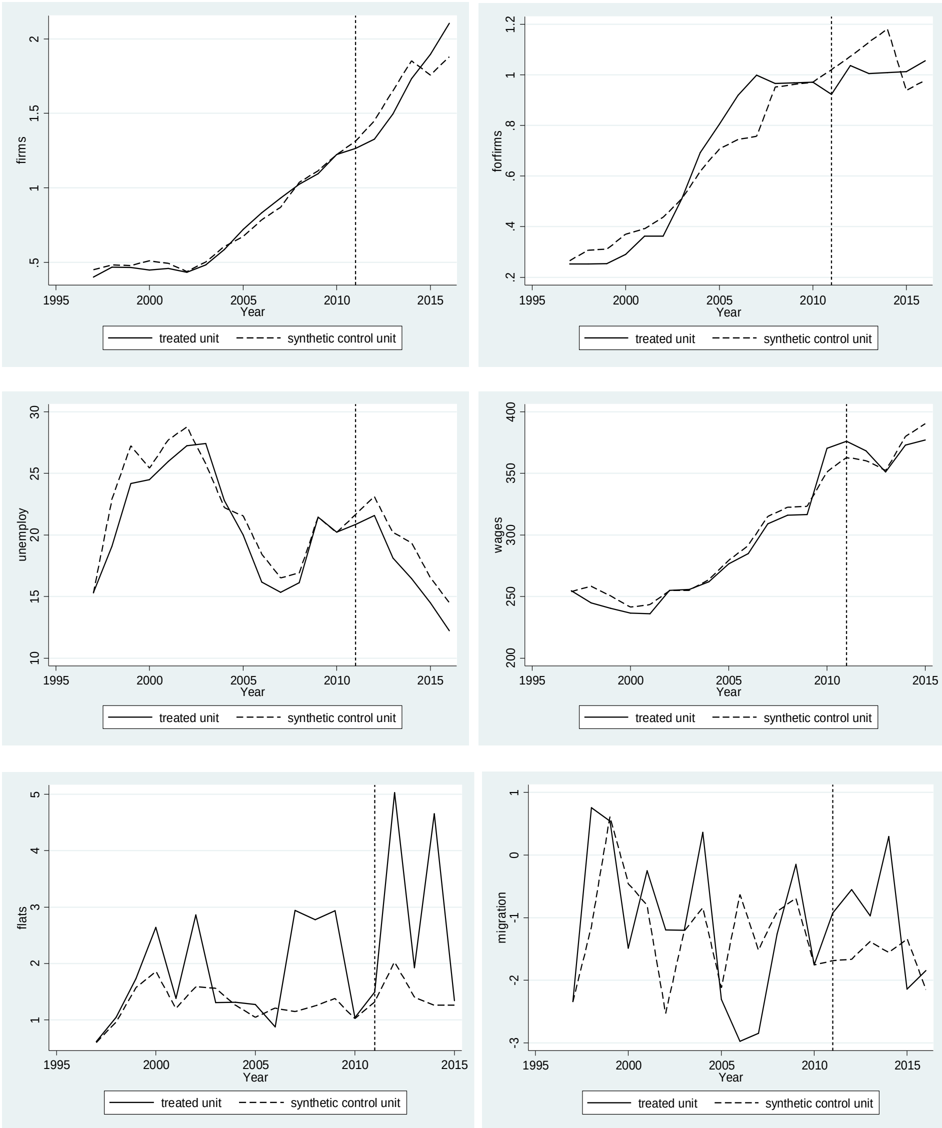
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2011	0.027	0.135	1.844	4.62	0.395	0.725
sc1	0.81 KK	0.53 BJ	0.86 NZ	0.32 NO	0.65 LV	0.24 TR
sc2	0.15 KN	0.37 NO	0.08 TR	0.16 SO	0.19 MY	0.22 DT
sc3	0.05 PT	0.06 MA	0.06 LV	0.13 MA	0.11 DS	0.19 MY
sc4	x	x	x	0.10 BS	x	0.15 KN
sc5	x	x	x	0.06 KE O	x	0.14 SA
Dif RMSPE ratios (2011 – 2005)	0.006	–0.025	0.32	1.02	–0.19	–0.2

Zvolen: Connected to TEN-T in 2011



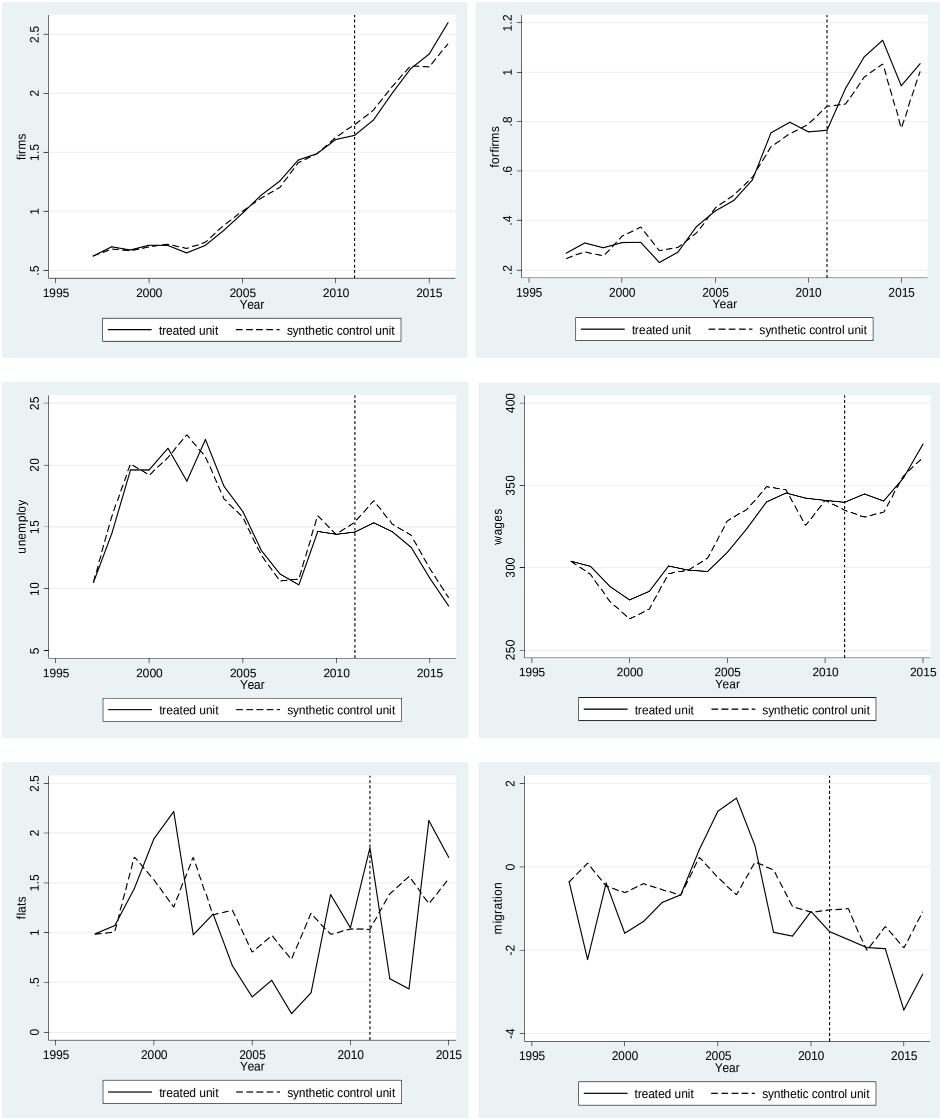
	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2011	0.053	0.113	0.896	5.079	0.811	1.19
sc1	0.33 BS	0.48 KE 3	0.59 TR	0.31 PK	0.45 DT	0.38 BS
sc2	0.30 HE	0.35 MT	0.26 PK	0.31 KE 1	0.45 MT	0.28 SI
sc3	0.27 KE 1	O.09 KE 1	0.15 KE 1	0.18 SO	0.11 BS	0.24 LM
sc4	0.10 PK	x	x	0.11 KE 4	x	0.08 MT
sc5	x	x	x	0.10 BJ	x	x
Dif RMSPE ratios (2011 – 2005)	–0.007	–0.003	–0.09	2.87	0.2	–0.19

Žarnovica: Connected to TEN-T in 2011



	Firms	Foreign firms	Unemployment	Wages	Flats	Migration
RMSPE 2011	0.035	0.094	1.781	8.382	0.855	1.07
sc1	0.51 PT	0.52 SN	0.21 VK	0.32 MA	0.54 KK	0.36 RA
sc2	0.47 SA	0.25 PE	0.22 DT	0.31 PE	0.28 LV	0.17 SO
sc3	x	0.11 KK	0.20 BS	0.28 DT	0.06 ML	0.12 KE 2
sc4	x	0.10 SA	0.13 RA	0.08 SO	0.05 PE	0.11 NO
sc5	x	x	0.13 SO	x	x	x
Dif RMSPE ratios (2011 – 2005)	0.021	0.041	0.36	3.5	0.27	0.37

Žiar nad Hronom: Connected to TEN-T in 2011



	Firms	**Foreign firms**	**Unemployment**	**Wages**	**Flats**	**Migration**
RMSPE 2011	0.026	0.036	1.273	9.753	0.512	1.139
sc1	0.29 MY	0.49 BR	0.44 TR	0.34 KK	0.38 LV	0.21 SA
sc2	0.13 BN	0.23 TO	0.30 DT	0.33 KE 2	0.24 MY	0.2 DT
sc3	0.10 DT	0.19 TR	0.14 VK	0.20 GL	0.20 RA	0.18 MY
sc4	0.08 MA	0.10 BS	0.07 LM	0.08 RS	0.10 KN	0.14 LM
sc5	x	x	0.05 KE 1	0.07 DT	x	0.14 BR
Dif RMSPE ratios (2011 – 2005)	0.026	0.002	–0.3	3.43	0.02	0.18

Source: Authors' computations.