Average Tax Rates and Economic Growth:
A Non-Linear Causality Investigation for the USA

by

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Abstract: This study uses a newly developed non-linear causality test proposed by Diks and Panchenko (2006) to investigate the relationship between two alternative average tax rates, namely the ratio of total tax revenues to GDP and alternatively, the ratio of taxes less subsidies on production and imports to GDP for the United States. The empirical evidence through the non-linear causality channel revealed the existence of a unidirectional non-linear causality running from the production tax rate to per capita GDP growth and a slight non-linearity vice versa. The results are in line with the empirical literature that attributes a growth determinant role to the average tax rates, only at a disaggregated level and they reveal new structures coming from non-linear methodology.

Keywords: non-linear causality, GDP growth, average tax rates

JEL Code: H20, E62

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1 For briefness hereafter, the aggregate tax rate will stand for the ratio of total tax revenues to GDP and the production tax rate will stand for the ratio of taxes less subsidies on production and imports to GDP.
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1. Introduction

In the taxes-growth nexus literature there is a variety of studies employing linear and non-linear models to determine the correlation between GDP growth and tax rates. Recently, in this nexus we come across a small part of empirical literature discussing the causality between the above two factors. In both fields, empirical literature lately tends to attribute merely to marginal tax rates the role of the appropriate determinants of the GDP growth. The aim of the present study is to reveal the potential existence of causality between average tax rates and economic growth in the USA, bringing out hence the importance of the aggregation level in average tax rates in this field of empirical literature.

For the purposes of our study, we have applied the nonparametric Diks-Panchenko (2006) causality test, instead of the most frequently used Hiemstra-Jones (1994) test – a modified version of Baek and Brock (1992). It is argued (Diks and Panchenko, 2006) that the Hiemstra-Jones test of non-linear causality may be inconsistent due to a bias, which cannot be removed simply by choosing a smaller bandwidth in the Hiemstra-Jones test statistic. The new nonparametric Granger causality test proposed by Diks and Panchenko (2006) reduces the bias and weakens the risk of over-rejection of the null hypothesis.
The paper is organised as follows. Section 2 reviews the relative literature. Section 3 presents the methodology of the nonparametric Diks-Panchenko causality test. Section 4 describes the data and the empirical results. Finally, section 5 concludes.

2. Literature review

In growth literature, neoclassical and endogenous theories employ growth models that discuss over the influence of taxes on economic growth. This has been conducted from a quite different perspective for the two strands of growth theory, with regard to the causes and the time dimension of the relationship between growth and taxes. In neoclassical growth models, there are exogenous forces, such as technological progress and population dynamics that cause steady state growth. Taxes may exert only a temporary influence on the growth rate of income in the transition to successive equilibrium growth paths. On the contrary, in the endogenous growth models, steady state growth is determined by the agencies of the economy. Taxes that affect parameters like the rate of return on capital accumulation or the volume of investments in R&D, influence permanently steady state growth. Therefore, in both theories, there is an implied negative relationship between taxes and growth which has not been conclusively supported from the empirical findings.

Several studies provide mixed evidences of the taxes–growth nexus. Koester and Kormendi (1989), Levine and Renelt (1992), Easterly and Rebelo (1993), Slemrod and Yitzhaki (1995), Mendoza et al. (1997) and Kneller et al. (1999) conclude that there is either a positive or in most cases an insignificant correlation, between the
average level of taxation and output dynamics both in the short and the long run. On the other hand, King and Rebelo (1990), Barro (1991), Plosser (1992), Engen and Skinner (1992), Kormendi and Meguire (1995), Wright (1996) and Leibfritz et al. (1997) find a negative correlation. Specifically, Leibfritz et al. (1997), examining the tax burden effects on GDP growth in a sample of OECD countries, concluded that an increase of 10% in the tax/GDP ratio could lead to a reduction of 0.5% in growth, with direct taxation reducing growth marginally more than indirect taxation.

The possible cause of the inconclusive empirical evidences could be the choice of inappropriate tax indicators, something that led the direction of other studies to employ and ample a variety of alternative tax rates like disaggregated average tax rates on indirect and direct taxes, the tax mix ratio of indirect to direct taxes and the effective marginal tax rates that are lately perceived to give a more appropriate measure for investigating how tax incidence affects output dynamics. Commenting on the appropriateness of the average tax rates, Engen and Skinner (1992) and Easterly and Rebelo (1993) concluded that average tax rates are not appropriate tax indicators while they are strongly correlated with public spending. Since some types of government expenditure, such as public capital and education, are growth enhancing (Barro and Sala-i-Martin, 1995), average tax rates may not be as statistically significant as growth determinant tax indicator, because of the simultaneous controversial effect that asserts over growth through the two channels of income and public expenditures.
Barro (1991) and de la Fuente (1997) follow a different scope in the growth literature; they consider the issue of fiscal policy effect on growth. In particular, they investigate how growth is related to the composition and the level of public sector spending. De la Fuente (1997) shows that if public spending -in the form of the ratio of total government expenditure to GDP- increases, growth is reduced, whereas an increase in public investment will boost growth.

According to Myles (2000), government spending may just be a proxy for the entire set of government non-price interventions, including for instance employment legislation, health and safety rules and product standards and it may be these, instead of the expenditure, that actually reduce growth. Also, it is not clear which hypothesis is being tested, since the share of public spending in GDP is very closely correlated to the average tax rate. Engen and Skinner (1996) propose a ‘bottom-up’ method, which calculates individually the effect of taxation on labour supply, investment and productivity and then sums these to obtain a total measure. They find that cuts of 5% in all marginal tax rates and 2.5% in average rates would raise the growth rate by 0.22%. Yammarik (2000) empirically tests the role of tax distortions in explaining state-level economic growth in the U.S. through the estimation of disaggregated tax rates in the form of personal income tax rate, general sales and property tax rates. The study concludes that the use of disaggregated marginal tax rates could generate predictions more consistent with growth theory than the use of the aggregated average tax rate. Padovano and Galli (2002) empirically justify that average taxation shows no noticeable growth effects, probably because of high correlation with the
average fiscal spending and conclude on the negative impact of marginal tax rates and tax progressivity on economic growth. Mamatzakis (2005) in a study with a dynamic impulse response analysis of Greek data sets found that, output growth responds negatively to an increase in the tax burden (given by the ratio of total taxes over GDP) while, there is a positive impact of tax mix (given by the ratio of indirect over direct taxes) on output growth. The impact of growth on the tax burden and the tax mix follows a cyclical pattern with a lag of one year, with a large positive response of the tax mix. The study concludes that indirect taxation benefits in the short term from high growth rates.

Distinguishing public expenditure to “productive” and “non-productive”, Angelopoulos et al. (2007) build upon Barro (1990) and Baier and Glomm (2001) and measure the productive and non-productive components of public sector expenditure as classified by Kneller et al. (1999). The average tax rate is being proxied by the tax revenue as a share of GDP and the associated fiscal size of the government measured by total government expenditure as a share of GDP. The study concludes that, the average tax rates are significantly negatively correlated with growth, while labour income tax rates are negatively related to growth, whereas capital income and corporate income tax rates are usually positively related.

3. Methodology: The Nonparametric Diks-Panchenko Causality Test

In 1969, Granger proposed a causality test to describe the dependence relations between economic time series. According to this, if two variables \( \{X_t, Y_t, t \geq 1\} \) are
strictly stationary, \( \{Y_t\} \) Granger causes \( \{X_t\} \) if past and current values of \( X \) contain additional information on future values of \( Y \). Suppose \( F_{X,t} \) and \( F_{Y,t} \) denote the information sets consisting of past observations of \( X_t \) and \( Y_t \) for time \( t \). \( \{Y_t\} \) Granger causes \( \{X_t\} \) if:

\[
(Y_{t+1},...,Y_{t+k})| (FX,t,FY,t) \sim (Y_{t+1},...,Y_{t+k})|FX,t \quad (1)
\]

where ‘\( \sim \)’ denotes equivalence in distribution and \( k \geq 1 \). However, in practice \( k = 1 \) is more oftenly used. In this case, Granger non-causality can be tested by comparing the one-step-ahead conditional distribution of \( \{Y_t\} \) with and without past and current observed values of \( \{X_t\} \). In order to test for Granger causality, we consider a two stationary time series model with a mean \( E(Y_{t+1}|(FX,t, FY,t)) \). We compare the residuals of a fitted autoregressive model of \( Y_t \) with those obtained by the regression of \( Y_t \) on past values of \( \{X_t\} \) and \( \{Y_t\} \) (Granger, 1969). Suppose that \( X^1 = (X_t-\ell X+1,\ldots, X_t) \) and \( Y^1 = (Y_t-\ell Y+1,\ldots, Y_t) \) are the delay vectors - where \( \ell X, \ell Y \geq 1 \). We examine the null hypothesis, that is whether past observations of \( X^1 \) contain any additional information about \( Y_{t+1} \) (beyond that in \( Y^1 \)):

\[
H_0 = Y_{t+1}|(X^1_{t+1}; Y^1_{t+1}) \sim Y_{t+1} | Y^1_{t+1} \quad (2)
\]

The null hypothesis becomes a statement about the invariant distribution of the \((\ell X + \ell Y + 1)\)-dimensional vector \( W_t = (X^1_{t+1}, Y^1_{t+1}, Z_t) \), where \( Z_t = Y_{t+1} \). If we ignore the time index and we assume that \( \ell X = \ell Y = 1 \), the distribution of \( Z - \) given that \( (X, Y) = (x, y) \) - is the same as that of \( Z - \) given \( Y = y \). In that case, equation (2)
is restructured to take into account the ratios of joint distributions. In that sense, the joint probability density function \( f_{X,Y,Z}(x,y,z) \) and its marginals should satisfy the following relationship:

\[
\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{X,Z}(y,z)}{f_Y(y)} \tag{3}
\]

In other words, equation (3) states that \( X \) and \( Z \) are independent, when \( Y = y \) for each fixed value of \( y \). Diks and Panchenko (2006) show that the restated null hypothesis implies:

\[
q \equiv E \left[ f_{X,Y,Z}(X,Y,Z)f_Y(Y) - f_{X,Y}(X,Y)f_Y(Y) - f_{Y,Z}(Y,Z) \right] = 0 \tag{4}
\]

Suppose \( \hat{f}_w(W_i) \) is a local density estimator of a \( d_W \)-variate random vector \( W \) at \( W_i \), defined by \( \hat{f}_w(W_i) = (2\varepsilon_n)^{-d_W} (n - 1)^{-1} \sum_{j \neq i} I_{ij} W \), where \( I_{ij} W = I(\|W_i - W_j\| < \varepsilon_n) \), \( I(\cdot) \) the indicator function and \( \varepsilon_n \) the bandwidth, which depends on the sample size \( n \).

Then, the test statistic is a scaled sample version of \( q \) in equation (4):

\[
T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i \left( \hat{f}_{X,Z,Y}(X_i,Z_i,Y_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i) \hat{f}_Y(Y_i) - \hat{f}_{Y,Z}(Y_i) \hat{f}_{Y,Z}(Y_i) \right) \tag{5}
\]

For \( \ell_X = \ell_Y = 1 \) and if \( \varepsilon_n = Cn^{-\beta} (C > 0, \frac{1}{4} < \beta < \frac{1}{3}) \), Diks and Panchenko (2006) prove that the test statistic in equation (5) satisfies the following:

\[
\sqrt{n} \left( T_n(\varepsilon_n) - q \right) \overset{D}{\rightarrow} N(0,1) \tag{6}
\]
where $\xrightarrow{D} \text{denotes convergence in distribution and } S_n \text{ is an estimator of the asymptotic variance of } T_n(\cdot)$ (Diks and Panchenko, 2006). In this study, the Diks and Panchenko's suggestion, to implement a one-tailed version of the test, has been employed. The null hypothesis is rejected if the left-hand-side of equation (6) is too large.

4. Data and Empirical results

4.1 Data and Preliminary analysis

The study is carried out using quarterly seasonally adjusted at annual rates data covering the time period 1964:1 to 2007:2 for the USA. GDPN stands for the Gross Domestic Product per capita in current prices. The variable GDPN is expressed in natural logarithms and has been interpreted in growth terms after taking the first differences on per capita GDP (DLGDPN). The tax rate PTGDP results from the revenue data of total government taxes less subsidies on production and imports by GDP and the tax rate TTGDP results from the National total State and Local tax revenue by GDP. Data for total government taxes less subsidies on production and imports and GDP quarterly are obtained from the OECD Quarterly National Accounts statistics while, data on National total State and Local tax revenue are obtained from the US Census Bureau Quarterly Tax Reports and at last, population figures are drawn from IMF’s International Financial Statistics. All data used are expressed in current prices. The use of current prices is incumbent in the case non-linear causality tests are contacted. This is because the transformation in constant prices could act as a filter producing distortions, especially when the underlying
mechanism generating data is non-linear. All time-series used in the test are in returns.

The use of the Diks-Panchenko non-linear causality test is justified by the presence of high kurtosis value (see table 1), suggesting heteroskedasticity structures in data sets (Diks and Panchenko, 2006).

As an initial step of the non-linear causality testing, stationarity tests must be performed for each of the variables. Although, there have been a variety of proposed methods for implementing stationarity tests, in this study, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) was employed. Table 2 reports the results of the ADF test both in levels and first differences. In the test equation, we have included both an intercept and a trend (table 2). The appropriate lag lengths are selected according to the Schwarz info criterion. The ADF statistic suggests that all variables are stationary in their first differences.

4.2 Non-linear causality results

In order to test for non-linear causality, we need first to remove the linear dependence. For this reason, we apply a Vector Autoregression (VAR) model and we use the estimate residuals to test for non-linear causality. If $\mathbf{Y}_t$ is the vector of endogenous variables and $l$ the number of lags, the VAR model is the following:
\[ Y_t = \sum_{s=1}^{l} A_s Y_{t-s} + \epsilon_t \]  

(7)

where \( Y_t = [Y_{t_1}, \ldots, Y_{t_l}] \) is the \( l \times 1 \) vector of endogenous variables, \( A_s \) is the \( l \times l \) parameter matrices and \( \epsilon_t \) the residual vector, for which \( E(\epsilon_t) = 0, E(\epsilon_t \epsilon_s) = \sum_{t=s}^{t} \epsilon_t \neq 0 \)

More specifically, in the case of two stationary time-series \{\( X_t \}\} and \{\( Y_t \}\), the following VAR model is estimated:

\[ X_t = a_{11}X_{t-1} + a_{12}X_{t-2} + \beta_{11}Y_{t-1} + \beta_{12}Y_{t-2} + \epsilon_t \sim N(0, \sigma_e^2) \]  

(8)

\[ Y_t = a_{21}X_{t-1} + a_{22}X_{t-2} + \beta_{21}Y_{t-1} + \beta_{22}Y_{t-2} + u_t \sim u_t \sim N(0, \sigma_u^2) \]  

(9)

where \( t=1,2,\ldots, N, a_{11}, a_{12}, a_{21}, a_{22}, \beta_{11}, \beta_{12}, \beta_{21} \text{ and } \beta_{22} \) are the coefficients in the lag operator. Two lags have been used in both cases. Tables 3a and 3b present the results from the estimation of the VAR model; they reveal the significance of the VAR model coefficients.

Insert Table 3a

Insert Table 3b

The non-linear Diks-Panchenko causality test is applied on the estimated residual series of the VAR model. Tables 4a and 4b show the resulting T statistics and p-values of the Diks-Panchenko testing. Specifically, table 4a presents the results of the non-linear causality test between the production tax rate and GDP growth, while table 4b presents the results of the non-linear causality test between the aggregate tax rate and GDP growth. The test has been applied in both directions for \( l_x = l_y = 1 \),
…, 5 and for bandwidth $\varepsilon=1.5$, which has been set according to the time series length $n$ (Diks and Panchenko, 2006).

Insert Table 4a

Insert Table 4b

The results obtained from the test indicate evidence of non-linear causality running from the production tax rate to per capita GDP growth. There is very weak evidence for the existence of non-linear causality from economic growth to the production tax rate and no evidence at all for the existence of non-linearity between the aggregate tax rate and economic growth.

5. Conclusions

In this paper we investigated the existence of non-linear causality between two alternative average tax rates - namely the aggregate tax rate and the production tax rate - and economic growth for the period 1964:1 to 2007:2 in the USA.

The investigation shows a unidirectional non-linear causality running from the production tax rate to GDP growth and only a slight non-linear causality vice versa. These findings are in line with the part of the empirical literature that concludes on the causality between disaggregated average tax rates and GDP growth and they reveal new structures coming from non-linear methodology. The empirical findings
provide evidence to the empirical USA growth literature for the appropriateness of
the disaggregated average tax rates as growth determinants contrary to the part of the
empirical literature that either concludes on the lack of any determining power of the
tax rates on the GDP growth or attributes a determinant role solely to the marginal
tax rates.

Additionally, the study shows no causality between the average aggregate tax rates
and GDP growth. The later could be attributed to the two sided nature of the average
aggregate tax burden, such as revenue as well as expenditure.

At last, we should also consider the very thin (but existing) non-proportional and
unpredictable influential role of economic growth on the tax burden on production
and imports.

Future research should be extended to include more disaggregated tax revenue
series, and it should be applied to different economies. In such a way, we could
extract information on the role of the aggregation level of tax data and, also the role
of the different economies in the taxes-growth causality nexus.

References
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Economy, Vol. 98, pp. 103–125.
Research, Discussion Paper, No. 1755.
Table 1: Descriptive statistics of the data

<table>
<thead>
<tr>
<th></th>
<th>DPTGDP</th>
<th>DTTGDP</th>
<th>DLGDPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.00000692</td>
<td>0.000104</td>
<td>0.015095</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.000926</td>
<td>0.001753</td>
<td>0.009733</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.361581</td>
<td>51.57016</td>
<td>4.615081</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.360447</td>
<td>-0.731073</td>
<td>0.562097</td>
</tr>
</tbody>
</table>

Table 2: Tests of the unit root hypothesis (intercept and trend included)

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF test statistic</th>
<th>Test critical values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Levels</td>
<td>First differences</td>
</tr>
<tr>
<td>PTGDP</td>
<td>-1.493266</td>
<td>-11.27426</td>
</tr>
<tr>
<td>LGDPN</td>
<td>-4.550050*</td>
<td>-3.468</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the 1%, 5% and 10% level.

Table 3a: VAR Results (DPTGDP and DLGDPN)

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Values</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>a_{11}</td>
<td>0.113895</td>
<td>1.44423</td>
</tr>
<tr>
<td>a_{12}</td>
<td>0.033163</td>
<td>0.41387</td>
</tr>
<tr>
<td>a_{21}</td>
<td>1.955431</td>
<td>2.27430*</td>
</tr>
<tr>
<td>(a_{22})</td>
<td>0.866933</td>
<td>0.99233</td>
</tr>
<tr>
<td>(\beta_{11})</td>
<td>-0.005404</td>
<td>-0.82653</td>
</tr>
<tr>
<td>(\beta_{12})</td>
<td>-0.001468</td>
<td>-0.22335</td>
</tr>
<tr>
<td>(\beta_{21})</td>
<td>0.457425</td>
<td>6.41690*</td>
</tr>
<tr>
<td>(\beta_{22})</td>
<td>0.442824</td>
<td>6.18068*</td>
</tr>
</tbody>
</table>

Notes: \(X= DPTGDP, Y=DLGDPN\)  
*: \(p<0.05\) (statistically significant at 5%)

Table 3b: VAR Results (DTTGDP and DLGDPN)

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Values</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_{11})</td>
<td>-0.345486</td>
<td>-4.35976*</td>
</tr>
<tr>
<td>(a_{12})</td>
<td>-0.081160</td>
<td>-1.0395</td>
</tr>
<tr>
<td>(a_{21})</td>
<td>1.032788</td>
<td>2.20589*</td>
</tr>
<tr>
<td>(a_{22})</td>
<td>1.344590</td>
<td>2.91497*</td>
</tr>
<tr>
<td>(\beta_{11})</td>
<td>-0.003294</td>
<td>-0.27083</td>
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<tr>
<td>(\beta_{12})</td>
<td>0.008379</td>
<td>0.68961</td>
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<tr>
<td>(\beta_{21})</td>
<td>0.446419</td>
<td>6.21215*</td>
</tr>
<tr>
<td>(\beta_{22})</td>
<td>0.435400</td>
<td>6.06527*</td>
</tr>
</tbody>
</table>

Notes: \(X= DTTGDP, Y=DLGDPN\)  
*: \(p<0.05\) (statistically significant at 5%)

Table 4a: Non-Linear Causality Test (DPTGDP and DLGDPN)

<table>
<thead>
<tr>
<th>Lx=Ly</th>
<th>DPTGDP → DLGDPN</th>
<th>DLGDPN → DPTGDP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T statistics</td>
<td>p-value</td>
</tr>
<tr>
<td>1</td>
<td>1.535</td>
<td>0.06242</td>
</tr>
<tr>
<td>2</td>
<td>1.830</td>
<td>0.03362*</td>
</tr>
<tr>
<td>3</td>
<td>1.464</td>
<td>0.07154</td>
</tr>
<tr>
<td>4</td>
<td>1.713</td>
<td>0.04331*</td>
</tr>
<tr>
<td>5</td>
<td>1.136</td>
<td>0.12792</td>
</tr>
</tbody>
</table>

Note: The null hypothesis suggests that DPTGDP does not cause DLGDPN and DLGDPN does not cause DPTGDP, respectively. * indicates that \(| p-value | <0.05\), therefore the null hypothesis is rejected.
Table 4b: Non-Linear Causality Test (DTTGDP and DLGDPN)

<table>
<thead>
<tr>
<th>Lx=Ly</th>
<th>DTTGDP $\Rightarrow$ DLGDPN</th>
<th>DLGDPN $\Rightarrow$ DTTGDP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T statistics</td>
<td>p-value</td>
</tr>
<tr>
<td>1</td>
<td>1.470</td>
<td>0.07075</td>
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<tr>
<td>2</td>
<td>1.236</td>
<td>0.10830</td>
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<tr>
<td>3</td>
<td>1.444</td>
<td>0.07436</td>
</tr>
<tr>
<td>4</td>
<td>1.311</td>
<td>0.09500</td>
</tr>
<tr>
<td>5</td>
<td>1.177</td>
<td>0.11954</td>
</tr>
</tbody>
</table>

Note: The null hypothesis suggests that DTTGDP does not cause DLGDPN and DLGDPN does not cause DTTGDP, respectively. * indicates that $|p-value| < 0.05$, therefore the null hypothesis is rejected.