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Output Convergence and the Role of Research and Development

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We ask whether failure to control for research and development (R&D) activity in an output convergence regression affects the coefficient estimates of initial output. We focus on output convergence to an economy's own steady-state growth path using time series regression framework and convergence across economies using panel estimation. We use data for the 30 member countries of the Organization for Economic Co-operation and Development (OECD) and US state-level real per capita output and per capita patents. The results indicate that after controlling for R&D activity the coefficient estimates increase in magnitude (in absolute terms) and in significance levels. Furthermore, the results are not sensitive to the dataset used or the estimation procedure.

Key Words: Output convergence; R&D; Omitted variable bias; Panel estimation; Panel unit root tests.
JEL Classification Numbers: O47, O11, O30.

1. INTRODUCTION

This paper contributes to the convergence debate by using recent data for the 30 member OECD countries that are more comparable and hence reliable than the data used in earlier studies. We also test our hypothesis using data for the fifty states of the US plus the District of Columbia. First we focus on the question of whether output convergence to an economy's

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own steady-state output level is affected by that economy's R&D activity.[1] We focus on the growth rate of real per capita output and its transitional dynamics after controlling for R&D activity in that economy. Then we use panel estimation to see if output convergence across economies is affected after controlling for the R&D activity. We measure an economy's R&D activity by the number of per capita patents issued to the residents of an economy.

Our results support the convergence hypothesis. Support for the convergence hypotheses becomes much stronger once we control for R&D activity. These results are not sensitive to datasets or estimation procedures. Using time series estimation the number of countries (OECD dataset) which carry statistically significant estimates with theoretically "correct" signs increases from thirteen to twenty two after we control for a country's R&D activity. The number of states (US state-level dataset) carrying statistically significant estimates and theoretically "correct" signs increases from nine to twenty nine. The panel estimation approach confirms the results of time series regressions. For both datasets, once we control for R&D activity, the magnitudes of coefficient estimates (in absolute terms) increase while maintaining the high significance levels.

Controlling for R&D is important while studying convergence. This is because in a neoclassical growth model, with growth rate of output as the dependent variable and the initial output as an independent variable, the expected sign of the coefficient associated with the initial level of output is negative (Solow 1956; Barro 1991; Barro and Sala-i-Martin 1995; Mankiw, Romer and Weil 1992; Crihfield and Panggabean 1995; Crihfield, Giertz and Mehta 1995; Islam 1995, 2003). However, R&D is expected to have a positive impact on the growth rate of output (Scherer 1984; Griliches 1988; Leahy and Neary 1997; Flster and Trofimov 1997; Aghion and Howitt 1998; Zachariadis 2004; Ha and Howitt 2007). An inability to control for R&D activity in a growth regression may result in biased estimates of the coefficient associated with the initial level of output.

Researchers in the area of economic growth have been fascinated by the question of whether poor economies grow faster than the rich ones. They and the policy makers have been trying to answer this question for almost five decades. Researchers and policy makers want to identify factors that contribute to economic growth so that success stories may be replicated in poor regions.

A number of descriptive analyses of data points to the decreasing variances of incomes across regions and across countries over time. Most studies (Baumol, Nelson, and Wolff 1994; Maddison 1987, 1994) find that during

[1] We use the word "economy" to refer to a country when used in the context of the OECD member countries, and to a state when used in the context of the US states.

the second half of the twentieth century, real incomes have been increasing progressively world-wide. Although the rates of growth differ widely across countries, the gap between the real incomes of the leader, i.e. the US, and the follower countries has been declining. In economic literature this phenomenon is referred to as "convergence."

There are two types of convergence: "conditional convergence" and "absolute convergence." Conditional convergence refers to the situation in which different economies are structurally similar in the sense that they have the same production function, saving rate, population growth rate, degree of unionization, rate of depreciation, openness of economy, etc. Absolute convergence, on the other hand, refers to the situation in which poor economies tend to grow faster than the rich economies regardless of their characteristics (Barro and Sala-i-Martin 1995, pp. 26-28; Islam 2003, p. 315).

A number of theories have been advanced to explain the observed decline in the variance of prosperity levels of regions and economies. Abramovitz (1986) and Baumol (1986) argue that less developed regions can adopt the technologies developed by rich regions relatively easily without going through the slow and costly process of developing the technologies themselves. Williamson (1991) posits that, for a given level of technology, diminishing returns to physical capital lead to a lower rate of productivity growth for regions that start with a higher level of labor productivity.

2. A BRIEF REVIEW OF LITERATURE

To say that the literature on the topic of convergence is extensive would be an understatement. A comprehensive review of such a rich body of theoretical and empirical literature is beyond the scope of this paper. Here we discuss some of the more important studies in different categories based on the data sets used. We will also identify some sources of disagreement among them as discussed in the literature. We refer the curious reader to Islam (2003) for an excellent review.

One may categorize studies based on whether the authors tested the convergence hypothesis using cross country data or data for one country, i.e., states, provinces, or regions of a country. Yet another way of categorization may be based on the use of time series versus cross sectional data. However, studies often fall into more than one category as authors try to examine the notion of convergence from different angles.

Some studies which use data for a single country focus on state- or regional-level datasets and ask whether income levels of the states or regions of that country are converging. Other studies using one-country data ask whether the country is converging to its own steady-state level, based on some measure of aggregate wellbeing, usually real per capita income.

These studies include Smith (1975); Crihfield, Giertz, and Mehta (1995); Barro and Sala-i-Martin (1991, 1995); Crihfield and Panggabean (1995); Dollar and Wolff (1994); Evans and Karras (1996); Swaine (1998); Hall and Ludwig (2006), to mention just a few.

Studies that use multi-country data to answer the question of whether different countries, with respect to some measure of aggregate output, are converging (or converging to their respective steady-states) include Barro (1991); Barro and Sala-i-Martin (1995); Mankiw et al. (1992); Blomstrm, et al. (1994); Evans and Karras (1996); Evans (1997); Bernard and Jones (1996); Caselli et al. (1996); Nonneman and Vanhoudt (1996). Furthermore, studies also differ with respect to the aggregate measures of output used to test the convergence hypothesis. For instance, Dollar and Wolff (1994); Bernard and Jones (1996) use aggregate output to test the convergence of total factor productivity of different countries, while others have made the convergence of real per capita incomes across countries the focus of attention.

Despite the wealth of empirical evidence, the answer to the question of output convergence remains ambivalent at best. The results are highly sensitive to datasets and data periods as well as to the units of observation used. This leaves the issue of convergence unresolved. Evans and Karras (1996) go a step further by questioning the traditional approach itself. The authors criticize the conventional approach on the basis that the assumptions of "identical first-order autoregressive dynamic structure" and "control of all permanent cross-country differences," which are critical to the validity of the results, are grossly violated. The authors stress the fact that although their approach yields the same results as the conventional approach, this does not mean that the conventional approach is correct. This is because there exists an overwhelming evidence of non-identical first-order autoregressive structure across regions.

The presence of cross-country heterogeneity has cast doubts on the results of earlier studies. Evans (1997) argues that the presence of cross-country heterogeneity leads to a rather wide range of estimates of the rates of convergence. Heterogeneity introduces such a strong bias that, "... convergence rates as far apart as 2% and 100% a year cannot be readily distinguished unless at least 95% of the cross-country heterogeneity can be controlled for." he writes (p.219).

Hall and Ludwig (2006) question the underlying assumptions of the Barro and Sala-i-Martin (1991, 1995) approach. In their study, Hall and Ludwig do not find support for these assumptions. (p.944)

More recently Alfo et al. (2008) address the issue of cross country heterogeneity and present a fix in the form of the so-called "finite mixture approach." They argue that using this approach the explanatory power of the Solow (1956) model is significantly enhanced.

In this paper we deal with the cross-economy heterogeneity issues in two ways. First we focus on the question of an economy's output convergence to its own steady-state output level. We use time series data of a given economy. Then we construct a panel and use panel estimation which controls for economy heterogeneity. For panel estimation following Islam (1995) we use a fixed-effects model.

Another point that leaves room for further research in the area of convergence of output is the role of R&D activity in an economy. As pointed out in Introduction, controlling for R&D activity is important in a convergence regression. This is because using the neoclassical framework, the literature points out that in a growth equation the coefficient of the initial level of output is negative (Solow, 1956; Barro, 1991; Barro and Sala-i-Martin, 1995; Mankiw et al., 1992; Crihfield and Panggabean ,1995; Crihfield et al., 1995; Islam, 1995, 2003). The literature also points out that R&D has a positive effect on the growth rate of the economy (Scherer, 1984; Griliches, 1988; Leahy and Neary, 1997; Flster and Trofimov, 1997; Aghion and Howitt, 1998; Zachariadis, 2004; Ha and Howitt, 2007). These studies point out that R&D expenditure has sizeable positive impact on output growth. For instance, according to the Coe and Helpman (1995) estimates, the return on R&D expenditure in terms of productivity gains for the G-7 countries is as high as 123% (as reported in Zachariadis 2004, p.424).

Zachariadis (2004) uses data from 1971 to 1996 for ten OECD countries. The author measures "R&D intensity" as the ratio of R&D expenditures to output. The results indicate that a one percent increase in R&D intensity leads to an output growth of the economy by 0.38 percent (p.424)

Although the estimates of the impact of R&D activity on output growth vary depending upon the dataset and the variables used, and the estimation procedures employed, the evidence pointing to the positive impact of R&D on output growth is overwhelming. As a result, estimating the impact of the initial level of output on the growth rate of output, without controlling for R&D activities, may bias the coefficient estimates of the initial level of output. The flip side of the argument is that estimating the impact of R&D without controlling for the initial value of output, may bias the coefficient estimates of R&D in a regression equation. Thus, our paper focuses on the role of R&D activity in affecting the coefficient estimates of the initial level of real per capita output in a growth equation. Furthermore, the present study not only focuses on the effects of R&D on output convergence towards an economy's steady-state path using time-series data, but also convergence across economies making use of panel estimation. We present more details on how we accomplish this in the Model section below.

3. MODEL

In this study we use a variant of models used by Baumol (1986); Barro (1991); Barro and Sala-i-Martin (1991, 1992, 1995); Crihfield and Panggabean (1995); Crihfield et al. (1995); Islam (1995); and Bernard and Jones (1996). In its basic form, the model has growth rate of output as the dependent variable and the initial level of output as the independent variable. Other independent variables may include a region's saving rate, population growth rate, level of unionization, openness of the economy, etc. This paper differs from the existing literature in that we have included, along with the initial level of real per capita output of that economy, the R&D activity conducted in that economy as an independent variable. The growth rate of real per capita output is the dependent variable.

We measure R&D activity by the number of patents distributed in an economy (in per capita terms) in a given year.[2] In our opinion, patents represent relatively more closely the "productivity" of R&D, and hence its impact on output growth rate than expenditure on R&D. This view is supported in the literature on the topic. Zachariadis (2003) considers R&D expenditure to be an input in the "production of patents." Patents in turn serve as inputs for innovations leading to productivity gains. (p.570). In a more recent study Madsen (2008) uses number of patents as a measure of "innovative activity" in OECD countries. See also Griliches (1990) on the use of patents to proxy innovative activity.

Furthermore, for R&D expenditure to reach the point of a patent it requires a certain level of human capital in the area. In other words, to the extent that these skills are applied in the development of products, number of patents may also be used as a proxy for the skill level of workers.

Another point worth noting is that for patents to be issued, certain well functioning political, economic, and social institutions have to be present in the country issuing the patents. These institutions may include relatively stable political environment, a mature financial system, and institutions protecting property rights, among others. In regions where political and social calm is absent, for instance, Iraq and Darfur, one can hardly expect inventors applying for patents or governments to issue them. In this respect patents may also serve as a proxy for political stability.

In addition, applying for a patent indicates certain level of fruition of one's efforts. It may be considered a step between R&D expenditure and the production line where the product is actually being produced. As such, in situations where the length of time series data is an issue, a relatively short time series may produce meaningful results.

Literature indicates that the usual lag between R&D expenditure and its impact on economic growth is around five years. See for instance, Aghion

[2]More on this point in the Data section.

and Howitt (1998) on this point. Assuming one has the resources to finance the production, having a patent may be considered the last major step before one starts to produce output. As a result, the lag between the issuance of patents and economic growth may be much shorter.

Our time series version of the model takes the following form:

$$Gry_{t,t-1} = a_{10} + b_{11}y_{t-1} + \varepsilon_{1,t} \tag{1}$$

and $\varepsilon_{1,t} = \rho_{11}\varepsilon_{1,t-1} + \rho_{12}\varepsilon_{1,t-2} + \cdots + \rho_{1k}\varepsilon_{1,t-k} + \nu_{1,t}$

$$Gry_{t,t-1} = a_{20} + c_{21}pat_{t-1} + \varepsilon_{2,t} \tag{2}$$

and $\varepsilon_{2,t} = \rho_{21}\varepsilon_{2,t-1} + \rho_{22}\varepsilon_{2,t-2} + \cdots + \rho_{2k}\varepsilon_{2,t-k} + \nu_{2,t}$

$$Gry_{t,t-1} = a_{30} + b_{31}y_{t-1} + c_{32}pat_{t-1} + \varepsilon_{3,t} \tag{3}$$

and $\varepsilon_{3,t} = \rho_{31}\varepsilon_{3,t-1} + \rho_{32}\varepsilon_{3,t-2} + \cdots + \rho_{3k}\varepsilon_{3,t-k} + \nu_{3,t}$

Where $Gry_{t,t-1}$ is the growth rate of y from $t-1$ to t, and y is the log of real per capita output of an economy. The independent variable y_{t-1} is the log of real per capita output at time $t-1$ of an economy (hereafter lagged y), and pat_{t-1} is the log of per capita patents at time $t-1$ of an economy (hereafter lagged pat).[3] Patent data are divided by the economy's population to convert patent data into per capita terms. $\varepsilon_{m,t}$, for $m = 1, 2, 3$, is the error term which may have autocorrelation of order k, where k is determined by the data. Letters a, b, and c are the coefficients to be estimated. While using the OECD data we ran regressions for each of the 30 OECD member countries, and while using US state-level data we ran regression for each of the fifty states and District of Columbia.

Our primary interest is in the estimates of b_{11} (Model 1), and b_{31} (Model 3). Statistically significant negative estimates of b_{11} and b_{31} will indicate presence of convergence of output to a state's own steady-state. Please note that the coefficients, b_{11} and b_{31}, associated with y_{t-1} (Models 1 and 3, respectively) are equal to $(1-e^{-\beta t})$, where β is the speed of convergence. That is, the speed at which y_t reaches its steady-state value, y^*.[4]

The estimates of c_{21} and c_{32} (in Models 2 and 3, respectively) will be positive and statistically significant if patents have a positive effect on the dependent variable, the growth rate of y.

[3] In order to achieve stationarity we "rho-differenced" the data. As a result the variables lagged y and lagged pat are not "levels." We provide more details in Section 5, where we discuss the results and Appendix A, where we provide methodological details for "rho-differencing" the data to achieve stationarity.

[4] Because there are numerous sources dealing with the derivation of these types of models, we refrain here from the details and refer the curious reader to Mankiw et al. (1992); Barro and Sala-i-Martin (1995); and Aghion and Howitt (1998), among others.

4. DATA

In this paper we use real per capita output and number of per capita patents data for the 30 OECD countries, and for the fifty states of the US and District of Columbia.

The patent data for the OECD countries come from the so-called Triadic Patents Families data. As noted in the OECD document titled: Compendium of Patent Statistics 2006, statistics on patents issued by the home country of the inventor, although a good source of information, suffer from certain weaknesses including "home advantage bias." Other factors that may influence the home patenting office include "patenting procedures, trade flows, proximity, etc." (OECD 2006, p.10, Box 1.1). According to the Compendium, the Triadic Patent Families which are the patents taken at the European Patent Office, the Japanese Patent Office, and the US Patent Office, improve the "international comparability of patent-based indicators." (OECD 2006, p.10, Box 1.1)

In order to count the patent data OECD (2006) Compendium of Patent Statistics primarily uses the so-called "priority date" to count the number of patents. The priority date is defined as "first date of filing of a patent application, anywhere in the world, to protect an invention."(p.9).[5]

All data are annual. The countries included and the data periods for each country are provided in Table 1.

TABLE 1.

Country names and data periods.

Country	Data Period	Country	Data Period	Country	Data Period
Australia	1985-2003	Hungary	1991-2003	Norway	1985-2003
Austria	1985-2003	Iceland	1985-2003	Poland	1990-2003
Belgium	1985-2003	Ireland	1985-2003	Portugal	1985-2003
Canada	1985-2003	Italy	1985-2003	Slovak Republic	1992-2003
Czech Republic	1990-2003	Japan	1985-2003	Spain	1985-2003
Denmark	1985-2003	Korea	1985-2003	Sweden	1985-2003
Finland	1985-2003	Luxembourg	1985-2003	Switzerland	1985-2003
France	1985-2003	Mexico	1985-2003	Turkey	1985-2003
Germany	1985-2003	Netherlands	1985-2003	UK	1985-2003
Greece	1985-2003	New Zealand	1985-2003	USA	1985-2003

Source: www.oecd.org

[5] "Most indicators in this compendium are presented according to the priority date and the country of residence of the inventors and also use the applicant's residence for cross-border analysis." (OECD 2006, p.9). Please see OECD (2006) for methodological details.

The data period is dependent on the availability. For the OECD countries the source for real per capita output as well as the patent data is the OECD website. The URL is http://www.oecd.org.

The patent data at the US state-level are from the U.S. Patent and Trademark Office (USPTO), Electronic Information Products Division. (Table: PART A1- Table A1-1a). The URL is www.uspto.gov/web/offices/ac/ido/oeip/taf/tafp.html. The Patent Technology Monitoring Team of the USPTO publishes these data in an annual report. The report presents the number of patents granted in each state.[6] In order to convert patent data into per capita terms we divided the number of patents granted in a state by the population of that state. The source of state population data is the U.S. Bureau of Census. The URL is www.census.gov. The data source for the US state-level real per capita output is Bureau of Economic Analysis, Department of Commerce. The URL is www.bea.gov. All US state-level data are annual and range from 1963 to 2006.

5. RESULTS AND DISCUSSION

This section is divided into two sub-sections. Sub-section 5.1 presents and discusses results using time series data, and sub-section 5.2 presents and discusses results using panel data. Furthermore, in each sub-section we first present and discuss results using OECD data and then we present and discuss results using US state-level data.

5.1. Time Series Results

In this subsection we first present results using the OECD data and then the US state-level data. We let the data determine the degree of integration to make a time series stationary. As detailed in Appendix A, data were "rho-differenced" to achieve stationarity for both the OECD data and the US state-level data. The value of rho was determined by data using methods detailed in Appendix A. For both datasets, in order to test for stationarity of the original time series and the "rho-differenced" time series we used Augmented Dickey-Fuller test (ADF).[7] The ADF results pointed to the stationarity of the "rho-differenced" time series.

Furthermore, for both datasets, in order to calculate the coefficient significance levels we used the so-called heteroskedasticity- and autocorrelation-

[6] "This report displays the number of U.S. patents distributed by state and country of origin. The origin of a patent is determined by the residence of the first-named inventor." (http://www.uspto.gov/web/offices/ac/ido/oeip/taf/tafp.html)

[7] See Ramanathan (2002, pp. 455-459) for details of the test. In the interest of space we do not provide details of test results here. However, these results are available from the authors.

consistent (HAC) standard errors. For details on HAC standard errors please see Stock and Watson (2003, pp. 502-506), Hamilton (1994, pp.281-283), among others. The HAC standard errors are considered superior to the "regular" standard errors. As Stock and Watson (2003) point out, HAC standard errors are consistent whether or not there is heteroskedasticity, and whether or not there is autocorrelation. (p.504)

30 OECD countries. We ran regressions using Models 1-3 for each of the 30 OECD countries. In this sub-section along with presenting and discussing regression results we also present the implied speed of convergence and quantitative estimates of the omitted variable bias.

We present a summary of the results in Table 2 below. Details of the time series estimation procedure are provided in Appendix A, and details of the regression results are presented in Appendix B, Table B1. The results of the study strongly support our contention that the role of R&D should not be ignored in the analysis of the convergence hypothesis. The coefficient estimates of lagged y increase in statistical significance as well as in magnitude (in absolute terms) once we add lagged *pat*, representing the R&D activity in the country, to the model.

While using time series data in order to determine lag lengths in Models 1-3, we used Schwartz Baysian Information Criteria (SBC).[8] We ran regressions with lags up to 10 years. The use of SBC pointed one-year lag to be the optimal lag for our data and the variables included in the models. Time series regression results using one-year lag length are presented and discussed. Space limitations prohibit us from presenting time series results using longer lag lengths.[9]

To some readers the use of one-year lag may seem too short, especially when it comes to the impact of R&D on output growth. As discussed in Section 3, we are using number of patents as a proxy for that country's R&D activity. Applying for and issuance of patents may be considered intermediate steps between R&D expenditure and its impact on output. As such, it stands to reason that the lag between the issuance of patents and output growth will be shorter than the lag between R&D expenditure and output growth.

An argument has also been made that shorter lag lengths may produce upward biased coefficient estimates due to economic cycles (see, for instance, Caselli, Esquivel, and Lefort 1996, 372). However, it is important to note that the main focus of this study is not to find out the optimal lag length. Rather the focus is to see if the omission of R&D from a growth regression equation results in biased estimates, no matter what the lag length. Furthermore, because we test our model with and without R&D

[8]See Gweke and Meese (1981) on the use of SBC for lag length selection.

[9]The main implications of results were not sensitive to longer lag lengths. Results with longer lag lengths are available from the authors.

as an independent variable for the same lag length, the criticism of shorter lag length may not be applicable.

As shown in Appendix A and Appendix B, regression results are based on "rho-differenced" data. Strictly speaking, because "rho-differencing" was performed after taking natural logs of the data, independent variables, y_{t-1} and pat_{t-1}, are not "levels" of the respective variable.[10]

TABLE 2.

A summary of regression results using OECD data

	Model 1	Model 2	Model 3			Model 1	Model 2	Model 3	
Country	b_{11}(est)	c_{21}(est)	b_{31}(est)	c_{32}(est)	Country	b_{11}(est)	c_{21}(est)	b_{31}(est)	c_{32}(est)
Australia	0.008	0.006	-0.621^{a}	-0.02^{a}	Korea	-0.069^{b}	-0.011^{c}	-0.132	0.012
Austria	-0.036	0.024	-0.133^{a}	0.064^{a}	Luxembourg	-0.054	-0.002	-0.827^{a}	0.01^{a}
Belgium	-0.055	-0.013	-0.966^{a}	-0.056^{a}	Mexico	-0.165	0.015	-0.362^{b}	0.057^{b}
Canada	-0.344^{a}	0.009	-0.23	0.061	Netherlands	-0.184	0.042	-0.151^{c}	0.047
Czech Republic	-0.715^{a}	-0.021	-0.79^{a}	-0.027^{a}	New Zealand	0.009	0.024^{c}	-0.156	0.034^{b}
Denmark	0.007	0.014	-0.261^{a}	0.082^{a}	Norway	-0.024	-0.026	-0.346^{a}	-0.029^{a}
Finland	-0.196	0.02	0.202	0.046	Poland	-0.087^{c}	-0.004	-0.612^{a}	0.004
France	-0.082	0.045	-0.242^{a}	0.155^{a}	Portugal	-0.249^{b}	-0.009	-0.352^{b}	-0.004
Germany	-0.481^{a}	0.033	-1.938^{a}	0.468^{a}	Slovak Republic	-0.554^{a}	-0.004	-0.148^{c}	0.005
Greece	0.135^{b}	0.009	0.114^{c}	0.006	Spain	-0.108	-0.003	-0.504^{a}	0.053^{a}
Hungary	0.038	0.013	0.041	0.015	Sweden	-0.057	0.023	-0.14	0.05
Iceland	-0.608^{a}	0.000	-0.597^{a}	-0.000	Switzerland	-0.382^{a}	0.072	-0.496^{a}	0.133^{a}
Ireland	-0.025	-0.015	-0.602^{a}	0.018^{b}	Turkey	-1.412^{a}	-0.004	-1.388^{a}	-0.009^{a}
Italy	-0.104^{c}	0.057	-0.625^{a}	0.082^{a}	UK	-0.018	0.002	-0.683^{a}	0.089^{a}
Japan	-0.656^{a}	0.082	-0.749^{a}	0.097^{a}	USA	-0.027	-0.022	0.226	-0.124

Significance Levels: a = 1%; b = 5%; c = 10%. "(est)" stands the estimate of the given coefficient. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283).

In Table 2, the coefficient estimates associated with lagged y, b_{11}, are presented in column labeled Model 1. Recall that in Model 1 the only independent variable is lagged y. We find that only 13 countries carry statistically significant coefficients with theoretically "correct" negative signs. The implication is that a lower level of lagged real per capita output leads to a higher growth rate of output.

In Model 2 we include only lagged per capita patents, pat_{t-1}, as an independent variable. The coefficient estimates of c_{21} are presented in Table 2 under column labeled Model 2. We find that only one country, New Zealand, carries a statistically significant and theoretically "correct" positive sign. The implication of this result is that R&D activity undertaken in

[10]Note also that logs of variables could not be taken after performing "rho-differencing" because "rho-differencing" would have generated some negative values.

that country increases the growth rate of per capita output. The coefficient estimate for Korea, although significant at the 10% level, carries a negative sign.

In Model 3 we include both lagged y and lagged *pat* as independent variables. The coefficient estimates are presented in Table 2 in column labeled Model 3. We note that the coefficient estimates of lagged y, b_{31}, carrying statistically significant and theoretically "correct" sign increase from 13, in Model 1, to 22, in Model 3. Not only does the number of statistically significant coefficient estimates increases, the magnitudes and the levels of significance also increase. This implies that after controlling for the R&D activity in a country the correlation between the initial level of per capita output and the growth rate of per capita output increases (in absolute terms).

Next consider the coefficient estimates of lagged *pat*, c_{32}. In Model 2 where we did not control for the initial level of per capita output, we only had one country with a statistically significant and positive coefficient. In Model 3 once we control for the initial level of per capita output, the number of positive significant coefficients associated with lagged *pat* increases to 13. The implication of the results is that R&D activity under taken by a country leads to a higher growth rate of per capita output. These results render strong support to the hypothesis advanced in this study.

Our next task is to provide estimates of the implied speed of convergence for each of the OECD countries.

Speed of convergence using OECD data. Recall that the coefficients of lagged y in Model 1 and Model 3, b_{11} and b_{31}, respectively, are equal to $(1-e^{-\beta t})$, and β is the speed of convergence of y_t to y^*. In Table 3, Model 1 presents estimates of the speed of convergence where we do not control for a country's R&D activity. In Model 3 of Table 3 we present the estimates of the coefficients of speed of convergence by using lagged *pat* to control for a country's R&D activity.

As far as the speed of convergence is concerned, our results present a relatively mixed picture. When we control for the R&D activity the speed of convergence increases for 19 countries, decreases for five countries, and remains unchanged for five countries.[11]

Looking at these mixed results one may be tempted to conclude that the rise and fall in the estimates of speed of convergence tend to cancel each other out. Thus, on the average, controlling for the R&D activity may not

[11] Note that the coefficient estimates of b_{11} and b_{31} using data for Greece in Table 2, Models 1 and 3, respectively, are theoretically "incorrect" positive significant, leading to a negative estimate for the implied speed of convergence (presented in Table 3). The coefficient estimate for Australia in Model 1, b_{11}, Table 2, is also positive but insignificant.

TABLE 3.

Implied speed of convergence (estimates of β) using OECD data

Country	Model 1	Model 3	Country	Model 1	Model 3	Country	Model 1	Model 3
Australia	-0.008	0.483^a	Hungary	0.037	0.040	Norway	0.024	0.297^a
Austria	0.035	0.125^a	Iceland	0.475^a	0.468^a	Poland	0.083^c	0.477^a
Belgium	0.054	0.676^a	Ireland	0.025	0.471^a	Portugal	0.222^b	0.302^b
Canada	0.296^a	0.207	Italy	0.099^c	0.486^a	Slovak Republic	0.441^c	0.138^c
Czech Republic	0.539^a	0.582^a	Japan	0.504^a	0.559^a	Spain	0.103	0.408^a
Denmark	0.007	0.232^a	Korea	0.067^b	0.124	Sweden	0.055	0.131
Finland	0.179	0.184	Luxembourg	0.053	0.603^a	Switzerland	0.324^a	0.403^a
France	0.079	0.217^a	Mexico	0.153	0.309^b	Turkey	0.880^a	0.870^a
Germany	0.393^a	1.078^a	Netherlands	0.169	0.141^c	UK	0.018	0.521^a
Greece	-0.145^b	-0.121^c	New Zealand	0.009	0.145	USA	0.027	0.204

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. These significance levels are corresponding to estimates of b_{11} and b_{31} in Models 1 and 3, respectively. The estimates of b_{11} and b_{31}, along with their significance levels are presented in Table 2.

seem important.[12] However, this conclusion may be premature. Next we quantify the bias that may result from omitting R&D from the estimation specification and show that the bias caused by this omission is statistically significant.

Omitted variable bias estimates using OECD data. In order to quantify the magnitude of bias that may result from omitting R&D from a growth regression, we use the following auxiliary equation:

$$pat_t = \delta_0 + \delta_1 y_t + \omega_t \tag{4}$$

Where y_t, and pat_t are, as defined above, the real per capita income and number of per capita patents for a country at time t, respectively. ω_t is the classical error term. Table 4 provides the estimated values of δ_1, the coefficient of y_t in Equation 4.

A quantitative measure of the omitted variable bias is obtained by multiplying the estimate of c_{32} (Equation 3) by the estimate of δ_1 (Equation 4).[13] That is:

$$Bias = c_{32} \times \delta_1$$

[12] The mean difference in the statistically significant coefficient estimates of lagged y before (sample mean and variance are 0.36 and 0.055, respectively) and after (sample mean and variance are 0.436 and 0.055, respectively) controlling for R&D activity is not statistically significantly different from zero. The pooled variance is 0.055 and two-tailed p-value is 0.372. In this calculation we did not include coefficient estimates for Australia (Model 1) and Greece (Models 1 and 3).

[13] For details please refer to Studenmund (2006, 163-170).

TABLE 4.

Auxiliary Equation Estimates Using OECD Data

Country	δ_1(est)	Country	δ_1(est)	Country	δ_1(est)
Australia	2.523^a	Hungary	0.567	Norway	1.745^a
Austria	1.457^b	Iceland	15.867^b	Poland	0.73^c
Belgium	-0.41	Ireland	1.148^a	Portugal	4.421^b
Canada	3.328^a	Italy	1.427^a	Slovak Republic	0.442
Czech Republic	3.009	Japan	0.612	Spain	1.692^a
Denmark	1.781^c	Korea	5.153^a	Sweden	0.535
Finland	-0.042	Luxembourg	1.412^b	Switzerland	1.021
France	1.094^b	Mexico	4.534^a	Turkey	9.902
Germany	1.844^a	Netherlands	-1.415	UK	3.219^a
Greece	3.488^b	New Zealand	-7.312	USA	2.191^a

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. "(est)" stands the estimate of the given coefficient. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283).

TABLE 5.

Omitted variable bias using OECD data

Country	Bias	Country	Bias	Country	Bias
Australia	0.050	Germany	0.863	Mexico	0.258
Austria	0.093	Ireland	0.021	Norway	0.051
Denmark	0.146	Italy	0.117	Spain	0.090
France	0.170	Luxembourg	0.014	UK	0.286

Only countries for which coefficients in both equations (Equation 3 and Equation 4) were significant at least at the 10% level are included in the calculation.

The estimated bias figures are provided in Table 5. In calculating these estimates we only included countries for which coefficient in both equations, Equation 3 and Equation 4, were significant at least at the 10% level.

The magnitude of the mean bias is 0.18 with a standard error of 0.067. This gives a 95% confidence interval of $[0.033; 0.327]$, indicating that the omitted variable bias is statistically significantly different from zero at least at the 95% level.

In sum, these results support our hypothesis that failure to control for the R&D activity may bias the coefficient estimates of the convergence specification. In addition, in order to estimate the impact of R&D on the growth rate of a country's output, some measure of initial level of output should be taken into account.

Next we test the hypothesis presented in this study using data for the US states. The use of a different, and relatively disaggregated, dataset allows us to test the robustness and sensitivity of our results.

50 US states plus the District of Columbia. We ran regressions using Models 1-3 for each of the fifty states of the US plus the District of Columbia. We ran regressions with lag lengths up to ten years. As with the OECD dataset, we let the data determine lag lengths in Models 1-3. As in the case of the OECD data in order to determine lag lengths in Models 1-3, we used Schwartz Baysian Information Criteria (SBC). It is reassuring that again the use of SBC pointed one-year lag to be the optimal lag for our data and the variables included in the models. Time series regression results using one-year lag length are presented and discussed in the study.[14]

The results using the US state-level data also support our contention that the role of R&D should not be ignored in the analysis of the convergence hypothesis. The coefficient estimates of lagged y increase in magnitude (in absolute terms) as well as in significance levels when we add lagged *pat*, representing the R&D activity in a state, to the model.

Table 6 presents a summary of the regression results. Details of the estimation procedure are discussed in Appendix A and detailed regression results are presented in Appendix B, Table B2. The layout of Table 6 is the same as that of Table 2 which presents a summary of regression results using the OECD data.

In Table 6, Model 1, where the only independent variable is lagged y, y_{t-1}, although all coefficient estimates but one have theoretically "correct" sign, i.e. negative, only nine states carry a significant coefficient estimate. Coefficient estimate for Delaware is the exception. It carries a positive insignificant sign. The results of Model 1 indicate that although the evidence for convergence is there, it is not very convincing.

In Model 3 we include lagged *pat* to the regression equation to control for the R&D activity in a state. We find that the number of coefficient estimates carrying significant negative signs increases to twenty nine in Model 3. Note that the magnitude of estimates also increases (in absolute terms). Alaska and Massachusetts are the exceptions. Coefficient estimates for these two states become insignificant once lagged *pat* is added to the regression equation in Model 3.

Now let's look at the impact of R&D activity on a state's output growth rate. It is measured by the coefficient estimates of lagged *pat*, c_{21} and c_{32} in Model 2 and Model 3, respectively. In Model 2, Table 6, we only include lagged *pat* as an independent variable. We find that none of the estimates of c_{21} is statistically significantly positive. Most coefficient estimates (30)

[14]The main implications of results were not sensitive to longer lag lengths. Results with longer lag lengths are available from the authors.

TABLE 6.

A summary of regression results using US state-level data

	Model 1	Model 2	Model 3			Model 1	Model 2	Model 3	
State	b_{11}(est)	c_{21}(est)	b_{31}(est)	c_{32}(est)	State	b_{11}(est)	c_{21}(est)	b_{31}(est)	c_{32}(est)
Alabama	-0.019	-0.001	-0.021	0.01	Montana	-0.033	0.003	-0.056	0.02
Alaska	-0.112^c	0.065	-0.101	-0.022	Nebraska	-0.026^c	-0.014	-1.153^a	-0.03^a
Arizona	-0.034	0.001	-0.677^a	0.042^a	Nevada	-0.039	0.003	-0.048	0.012
Arkansas	-1.086^a	-0.01	-1.093^a	-0.037^a	New Hampshire	-0.022	-0.014	-0.596^a	-0.005^a
California	-0.011	0.004	-0.601^a	0.025^a	New Jersey	-0.012	-0.004	-0.013	-0.017
Colorado	-0.021	-0.007	-0.036	0.015	New Mexico	-0.016	0.003	-0.026	0.013
Connecticut	-0.013	-0.04	-0.014	-0.043	New York	-0.002	-0.015	-0.000	-0.015
DC	-0.013	0.005	-1.081^a	0.027^a	North Carolina	-0.022	-0.009	-0.871^a	0.059^a
Delaware	0.006	-0.02	-0.009	-0.025	North Dakota	-0.048	0.023	-0.065^c	0.045
Florida	-0.025	-0.025	-0.02	-0.004	Ohio	-0.021	-0.008	-0.024	-0.014
Georgia	-0.037	-0.027	-0.025	-0.011	Oklahoma	-0.037	0.003	-0.123^b	-0.075^c
Hawaii	-0.053	-0.045^a	-0.007	-0.043^a	Oregon	-0.022	0.000	-0.053	0.022
Idaho	-0.033	-0.000	-0.108^c	0.018	Pennsylvania	-0.657^a	-0.006	-0.677^a	0.012^a
Illinois	-0.013	-0.001	-0.778^a	0.041^a	Rhode Island	-0.002	-0.006	-0.56^a	0.021^a
Indiana	-0.016	0.012	-0.896^a	0.021^a	South Carolina	-0.037^c	-0.036	-0.029	0.011
Iowa	-0.025	0.026	-0.052^c	0.051^b	South Dakota	-0.028	0.014	-0.039^c	0.03
Kansas	-0.028^b	0.022	-0.029^b	0.024^c	Tennessee	-0.029	-0.035	-0.785^a	-0.063^a
Kentucky	-0.033	-0.002	-0.952^a	-0.009^a	Texas	-0.036	0.005	-0.051^c	0.03
Louisiana	-0.054	-0.081	-0.594^a	-0.093^a	Utah	-0.002	0.008	-0.682^a	0.028^a
Maine	-0.015	-0.008	-0.794^a	-0.008^a	Vermont	-0.895^a	-0.006	-0.902^a	0.009^a
Maryland	-0.012	0.002	-0.603^a	0.014^a	Virginia	-0.015	-0.003	-0.015	-0.002
Massachusetts	-0.385^a	-0.03	-0.005	-0.029	Washington	-0.024	0.006	-0.592^a	0.053^a
Michigan	-0.044	-0.023	-0.039	-0.011	West Virginia	-0.022	0.012	-0.852^a	0.008^a
Minnesota	-0.021	-0.009	-0.884^a	-0.02^a	Wisconsin	-0.013	0.003	-0.015	0.008
Mississippi	-0.041^b	-0.015	-0.054^b	0.013	Wyoming	-0.072	0.056	-0.047	0.048
Missouri	-0.024	-0.016	-0.027	-0.02					

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. "(est)" stands the estimate of the given coefficient. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). "DC" stands for District of Columbia.

carry a negative sign and as a matter of fact for Hawaii the coefficient estimate is negative and significant.

However the picture changes rather significantly once we control for the initial output by adding lagged y to the regression equation in Model 3. We find that in Model 3 the number of coefficient estimates of lagged pat which carry a positive significant sign increases to fifteen. These results imply that R&D affects the growth rate of output positively.

These results support the hypothesis advanced in this study. That is, in a growth regression neither the initial level of output nor the initial level of R&D should be ignored.

Our next task is to quantify the implied speed of convergence, i.e. the estimates of β.

Speed of convergence using US state-level data. The estimates of the implied speed of convergence, i.e., β, are presented in Table 7.

TABLE 7.

Implied speed of convergence using US state-level data

State	Model 1	Model 3	State	Model 1	Model 3	State	Model 1	Model 3
Alabama	0.019	0.021	Kentucky	0.032	0.669^a	North Dakota	0.047	0.063^c
Alaska	0.106^c	0.096	Louisiana	0.053	0.466^a	Ohio	0.021	0.024
Arizona	0.033	0.517^a	Maine	0.015	0.584^a	Oklahoma	0.036	0.116^b
Arkansas	0.735^a	0.739^a	Maryland	0.012	0.472^a	Oregon	0.022	0.052
California	0.011	0.471^a	Massachusetts	0.326^a	0.005	Pennsylvania	0.505^a	0.517^a
Colorado	0.021	0.035	Michigan	0.043	0.038	Rhode Island	0.002	0.445^a
Connecticut	0.013	0.014	Minnesota	0.021	0.633^a	South Carolina	0.036^c	0.029
Delaware	0.006	0.733	Mississippi	0.04^b	0.053^b	South Dakota	0.028	0.038^c
DC	0.013	0.009^a	Missouri	0.024	0.027	Tennessee	0.029	0.579^a
Florida	0.025	0.02	Montana	0.032	0.054	Texas	0.035	0.05^c
Georgia	0.036	0.025	Nebraska	0.026^c	0.767^a	Utah	0.002	0.52^a
Hawaii	0.052	0.007	Nevada	0.038	0.047	Vermont	0.639^a	0.643^a
Idaho	0.032	0.103^c	New Hampshire	0.022	0.468^a	Virginia	0.015	0.015
Illinois	0.013	0.575^a	New Jersey	0.012	0.013	Washington	0.024	0.465^a
Indiana	0.016	0.64^a	New Mexico	0.016	0.026	West Virginia	0.022	0.616^a
Iowa	0.025	0.051^c	New York	0.002	0	Wisconsin	0.013	0.015
Kansas	0.028^b	0.029^b	North Carolina	0.022	0.626^a	Wyoming	0.07	0.046

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. These significance levels are corresponding to estimates of b_{11} and b_{31} in Models 1 and 3, respectively. The estimates of b_{11} and b_{31}, along with their significance levels are presented in Table 1. "DC" stands for District of Columbia.

In Table 7 column labeled Model 1 presents the speed of convergence implied by the coefficient estimates of b_{11} presented in Table 6. Recall that in Model 1 the only independent variable is lagged y. Looking at the results we find that there is great variation in speeds of convergence estimates.[15] The average speed of convergence using only significant estimates (nine states) of Model 1 is about 27% per year with a standard error of 0.096. Nebraska has the lowest estimate of about 2.5% and Arkansas has the highest estimate of about 73.5%. The 95% confidence interval for the speed

[15] The variation in speeds of convergence finds support in the literature. See Evans (1997), for instance.

of convergence estimates is $[0.0498; 0.4927]$, indicating that the speed of convergence is statistically significantly different from zero.

The implied speed of convergence after we control for a states R&D activity by adding lagged *pat* to the regression equation is presented in Table 7 under column labeled Model 3. The implied speed of convergence after controlling for a state's R&D is derived from the estimates of b_{31} which are presented in Table 6.

As we noted while discussing the regression results, once we control for a state's R&D activity, the number of states carrying significantly negative coefficient estimates for lagged y increases to twenty nine. Looking at the implied speed of convergence we find that the average speed of convergence increases to about 41.1% per year with a standard error of 0.0474. This gives us a 95% confidence interval of $[0.314; 0.508]$. These results not only indicate that the implied speed of convergence increases after we control for the R&D activity, they also point out that the standard error also decreases making the estimates more precise.

Next we quantify the possible bias due to omitting R&D from growth regressions.

Omitted variable bias using US state-level data. In order to quantify the magnitude of bias that may result due to omitting R&D from a growth regression we use Equation 4, reproduced here for convenience.

$$pat_t = \delta_0 + \delta_1 y_t + \omega_t \tag{5}$$

A quantitative measure of the omitted variable bias is obtained by multiplying the estimate of c_{32} (Equation 3) by the estimate of δ_1 (Equation 4). That is:

$$Bias = c_{32} \times \delta_1$$

Estimated coefficient values of δ_1 are presented in Table 8.

The estimated omitted variable bias using only the statistically significant coefficient estimates of c_{32}, Equation (3) and δ_1, Equation (4), are reported in Table 9.

The mean of the estimated omitted variable bias is 0.0338 with a standard error of 0.0075, indicating that the omitted variable is statistically significantly different from zero at the 95% level.

These results further support our hypothesis that failure to control for the R&D activity may bias the coefficient estimates in a growth regression. In addition, in order to estimate the impact of R&D on the output growth rate of a state some measure of initial level of output should be taken into account.

Now we turn to the panel estimation results. The datasets used for the panel estimations are the same as the ones used for the time series estimations.

TABLE 8.

Regression results Equation (4) using US state-level data

State	δ_1(est)	State	δ_1(est)	State	δ_1(est)	State	δ_1(est)
Alabama	0.288	Illinois	0.683	Montana	1.218^a	Rhode Island	0.595
Alaska	-0.607^b	Indiana	0.135	Nebraska	0.625^a	South Carolina	0.717^a
Arizona	0.638^a	Iowa	0.535	Nevada	0.504	South Dakota	0.380
Arkansas	0.536	Kansas	0.202	New Hampshire	0.898^a	Tennessee	0.638^c
California	0.881	Kentucky	0.016	New Jersey	-0.447^b	Texas	0.316
Colorado	1.141^a	Louisiana	−0.107	New Mexico	0.688	Utah	0.975^a
Connecticut	−0.036	Maine	0.651^a	New York	0.331	Vermont	1.844^a
Delaware	−0.515	Maryland	0.055	North Carolina	1.016^a	Virginia	−0.004
DC	−0.261	Massachusetts	0.728^c	North Dakota	0.473	Washington	1.496^a
Florida	0.354	Michigan	0.466	Ohio	0.124	W. Virginia	-0.716^b
Georgia	1.094^a	Minnesota	1.111^a	Oklahoma	-1.106^a	Wisconsin	0.553
Hawaii	1.178^a	Mississippi	0.870^b	Oregon	1.606^a	Wyoming	−0.206
Idaho	0.158	Missouri	−0.137	Pennsylvania	−0.165		

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. "(est)" stands the estimate of the given coefficient. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). "DC" stands for District of Columbia.

TABLE 9.

Omitted variable bias using US state-level data

State	Bias	State	Bias	State	Bias
Arizona	0.0268	Nebraska	0.0188	Tennessee	0.0402
Hawaii	0.0506	New Hampshire	0.0045	Utah	0.0273
Maine	0.0052	North Carolina	0.0599	Vermont	0.0166
Minnesota	0.0222	Oklahoma	0.0829	Washington	0.0793
				West Virginia	0.0057

Mean = 0.0338; Standard Error = 0.0075; 95% Confidence Interval = $[0.018; 0.0502]$. Only states for which coefficients in both equations (Equation 3 and Equation 4) were significant at least at the 10% level are included in the calculation.

5.2. Results Using Panel Data Estimation

In this sub-section we present and discuss regression results using panel data. Following panel estimation convention (see, for instance, Islam 1995) we rewrite our model presented in the Model section in the following form. Equations (5), (6), and (7) are the panel counterparts of Equation (1), (2), and (3) above.

$$Gry_{it,t-j} = a_{50} + b_{51} y_{it-j} + \varepsilon_{i5,t} \tag{6}$$

and $\varepsilon_{i5,t} = \rho_{51}\varepsilon_{i5,t-1} + \rho_{52}\varepsilon_{i5,t-2} + \cdots + \rho_{5k}\varepsilon_{i5,t-k} + \nu_{i5,t}$

$$Gry_{it,t-j} = a_{60} + c_{61}pat_{it-j} + \varepsilon_{i6,t} \tag{7}$$

and $\varepsilon_{i6,t} = \rho_{61}\varepsilon_{i6,t-1} + \rho_{62}\varepsilon_{i6,t-2} + \cdots + \rho_{6k}\varepsilon_{i6,t-k} + \nu_{i6,t}$

$$Gry_{it,t-j} = a_{70} + b_{71}y_{it-j} + c_{72}pat_{it-j} + \varepsilon_{i7,t} \tag{8}$$

and $\varepsilon_{i7,t} = \rho_{71}\varepsilon_{i7,t-1} + \rho_{72}\varepsilon_{i7,t-2} + \cdots + \rho_{7k}\varepsilon_{i7,t-k} + \nu_{i7,t}$

Where $Gry_{it,t-j}$ is the growth rate of real per capita output, y_i, of economy i from year $t-j$ to t, and y_{it} and pat_{it} are the logs of real per capita output and per capita patents granted in economy i at time t, respectively. y_{it-j} and pat_{it-j} are values of y_i and pat_i lagged j periods. $\varepsilon_{im,t}$, for $m = 5, 6, 7$, is the error term which may have an autocorrelation of order k, where k is determined by the data. Letters a, b, and c are the coefficients to be estimated. First, staying consistent with the time series results, we estimate growth rates over one-year, i.e., $j = 1$. Then, following Islam (1995) we estimate growth rates over a five-year period, i.e. $j = 5$. Then we go a step further and also estimate growth rates over a ten-year period, i.e., $j = 10$. That is, we present and discuss results for $j = 1, 5$, and 10.These different lag periods allow us to test for the sensitivity of our results.

Following the arguments made by Islam (1995, 1138) and the analysis of Balestra and Krishnakumar (2008), we use the fixed-effects approach model. As Islam (1995, p.1138) points out that the choice between a fixed-effects and a random-effects model depends upon the correlation between the individual effects and the right-hand-side variables. For a random-effects model to be appropriate it is assumed that the individual effects are uncorrelated with the right-hand-side variables. However in our case it is precisely this correlation that caused the omitted variable bias shown in time series regression results (Tables 5 and 9 above), and the presence of this correlation is the reason for using a panel estimation.

We also find support for using a fixed-effects model from the Hausman test statistics in both datasets. With regard to the Hausman test statistics, Johnston and DiNardo (1997, p.404) note that in datasets such as this, it is preferable to use a fixed-effects model even if the Hausman test statistic turns out to be insignificant.

In order to calculate the coefficient significance levels we used the so-called heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. For details on HAC standard errors please see Stock and Watson (2003, pp. 502-506), Hamilton (1994, pp.281-283), among others.

In order to test for panel unit roots in the data we used tests suggested by Breitung and Pesaran (2008, pp.295-298). We used two panel unit root tests. One based on Breitung and Pesaran (2008) Equation (9.37) page 296, and the other so-called cross sectionally augmented Dickey-Fuller (CADF) test suggested by Breitung and Pesaran (2008) on page 297. Coakley, et al. (2005) use a variant of the CADF test while testing the Purchasing Power Parity hypothesis using data for fifteen OECD countries. We follow Coakley, et al. (2005) and apply their Equation (6), p.210, to test unit roots in real per capita output, y, and per capita patents, pat, in our data. More specifically, in order to test unit root in output, y, we used Equations (8) and (9) below.

$$\Delta y_{it} = \alpha_i + \varphi_i y_{i,t-1} + u_{it} \quad \text{for} \quad i = 1, \ldots, n; \quad t = 1, \ldots, T \tag{9}$$

The CADF variant of this test takes the following form:

$$\Delta y_{it} = \alpha_i + \varphi_i y_{i,t-1} + \gamma_i \overline{y}_{t-1} + \delta_i \Delta \overline{y}_t + \xi_i \Delta y_{i,t-1} + \eta_{it} \tag{10}$$

In both equations we test the null:
$H_0 : \varphi_i = 0$ for all i against the alternative[16]
$H_1 : \varphi_i < 0$ for all $i = 1, \ldots, N_1$; and $\varphi_i = 0$ for all $i = N_1 + 1, \ldots, N$.
Where $\overline{y_t}$ is the cross sectional mean of y_{it}.
Unit root test for per capita patents, pat, were conducted analogously.

We use this model and these panel unit root tests for both the OECD dataset and the US state-level dataset.

At this point it is important to note that our time series estimates are not directly comparable with panel regression estimates. The reason is that while using the time series model, we tested the hypothesis of output convergence to an economy's own steady-state. In using panel estimation we are exploiting the cross-sectional as well as time series dimensions of data and testing the hypothesis of output convergence across economies.

Panel estimation results using OECD data. As noted in Table 1, not all 30 OECD countries have data available from 1985 to 2003. In order to "balance" the panel we exclude countries which had a shorter time series. That is, we exclude the Czech Republic, Hungary, Poland, and the Slovak Republic. This leave us with a panel of 26 countries (i.e., $i = 1, \ldots, 26$). Using data for these 26 countries we conduct panel unit root tests using Equations 8 and 9. Results are presented in Table 10.

Both panel unit root tests reject the null of $\varphi_i = 0$, for all i, at the 1% significance levels. The implication is that most time series included in the panel are stationary.[17] Having satisfied the stationarity issue, we proceed with panel estimation.

Table 11 below presents the panel estimation results using OECD data for the growth rates over one-, five-, and ten-year periods. In Table 11, the

[16] The alternative is the so-called "heterogeneous alternative." See Breitung and Pesaran (2008, p.282).

[17] See Breitung and Pesaran (2008) for an in-depth discussion of panel unit root tests.

TABLE 10.

Panel unit root test results using data for 26 OECD countries

Variable	Equation 8, φ(est) (p-values)	Equation 9, φ(est) (p-values)
y	-0.973^a	-1.22^a
	(0.000)	(0.000)
pat	-0.993^a	-1.181^a
	(0.000)	(0.000)

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. "(est)" stands the estimate of the given coefficient. Estimates based on "panel corrected standard errors" suggested by Beck and Katz (1995).

dependent variable Gry_1 indicates that the growth rate of real per capita output is calculated over a one-year period, and the independent variables y_{t-1} and pat_{t-1} are the values of the y and pat lagged one year. Analogous explanations are used for Gry_5, y_{t-5}, and pat_{t-5}, and Gry_{10}, y_{t-10}, and pat_{t-10}, for five- and ten-year periods, respectively.

TABLE 11.

Panel estimation results using data for 26 OECD countries

Dependent Variable: Gry_1				Dependent Variable: Gry_5				Dependent Variable: Gry_{10}			
Variable	Model 5	Model 6	Model 7	Variable	Model 5	Model 6	Model 7	Variable	Model 5	Model 6	Model 7
Const.	0.132^a	0.016	0.161^a	Const.	0.6^b	0.11^b	0.729^a	Const.	1.075^a	0.193^a	1.095^a
	(0.000)	(0.202)	(0.007)		(0.011)	(0.011)	(0.0099)		(0.001)	(0.000)	(0.001)
y_{t-1}	-0.037^b		-0.043^b	y_{t-5}	-0.165^b		-0.193^b	y_{t-10}	-0.294^a		-0.298^a
	(0.016)		(0.015)		(0.037)		(0.032)		(0.008)		(0.007)
pat_{t-1}		-0.001	0.002	pat_{t-5}		0.00	0.009	pat_{t-10}		-0.003	0.002
		(0.635)	(0.394)			(0.963)	(0.184)			(0.694)	(0.715)
$\overline{R}^2$	0.16	0.13	0.17	$\overline{R}^2$	0.5	0.46	0.51	$\overline{R}^2$	0.84	0.81	0.84
F-stat	4.49^a	3.85^a	4.54^a	F-stat	14.67^a	13.14^a	14.84^a	F-stat	46.94^a	40.58^a	45.71^a
(p-value)	(0.000)	(0.000)	(0.000)	(p-value)	(0.000)	(0.000)	(0.000)	(p-value)	(0.000)	(0.000)	(0.000)
Implied β	0.036		0.042	Implied β	0.031		0.035	Implied β	0.023		0.026
H-stat	9.48^a	0.09	8.89^b	H-stat	9.58^a	0.38	7.69^b	H-stat	8.61^a	0.11	8.09^b
(p-value)	(0.002)	(0.761)	(0.012)	(p-value)	(0.002)	(0.538)	(0.021)	(p-value)	(0.003)	(0..739)	(0.018)
SBC	-1966.1	-1949.1	-1961.7	SBC	-860.88	-896.1	-860.27	SBC	-587.98	-546.89	-582.73

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). F-stat represents the test statistics (with p-value in parentheses) for a common group intercept. The null hypothesis is that the groups have a common intercept. H-stat represents the Hausman test statistic. A significant value points to the preference for the use of a fixed-effect model. Implied β is the implied speed of convergence. SBC stands for Schwartz Baysian Information Criteria.

The panel estimation results confirm the conclusions of the time series regression results.[18] Once we control for R&D, the coefficient estimates of the initial level of output increase in magnitude (in absolute terms) while maintaining the significance levels.

Let us start with the results with the dependent variable is Gry_1. That is, where the growth rate of real per capita output is calculated over one year. In Model 5 where the only independent variable is y_{t-1} (y lagged one-year), the coefficient estimate is -0.037 and it is significant at the 5% level. Once we control for R&D in Model 7, the coefficient value associated with y_{t-1} increases (in absolute terms) to -0.043 while staying significant at the 5% level.

We find similar pattern in the results where the dependent variables are Gry_5 and Gry_{10}. That is, where growth rates are measured over five- and ten-year periods, respectively. For instance, with the dependent variable Gry_5 in Model 5 where the only independent variable is y_{t-5} (y lagged five-years) the coefficient estimate is -0.165 and it is significant at the 5% level. Once we control for R&D activity in Model 7, the coefficient estimate increases (in absolute terms) to -0.193 and stays significant at the 5% level. These results indicate that the omission of the R&D activity of a country from a growth regression may lead to biased estimates.

In addition, the estimates of the implied speed of convergence (Implied β in Table 11) also increase when we control for the R&D activity. For instance, in models where we calculate growth rate over a five-year period, the implied speed of convergence increases from 0.031 per year in Model 5 to 0.0352 per year in Model 7. We find a similar pattern when we calculate growth rate over a one-year or a ten-year period. The estimates of the implied speed of convergence fall within the range reported in the literature (Islam 1995, 2003).

The coefficient estimates of pat_{t-l}, for $l = 1, 5$, or 10, the variable representing a country's R&D activity, are not significant in any model. This is true whether we control for the initial level of output or not. One explanation for these results may be that we are using a panel estimation procedure and the effects of a country's R&D activity are being captured by the constant terms. Since, the estimates of the constant terms increase and remain significant as we add both pat_{t-l} and y_{t-l}, for $l = 1, 5$, or 10, to the regression equation, the constant term serves as the Pandora's Box.

Furthermore, even though the coefficient estimates of pat are not significant in any regression, they follow a pattern that points to the need for controlling for the initial level of output while estimating the impact of R&D on the growth rate. For instance, in Model 6 using growth rate

[18]It is again reassuring to see that in panel estimation, as in time series regressions, the SBC statistics point out that one-year lag is appropriate for this dataset and the variables used in this model.

over a five-year period, where the only independent variable is pat_{t-5} the estimated coefficient value is 0.00 with a p-value of 0.963. Whereas, in Model 7, when we add the output variable to the regression equation the estimated value of pat_{t-5} increases to 0.009 with a p-value of 0.184. We find a similar "directional" pattern when we measure growth rate over a one- or a ten-year period.

Next we present and discuss penal estimation results using US state-level data.

Panel estimation results using US state-level data. We start by presenting panel unit root tests using US state-level data. We use Equations 8 and 9 to conduct panel unit root tests. Results are presented in Table 12.

TABLE 12.

Panel unit root test results using US state-level data

Variable	Equation 8, φ (est) (p-values)	CADF, Equation 9, φ (est) (p-values)
y	-0.43^a	-1.05^a
	(0.000)	(0.000)
pat	-0.919^a	-1.06^a
	(0.000)	(0.000)

Significance Levels: a = 1%; b = 5%; c = 10%. "(est)" stands the estimate of the given coefficient. Estimates based on "panel corrected standard errors" suggested by Beck and Katz (1995).

Here again, both panel unit root tests reject the null of $\varphi_i = 0$, for all i, at the 1% significance levels, pointing to the stationarity of the panel.

Using the US state-level data panel estimation results of a fixed-effects model are presented in Table 13.

It is again reassuring to find that the results of the panel estimation also support our hypothesis. It is also reassuring that the main results of the study are not sensitive to lag length. First of all, the coefficient estimates of lagged y are statistically significant at the 1% level and carry theoretically "correct" negative signs in all estimations.

Second, once we control for the R&D activity by adding lagged pat to the regression equation in Model 7 the coefficient estimates of lagged y increase in magnitude (in absolute terms) for estimations using one-year and five-year growth rates of real per capita output as dependent variables. The estimates also maintain their significance levels. In the regression equation where we use the growth rate of real per capita output over a ten-year period, the coefficient estimates of lagged y are identical in magnitude as well as in significance level with or without lagged pat, Model 7 and Model 5, respectively.

TABLE 13.

Panel estimation results using US state-level data

Dependent Variable: Gry_1				Dependent Variable: Gry_5				Dependent Variable: Gry_{10}			
Variable	Model 5	Model 6	Model 7	Variable	Model 5	Model 6	Model 7	Variable	Model 5	Model 6	Model 7
Const.	-0.165^a	-0.009	-0.149^a	Const.	-0.827^a	0.001	-0.746^a	Const.	-1.521^a	0.194	-1.554^a
	(0.000)	(0.685)	(0.000)		(0.000)	(0.992)	(0.000)		(0.000)	(0.585)	(0.000)
y_{t-1}	-0.023^a	-	-0.024^a	y_{t-5}	-0.112^a	-	-0.115^a	y_{t-10}	-0.206^a	-	-0.206^a
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.001)
pat_{t-1}	-	-0.004	0.003	pat_{t-5}	-	-0.012	0.013	pat_{t-10}	-	-0.003	-0.004
		(0.141)	(0.319)			(0.399)	(0.479)			(0.942)	(0.922)
$\overline{R}^2$	0.02	-0.01	0.02	$\overline{R}^2$	0.12	0.02	0.12	$\overline{R}^2$	0.21	0.06	0.2
F-stat	1.136	0.44	1.164	F-stat	4.249^a	1.623^a	4.307^a	F-stat	7.243^a	3.135^a	7.059^a
	(0.24)	(0.999)	(0.203)		(0.000)	(0.004)	(0.000)		(0.000)	(0.000)	(0.000)
H-stat	37.13^a	1.31	39.43^a	H-stat	99.74^a	2.01	102.63^a	H-stat	87.82^a	0.344	83.11^a
	(0.000)	(0.253)	(0.000)		(0.000)	(0.157)	(0.000)		(0.000)	(0.558)	(0.000)
Implied β	0.023	-	0.024	Implied β	0.024	-	0.024	Implied β	0.023	-	0.023
SBC	-8051.4	-7983.5	-8045.3	SBC	-3839.5	-3612.0	-3836.1	SBC	-2313.4	-2018.9	-2306.0

Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$. Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). F-stat represents the test statistics (with p-value in parentheses) for a common group intercept. The null hypothesis is that the groups have a common intercept. H-stat represents the Hausman test statistic. A significant value points to the preference for the use of a fixed-effect model. Implied β is the implied speed of convergence. SBC stands for Schwartz Baysian Information Criteria.

As was the case with the OECD data, the coefficient estimates of lagged *pat*, the variable representing R&D activity of states, do not turn out to be significant in any panel estimation. In fact the signs of the coefficients are negative in Model 6 whether the growth rate is measured over one-, five-, or ten-year periods. One finds some consolation in the fact that when we control for lagged y in Model 7, at least the negative sign for the lagged *pat* coefficient disappears, except in the estimation where the growth rate is measured over a ten-year period.

The implied speed of convergence (Implied β in Table 13) is between 2.3% and 2.4% per year. This is in broadly in line with the results of studies using similar data and methodology. See Islam (2003) for an excellent review of literature on the topic.

To sum it up, our results support the hypothesis advanced in this study. That is, while estimating the impact of the initial level of output in a growth equation one cannot ignore the impact of R&D in an economy. These results are not sensitive to the estimation procedures or the two datasets used in this study.

In the case of panel estimation the results are more pronounced when the OECD data are used. This is especially the case with regard to the coefficient estimates of lagged y. However, the coefficient estimates of lagged pat in panel data estimation do not turn out to be significant in either dataset. But we do find that even in this case the results are "directionally" similar to the time series results.

6. CONCLUSION

In this paper we ask the question whether failure to control for an economy's R&D activity results in a biased estimates of the initial output in a growth equation. We test this hypothesis using recent OECD member countries' and US state-level real per capita output and per capita patents data. We use number of per capita patents as a proxy for an economy's R&D activity. Our results support the hypothesis advanced in this study. Coefficient estimates of the initial output variable increase in magnitude (in absolute value) and in statistical significance after we control for an economy's R&D activity. Furthermore, while measuring the impact of R&D on output growth rate using time series estimation the coefficient estimates for the R&D activity become positive and significant once we control for the initial of output variable.

These results indicate that without controlling for R&D activity the coefficient estimates will suffer from omitted variable bias. The size of omitted variable bias is statistically significantly different from zero.

We also use panel estimation. The results of the panel estimation render further support to the hypothesis advanced in this study. Not only do we find evidence of output convergence across economies, the coefficient estimates of the initial output variable in our growth regression also increase in magnitude once we control for R&D. These results are important from a policy perspective. Public policies based on imprecise and biased estimates rarely reach their intended targets.

APPENDIX A

Details of Time Series Estimation Procedure

This appendix explains the estimation procedure used for regression coefficient estimates. It is based on Ramanathan (2002), Chapters 9 and 10. The steps provided here are as outlined on pp. 392-395 and pp. 449-450.

Assume that our model is given by

$$y_t = b_0 + b_1 y_{t-1} + b_2 pat_{t-1} + \varepsilon_t \tag{A.1}$$

and

$$\varepsilon_t = \rho \varepsilon_{t-1} + \nu_t \tag{A.2}$$

We assume that ν_t is white noise. Because ε_t depends upon its lagged value, ε_{t-1}, this means that y_{t-1} (and pat_{t-1}) are correlated. This violates the regression assumptions and Ordinary Least Squares (OLS) procedure cannot be used to estimate bs. The OLS estimates will be biased and incosistent. To overcome this problem we used a "mix" of the Cochrane-Orcutt itterative procedure (CO) and the Hildreth-Lu search procedure (HL). See Ramanathan (2002, pp. 396-397) for details. The steps followed are:

1. We chose a value of ρ (say ρ_1) between -1 and $+1$ and transformed the variables as: $y^*_t = y_t - \rho y_{t-1}$; $pat^*_{t-1} = pat_{t-1} - \rho pat_{t-2}$; $b^*_0 = b_0(1-\rho)$, for all (remaining) t. There will be missing values due to lagging of variables.
2. Using the transformed variables we estimated Equation (A.1) by OLS.
3. We derived $\hat{\varepsilon}_t$ from Equation (A.1) and the associated error sum of squares (ESS), and called it ESS(ρ_1). Next we chose another ρ (say ρ_2) and repeated Steps 1 and 2.
4. By varying the values of ρ by 0.1 (between -1 and $+1$) we obtained a series of ESSs. Next we picked the ρ that minimized the ESS. This ensures a global minimum.
5. We used the ρ picked in Step 4 to start the CO iterative procedure. We continued the CO iterative procedure until the difference in successive $\hat{\rho}$, the estimate of ρ, was less than 0.005

Although the estimates obtained with this procedure will be consistent, the standard errors will be inconsistent (Ramanathan, 2002, p.450). Following Ramanathan's recommendation, in order to obtain consistent standard errors we carried out the final step.

6. We regressed $\hat{\nu}_t$, the estimate of ν_t from Equation (A.2), on y^*_{t-1}; pat^*_{t-1}; and $\hat{\varepsilon}_{t-1}$. We used the standard errors of regression coefficients obtained in Step 6 (which are consistent) to calculated the levels of significance reported in the study.

APPENDIX B

Detailed Time Series Regression Results

The following models (reproduced here for convenience) have been estimated in these regressions. Details of estimation procedure are provided in Appendix A.

$$Gry_{t,t-1} = a_{10} + b_{11}y_{t-1} + \varepsilon_{1,t} \tag{B.1}$$

and $\varepsilon_{1,t} = \rho_{11}\varepsilon_{1,t-1} + \rho_{12}\varepsilon_{1,t-2} + \cdots + \rho_{1k}\varepsilon_{1,t-k} + \nu_{1,t}$

$$Gry_{t,t-1} = a_{20} + c_{21}pat_{t-1} + \varepsilon_{2,t} \tag{B.2}$$

and $\varepsilon_{2,t} = \rho_{21}\varepsilon_{2,t-1} + \rho_{22}\varepsilon_{2,t-2} + \cdots + \rho_{2k}\varepsilon_{2,t-k} + \nu_{2,t}$

$$Gry_{t,t-1} = a_{30} + b_{31}y_{t-1} + c_{32}pat_{t-1} + \varepsilon_{3,t} \tag{B.3}$$

and $\varepsilon_{3,t} = \rho_{31}\varepsilon_{3,t-1} + \rho_{32}\varepsilon_{3,t-2} + \cdots + \rho_{3k}\varepsilon_{3,t-k} + \nu_{3,t}$

Details of variables are as provided in the Model section.

Note that Models 1-3 can be rewritten as having a lagged dependent variable form. This is because $Gry_{t,t-1} = y_t - y_{t-1}$. Using this fact we can, for instance, rewrite Model 1 as:

$$\begin{aligned} y_t - y_{t-1} &= a_{10} + b_{11}y_{t-1} + \varepsilon_{1,t} \\ y_t &= y_{t-1} + a_{10} + b_{11}y_{t-1} + \varepsilon_{1,t} \\ y_t &= a_{10} + (1 + b_{11})y_{t-1} + \varepsilon_{1,t} \end{aligned}$$

Analogously for Model 2. Model 3 will take the form:

$$y_t = a_{20} + y_{t-1} + c_{21}pat_{t-1} + \varepsilon_{2,t}$$

And the error structures are as defined above in all three models.

In the presence of a lagged dependent variable the use of Durbin-Watson statistic to detect first-order serial correlation in error terms is no longer valid (See for instance, Ramanathan 2002, Chapter 10). An alternative is use the so called Durbin h-test (Durbin 1970). However the Durbin h-test is not valid under certain condition including the presence of higher order serial correlation, which might be the case in the data used in this paper. As a result we use the Breusch-Godfrey Lagrange Multiplier test (BG-LM test). Under the null hypothesis all ρs are equal to zero; and under the alternative not all ρs are equal to zero. The test statistic, represented in the following tables by λ, has a χ^2 distribution with degrees of freedom equal to k, the order of autocorrelation of the error term. A higher p-value associated with the λ statistic indicates an absence of autocorrelation. See Ramanathan (2002, Chapter 10, 446-448).

Note that the coefficients, b_{11} and b_{31}, associated with y_{t-1} (Models 1 and 3, respectively) are equal to $(1-e^{-\beta t})$, where β is the speed of convergence. That is, the speed at which y_t reaches its steady state value, y^*. The coefficients estimates are based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003).

In the following tables p-values are provided in the parentheses, n is the time series number of observations, $\overline{R}^2$ is the adjusted R^2, and λ is the BG-LM test statistic. The λ statistics provided in the results below are based on "rho-differenced" data.

Table B.1 Detailed regression results using OECD time series data

Country	Australia			Austria			Belgium			Canada			Czech Republic		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.002	0.049	146.84^b	0.135	0.107	0.676^a	0.192	0.025	3.28^a	1.176^c	0.056	1.019	2.241^a	-0.123	197.14^a
y_{t-1}	0.008	-	-0.621^a	-0.036	-	-0.133^a	-0.055	-	-0.966^a	-0.344^a	-	-0.23	-0.715^a	-	-0.79^a
pat_{t-1}	-	0.006	-0.02^a	-	0.024	0.064^a	-	-0.013	-0.056^a	-	0.009	0.061	-	-0.021	-0.027^a
$\overline{R}^2$	0.09	0.1	0.08	0.05	0.09	0.46	0.08	0.02	0.11	0.26	0.25	0.3	0.19	0.38	0.52
λ	0.588	0.533	3.2^c	0.227	0.588	0.553	0.062	0.015	3.042^c	0.538	0.617	1.191	0.403	0.891	4.065
Country	Denmark			Finland			France			Germany			Greece		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.01	0.064	1.142^a	0.641	-0.074	0.777	0.277	0.167	1.307^a	1.539^c	0.053	7.459^a	-0.377^c	0.092	-0.266
y_{t-1}	0.007	-	-0.261^a	-0.196	-	-0.202	-0.082	-	-0.242^a	-0.481^a	-	-1.938^a	0.135^b	-	0.114^c
pat_{t-1}	-	0.014	0.082^a	-	0.02	0.046	-	0.045	0.155^a	-	0.033	0.468^a	-	0.009	0.006
$\overline{R}^2$	-0.06	0.04	0.52	0.46	0.43	0.5	0.22	0.2	0.55	0.12	-0.05	0.52	0.23	0.13	0.2
λ	0.473	0.143	3.441	2.668	1.662	3.818	0.075	1.028	0.05	0.029	0.023	0.88	0.283	0.065	0.388
Country	Hungary			Iceland			Ireland			Italy			Japan		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.52	0.12	0.029	2.103^b	0.013	2.066^b	0.134	-0.013	3.57^b	0.344^b	0.269	2.407^a	2.13^a	0.207	2.667^a
y_{t-1}	0.038	-	0.041	-0.608^a	-	-0.597^a	-0.025	-	-0.602^a	-0.104^c	-	-0.625^a	-0.656^a	-	-0.749^a
pat_{t-1}	-	0.013	0.015	-	0.000	-0.000	-	-0.015	0.018^b	-	0.057	0.082^a	-	0.082	0.097^a
$\overline{R}^2$	0.56	0.59	0.55	0.09	0.08	0.02	0.16	0.17	0.13	0.39	0.32	0.54	0.62	0.43	0.72
λ	0.88	0.747	0.835	0.515	0.368	0.838	0.027	0.186	4.188	0.272	1.632	0.11	1.321	1.746	1.215

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

Table B.1 *continued*

Country	Korea			Luxembourg			Mexico			Netherlands			New Zealand		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.227^a	-0.013	0.453	0.236	0.028	3.583^a	0.358	-0.154	1.3^b	0.62	0.135	0.648^c	-0.016	-0.131^b	0.646
y_{t-1}	-0.069^b	-	-0.132	-0.054	-	-0.827^a	-0.165	-	-0.362^b	-0.184	-	-0.151^c	0.009	-	-0.156
pat_{t-1}	-	-0.011^c	0.012	-	-0.002	0.01^a	-	0.015	0.057^b	-	0.042	0.047	-	0.024^c	0.034^b
$\overline{R}^2$	0.2	0.17	0.16	0.1	0.01	0.08	0.03	-0.03	0.27	0.43	0.43	0.48	0.09	0.31	0.37
λ	0.034	0.038	0.07	0.502	0.037	1.793	0.185	0.011	1.081	1.794	1.986	2.299	0.288	0.223	2.727
Country	Norway			Poland			Portugal			Slovak Republic			Spain		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.1	-0.087	1.347	0.24^b	0.01	1.707^a	0.717^b	0.048	0.985^b	1.432^b	0.008	0.345	0.342	0.007	2.04^b
y_{t-1}	-0.024	-	-0.346^a	-0.087^c	-	-0.612^a	-0.249^b	-	-0.352^b	-0.554^a	-	-0.148^c	-0.108	-	-0.504^a
pat_{t-1}	-	-0.026	-0.029^a	-	-0.004	0.004	-	-0.009	-0.004	-	-0.004	0.005	-	-0.003	0.053^a
$\overline{R}^2$	0.31	0.37	0.38	0.48	0.24	0.45	0.63	0.51	0.62	0.44	0.16	0.37	0.44	0.37	0.48
β	0.995	0.554	4.853	0.219	0.889	0.498	1.132	0.59	0.822	1.479	1.605	0.707	1.423	0.968	0.935
Country	Sweden			Switzerland			Turkey			UK			USA		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.198	0.077	0.594	1.292^c	0.162	1.964^a	2.703^a	-0.024	2.621^a	0.076	0.03	4.28^b	0.11	-0.048	-1.129
y_{t-1}	-0.057	-	-0.14	-0.382^a	-	-0.496^a	-1.412^a	-	-1.388^a	-0.018	-	-0.683^a	-0.027	-	0.226
pat_{t-1}	-	0.023	0.05	-	0.072	0.133^a	-	-0.004	-0.009^a	-	0.002	0.089^a	-	-0.022	-0.124
$\overline{R}^2$	0.27	0.3	0.33	0.3	0.21	0.47	0.23	0.12	0.38	0.35	0.34	0.41	0.08	0.11	0.15
λ	0.193	0.175	0.309	1.009	0.296	1.017	0.524	0.964	0.384	1.357	1.837	3.766^c	0.032	0.027	0.102

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

Table B.2 Detailed regression results using US state-level time series data

State	Alabama			Alaska			Arizona			Arkansas			California		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.139	0.019	-0.083	-0.845^c	0.657	-0.542	-0.269	0.03	-4.915^a	-8.468^a	-0.078	-8.884^a	-0.075	0.054	-3.631^a
y_{t-1}	-0.019	-	-0.021	-0.112^c	-	-0.101	-0.034	-	-0.677^a	-1.086^a	-	-1.093^a	-0.011	-	-0.601^a
pat_{t-1}	-	-0.001	0.01	-	0.065	-0.022	-	0.001	0.042^a	-	-0.01	-0.037^a	-	0.004	0.025^a
$\overline{R}^2$	0.03	-0.01	0.01	0.09	0.03	0.07	0.1	0.08	0.11	0.07	-0.01	0.1	0.15	0.15	0.14
λ	0.135	0.246	0.211	0.276	0.029	0.008	0.277	0.395	1.048	0.043	0.041	1.294	1.102	1.099	1.436
State	Colorado			Connecticut			District of Columbia			Delaware			Florida		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.15	0.033	-0.148	-0.08	-0.278	-0.416	-0.061	0.082	-3.945^a	0.073	-0.116	-0.227	-0.189	-0.203	-0.18
y_{t-1}	-0.021	-	-0.036	-0.013	-	-0.014	-0.013	-	-1.081^a	0.006	-	-0.009	-0.025	-	-0.02
pat_{t-1}	-	-0.007	0.015	-	-0.04	-0.043	-	0.005	0.027^a	-	-0.02	-0.025	-	-0.025	-0.004
$\overline{R}^2$	0.12	0.1	0.11	0.15	0.17	0.16	0.02	-0.01	0.08	-0.02	0.01	-0.01	0.21	0.2	0.38
λ	0.082	0.064	0.12	0.297	0.505	0.528	0.108	0.079	0.541	0.136	0.031	0.133	1.987	1.78	0.193
State	Georgia			Hawaii			Idaho			Illinois			Indiana		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.284	-0.226	-0.287	-0.418	-0.428^a	-0.474^c	-0.26	0.017	-0.742^c	-0.085	0.009	-4.584^a	-0.114	0.124	-6.493^a
y_{t-1}	-0.037	-	-0.025	-0.053	-	-0.007	-0.033	-	-0.108^c	-0.013	-	-0.778^a	-0.016	-	-0.896^a
pat_{t-1}	-	-0.027	-0.011	-	-0.045^a	-0.043^a	-	-0.000	0.018	-	-0.001	0.041^a	-	0.012	0.021^a
$\overline{R}^2$	0.22	0.21	0.2	0.29	0.42	0.41	0.04	0.01	0.08	0.06	0.05	0.07	-0.01	-0.01	-0.03
λ	0.421	0.247	0.366	0.348	0.162	0.557	0.362	0.139	0.36	0.092	0.153	1.049	0.118	0.004	0.28

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

Table B.2 *continued*

State	Iowa			Kansas			Kentucky			Louisiana			Maine		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.191	-0.253	0.036	-0.213^c	0.226	-0.003	-0.258	0.002	-7.53^a	-0.422	-0.69	-5.599^a	-0.108	-0.051	-5.082^a
y_{t-1}	-0.025	-	-0.052^c	-0.028^b	-	-0.029^b	-0.033	-	-0.952^a	-0.054	-	-0.594^a	-0.015	-	-0.794^a
pat_{t-1}	-	0.026	0.051^b	-	0.022	0.024^c	-	-0.002	-0.009^a	-	-0.081	-0.093^a	-	-0.008	-0.008^a
$\overline{R}^2$	0.00	0.01	0.08	0.08	0.02	0.12	0.04	-0.02	0.02	0.14	0.17	0.19	0.04	0.03	0.02
λ	0.149	0.045	0.136	0.014	0.048	0.083	0.076	0.015	0.032	0.584	0.45	0.404	0.028	0.013	0.145
State	Maryland			Massachusetts			Michigan			Minnesota			Mississippi		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.075	0.036	-3.488^a	-2.663^a	-0.222	-0.25	-0.35	-0.173	-0.405	-0.147	0.056	-6.363^a	-0.332^b	-0.134	-0.307^b
y_{t-1}	-0.012	-	-0.603^a	-0.385^a	-	-0.005	-0.044	-	-0.039	-0.021	-	-0.884^a	-0.041^b	-	-0.054^b
pat_{t-1}	-	0.002	0.014^a	-	-0.03	-0.029	-	-0.023	-0.011	-	-0.009	-0.02^a	-	-0.015	0.013
$\overline{R}^2$	0.15	0.14	0.13	0.36	0.38	0.37	0.01	-0.01	-0.02	0.02	-0.00	0.00	0.12	0.01	0.11
λ	0.045	0.051	0.168	2.082	2.478	2.452	0.11	0.001	0.14	0.12	0.076	0.261	0.06	0.131	0.05
State	Missouri			Montana			Nebraska			Nevada			New Hampshire		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.183	0.121	-0.387	-0.0263	0.047	-0.273	-0.196	-0.111	-8.977^a	-0.301	0.045	-0.261	-0.162	-0.092	-4.295^a
y_{t-1}	-0.024	-	-0.027	-0.033	-	-0.056	-0.026^c	-	-1.153^a	-0.039	-	-0.048	-0.022	-	-0.596^a
pat_{t-1}	-	-0.016	-0.02	-	0.003	0.02	-	-0.014	-0.03^a	-	0.003	0.012	-	-0.014	-0.005^a
$\overline{R}^2$	0.05	0.03	0.04	0.01	-0.02	0.02	0.08	0.02	0.08	0.16	0.14	0.15	0.17	0.17	0.15
λ	0.126	0.037	0.123	0.079	0.023	0.049	0.095	0.053	1.165	0.487	0.543	0.611	0.191	0.238	0.248

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

Table B.2 *continued*

State	New Jersey			New Mexico			New York			North Carolina			North Dakota		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.076	-0.008	-0.217	-0.113	0.052	-0.083	-6.936	-0.102	-0.104	-0.158	-0.085	-6.776^a	-0.378	0.029	-0.092^c
y_{t-1}	-0.012	-	-0.013	-0.016	-	-0.026	-0.002	-	-0.000	-0.022	-	-0.871^a	-0.048	-	-0.065^c
pat_{t-1}	-	-0.004	-0.017	-	0.003	0.013	-	-0.015	-0.015	-	-0.009	0.059^a	-	0.023	0.045
$\overline{R}^2$	0.25	0.24	0.27	0.01	-0.01	-0.02	0.17	0.18	0.16	0.04	0.03	0.08	0.04	0.01	0.07
λ	0.521	0.958	1.875	0.002	0.001	0.004	0.02	0.156	0.172	0.008	0.001	0.389	0.095	0.057	0.077
State	Ohio			Oklahoma			Oregon			Pennsylvania			Rhode Island		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.153	0.051	-0.297	-0.294	0.049	-1.656^c	-0.163	0.025	-0.24	-4.17^a	-0.028	-4.028^a	0.008	-0.031	-0.565
y_{t-1}	-0.021	-	-0.024	-0.037	-	-0.123^b	-0.022	-	-0.053	-0.657^a	-	-0.677^a	-0.002	-	-0.56^a
pat_{t-1}	-	-0.008	-0.014	-	0.003	-0.075^c	-	0.000	0.022	-	-0.006	0.012^a	-	-0.006	0.021^a
$\overline{R}^2$	0.03	0.01	0.01	0.1	0.07	0.15	0.05	0.04	0.05	0.11	0.11	0.09	0.18	0.19	0.18
λ	0.122	0.017	0.115	0.291	0.267	1.784	0.044	0.036	0.055	0.146	0.106	0.792	0.371	0.448	1.914
State	South Carolina			South Dakota			Tennessee			Texas			Utah		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.29^c	0.309	-0.324	-0.206	0.168	-0.011	-0.219	-0.295	-6.558^a	-0.272	0.071	-0.143	0.002	0.092	125.696^a
y_{t-1}	-0.037^c	-	-0.029	-0.028	-	-0.039^c	-0.029	-	-0.785^a	-0.036	-	-0.051^c	-0.002	-	-0.682^a
pat_{t-1}	-	-0.036	0.011	-	0.014	0.03	-	-0.035	-0.063^a	-	0.005	0.03	-	0.008	0.028^a
$\overline{R}^2$	0.14	0.12	0.12	0.04	0.01	0.07	0.07	0.06	0.1	0.15	0.1	0.16	0.1	0.1	0.1
λ	0.202	0.106	0.19	0.087	0.01	0.123	0.198	0.196	0.116	0.524	0.46	0.661	0.164	0.292	0.601

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

Table B.2 *continued*

State	Vermont			Virginia			Washington			West Virginia			Wisconsin		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-6.533^a	-0.026	-6.535^a	-0.102	0.003	-0.122	-0.172	0.071	-4.064^a	-0.17	0.134	-6.486^a	-0.085	0.045	-0.042
y_{t-1}	-0.895^a	-	-0.902^a	-0.015	-	-0.015	-0.024	-	-0.592^a	-0.022	-	-0.852^a	-0.013	-	-0.015
pat_{t-1}	-	-0.006	0.009^a	-	-0.003	-0.002	-	0.006	0.053^a	-	0.012	0.008^a	-	0.003	0.008
$\overline{R}^2$	0.01	-0.00	0.01	0.16	0.14	0.14	0.17	0.15	0.2	0.03	0.02	0.005	0.03	0.02	0.01
λ	0.197	0.153	0.201	0.39	0.324	0.39	1.534	1.364	0.945	0.22	0.137	0.148	0.03	0.01	0.033

State	Wyoming		
Variable	Model 1	Model 2	Model 3
Constant	-0.555	0.548^c	0.092
y_{t-1}	-0.072	-	-0.047
pat_{t-1}	-	0.056	0.048
$\overline{R}^2$	0.13	0.15	0.14
λ	0.082	0.253	0.306

Estimates based on hetroskediasticy- and autocorrelation-consistent standard errors (See Stock and Watson, 2003, pp. 502-506; Hamilton, 1994, pp.281-283). λ is the BG-LM test statistic based on "rho-differenced" data. Significance Levels: $a = 1\%$; $b = 5\%$; $c = 10\%$.

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