Application of Region Specific Depreciation Formulas in Highway Capital Stocks: Evidence from New York and New Jersey

Onur Kalan

1 **APPLICATION OF REGION SPECIFIC DEPRECIATION FORMULAS IN HIGHWAY**
2 **CAPITAL STOCKS: EVIDENCE FROM NEW YORK AND NEW JERSEY**
3
4 **Onur Kalan, Ph.D.**
5 Research Associate, C2SMART Center,
6 Department of Civil and Urban Engineering,
7 Tandon School of Engineering, New York University
8 15 MetroTech Center, 6th Floor, Brooklyn, NY 11201, USA
9 Tel: (646) 997-3049
10 E-mail: ok22@nyu.edu
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30 Word count: 6,718 Text + 1 Table x 250 = 6,968 words
31 Submission Date: August 1st, 2018
32
33
34
35
36
37
38
39
40   Paper accepted for Presentation in the

41   *Transportation Research Board's 98th Annual Meeting*, Washington, D.C., 2019
42
43
44

1   **ABSTRACT**
2   Highways are significant instruments for transportation in United States, and the common opinion
3   is that increasing highway networks leads to major changes in economic development. In general,
4   the quantification of the highways is performed by capital stock approach in monetary terms. In
5   capital theory, the increase of the stock value can be calculated by gross investment values. On the
6   contrary, deduction is performed with the assumption of different depreciation patterns which their
7   representations of the real deduction in the assets have been questioned. This paper provides an
8   empirical evaluation that focuses on the representability of new depreciation patterns which are
9   derived from the deterioration functions of New Jersey State bridge decks. This study measures
10   the Gross County Product (GCP) change between 1999 and 2013 in 18 counties of NY/NJ regional
11   area in an econometric model with geometric depreciation pattern and proposed 22 new
12   depreciation patterns. The results show that an increase in highway capital stock has a significant
13   and positive impact on economic growth in the region. The models are used in the forecast of year
14   2016 GCP values of each county. Although some of the counties in the models do not reflect
15   significant improvement in the new depreciation models, some of the counties show an observable
16   decrease in the estimation errors. It is indicated that in the counties where the models give positive
17   improvements, the new depreciation patterns can be used as a tool to estimate more precise GCP
18   values for policy makers.
19
20
21   *Keywords*: highway investment, highway capital, economic growth, depreciation,
22   deterioration, panel data, dynamic panel model

23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45

INTRODUCTION

Transportation expansion and improvement of the existing capacities are the key determinants for the performance of the infrastructure systems. An efficient transportation system can lead to greater economic and social benefits by improving market accessibility, increasing production efficiency, providing balanced growth of regional economies, providing employment and enabling labor force mobility (*1*) (*2*) (*3*).

Many of the previous studies have identified relationships between transportation investment and economic development (*4*) (*5*) (*6*) (*7*). However, other studies show an insignificant and even negative relationship between transportation investments and economic growth. Possible reasons for those results include construction of an excess of roadways, underutilized capacities of existing networks, negative spillover effects, not to achieve corresponding cost utilizations or easiness in logistics, etc (*8*).

In some of the studies, a positive relationship between transportation investment and economic growth exists. The relationships are established using Production Function forms where the economical outputs are explained by capital stock-based regressors, of which highways are one of the capital stock values. These capital stock values change over time to reflect wear and tear, deterioration and some other factors. Capital stock is a product that loses value every year until new investments help to increase its value a specified amount. However, calculating the decrease in capital stock value is not as easy and clear as calculating the increase in that value. Existing methodologies to calculate this decrease in the value of the capital stock are called Depreciation Rate or Pattern. The common methods used in highway capital stock decrease are Geometric Rate and Linear Depreciation (*9*).

On the other hand, there are some questions for the representation of these depreciation patterns in the computation of decrease in certain type of capital stocks. For example, using a linear depreciation pattern for a capital stock, in which the value decreases the same amount during every year or period, may not provide the real change of that stock value. Additionally, the existing depreciation methodologies in the literature, especially for the public stocks, provide models to sustain the homogeneity among the differentiations of countries, technical considerations and other characteristics. This makes it difficult to calculate the exact or close to real depreciation values. In the scope of highway capital stock, this problem is disclosed by Ozbay, Ozmen-Ertekin and Berechman (*7*). In their study, a geometric depreciation pattern is used due to the lack of a better option. It is mentioned that "the use of a variable depreciation rate in calculating the highway capital stocks would be much more realistic". Additionally, their future recommendations suggest that "development of a depreciation rate in a functional from which varies with traffic volume and environmental conditions, among other variables requires careful consideration which could be provided in a future study" (*7*).

The objective of this paper is to recommend new depreciation patterns in the calculations of highway capital stock values. Due to the aforementioned reasons, achieving positive results may not be possible in certain areas and timeframes. Therefore, the same area and nearest time interval of Ozbay, Ozmen-Ertekin and Berechman (*7*) study, which includes 18 counties of NY/NJ metropolitan areas, is chosen but different time periods from 1999 to 2013. The suggested new depreciation patterns are selected from the study of Lou et al. 2016, which displays the deck deterioration patterns of 24 different highways in New Jersey State data from 1992 to 2013. The reasons for choosing these patterns are: (1) it is the most recent dataset to represent the retirement pattern for highways or bridge decks in the region; (2) this dataset reflects all the physical factors

1   that have direct impacts on the decks, such as traffic loads, climatic conditions, and especially
2   overweight trucks, which is not an easy task to incorporate into a depreciation formula.
3   Another aim of this paper is to test the results of the models with new depreciation patterns
4   with 2016 real Gross County Product values of each county.

5   **LITERATURE REVIEW**
6   The effects of transportation and highway investments on economic growth in different countries
7   and regions are evaluated in some of the studies in the literature (*4*) (*10*). The literature depicts a
8   significant variety in the relationships between transportation investments and economic changes,
9   in terms of the positive or negative impact and output elasticity values as well. Some of these
10 existing studies find that transportation has a positive impact on economic growth output (*4*) (*6*)
11 (*11*) (*12*) . The output elasticity results differ from high to low values such as, 0.39-0.56 (*13*), 0.33
12 (*14*), 0.25 (*11*), 0.135-0.206 (*15*), 0.04 (*12*), 0.08 (*16*). The difference of coefficients in the models
13 stems from the differences in the definition of capital stock, estimation methods and level of
14 analysis. However, some of the studies find light evidence for transport-led economic growth
15 contention, such as Chandra and Thompson (*17)* and Evans and Karras (*18)*.
16   The spillover effect is another important issue in the relationship between transportation
17 and economic growth. The spillover effect is the spreading impact of an action that occurred in
18 one location to any other neighbor locations in a positive or negative direction. For example, an
19 increase in highway capital stock in a location can create a positive or negative impact on economic
20 output of a neighbor location. Some of the studies in transportation literature question the
21 consequences of spillover. According to Munnell (*19)* highway capital creates positive spillover
22 effects. Boarnet (*20)* indicates that the effects of transportation infrastructure on the economy are
23 divided into a direct and an indirect effect concept. The results show that both effects were
24 equivalent to each other by plus and minus, contrary signs. Highway investment has an indirect
25 effect on the neighbor states in a study by Holtz-Eakin and Schwartz (*21)*.
26   However, positive effect of spillover is not generally accepted by all of the researchers. For
27 example, Chandra and Thompson (*17)* collected data in the US from 1969 to 1993, and they show
28 that national acting industries benefitted from these transportation investments, while only a
29 redistribution of economic activity is observed in local acting industries (*17)*. A cost function was
30 used by to manufacturing data ranging from 1982 to 1996. In this study, production, capital, labor
31 and materials of existing states and the neighbours' regressors are used. Results indicate that if a
32 neighboring state's infrastructure stock is not included, the elasticity is around 0.15. But, when
33 you consider spillover, elasticity value increases up to 0.23 (*22*). Pereira and Roca i Sagalés (*23*)
34 investigated the regional effects in Spain and the potential presence of spillover effects by using
35 data from 1970 to 1995. Employment, private and public capitals are chosen as regressors. Their
36 suggestion is that output is affected by public capital with an elasticity of 0.523. The main finding
37 of that study is that the spillover effect is much more significant than the public capital impact on
38 the one region by itself (*23*).
39 **Depreciation Literature**
40 In calculating economic growth, a hypothesis based on aggregate production function is commonly
41 used. This hypothesis stems from the neoclassical theory of capital and establishes a relationship
42 between output, labor and capital. The most problematic element among them is capital. The
43 reason behind this is that the theory defines capital as a measure in terms of value. Labor and
44 output are commonly agreed on the type of their quantifications, however, there are some issues
45 in the calculation of capital. It has its law of motion with additions and deductions. Increase in the
46 capital stock value is a clear-cut concept with a single gross investment factor. However, decreases

in capital stock are not as easily and accurately quantified. Therefore, a concept called depreciation has been derived to quantify reductions in capital stock over time (*24*).

Faced with the necessity of deduction calculations in capital stock, Jorgenson (*25)* pioneered a work known as proportionality theorem in 1963. This theorem indicates that depreciation and replacement of capital goods is done at a constant rate, proportional to the corresponding capital stock. This procedure is known as the perpetual inventory method (PIM) and gives quantity of capital stocks with the accumulation of the investments:

$$K_t = K_{t-1}(1 - \delta) + I_t \tag{1}$$

This way of interpreting the phenomenon of depreciation is common in quantitative measurement. The main problem of this theorem is that it focuses on age and ignores the role of economic variables, such as intensity of use, maintenance and repair, obsolescence caused by embodied technical progress, uncertainty, or the business cycle, in determining the depreciation of capital assets (*24*).

After a long period of theoretical discussions, OECD carried out studies to establish a framework for a depreciation concept and prepared proposals. The purpose of these proposals is twofold: to harmonize the uses and criteria of the different national statistical agencies and achieve the highest degree of homogeneity among the indicators calculated for the different countries. The most common practice is to assign accounting values based on assumptions about the mathematical functional form of survival (retirement) profile, efficiency profile according to age, and age-price profile of an asset or cohort of assets (*9*).

In this context, the precision of perpetual inventory method in the implementation directly relates to the particular choice of the asset retirement distribution. A survival profile pertinent to this retirement process is necessary, and a key factor in this approach is the average service life (*24*).

As it is addressed in OECD publication in 2009, the mortality and survival functions can be defined in four categories in terms of the common practices of the OECD countries: Linear, Delayed Linear, Bell-Shaped and Simultaneous Exit (*9*).

In the linear retirement pattern, the assumption is that the assets will be discarded at the same rate each year from the time of installation until twice the average service life. However, assets are by definition expected to remain in use for several years, and discards in the years immediately after installation are likely to be rare for most assets. Thus, linear retirement fails the test of plausibility (*9*).

The simultaneous exit retirement function assumes that all assets are retired from the capital stock at the moment when they reach the average service life for the type of asset concerned. The survival function therefore shows that all assets of a given type and cohort (i.e. year of installation) remain in the stock until time T, at which point they are all retired together. However, it is not plausible to assume that all assets are withdrawn at the moment when they reach the average service life for that asset type. Some assets may be discarded earlier due to overuse, poor maintenance or accidents, while others can continue to provide good service several years beyond their average life expectancy. Simultaneous exit must be regarded as an inappropriate retirement pattern (*9*).

With a bell-shaped mortality pattern, retirements start gradually a certain time after the year of installation, build up to a peak around the average service life and then tear down in a similar gradual fashion some years after the average. There are a variety of functions which provide the flexibility to fit into the deduction fashion appropriately as regards skewness and peakedness (or kurtosis). They include gamma, quadratic, Weibull, Winfrey and lognormal functions (*9*).

1   In the OECD Manual, a different bell-shaped methodology is also proposed. These
2 'Winfrey curves' are defined as more realistic approaches. Winfrey curves are named after Robley
3 Winfrey, a research engineer who worked at the Iowa Engineering Experimentation Station during
4 the 1930s. Winfrey (*26)* collected information on dates of installation and retirement of 176 groups
5 of industrial assets and calculated 18 "type" curves that gave good approximations to their
6 observed retirement patterns. These 18 Winfrey curves in total are: six 'S' or symmetric curves,
7 six 'L' or left skewed curves and six 'R' or right skewed curves (*26)* (*9)*. The curves are described
8 as in Equation 2;

9    $$F_T = F_0(1 - \frac{T^2}{a^2})^m \tag{2}$$

10   In the equation, F_T is the marginal probability of an asset retiring at age T, where the age
11 has been expressed as a share of the average service life. Thus, T varies from zero to infinity and
12 F_T is largest at the average service life (*9)*.
13   In the study of Derbyshire, Gardiner and Waights (*27)*, in addition to estimates produced
14 using 'Simultaneous Exit', two alternative mortality methods are used: The Winfrey S-2 function
15 and the Winfrey S-3 function (*27)*. These functions are stated in the OECD Manual to be two of
16 the most widely employed. Furthermore, the Winfrey S-3 function is shown to be the most
17 commonly employed by EU countries in the survey of EU national statistical offices described in
18 that study (*9)*.
19   In our paper, new depreciation patterns are used. These models are the deterioration
20 functions of New Jersey State Bridge Decks derived from data between 1992 to 2013. As it is also
21 recommended as a future study in Ozbay, Ozmen-Ertekin and Berechman (*7)*, common use of
22 geometric depreciation pattern could be improved by considering climate, traffic density and other
23 factors for the highway links. This paper aims to improve the conventional linear or geometric
24 pattern methods in calculating highway capital stocks by replacing them with more highway
25 specific approaches. The aforementioned deterioration functions consider the New Jersey highway
26 bridge conditions and overweight truck problem as well. Therefore, these deterioration functions
27 are selected to represent the region's overall highway retirement patterns.
28 **STUDY AREA AND DATA**
29 The study area includes Sussex, Passaic, Bergen, Essex, Hudson, Hunterdon, Ocean, Warren,
30 Monmouth, Morris, Somerset, Middlesex and Union counties in NJ, and Bronx, Kings, Queens,
31 Richmond and New York counties in NY. These are the same counties used in the study of Ozbay,
32 Ozmen-Ertekin and Berechman (*7)*. The first reason to choose the same locations is the results
33 achieved in that study for the dataset between 1990 and 2000 are significant and therefore, it is
34 more likely to get promising results for the future dataset. The second reason is that the
35 deterioration functions derived by Lou et al. (*28)* and used in this paper are mostly specific for the
36 above mentioned region. Therefore, application of these deterioration patterns to another region
37 may not deliver significant results. Another county or region may follow a different deterioration
38 pattern for different reasons.
39   The dataset employed consists of output (i.e., GCP), labor, private capital, highway
40 investment, and highway capital for these 18 counties between 1999 and 2013. All monetary
41 variables were measured in real dollars and were converted to year 2000 dollars. We estimated
42 GCP values by apportioning gross domestic product (GDP) data obtained from the Bureau of
43 Economic Analysis BEA (*29)* between the counties according to each county's personal incomes.
44 This is the same approach applied in Ozbay, Ozmen-Ertekin and Berechman (*7)*. Due to the lack
45 of disaggregated data at the county level, a similar approach is implemented in this paper.

1   Employment data were obtained from the Real Estate Center database of Texas A&M
2   University (*30*).
3   Private Capital Stock is obtained from Bureau of Economic Analysis BEA (*29)*, and
4   apportioned among the counties by using personal income ratios. This is the same methodology
5   used in the GDP allocation. Using the same approach for apportioning the overall state values to
6   counties is appropriate given the limited data availability for this particular study.
7   Street and highway investments were based on annual street and highway expenditures in
8   each county obtained from the ''Highway Finance'' section of the Highway Statistics Series
9   published by the FHWA (*31)*. As with private capital stock and GDP allocation, highway
10   investment values are obtained at a per state level then proportioned by Personal Income values of
11   each county. Another issue in highway investment data is the gaps for some years in the dataset.
12   These gaps are filled using interpolation between the existing years of data. Although this approach
13   disrupts the real variation in the dataset, the estimations of the models provide promising results
14   and low error percentages, as shown in the Result & Discussion section of the paper.
15   In this study, the amount of street and highway capital stocks are estimated based on annual
16   street and highway investments in each county using the Perpetual Inventory Method (PIM). Given
17   annual investment flows for each county between 1990 and 2013, highway capital stocks were
18   computed using the following perpetual inventory accounting formula:
19   $K_t = K_{t-1}(1 - \delta) + I_t$ (3)
20   Where "K" is capital stock, "I" is investment, "δ" is depreciation rate.
21   The conventional depreciation method is chosen as a geometric depreciation pattern with
22   4.1%, as used in the study of Ozbay, Ozmen-Ertekin and Berechman (*7)*, due to a lack of a better
23   option. In this paper, this approach is used as the baseline to which the new depreciation pattern
24   assumptions are compared. The highway capital stock values are estimated by using the year 1990
25   highway capital stock values in NJ and NY: $23,400 million for NJ and as $218,408 million for
26   NY (*7)*. Using the percentage of highway investment in each county (i.e., %share of each county
27   from the total statewide investment), the state values were apportioned among the counties.
28   The new depreciation patterns are achieved from the study of Lou et al. (*28)*, which focuses
29   on the Overweight Truck and Deck Deterioration Analysis for New Jersey State. They collected
30   data between 1992 to 2013. Their study reveals 24 different models for 24 different highways as
31   shown in the table below.
32   $CR = M_0 + M_1 x + M_2 x^2 + M_3 x^3$ (4)
33   Where "CR" is condition rating, "x" is time period in years.
34   For each different model, the deterioration parameters are shown in (Table 1**TABLE *1***).
35
36
37   **TABLE 1 Deterioration Models for New Jersey Bridge Decks (*28*)**

Highway No	Highway	M_0	M_1	M_2	M_3	R^2	Expected Service Life (years)
1	I-80	8.457	-0.27901	0.013952	-0.000314	0.76	30.5
2	I-78	8.906	-0.37056	0.020138	-0.000455	0.68	29.0
3	I-676	8.689	-0.14916	0.003358	-0.00004	0.74	55.4
4	I-295	8.731	-0.28146	0.017453	-0.000386	0.67	34.4
5	I-195	9.257	-0.14778	0.00432	-0.000052	0.55	63.3

6	I-95	9.263	-0.30975	0.012759	-0.000196	0.76	42.9
7	I-287	8.285	-0.07183	-0.00342	0.000006	0.91	26.9
8	I-280	9.282	-0.17118	0.003212	-0.000054	0.87	40.6
9	US-30	8.881	-0.49361	0.039417	-0.001203	0.84	22.5
10	US-46	8.749	-0.27413	0.00866	-0.000111	0.63	43.8
11	US-9	8.359	-0.18221	0.006012	-0.000086	0.72	48.0
12	US-40	8.575	-0.17421	0.003439	-0.000029	0.81	62.6
13	US-322	8.185	-0.11593	0.00236	-0.000031	0.70	53.1
14	US-202	8.394	-0.18266	0.004732	-0.000057	0.62	49.6
15	US-206	8.344	-0.11167	0.002289	-0.000037	0.91	49.0
16	US-130	8.146	-0.12501	0.00223	-0.000023	0.68	56.7
17	US-130	8.593	-0.26452	0.008185	-0.000114	0.75	38.7
18	US-22	8.826	-0.23851	0.00736	-0.000083	0.76	56.1
19	NJ-31	8.572	-0.21097	0.003373	-0.00002	0.86	46.3
20	NJ-15	8.837	-0.1623	0.002751	-0.000018	0.90	86.1
21	NJ-18	8.375	-0.11301	0.002884	-0.000041	0.76	54.9
22	NJ-33	8.141	-0.03931	-0.00071	0.000007	0.77	76.6
23	NJ-55	8.032	-0.06377	0.000213	-0.000004	0.66	61.0
24	NJ-73	8.216	-0.10314	0.00251	-0.000031	0.82	62.4

In compliance with the Perpetual Inventory Method, the highway capital stocks for each year are calculated for each corresponding year and county.

Production Function Based Model

There are many studies about the production function based models. The Cobb-Douglas structure is (*32*):

$$Y_t = (MFP)_t L_t^\alpha P_t^\beta G_t^\gamma \tag{5}$$

Where Y is the aggregate output (for example GDP), MFP is a measure of multi-factor productivity (for example technology), and L, P and G are, respectively, labor, private and public capital stocks.

Typically, if the production form is linearized, the natural logarithm of both sides can be taken as:

$$\ln Y_t = ln(MFP)_t + \alpha lnL_t + \beta lnP_t + \gamma lnG_t \tag{6}$$

However, in our dynamic panel data models, to decrease the number of variables the labor variable is extracted by subtracting each variable with ln(L). Therefore, the economic indicators become another useful representation as capital/labor ratios. These indicators inherently give higher values in well-developed areas and relatively lower values for the relatively less expensive labor areas. In general, it can be linked through the average labor productivity. Therefore, in our models the general form becomes:

$$(\ln Y_t - lnL_t) = ln(MFP)_t + \beta(lnP_t - lnL_t) + \gamma(lnG_t - lnL_t) \tag{7}$$

where α, β, γ are the coefficients of the log-transform regressions.

MODEL SPECIFICATION

In this paper, a panel data approach is used. The general aim of using panel data is to search for unobserved factors that impact the output. There are two types of those factors: constant or varying over time. Let i represent the location and t the time, a single regressor observed model is (*33*):

$$y_{it} = \beta_0 + \delta d2_t + \beta_1 x_{it} + \alpha_i + u_{it} \quad t = 1,2 \dots \tag{8}$$

The variable $d2_t$ is a dummy variable that equals zero when t = 1 and one when t = 2. The dummy variable does not change between locations. Therefore, the intercept for t =1 is β_0, and the

intercept for t = 2 is β₀+δ₀. In independently pooled cross sections, allowing the intercept is allowed to change over time (*33*).

The a_i variable includes all time-constant and unobserved factors over y_{it}. A_i is called unobserved effect and does not change over time. The error u_{it} is generally named as time-varying error or idiosyncratic error. It displays the unobserved effects that change over time (*33*).

If the model (1) considered, a two-year period can be thought of in two ways: just pooling two years and using OLS, and assuming that a_i is uncorrelated with x_{it} (*33*):

$$y_{it} = \beta_0 + \delta d2_t + \beta_1 x_{it} + v_{it} \tag{9}$$
$$v_{it} = \alpha_i + u_{it} \tag{10}$$

But, if a_i and x_{it} are correlated, OLS is biased and therefore the results are biased. It is called heterogeneity bias, resulting from omitting a time-constant variable. According to our panel dataset and panel data methodology, existence of the time-constant variable is tested with Hausman-Taylor methodology. The results showed that this variable exists in the model (*33*).

To eliminate this bias, some methodologies can be used. One is taking the difference of the model with respect to previous year's model, and therefore the time-constant effect can be eliminated. An alternative and a common way to eliminate this unobserved time-constant effect, a_i is fixed effect estimation. The fixed-effect estimation for one explanatory variable (*33*):

$$y_{it} = \beta_1 x_{it} + \alpha_i + u_{it} \qquad t = 1,2,...T \tag{11}$$

For each i, taking averages over time gives:

$$y_i = \beta_i \bar{x}_i + \bar{\alpha}_i + \bar{u}_i \tag{12}$$

When the equation (11) is subtracted from Equation (10);

$$y_{it} - \bar{y}_i = \beta_i(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \qquad t = 1,2,...T \tag{13}$$

In other terms;

$$\dot{y}_{it} = \beta_1 \dot{x}_{it} + \dot{u}_{it} \qquad t = 1,2,...T \tag{14}$$

Where $\dot{y}_{it} = y_{it} - \bar{y}_i$ is the demeaned data on y. This method is called within transformation or fixed effect approach. A pooled OLS estimator that is based on time-demeaned variables is called fixed effect estimator or within estimator (*33*).

In our analysis, the panel dataset is applied in fixed-effect model. After the results are achieved, a test is performed to reveal the direction of causality. The test results showed that the causality runs for both directions. However, in Ozbay, Ozmen-Ertekin and Berechman (*7*), it is found that the causality runs for one direction, from highway capital stock increase to GDP growth for the same counties and the time interval in that paper. Therefore, this situation leads us to a problem called endogeneity. An endogeneity problem is the relation of one or more independent variables with the error term in the model. This type of problem can generally occur for different reasons, such as measurement error, autoregression with autocorrelated errors, simultaneous causality, omitted variables etc. Additionally, cross-sectional dependency can be a strong reason for this endogeneity problem. Also, in the same study of Ozbay, Ozmen-Ertekin and Berechman (*7*), spillover effect is observed in some of the models, which is evidence for existing cross-sectional dependency in this New York and New Jersey area. To overcome this problem, spatial based models can be used, such as the studies of Xie et al. (*34*) and Xie, Ozbay and Yang (*35*). There are also some panel data methodologies such as simultaneous equations approach, using instrumental variables, etc. In this study, a dynamic linear panel data methodology will be used which is called Arellano–Bover/Blundell–Bond linear dynamic panel-data estimation. In the following parts, this methodology is explained in detail (*36-38*).

A dynamic panel data model can be expressed as:

$$y_{it} = \sum_{j=2}^p \alpha_j y_{i,t-j} + x_{i,t}\beta_1 + w_{i,t}\beta_2 + v_i + \varepsilon_{i,t} \tag{15}$$

1   Where $i = 1, \ldots N \qquad t = 1, \ldots T_i$ and;

2

3   • a$_j$ and p are the parameters to be estimated
4   • x_{it} is a $1 \times k_1$ vector of strictly exogenous covariates,
5   • β_1 is a $k_1 \times 1$ vector of parameters to be estimated,
6   • w_{it} is a $1 \times k_2$ vector of predetermined or endogenous covariates,
7   • β_2 is a $k_2 \times 1$ vector of parameters to be estimated,
8   • v_i are the panel-level effects (which may be correlated with the covariates), and
9   • ϵ_{it} are i.i.d. over the whole sample with variance σ^2_ϵ
10   The v_i and the ϵit are assumed to be independent for each i overall t. In this model, the
11 fundamental problems are:
12   1. Due to y_{it} is a function of v_i, so is $y_{i;t-1}$, Ordinary Least Square is biased and inconsistent
13   even if the e_{it} are not serially correlated.
14   2. Since the within transformation clears the mi, but we get problems because the correlation
15   with $y_{i;t-1}$ and $e_{avg;i}$ (this mean contains $e_{i,t-1}$). Therefore, Fixed Effect is biased but still
16   consistent for T→∞.
17   Blundell and Bond (*38)* show that the lagged-level instruments in the Arellano–Bond
18 estimator become weak as the autoregressive process becomes too persistent or the ratio of the
19 variance of the panel-level effects v_i to the variance of the idiosyncratic error ϵ_{it} becomes too large.
20 Building on the work of Arellano and Bover (*37)* and Blundell and Bond (*38)* proposed a system
21 estimator that uses moment conditions in which lagged differences are used as instruments for the
22 level equation in addition to the moment conditions of lagged levels as instruments for the
23 differenced equation. The additional moment conditions are valid only if the initial condition
24 $E[v_i \Delta y_{i2}] = 0$ holds for all i (*39)*.
25   Therefore, our model becomes:

26 $\ln(gcp_{i,t}) - \ln(labor_{i,t}) = \alpha_0 + \alpha_1\big[\ln(gcp_{i,t-1}) - \ln(labor_{i,t-1})\big] + \alpha_2\big[\ln(gcp_{i,t-2}) -$
27 $\ln(labor_{i,t-2})\big] + \alpha_3\big[\ln(prstock_{i,t}) - \ln(labor_{i,t})\big] + \alpha_4\big[\ln(hgstock_{i,t}) - \ln(labor_{i,t})\big] +$
28 $\varepsilon_{i,t}$ (16)
29   where "gcp" is the Gross County Product, "prstock" is the private capital stock value,
30 "hgstock" is the highway capital stock value in 2000$. "labor" is the employment data (number of
31 total jobs), i is county and t is time index.
32   As mentioned in the Study Area and Data section, the highway stock value is evaluated
33 using the Perpetual Inventory Method. The new highway depreciation patterns are incorporated to
34 highway investments and the other 22 new highway capital stocks are represented with the
35 numbers in the order shown in (Table 1).
36   In the following section, the model results are represented and the year 2016 GCP
37 estimations are compared with the real data for the robustness of the new models.

38 **RESULTS & DISCUSSION**
39 Each result from the new depreciation model suggestions are evaluated using the log-transform
40 models. The results show significant values within the 5% and 10% confidence intervals. Highway
41 capital stock per labor estimations vary between 0.06 and 0.17 for different highway stock
42 depreciation patterns. On the other hand, lagged terms of Gross County Product per labor for each
43 corresponding year also give significant values. The first lagged of gcp per labor values ranges
44 from 0.39 to 0.57, indicating it has a positive effect on the current year's gcp. However, the second
45 lag of the gcp per labor produces negative, but still significant, values varying from -0.10 to -0.13.

1   Private stock per labor value differs from 0.47 to 0.54 among different models of highway stock
2   depreciation patterns, significantly. The results are not tabulated here due to space constraints.
3   The model results are used to forecast the year 2016 GCP values of the counties used in
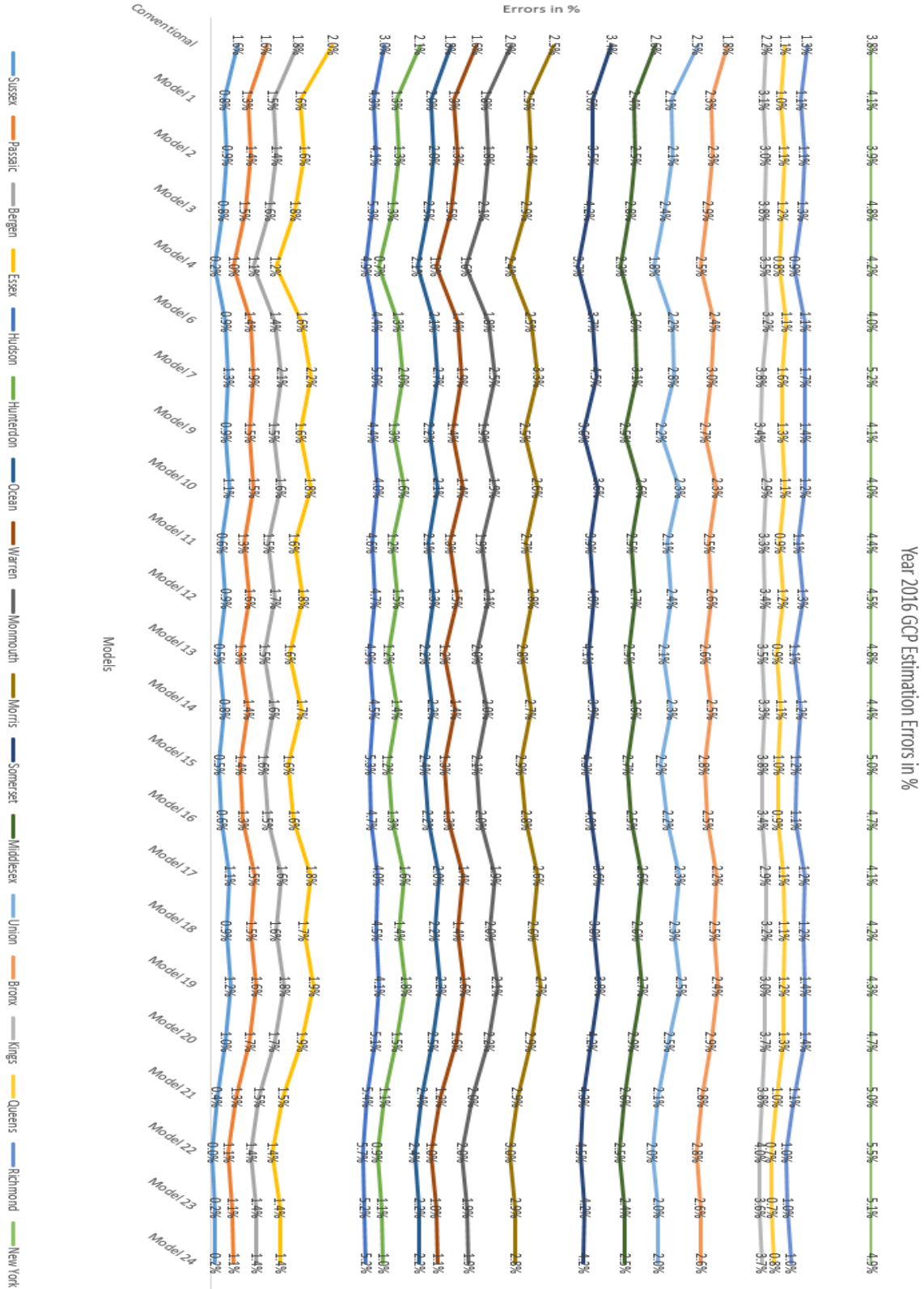4   the dataset. The errors are estimated and displayed in (Figure 1).

FIGURE 1 Year 2016 GCP Estimation Errors in % per county

1   First of all, the estimations in the conventional method give low error margins, varying
2   from 1.1% to 3.8%. When the improvement model is used, although some of the counties show
3   significant changes, some of them do not change excessively and some are even affected
4   negatively.
5   In the proposed depreciation patterns, the counties of Sussex, Passaic, Bergen, Essex,
6   Hunterdon, Warren and Union reflect an improvement trend for the error percentages in general.
7   However, Model 7 (I-287) and Model 20 (NJ-15) do not provide significant depreciation indicators
8   for these county highway capital stocks, except Sussex and Hunterdon. On the other hand, Hudson,
9   Ocean, Somerset, Bronx, Kings, New York counties show negative impacts on the estimation of
10 the year 2016 GCP values for all the models. The remaining counties, Morris, Middlesex, Queens
11 and Richmond, do not give consistent enough results to show a definitive trend.
12   These results show that some of the counties' highway capital stock patterns are
13 appropriate for the application of the deterioration models of the New Jersey State bridge decks.
14 On the other hand, some of the counties, especially for New York state, are not good for such an
15 approximation. In conclusion, a better representation of the depreciation patterns for state
16 highways in general is not possible using currently available data. However, it is possible to apply
17 some of the models to certain counties that show better error results. But, when these models do
18 not represent the depreciation trends of those counties' highway capital, the better approach is to
19 use the conventional practices in the literature, such as geometric pattern, which assumes a
20 homogenous distribution over the time period of the service life.

21 **SENSITIVITY ANALYSIS**
22 Given the above mentioned results, how can policy makers use the developed models to determine
23 the effects of the changes in the amount of highway capital investment on the GCP levels? To
24 answer this question, a sensitivity analysis is performed for different models.
25   The impact of increasing and decreasing highway capital per labor by 5%, 10%, 15% and
26 20% relative to the current level of GCP per labor values for the conventional method and Models
27 4 and 22, as the most GCP estimation improvements observed, is analyzed.
28   The results from the sensitivity tests presented in (Figure 2) show that, for all models, GCP
29 per labor is sensitive to the changes in highway capital investment per labor.
30   Figure 2 shows the rate of percentage change in the GCP per labor versus the percentage
31 change in the amount of highway capital per labor. It implies that the sensitivity of the GCP per
32 labor to the changes in highway capital is the highest at 20%.
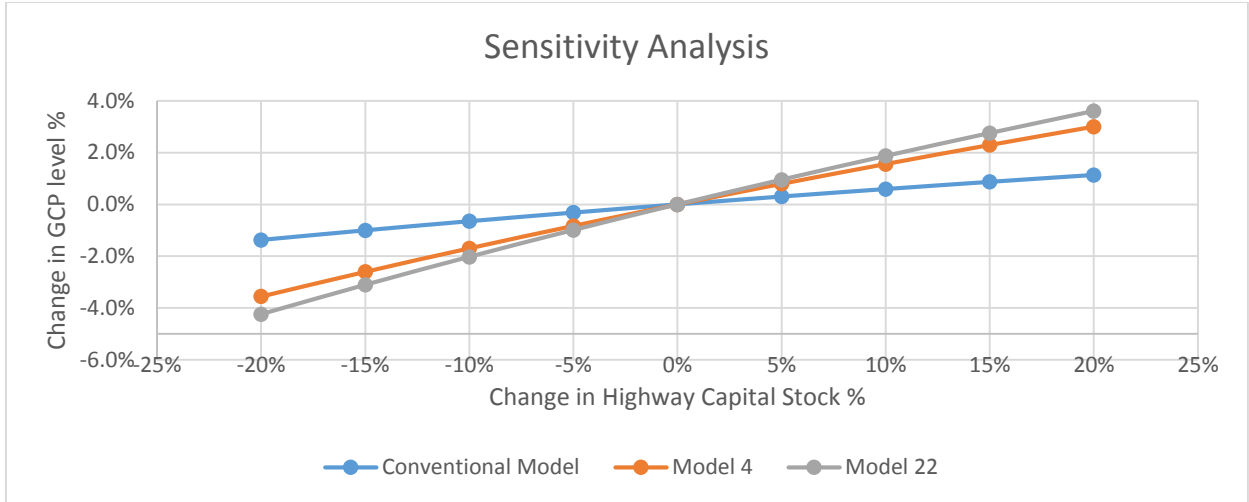
FIGURE 2 Sensitivity Analysis for Conventional Model, Model 4 and Model 22

CONCLUSION & FUTURE STUDIES

In many studies, the transportation infrastructure and changes in the economic indicators are examined by using the appropriate data to represent the variables. One of the important variables commonly used is capital stock values of the transportation infrastructure. In this paper, highway capital stock and its impact on economic growth is scrutinized by using different depreciation patterns, and it is examined whether the proposed models are providing lower error margins in the GCP estimations or not.

For public capital stock calculations, general methods are explained in OECD Manual (*9*) to seek the homogeneity among the different assets, countries and conditions. These methods are: linear, simultaneous exit, delayed linear and belly-shaped functions. The most common methodology for calculating the highway capital stocks is geometric depreciation. In this paper, it is examined whether a regional deterioration model that includes those factors can represent the highway capital stock depreciation patterns for the regions. For this purpose, data from 18 counties in the New York and New Jersey region are used between 1999 and 2013 in a dynamic Arellano Bover/Blundell linear dynamic panel data model which considers gross domestic product for the county level (GCP), private capital stock and highway capital stocks. These variables are incorporated in the models by dividing each of them to the employment numbers of these counties in each year (*37; 38*).

The different depreciation patterns are derived from the region-specific deck deterioration models computed by Lou et al. (*28*). 22 different deterioration models are converted into depreciation models for testing the improvement in the GCP estimations for those counties.

As a conclusion, all of the depreciation models among 22 deterioration patterns and the conventional geometric pattern give significant estimations in the econometric models. The resultant model coefficients are used to forecast the year 2016 GCP values for the counties.

The results in the conventional method provide GCP estimations with low error margins, varying from 1.1% to 3.8%. In the proposed depreciation patterns, the counties of Sussex, Passaic, Bergen, Essex, Hunterdon, Warren and Union reflect an improvement trend for the error percentages in general. On the other hand, Hudson, Ocean, Somerset, Bronx, Kings, and New York counties reflect negative impacts on the estimation of the year 2016 GCP values for all the models. Morris, Middlesex, Queens and Richmond counties do not present consistent results.

These result show that some of the counties, such as Bergen, Sussex, Hunterdon, reflect promising improvements in the new models for estimating year 2016 GCP values. For these counties, the new depreciation models can be used in policy decisions due to their precise results. However, none of the models represent the whole region's depreciation pattern perfectly.

The results also show that the best approximation for the depreciation pattern is estimating them for each highway link itself. This may not be possible with existing data, but may be possible in future due to FHWA's MAP-21 requirements that agencies collect disaggregate-level data on their infrastructure assets, such as structural condition data of each bridge in element level (*40*). Additionally, for the future studies, if each county's level of investment is known exactly, the capital stock values for each of them can be assigned specifically, producing more precise results.

AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design: Onur Kalan; data collection: Onur Kalan; analysis and interpretation of results: Onur Kalan; draft manuscript preparation: Onur Kalan. The author reviewed the results and approved the final version of the manuscript.

REFERENCES
[1] Eberts, R. Understanding the impact of transportation on economic development. *Transportation in the New Millennium*, 2000.
[2] Litman, T. Evaluating Transportation Economic Development Impacts. 2010.
[3] OECD. *OECD Data-Infrastructure Investment*. https://data.oecd.org/transport/infrastructure-investment.htm. Accessed July, 2018.
[4] Aschauer, D. A. Highway capacity and economic growth. *Economic perspectives,* Vol. 14, No. 5, 1990, pp. 4-24.
[5] Ozbay, K., D. Ozmen-Ertekin, and J. Berechman. Empirical analysis of relationship between accessibility and economic development. *Journal of Urban Planning and Development,* Vol. 129, No. 2, 2003, pp. 97-119.
[6] Ozbay, K., D. Ozmen, and J. Berechman. Modeling and analysis of the link between accessibility and employment growth. *Journal of Transportation Engineering,* Vol. 132, No. 5, 2006, pp. 385-393.
[7] Ozbay, K., D. Ozmen-Ertekin, and J. Berechman. Contribution of transportation investments to county output. *Transport Policy,* Vol. 14, No. 4, 2007, pp. 317-329.
[8] Kalan, O. THE RELATIONSHIP BETWEEN ECONOMIC GROWTH AND ROAD INFRASTRUCTURE: EVIDENCE FROM TURKEY.In, Bogaziçi University, 2017.
[9] Manual, O. *Measuring Capital - OECD Manual 2009*. 2009.
[10] Asomani-Boateng, R., R. J. Fricano, and F. Adarkwa. Assessing the socio-economic impacts of rural road improvements in Ghana: A case study of Transport Sector Program Support (II). *Case Studies on Transport Policy,* Vol. 3, No. 4, 2015, pp. 355-366.
[11] Moomaw, R. L., and M. Williams. Total factor productivity growth in manufacturing further evidence from the states. *Journal of Regional Science,* Vol. 31, No. 1, 1991, pp. 17-34.
[12] Garcia-Mila, T., and T. J. McGuire. The contribution of publicly provided inputs to states' economies. *Regional Science and Urban Economics,* Vol. 22, No. 2, 1992, pp. 229-241.
[13] Aschauer, D. A. Is public expenditure productive? *Journal of monetary economics,* Vol. 23, No. 2, 1989, pp. 177-200.
[14] Munnell, A. H., and L. M. Cook. How does public infrastructure affect regional economic performance? *New England Economic Review*, No. Sep, 1990, pp. 11-33.
[15] Calderón, C., and L. Servén. *The effects of infrastructure development on growth and income distribution*. The World Bank, 2004.
[16] Duffy-Deno, K. T., and R. W. Eberts. *Public infrastructure and regional economic development: a simultaneous equations approach*. Federal Reserve Bank of Cleveland, Research Department, 1989.
[17] Chandra, A., and E. Thompson. Does public infrastructure affect economic activity?: Evidence from the rural interstate highway system. *Regional Science and Urban Economics,* Vol. 30, No. 4, 2000, pp. 457-490.
[18] Evans, P., and G. Karras. Are government activities productive? Evidence from a panel of US states. *The review of Economics and Statistics*, 1994, pp. 1-11.

[19] Munnell, A. H. Policy watch: infrastructure investment and economic growth. *Journal of Economic Perspectives,* Vol. 6, No. 4, 1992, pp. 189-198.

[20] Boarnet, M. G. The direct and indirect economic effects of transportation infrastructure. 1996.

[21] Holtz-Eakin, D., and A. E. Schwartz. Spatial productivity spillovers from public infrastructure: evidence from state highways. *International Tax and Public Finance,* Vol. 2, No. 3, 1995, pp. 459-468.

[22] Cohen, J. P., and C. J. M. Paul. Public infrastructure investment, interstate spatial spillovers, and manufacturing costs. *Review of Economics and Statistics,* Vol. 86, No. 2, 2004, pp. 551-560.

[23] Pereira, A. M., and O. Roca i Sagalés. On the regional impact of public capital formation in Spain. 2006.

[24] Escribá-Pérez, F., M. Murgui-García, and J. Ruiz-Tamarit. Economic and Statistical Measurement of Physical Capital with an Application to the Spanish Economy.In, 2017.

[25] Jorgenson, D. W. Capital theory and investment behavior. *The American Economic Review,* Vol. 53, No. 2, 1963, pp. 247-259.

[26] Winfrey, R. *Statistical analysis of industrial property retirements*. Iowa state college of agriculture and mechanic arts, 1935.

[27] Derbyshire, J., B. Gardiner, and S. Waights. Estimating the capital stock for the NUTS2 regions of the EU27. *Applied Economics,* Vol. 45, No. 9, 2013, pp. 1133-1149.

[28] Lou, P., H. Nassif, D. Su, and P. Truban. Effect of Overweight Trucks on Bridge Deck Deterioration Based on Weigh-in-Motion Data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2592, 2016, pp. 86-97.

[29] BEA. *Bureau of Economic Analysis*. https://www.bea.gov/. Accessed June, 2018.

[30] Center, R. E. *Employment and Unemployment Data.* Texas A&M University. https://www.recenter.tamu.edu/data/employment. Accessed June, 2018.

[31] FHWA. *Highway Statistics Series*. https://www.fhwa.dot.gov/policyinformation/statistics.cfm. Accessed June, 2018.

[32] Coma, C. W., and P. H. Douglas. A theory of production.In *Proceedings of the Fortieth Annual Meeting of the American Economic Association, No. 139*, 1928. p. 165.

[33] Wooldridge, J. M. Introductory econometrics: a modern approach. 2003.

[34] Xie, K., X. Wang, K. Ozbay, and H. Yang. Crash frequency modeling for signalized intersections in a high-density urban road network. *Analytic Methods in Accident Research,* Vol. 2, 2014, pp. 39-51.

[35] Xie, K., K. Ozbay, and H. Yang. Spatial analysis of highway incident durations in the context of Hurricane Sandy. *Accident Analysis & Prevention,* Vol. 74, 2015, pp. 77-86.

[36] Arellano, M., and S. Bond. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies,* Vol. 58, No. 2, 1991, pp. 277-297.

[37] Arellano, M., and O. Bover. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics,* Vol. 68, No. 1, 1995, pp. 29-51.

[38] Blundell, R., and S. Bond. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics,* Vol. 87, No. 1, 1998, pp. 115-143.

[39] Manual, S. *xtdpdsys-Arellano–Bover/Blundell–Bond linear dynamic panel-data estimation*. https://www.stata.com/manuals13/xtxtdpdsys.pdf. Accessed June, 2018.

[40] U.S. Department of Transportation Federal Highway Administration. https://www.fhwa.dot.gov/map21/guidance/guideeldnhsb.cfm. Accessed November, 2018.