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The convergence of U.S. state-level energy intensity

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ABSTRACT

This study extends a neoclassical growth model to include the accumulation of physical capital and energy consumption within a panel of fifty states (plus the District of Columbia) in the U.S. The theoretical model allows us to examine the implications for convergence in economic growth and energy intensity. From the theoretical model, we formulate an empirical approach using a dynamic panel model that is estimated using a general method of moments framework to test the conditional rates of convergence. The empirical results indicate convergence in energy intensity, and our estimates accurately predict both the growth in and convergence of energy intensity across our entire sample. Consistent with other findings in the literature, our results imply that energy use, over the past four decades, plays a small and positive role in state-level, per capita economic growth and convergence. Based on these results, we discuss policy implications for state-level income growth and energy consumption.

1. Introduction

The economic literature is replete with studies that have explored the relationship between energy consumption and economic growth, and after four decades of empirical research there is still no consensus on the causal link between energy consumption and real income (Payne, 2010; Ozturk, 2010). The relationship between energy and growth gained the attention of scholars, and the public alike, after the two global oil crises in the 1970s. Interest in the topic re-emerged in the 2000s in conjunction with the run-up in oil prices, which peaked at nearly $150 per barrel in 2008 (compared to an average global price of $25 per barrel in the 1990s) (Energy Information Administration, 2016). The fundamental problem within the literature is in identifying a causal link, if any exists, between energy and growth.

Two recent studies, offered by Csereklyei and Stern (2015) and Rühl et al. (2012), observe that global energy consumption has been on the rise for the past few decades, but energy intensity is declining for developed countries such as the U.S. and the U.K. These observations motivated Csereklyei and Stern (2015) to question whether economic growth has less of an effect on the growth in energy use in richer countries, which they describe as a "decoupling of energy and growth." The authors test a weak and strong version of the decoupling hypothesis. The strong hypothesis is that economic growth has less of an effect on energy use as income grows through time; while the weak hypothesis is that energy use is declining in developed countries through time. Similar to Csereklyei and Stern (2015), we find strong evidence of convergence in energy intensity and weak decoupling, but no evidence of strong decoupling.

In this paper, we derive a theoretical model strongly grounded in macroeconomic growth theory. In our case, however, we treat energy resources as an input (factor of production) into an economy's income formation through time. Thus, our extension of the model allows for a closer examination of the energy-growth relationship and constructs its empirical counterpart using disaggregated U.S. state-level data between 1970 and 2013.[3] Specifically, our framework offers two testable hypotheses regarding the energy-growth

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[3] For the sake clarity, our exposition regarding the energy-growth relationship does not explicitly relate economic "growth" to energy consumption, but rather the effect of energy consumption on the level of state-level income. However, our derived convergence model specifications have direct implications for the economic growth path through time, so we will use the term "growth," in a general sense, throughout the remainder of the manuscript.

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relationship that closely mirror Csereklyei and Stern's (2015) definitions of strong and weak decoupling. The first hypothesis differs slightly from the strong decoupling definition as we do not directly test the effect of economic growth on energy. Instead, we test whether energy is a determinant of economic growth. Our second hypothesis tests the co-evolution of an economy's growth and energy intensity through time, where energy intensity is defined as consumption per unit of gross domestic product (GDP).

The two concepts are interrelated in that if the first hypothesis (energy is necessary for economic growth) is rejected, but an examination of the second hypothesis (the convergence of energy intensity) results in a failure of rejection, then it would suggest that energy resources need not be a constraint for future economic growth. In other words, energy resource consumption would not necessarily constitute a constraint because the economy is consuming its energy resources more efficiently — as evidenced by the economy's decreasing trends in energy intensity through time. Fig. 1 demonstrates the trends in energy intensity among U.S. states over the past four decades. For ease of exposition, we have averaged the state-level intensities across Census regions. The figure clearly suggests convergence in intensity across states, as demonstrated by the clustering in the series near the last periods of observation.

In order to empirically test our two hypotheses regarding the energy-growth relationship, we estimate the models using a two-step system GMM framework on U.S. state-level data from 1970–2013. Our examination of disaggregate national data is consistent with the insights of Barro and Sala-i-Martin (1991), who posited that convergence in income is more likely to occur *among* regions within a country than *across* different countries. Figs. 2 and 3 further illustrate the point that within the U.S., states are converging (exemplified by the negative slope of the trend line within each graph) in terms of per capita income and per capita energy expenditures.

We offer three unique contributions to the energy-growth literature. One, we offer a simple extension of the Solow growth model, based on seminal past works within the growth literature (Solow, 1956; Mankiw et al., 1992; Islam, 1995; Caselli et al., 1996; Bond et al., 2001), that includes energy resources as a factor of production (Stern, 1993, 2000; Stern and Kander, 2012). Based on the extended model, our second contribution consists of deriving the theoretical rate of convergence and then developing an empirical estimation model based directly on the derivation. Third, we estimate the empirical model using a GMM approach, which is consistent and asymptotically efficient.

This study differs from related research, such as Stern and Kander (2012), who develop a theoretical model to analyze the relationship between energy and economic growth and test the model's hypotheses using empirical specifications that correspond to the theoretical model. In contrast, our main focus is to examine the implications of economic and energy growth *convergence* within a set of advanced economies. We find strong evidence that state-level energy intensities are converging and energy consumption plays a significant role in explaining the energy-intensity convergence process. At the same time, we find that energy consumption plays a small (positive) and significant role in economic growth and convergence, which is similar to the results of Csereklyei and Stern (2015), who did not find of evidence of the aforementioned strong decoupling hypothesis.

The current study is organized as follows. In the next section we establish the theoretical growth model, which is extended to include energy resources as a factor of production in state-level income, and we motivate the empirical specification that directly corresponds to the theoretical model. In section three we describe the data, and in section four we briefly develop the GMM framework used to empirically verify the predictions of the theoretical model. In section five and six we discuss the empirical findings and the potential policy implications.

2. Adding energy resource accumulation to the Solow growth model

2.1. Adding energy resource accumulation to the Solow model

As outlined in Mankiw et al. (1992), the Solow growth model can easily be extended to three factors:

$$Y(t) = K(t)^{\alpha} \cdot E(t)^{\beta} \cdot (A(t) \cdot L(t))^{1-\alpha-\beta} \quad 0 < \alpha, \beta < 1, \tag{2.1}$$

where where Y denotes output, K is physical capital, L is labor, A is a labor-augmenting level of technology, and E denotes energy resources (both non-renewable and renewable energy). (For the readers not familiar with the Solow growth model, we have provided a brief outline of the model and underlying assumptions in the Appendix.) The same assumptions for the production function specified within the original Solow (1956) model, provided in the Appendix, hold here.

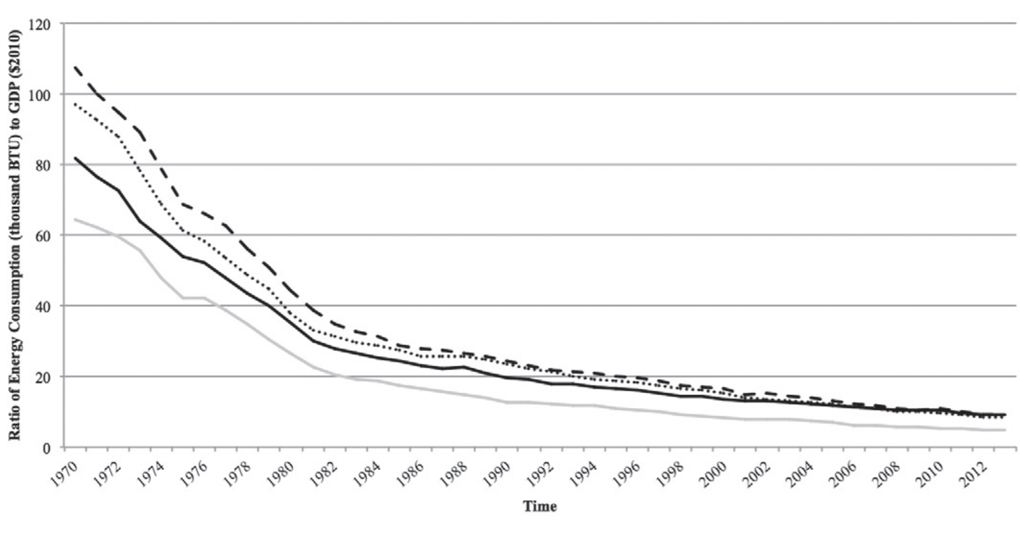

Fig. 1. U.S. Regional Energy Intensity (Energy use per unit of GDP), 1970–2013.

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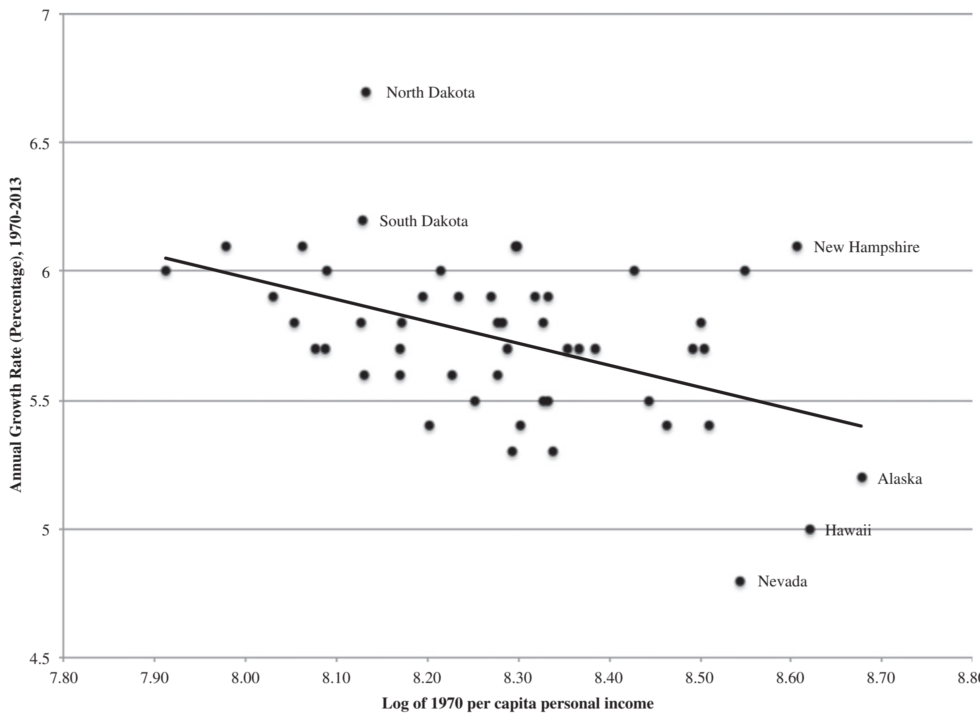

Fig. 2. Convergence of per capita income across U.S. states: 1970 per capita income and 1970–2013 income growth rate.

Upon examining the specified production function above, the reader may wonder why we have not added an energy- or capital-augmenting technology term, especially given the tremendous technological progress in U.S. energy production for the past several decades. Unfortunately, the specification of labor-augmenting technology is an artifact of this particular model — see Barro and Sala-i-Martin (2004, p.78–80) for the formal proof. In other words, the model must be specified with a labor-augmenting technology in order to have a steady state (with constant or exogenous growth rates). However, we will generalize this somewhat limiting assumption by expressing a variable for technology on the right-hand side of the empirical model (the regression model) — looking ahead, we assume that the variable for technology, similar to Islam (1995), is subsumed into the fixed effect variable within the panel data model.

Eq. (2.1) can be re-expressed in intensive form as $y(t) = k(t)^{\alpha} \cdot e(t)^{\beta}$, where $y(t)$ denotes output per effective unit of labor, $k(t)$ denotes capital per effective unit of labor, and $e(t)$ denotes the level of energy resources per effective unit of labor — this definition is loosely analogous to the level of per-capita energy consumption within the economy. To solve for capital and energy, we must specify three equations (the production function and two equations of

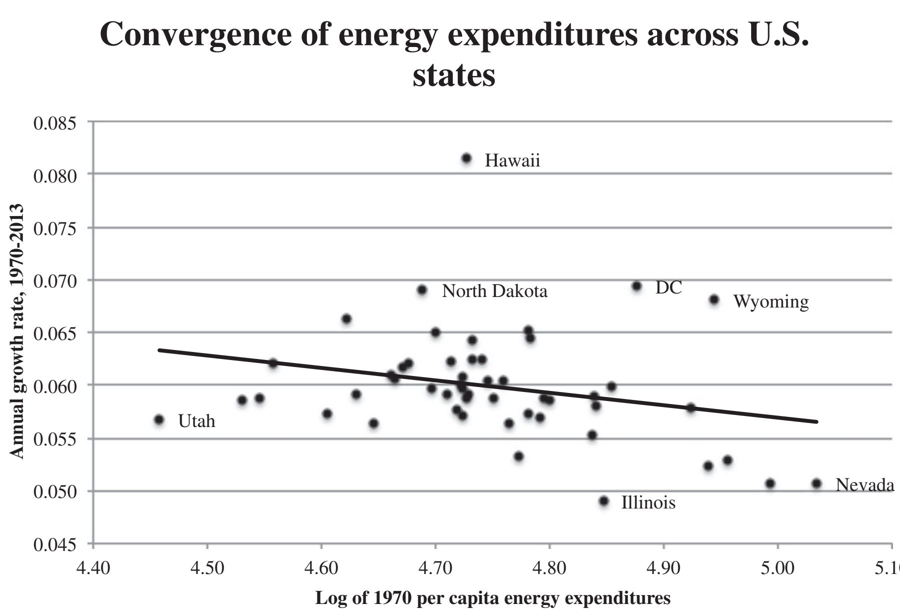

Fig. 3. Convergence of per capita energy expenditures across U.S. states: 1970 energy expenditures and 1970–2013 energy expenditure growth rate.

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motion). Hence, in addition to the production function, there are two equations of motion for capital and energy:

$$\dot{k}(t) = s_k \cdot k(t)^{\alpha} \cdot e(t)^{\beta} - (n + g + \delta) \cdot k(t), \tag{2.2}$$

$$\dot{e}(t) = s_e \cdot k(t)^{\alpha} \cdot e(t)^{\beta} - (n + g + \delta) \cdot e(t). \tag{2.3}$$

The equations of motion assume that a constant fraction of income, s_k, is saved for the accumulation of physical capital and a constant fraction of income, s_e, is saved for the consumption of future energy resources. Additionally, we assume that s_k is independent of s_e and vice versa. A list, of all of the study's variables and parameters, is provided in Table 1.

Eqs. (2.2) and (2.3) imply that capital and energy converge to a steady state defined by

$$k^* = \left(\frac{s_k^{1-\beta} \cdot s_e^{\beta}}{n + g + \delta} \right)^{1/(1-\alpha-\beta)} \tag{2.4}$$

$$e^* = \left(\frac{s_k^{\alpha} \cdot s_e^{1-\alpha}}{n + g + \delta} \right)^{1/(1-\alpha-\beta)}. \tag{2.5}$$

The steady state equations above are only stable provided that $\alpha + \beta < 1$, and if $\alpha + \beta = 1$, then the steady states are arguably undefinable. By substituting Eqs. (2.4) and (2.5) into the production function and transforming the variables to natural logs, then we can derive the following equation for income per capita:

$$\ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + g \cdot t - \left(\frac{\alpha + \beta}{1 - \alpha - \beta}\right) \ln(n + g + \delta) + \left(\frac{\alpha}{1 - \alpha - \beta}\right) \ln(s_k) + \left(\frac{\beta}{1 - \alpha - \beta}\right) \ln(s_e). \tag{2.6}$$

Table 1
Nomenclature.

Variable or Parameter	Description
$Y(t)$	Income or output
$A(t)$	Labor-augmenting level of technology
$L(t)$	Labor force
$K(t)$	Physical capital stock
$E(t)$	Energy resources
$\dot{x}$	Derivative of variable x with respect to time, or $\dot{x} = dx/dt$
$I(t)$	Capital investment
n	Exogenous growth rate of work age-related population
g	Exogenous growth rate of labor-augmenting technology
δ	Exogenous depreciation rate of physical capital
$y(t)$	Output per effective unit of labor
$k(t)$	Physical capital per effective unit of labor
$e(t)$	Energy resources per effective unit of labor
α	Parameter representing the factor share (output elasticity) of capital in the production of output
β	Parameter representing the factor share (output elasticity) of energy in the production of output
s	Exogenous savings rate of current income (for future capital investment)
s_i	Exogenous savings rate of current income (for future capital investment if $i = k$ and energy resources if $i = e$)
λ	The convergence rate
τ	Predetermined time-interval between years of observation
μ_i	State-level fixed effect for state i
η_t	Time fixed effect for year t
γ	Estimated rate of convergence
$\hat{\lambda}$	Implied rate of convergence, based upon estimated rate of convergence

Eq. (2.6) implies that income per capita is decreasing with population growth, and per-capita income is increasing with technological growth and the accumulation of physical capital and energy resources. The parameters α and β denote the factor shares of capital and energy, respectively. Historically, parameter estimates of α have been approximately equal to one third (Mankiw et al., 1992; Islam, 1995; Barro and Sala-i-Martin, 2004).

Eq. (2.6) makes a prediction about a empirical analysis of per-capita income. Specifically, if the accumulation of energy resources are omitted from a regression of per-capita income, then the fourth term on the right-hand side of Eq. (2.6) would be subsumed into an error term, and if significant, would result in biased coefficient estimates on population growth and the accumulation of physical capital (the direction of bias depends on whether the accumulation of energy resources are positively or negatively correlated with population growth and the accumulation of physical capital). For example, let's assume (for the sake of argument) that $\alpha = 1/3$ and $\beta = 1/4$. These values would imply that the coefficient estimates on a model of per-capita income growth excluding the accumulation of energy resources, provided in Eq. (A.8) of the Appendix, would equal approximately 0.5, whereas the coefficient estimates in Eq. (2.6) would equal approximately 1.4 for population growth and 0.8 for the accumulation of physical capital. Therefore, if energy resources are omitted from a regression, then population growth and (the accumulation of) physical capital would arguably underpredict (in absolute terms) per-capita income.

If one converts Eq. (2.5) into natural logs and substitutes this into Eq. (2.6), then the equation for income per capita can be rewritten as

$$\ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + g \cdot t + \left(\frac{\alpha}{1 - \alpha}\right) \ln(s_k) + \left(\frac{\beta}{1 - \alpha}\right) \ln(e^*) - \left(\frac{\alpha}{1 - \alpha}\right) \ln(n + g + \delta), \tag{2.7}$$

where this equation expresses per-capita income as a function of the accumulation of physical capital, the population growth rate, and the *level* of energy resource consumption, e^*. As before, this equation implies that if the level of energy resources are omitted from a regression on per-capita income, then it would result in biased coefficients estimates for population growth and physical capital. Thus, Eq. (2.7) will serve as the basis for the empirical analysis (and hypotheses tests) conducted within this study.

Further, we can convert Eq. (2.7) into an expression of the *energy intensity* of income by subtracting the term $\ln(e(t))$ from both sides of the equation, to yield:

$$\ln\left[\frac{Y(t)}{E(t)}\right] = \left(\frac{\alpha}{1 - \alpha}\right) \ln(s_k) + \left(\frac{\beta}{1 - \alpha}\right) \ln(e^*) - \ln(e(t)) - \left(\frac{\alpha}{1 - \alpha}\right) \ln(n + g + \delta), \tag{2.8}$$

where the energy intensity of income is defined as the ratio of output to energy consumption (Galli, 1998; Metcalfe, 2008). Technically, the term on the left-hand side of Eq. (2.8) is the inverse of how the "energy intensity" of income is typically measured in the literature. However, it is a trivial task to convert the equation to the ratio of energy consumption to output; i.e., multiply both sides of Eq. (2.8) by negative one and add the term $\ln(e(t))$ to both sides of the equation.

We now turn briefly to the concept of "convergence" within the Solow growth model.

2.2. Convergence

Solow's (1956) model predicts that countries or states reach different steady state levels based on either the state's savings rate, its accumulation of physical capital, or the population growth rate. Solow's model does not necessarily predict convergence across states, but rather it predicts that a state's per-capita income will converge to its own steady-state level. Hence, the model only predicts convergence across states after controlling for the determinants of the steady state — this is often referred to as "conditional convergence" (Mankiw et al., 1992).

Additionally, Solow's model makes predictions about the speed of convergence, which is given by

$$\frac{d\ln(y(t))}{dt} = -\lambda\cdot[\ln(y(t)) - \ln(y^{*})], \tag{2.9}$$

where $\lambda \equiv (1-\alpha-\beta)\cdot(n+g+\delta)$, and y^{*} denotes the steady state level of per capita income. We derived the expression for the speed of convergence by using Eq. (2.6) and log-linearizing around the steady state level of per capita income. (Specifically, we take a first-order Taylor series approximation of the equation of per-capita income around the steady state level of per-capita income. A proof for this derivation is provided for the interested reader in the Appendix.)

If $\alpha = 1/3, \beta = 1/4$, and $(n+g+\delta) = 0.05$, then the equation for the rate of convergence, λ, would approximately equal 0.02 — which implies that an economy moves half way to its (per-capita income) steady state in 35 years. Historically, most empirical studies of cross-sectional convergence find an approximate rate of convergence of 2% (Barro and Sala-i-Martin, 2004); however, panel-data studies often estimate slightly higher rates of convergence (Islam, 1995; Caselli et al., 1996).

Our augmented Solow growth model, expressed in terms of the *energy intensity* of income (heretofore, "energy-intense income"), also makes predictions about the speed of convergence given by

$$\frac{d\ln(y/e)}{dt} = -\lambda_e\cdot\left[\ln(y/e) - \ln(\overset{*}{y/e})\right], \tag{2.10}$$

where $\lambda_e \equiv (2-\alpha-\beta)\cdot(n+g+\delta)$, and $\overset{*}{y/e}$ denotes the steady state of energy-intensity income. The proof for Eq. (2.10) is nearly identical to the proof provided in the Appendix. (For the sake of brevity, we do not provide a proof for the derivation of the energy-intense speed of convergence; however, the authors are happy to provide the proof upon request). The only slight difference is that we assume that the equations of motion for both capital and energy resources are augmented so that the output production function is expressed in the form of energy-intense output, $Y/E \equiv y/e$. That is, we assume the following

$$\dot{k(t)} = s_k\cdot\frac{y(t)}{e(t)} - (n+g+\delta)\cdot k(t),$$
$$\dot{e(t)} = s_e\cdot\frac{y(t)}{e(t)} - (n+g+\delta)\cdot e(t).$$

With the above specifications, it is assumed that the investment of capital and energy resources is determined by the product of the exogenous savings rate (for capital and energy separately) and the energy—intense level of income, rather than the product of the savings rate and the level of per-capita income in Eq. (A.4).

As above, if we use the same assumed values for the factor shares ($\alpha = 1/3, \beta = 1/4$, and $(n+g+\delta) = 0.05$), then the convergence rate of energy-intense income, λ_e, is approximately equal to 0.07. This implies that the economy moves half way to its (energy-intense income) steady state in 10 years. The reason for the higher implied rate of convergence (in absolute terms) is because the investment level of capital and energy is larger when income is expressed in energy intense form. In other words, if capital investment is equal to three billion dollars and output (or income) is equal to ten billion dollars then the savings rate of capital, $s_k = I_k/Y$, would approximately equal 30%. On the other hand, if capital investment is equal to three billion, output is equal to ten billion, and energy expenditures are equal to two billion, then the savings rate of capital (in energy-intense form), $s_k = I_k/(Y/E)$, would approximately equal 60%.

Although the difference between the convergence rates in per-capita income form versus energy-intense income form seems trivial, the assumptive forms lead to large differences in the theoretical speed of convergence. Therefore, estimates of the implied speed of convergence (based on the empirical analysis), in both assumptive forms of income, provide a relatively simple robustness check against the assumption of the exogenously determined savings rates.

2.3. *Converting the theoretical speeds of convergence into estimable equations*

Eq. (2.9) implies the following:

$$\begin{aligned}\ln(y(t)) - \ln(y(0)) &= (1-\exp\{-\lambda\cdot t\})\ln(y^{*}) - (1-\exp\{-\lambda\cdot t\})\ln(y(0)) \\ &= (1-\exp\{-\lambda\cdot t\})(\ln(y^{*}) - \ln(y(0))).\end{aligned} \tag{2.11}$$

The above equation is sometimes referred to as a partial adjustment model — it suggests that the optimal value of the dependent variable is determined by the explanatory variables of the initial period, $y(0)$. Moreover, we can generalize the above equation into a partial adjustment model between two intervening periods of time as

$$\ln(y(t_2)) - \ln(y(t_1)) = (1-\exp\{-\lambda\cdot\tau\})(\ln(y^{*}) - \ln(y(t_1))), \tag{2.12}$$

where $\tau = (t_2 - t_1)$ (Islam, 1995). Next, we can substitute Eq. (2.7) in for the $\ln(y^{*})$ term in Eq. (2.12) to derive

$$\begin{aligned}\ln(y(t_2)) - \ln(y(t_1)) =& (1-\exp\{-\lambda\cdot\tau\})\cdot\ln(A(0)) \\ &+ g\cdot(t_2 - \exp\{-\lambda\cdot\tau\}\cdot t_1) \\ &+ (1-\exp\{-\lambda\cdot\tau\})\cdot\left(\frac{\alpha}{1-\alpha}\right)\ln(s_k) \\ &+ (1-\exp\{-\lambda\cdot\tau\})\cdot\left(\frac{\beta}{1-\alpha}\right)\ln(e^{*}) \\ &- (1-\exp\{-\lambda\cdot\tau\})\cdot\left(\frac{\alpha}{1-\alpha}\right)\ln(n+g+\delta) \\ &- (1-\exp\{-\lambda\cdot\tau\})\cdot\ln(y(t_1)).\end{aligned} \tag{2.13}$$

As in Islam (1995), we can re-express Eq. (2.13) as a dynamic panel data model with the term $(1 - exp\{-\lambda\cdot\tau\})\cdot ln(A(0))$ treated as the time-invariant individual state-level fixed effect. This treatment implies that the embedded technological growth process, $\ln(A(0))$, is unique to each state, but is approximately fixed over the period of observation. Given this assumption, we can express Eq. (2.13) using conventional notation for a dynamic panel data model as

$$y_{it} = \gamma\cdot y_{i,t-1} + \sum_{j=1}^{3}\beta_j\cdot x_{it}^{j} + \eta_t + \mu_i + v_{it}, \tag{2.14}$$

where $v_{it} \sim N(0,\sigma_v)$ is a transitory error term that varies across states and time periods. Similar to Islam (1995), we define each the variables (i.e., the correspondence between Eqs. (2.13) and (2.14)) as follows:

$$\begin{aligned} y_{it} &= \ln(Y(t_2)/L(t_2)), \\ y_{i,t-1} &= \ln(Y(t_1)/L(t_1)), & x^1_{it} &= \ln(s_k), \\ \gamma &= \exp\{-\lambda\cdot\tau\}, & x^2_{it} &= \ln(e^*) \\ & & x^3_{it} &= \ln(n+g+\delta), \\ \beta_1 &= (1-\exp\{-\lambda\cdot\tau\})\cdot\tfrac{\alpha}{1-\alpha}, & \mu_i &= (1-\exp\{-\lambda\cdot\tau\})\cdot\ln(A(0)), \\ \beta_2 &= (1-\exp\{-\lambda\cdot\tau\})\cdot\tfrac{\beta}{1-\alpha}, & \eta_t &= g(t_2-\exp\{-\lambda\cdot\tau\}\cdot t_1). \\ \beta_3 &= -(1-\exp\{-\lambda\cdot\tau\})\cdot\tfrac{\alpha}{1-\alpha}, \end{aligned}$$

Note that Eq. (2.13) (and the corresponding Eq. (2.14)) is based on an approximation around the steady state; therefore, it is valid for cross-sectional analysis (i.e., assuming $y(t_1)=y(0)$ and $y(t_2)=y(T)$) as well as with shorter time intervals defined by the panel data specification. Following Islam (1995), we specify our empirical model with non-overlapping five-year time intervals, which helps filter out the effects of business cycles on physical capital accumulation, population growth, and energy resource consumption. In Mankiw et al. (1992), it was assumed that s_k and n were constants over the entire period of observation — with our panel data specification, we treat s_k, n, and e as constant between each time interval. In other words, the specification in Eq. (2.14) allows for convergence, after controlling for individual state-specific fixed effects, to occur over several consecutive time intervals.

Moreover, the estimable Eq. (2.14) can be re-expressed in energy-intense income form as follows:

$$\frac{y_{it}}{e_{it}} = \gamma\cdot\frac{y_{i,t-1}}{e_{i,t-1}} + \sum_{j=1}^{3}\beta_j\cdot x^j_{it} + \eta_t + \nu_{it}. \tag{2.15}$$

The variables only differ by the following definitions:

$$\begin{aligned} e_{it} &= \ln(e(t_2)), \\ e_{i,t-1} &= \ln(e(t_1)), \\ \beta_2 &= -(1-\exp\{-\lambda\cdot\tau\})\cdot\left(\frac{1-\alpha-\beta}{1-\alpha}\right). \end{aligned}$$

Otherwise, the rest of the variables are identical to those defined in Eq. (2.14). It is worth noting that the fixed effect term drops out of the specification in Eq. (2.15). This is due to the conversion into the form of energy-intense income. To see this, note that the definition of energy-intense income is Y/E. We can convert this definition to the ratio of output-per-effective-worker to energy-per-effective-worker by multiplying energy-intense income by $(1/AL)/(1/AL)$, which yields y/e. This conversion provides a convenient definition of energy-intense income but it omits the (labor-augmenting) technological growth term from the right-hand side of the equation (as in Eq. (2.14) above). Thus, technological growth itself is now embedded in the very definition of energy-intense income, y/e.

Finally, based on the estimated rates of convergence, the implied rate of convergence is calculated according to

$$-\hat{\lambda} = \frac{1}{\tau}\cdot\ln(\hat{\gamma}),$$

and the implied half-life, given the implied rate of convergence is calculated according to

$$\exp\{-\lambda\cdot\tau\} \to \frac{\ln(2)}{\hat{\lambda}}.$$

The half-life of convergence is defined as the time it takes for half of the initial gap (i.e., the gap between some initial level and its steady state level) to be eliminated (Barro and Sala-i-Martin, 2004).

2.4. Potential problems with the estimating convergence with dynamic panel data models

The three previous subsections laid out a relatively simple neoclassical growth model and a theoretical rate of convergence, for both per-capita income and energy-intense income. From the theoretical model, we developed estimable approaches (empirical models), based on previous work by Mankiw et al. (1992) and Islam (1995), to test the predictions of the theoretical model. Despite the straightforward method of translating the theory to estimable form, there are two sources of inconsistency in the existing empirical work on growth: correlated individual effects and endogenous explanatory variables (Caselli et al., 1996).

For example, Islam (1995) identified that Mankiw et al.'s (1992) estimates are potentially characterized by omitted variable bias because they estimated the conditional rate of convergence in a cross-sectional context and omitted potentially relevant country-level heterogeneous effects (which in the context of Islam (1995) is a measure of technological growth). Islam's (1995) study mitigates this potential bias by estimating conditional convergence using a dynamic panel data approach, which allows him to control for country-level fixed effects and time fixed effects.

However, Islam's (1995) estimable model also potentially suffers from inconsistent estimates by assuming that the explanatory variables are exogenous (i.e. the explanatory variables are not correlated with the error term). He, of course, recognizes this potential limitation and carefully explains the "Minimum distance" estimation approach in his study to control for potential endogeneity issues (Islam, 1995, p.1167–1169). Despite the properties of the "Minimum distance" estimator, the general method of moments (GMM) has arguably become a widely accepted estimation framework in the empirical, economic growth literature (Arellano and Bond, 1991; Arellano and Bover, 1995; Caselli et al., 1996; Bond et al., 2001). As such, we employ the system GMM estimator proposed by Arellano and Bover (1995). This estimator addresses the potential biases that arise from the correlation between country fixed effects, the lagged dependent variable, and the endogeneity of the other explanatory variables.

In the next two sections, we explain the data used within the current study and then explore the empirical model and estimation results.

3. Data

The (BEA) Bureau of Economic Analysis (2015a) provides data on the state-level physical capital stock, where all observations are reported as the net capital stock. This means the BEA reports the data net of depreciation of the existing capital stock in preceding years. Additionally, the BEA only provides the data at the national level, broken down by industry and year (one-digit Standard Industrial Classification (SIC) codes and/or the North American Industry Classification System (NAICS) codes). Given the lack of state-level data, Garfalo and Yarmarik (2002) and Yarmarik (2013) develop a method for estimating the state-by-state capital stock. In particular, their methodology consists of weighting a state's industry (income) contribution relative to the national industry (income) contribution to overall GDP. This weight is multiplied by the national industry-level stock of capital to obtain an estimate of the state's industry-level stock of capital (which assumes that the state-level industry capital stocks are roughly proportional to the state-level industry's contribution to the same industry's total income at the national level). Finally, the one-digit, state-specific, industry-level capital stocks are summed to derive an overall estimate of the state's total (net) capital stock within a given year. The authors' original methodology was developed for industry SIC codes, but later Yarmarik (2013) extended the methodology to account for industry NAICS codes. Fundamentally, the code-system classification differs only slightly with how they aggregate certain industries into one-digit industry categories; otherwise, the sums should approximately be the same despite the differences in code-system classification. Given that our period of observation falls within both code-system classifications (used by the BEA), we aggregate the state-level physical stock according to SIC codes in the period of 1970 to 1997 and aggregate the state-level physical stock according to NAICS codes in the period of 1998 to 2013.

To estimate the accumulation of physical capital, we follow the methodology of Yarmarik (2013) and calculate the difference in the net physical stock between subsequent years — which creates an annual series of observations from 1970 to 2013. That is, Yarmarik (2013) estimates the gross investment series from the series on capital using the accumulation equation: $i_{ij}(t) = k_{ij}(t) - (1 - \delta_{ij}(t)) \cdot k_{ij}(t-1)$, where $k_{ij}(t)$ denotes the present level of the capital stock in industry i and state j. Likewise, he defines δ as the depreciation rate and $k_{ij}(t-1)$ as the capital stock in the preceding period, using the same subscript notation.

The Bureau of Economic Analysis (2015b) also compiles data on total state-level income (or output). Because the state-level income is in terms of nominal dollars, we convert the reported income to real dollars using the U.S. GDP deflator from the World Development Indicators.

The Energy Information Administration (2015b) provides energy resource data, from which we collect "total energy consumption" by state for the years 1970 to 2013. Total energy consumption contains a state's total energy use, including both renewable and non-renewable sources, net of electricity that has been transmitted outside of a state's border. The unit of measurement is reported in billion British thermal units (BTUs), which is the amount of work needed to raise the temperature of one pound of water by one degree Fahrenheit. Reporting energy in BTUs provides consistency across all the different measurements of energy resources, which are often measured in separate units, such as barrels of oil, tons of coal, and kilowatts of electricity.

We gather the degree day data from the National Oceanic and Atmospheric Administration (2016). In particular, heating and cooling degree days measure the difference between outdoor temperatures and a temperature that people generally find comfortable indoors. Degree days help determine the influence of temperature change on energy demand. According to Diaz and Quayle (1980), a degree day is determined by comparing the daily average outdoor temperature with a defined baseline temperature for indoor comfort. The National Oceanic and Atmospheric Administration (NOAA) measures degree days as the comparative daily average against a baseline temperature of 65° Fahrenheit. Following the literature, we define degree days as the product of the difference in the daily average temperature (from the baseline) and the number of days throughout the year in which the average temperature deviates from the baseline. For example, if the daily average temperature deviates (in absolute terms) from the baseline by 15° Fahrenheit for 200 days out of the year, then the state would record 3000 ($15 \cdot 200$) degree days in that particular year. NOAA aggregates the two metrics, heating and cooling degree days, by measuring the daily average temperature in absolute terms. We treat degree days as exogenous, which provides a valid instrument to help control for the demand of energy (interior heating or cooling services) within a particular state.

We compile data on the working age population from the Census Bureau (2015), given that the Census provides data on historical, age-related population estimates for the years 1970 to 2013. Specifically, the Census reports state-level population data estimates, by single year of age, for each year. We therefore sum the data, by state and by year, for anyone in the population whose single year of age ranged between 16 and 65 years old. After calculating the annual work-related population by state and by year, we estimate the growth rate of the population as the average difference in population between intervening years. Recall though that population growth is augmented by technology growth and the depreciation rate, which both Mankiw et al. (1992) and Islam (1995) assume to grow at 5% per year, so we add 0.05 to the above annual growth rate to derive $(n + g + \delta)$.

As a robustness check to our derived growth model, we also include a commonly explored explanatory variable within the economic growth and convergence literature. That is, we add human capital investment to the data-set (Mankiw et al., 1992; Barro, 2001). As a proxy for human capital investment, we use the percentage of the population, 25 years and older with a bachelor's degree or higher, which we simply label as educational attainment. We obtain the educational attainment data from the Census Bureau (2016). Because the Census Bureau only provides state-level educational attainment data with every decennial (10-year) census, we interpolate the growth rate between each corresponding decennial census year (i.e., each ten-year census period) using 'intercensal interpolation' (Census Bureau, 2012). The Census uses the same technique to estimate population levels between each 10-year census. Based on the interpolation, we are able to estimate state-level educational attainment for the years 1970–2013.

The summary statistics for each variable is included in Table 2.

4. Empirical specification and estimation

4.1. The time series implications of the panel or longitudinal data

Strongly persistent time series are often described as "nonstationary". Using time series data with strong persistence, such as series displayed by a unit root process (processes that are integrated of order one or I(1)), in a regression equation can lead to incorrect results including spurious regressions (that is, finding a spurious relationship between two or more time series that have similar increasing or decreasing trends) (Wooldridge, 2006). For example, assume that the true data generating process for one of our time series variables, defined as y_t, is characterized as a unit root: $y_t = \rho_1 \cdot y_{t-1} + e_t$, where $\rho_1 = 1$ and e_t is a noise term. Since the parameter ρ_1 is equal to one in this example, the current observation of y_t is highly dependent on previous realizations of the same variable y_{t-1}. In this case, the random noise term e_t is not stationary and regression results, based on this series, can be highly misleading.

Im et al. (2003) derive a test for the presence of unit roots in panels that combines information from the time series dimension with that from the cross-section dimension, resulting in fewer time observations needed for the test to have power. Their test also allows the autoregressive parameter to be panel specific and is more powerful than the individual augmented Dickey–Fuller tests (ADF) in

Table 2
Descriptive statistics for annual state-level observations, 1970–2013.

	(1) N	(2) Mean	(3) Standard deviation
Total energy consumption (Billion BTU)	2244	1.69e+06	1.85e+06
Fossil fuel energy consumption (Billion BTU)	2244	1.46e+06	1.67e+06
Degree days	2244	6524.65	1797.25
Investment (%)	2244	14.92	12.35
Population (%)	2244	6.07	1.14
Educational attainment (%)	2244	20.51	6.74
Real GDP per capita	2244	36,538.97	16,360.82
Number of states plus Washington DC	51	51	51

rejecting the null hypothesis that unit roots characterize every time series under consideration. We therefore employ the Im–Pesaran–Shin (IPS) test using the annual data series between 1970 and 2013, where our null hypothesis is that each of the regressors follows a unit-root process .

The starting point of the IPS test requires state-by-state ADF regressions of the form

$$\Delta y_{it} = \alpha_i + \delta_i time + \beta_i y_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta y_{i,t-j} + \varepsilon_{it}, \tag{4.1}$$

where Δy_{it} is the first difference of GDP per capita (or the variable of interest for the unit root test), the α_i includes the state-specific intercept, time is the time trend, and p is the specified lag length included to mitigate the problem of serial correlation. The number of lags for each state is determined by minimizing the Akaike Information Criteria, subject to the maximum of eight lags. Because U.S. states have many similarities, our results could be impacted by cross-sectional correlation. To control for this correlation, we remove cross-sectional averages from the data as first suggested by Levin et al. (2002).

The IPS test estimates each state-specific ADF regression and averages the resulting t statistics, with the null hypothesis being that all panels contain a unit root (i.e. all panels are non-stationary). Table 3 presents our IPS test results and reveals that for education, real GDP per capita, total energy consumption, and real GDP per fossil fuel consumption the null hypothesis of non-stationarity cannot be rejected. The non-stationarity of some of our variables re-enforces the choice to implement non-overlapping time intervals, which is widely accepted in the growth literature (Islam, 1995; Caselli et al., 1996; Bond et al., 2001.) Islam (1995) also argues that yearly time spans are too short a period to study growth convergence.

Using five year averaged data between 1970 and 2013, we divide our sample into nine (time) periods for each state: 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, and 2010. This implies that when $t = 1975$, then $t-1 = 1970$. Likewise, the endogenous regressors (for example, savings rate of physical capital, population growth, and energy resource consumption in the per capital GDP equation) are averaged over the period 1970 to 1975 (and each of the subsequent five-year intervals). Because the random error terms, v_{it}, are now in five-year intervals, fluctuations in business cycles should have less influence on the error terms (Islam, 1995). Furthermore, dividing the observations into five-year intervals should also mitigate any serial correlation within the error term.

Table 3
Im–Pesaran–Shin panel unit root tests for annual state-level observations, 1970–2013.

	(1) *t-bar* statistic	(2) *p*-Value
Total energy consumption (Billion BTU)	2.357	0.991
Fossil fuel energy consumption (Billion BTU)	−3.231	0.001***
Investment (%)	−20.639	0.000***
Population (%)	−8.307	0.000***
Education (%)	1.418	0.929
Real GDP per capita	−1.105	0.135
Log(real GDP per capita)	−2.384	0.009***
Real GDP per total energy consumption	−3.360*	0.000***
Real GDP per fossil fuel consumption	−0.260**	0.398

Notes: The null hypothesis of the IPS test is that the time series variable contains a unit root. Thus, a rejection of the null implies that the series is stationary or weakly dependent. Variables are demeaned. For all variables, both the trend and the constant are included. These tests were implemented by using the "xtunitroot" command within Stata 12.0.

* Denotes 10% significance level.
** Denotes 5% significance level.
*** Denotes 1% significance level.

4.2. Empirical model and estimation method

Our augmented neoclassical growth model predicts that increasing the level of energy increases growth in the transition to the new steady-state, and that conditional convergence in energy intensity across U.S. states emerges over time. To test the strong and weak version of the decoupling hypothesis, we use a unified empirical framework which relies on non-overlapping five-year averaged data and takes on the following dynamic panel regression specification:

$$Z_{it} = \gamma Z_{it-5} + \beta' X_{i(t-5,t)} + \mu_i + \eta_t + \varepsilon_{it}. \tag{4.2}$$

Z_{it} is equal to the logarithm of per capita GDP or energy intensity (depending on the variable of interest) and the lagged dependent variable, Z_{it-5}, is included to capture the convergence in the corresponding variable. The set of control variables in the vector $X_{i(t-5,t)}$ are averages between the period $t-5$ and t and include the investment rate and population growth. Our specifications also control for unobserved, time-invariant state effects, μ_i, and common time-effects, η_t that capture global shocks.

As the right-hand side of both equations includes a lagged dependent variable, careful consideration in choosing the estimation technique is necessary. Specifically, conventional longitudinal data approaches such as the panel ordinary least squares (OLS) and the within estimator (fixed effect model) can yield biased estimates if the time dimension of the panel data set is small or if there is a correlation between the country fixed effects and the lagged dependent variable. Even first difference OLS would yield inconsistent estimates of the differenced lagged dependent variable as it is correlated with the differenced error term (Cameron and Trivedi, 2005). Consistency may also be undermined by endogeneity caused by measurement errors or reverse causality.

In light of these issues, various consistent, dynamic panel data models have been developed, including the bias-corrected least squares dummy variable model (Judson and Owen, 1999) and first differences OLS with instrumental variables (Anderson and Hsiao, 1981). Anderson and Hsiao's (1981) method, in particular, provides consistent estimates as it proposes to use a lagged observation of the explanatory variable as an instrument, since the lagged observation is not correlated with the current error term (provided there is no serial correlation within the underlying data). Arellano and Bond (1991) build upon this by proposing additional lags as instruments, as it should lead to more efficient estimates of the explanatory variables (Cameron and Trivedi, 2005). In particular, the difference-GMM estimator of Arellano and Bond (1991) uses only the first-difference equations, instrumented by the lagged levels of the explanatory variables. A limitation of the approach is that if the explanatory variables are persistent, then their lagged levels are shown to be weak instruments (Arellano and Bover, 1995; Blundell and Bond, 1998).

To avoid this drawback of the difference-GMM estimator, we estimate dynamic Eq. (4.2) using a two-step system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998) with the Windmeijer (2005) finite-sample correction. The system-GMM estimator combines the first-difference equations, whose regressors are instrumented by their lagged levels, with equations in levels, whose regressors are instrumented by their first-differences. The two-step GMM estimator developed by Ahn and Schmidt (1995, 1999) and Blundell and Bond (1998) is consistent and asymptotically efficient in the presence of heteroskedastic errors. Because the two-step system GMM estimator may produce downward biased results when using finite samples, Windmeijer (2005) proposes a finite sample correction for the variance–covariance matrix.

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For panel data sets with short-time dimensions, the two-step system estimator addresses the potential biases that arise from the correlation between the state-level fixed effects, μ_i, and the lagged dependent variable, Z_{it-5}, as well as the endogeneity of other explanatory variables. We treat all potential determinants as endogenous and use lags of the variables as GMM-type instruments. (We also use the collapse option in Stata, which creates one instrument for the endogenous variable and lag distance, rather than one for each time period, variable, and lag distance. This option minimizes the potential bias that might arise as the number of instruments increases, and as the instruments overfit the endogenous regressors. See Roodman (2005) for more details). The consistency of the system GMM estimator depends on two hypotheses. First, the instrumental variables are not correlated with the error terms (this is verified using the Hansen *J* test of overidentifying restrictions, where the null hypothesis is that the error term is uncorrelated with the instruments). Second, the residuals are not second-order serially correlated (this is verified using the Arellano–Bond tests, where the null is that there is no autocorrelation of order 2 in the residuals). We report the Hansen *J* tests of over-identification to confirm our instrument's validity, as well as the *p*-values of the tests for second order serial correlation.

5. Estimation results

5.1. Effects on per capita GDP (income)

The estimates for the convergence in state-level, per capita income and energy intensity are listed in Tables 4 and 5, respectively. To capture the impact of energy intensity on per-capita income levels, we incorporate a measure of total renewable and nonrenewable energy consumption as well as a measure of nonrenewable energy in the form of fossil fuel consumption. Table 4 highlights that energy intensity, as measured by total energy consumption (in column 1 and column 3), is an income-enhancing factor in a state's growth process through time. Specifically, the parameter estimates are positive and significant at 5% , implying that a 10% increase in the total energy intensity results in an increase in state-level, per capita income between 0.21 to 0.24%. This effect is more than three and a half times the impact of fossil fuel consumption alone, confirming the intuition that total renewable and nonrenewable energy consumption should matter more for per capita income. Based on recent observed trends in economic growth and energy consumption, our finding may partially reflect a weak decoupling of primary energy consumption and economic growth in the U.S. According to Bloomberg News Energy Finance (2016), over the period 2007–2015 the U.S. economy grew by 10% , whereas primary energy consumption (fossil fuel consumption) fell by 2.4% and electricity consumption remained flat during that same period.

The estimates on the lagged real GDP per capita in the first row of Table 4 robustly support the existence of conditional convergence, with the coefficients ranging from 0.751 to 0.857. These estimates yield an implied speed of convergence around 3-5.7% per year and a half-life ranging from 12 to 22.4 years. The estimated rate of convergence contrasts with the findings of Markandya et al. (2006), who estimate a 1.7% rate of per capita income-convergence for a panel of Eastern European countries (transitional economies), with an implied half-life of approximately 41 years. At a convergence rate of 4%, the half-life implies that if there is some gap between the initial observed level of per capita income and its steady state level, then half of the initial gap will be eliminated in approximately 17 years. The consensus of economic rates of convergence tend toward 2% (Mankiw et al., 1992; Barro and Sala-i-Martin, 2004) so our estimates are slightly larger than what is typically found within the literature; however, dynamic panel data models generally yield slightly higher estimated rates of convergence (Islam, 1995; Caselli et al., 1996).

Consistent with the predictions of the theoretical model, the investment share of capital is positive and statistically significant at the 1% level in all specifications. Quantitatively, the parameter estimates suggest that a 10% increase in the investment share results in an increase in state-level, per capita income between 0.68 to 0.8%.

Table 4
Determinants of per capita income for the United States.

	(1)	(2)	(3)	(4)
Lagged log of initial GDP per capita	0.778***	0.857***	0.751***	0.807***
	(0.0590)	(0.0632)	(0.0642)	(0.0690)
Log investment share	0.0746***	0.0679***	0.0808***	0.0819***
	(0.0163)	(0.0160)	(0.0177)	(0.0197)
Log population	0.0399	0.0849	0.0183	0.0486
	(0.0785)	(0.0826)	(0.0827)	(0.0879)
West	−0.0584**	−0.0576***	−0.0501*	−0.0500*
	(0.0253)	(0.0213)	(0.0276)	(0.0257)
Midwest	−0.0459	−0.0203	−0.0262	0.000727
	(0.0367)	(0.0241)	(0.0310)	(0.0264)
South	−0.0911**	−0.0594*	−0.0627	−0.0280
	(0.0355)	(0.0315)	(0.0392)	(0.0393)
Log total energy consumption	0.0244**		0.0206**	
	(0.0107)		(0.00882)	
Log total fossil fuel energy consumption		0.00695		0.00249
		(0.0108)		(0.0103)
Log education			0.110	0.143*
			(0.0784)	(0.0877)
Implied rate of convergence	0.050	0.031	0.057	0.043
Implied half-life	13.808	22.432	12.097	16.157
Observations	459	459	459	459
US states and Washington DC	51	51	51	51
Hansen *p*-value	0.217	0.180	0.232	0.179
Arellano–Bond *p*-value for AR(2)	0.674	0.346	0.801	0.516

Notes: The dependent variable is the log of initial GDP per capita. The estimates and standard errors are obtained from the two-step system GMM procedure with the Windmeijer (2005) small-sample correction. A set of year effects and a constant are included in all specifications. Standard errors are in parentheses. The *p*-values for the Hansen over-identification test and the Arellano–Bond second order serial correlation tests are reported.

* Denoted significance at the 10% level.
** Denoted significance at the 5% level.
*** Denoted significance at the 1% level.

Table 5
Determinants of energy intensity for the United States.

	(1)	(2)
	Energy intensity:	Energy intensity:
	Total energy	Fossil fuels
Lagged log of energy intensity	0.933***	0.962***
	(0.0562)	(0.0401)
West	−0.0738**	−0.0809**
	(0.0330)	(0.0331)
Midwest	−0.0350	−0.0392*
	(0.0221)	(0.0219)
South	−0.0866*	−0.0748*
	(0.0482)	(0.0417)
Log investment Share	0.0411*	0.0625**
	(0.0243)	(0.0311)
Log population	0.149	0.0735
	(0.107)	(0.158)
Log degree days	−0.0657	−0.0638
	(0.0533)	(0.0419)
Implied rate of convergence	0.014	0.008
Implied half-life	49.511	86.643
Observations	459	459
US States plus Washington DC	51	51
Hansen *p*-value	0.178	0.147
Arellano–Bond *p*-value for AR(2)	0.269	0.406

Notes: The energy variable in column 1 is total energy consumption using both renewable and nonrenewable energy. The energy variable in column 2 is energy consumption using fossil fuels only. The estimates and standard errors are obtained from the two-step system GMM procedure with the Windmeijer (2005) small-sample correction. A set of year effect are included in all specifications and a constant are included in all specifications. Standard errors are in parentheses. The *p*-values for the Hansen over-identification test and the Arellano–Bond second order serial correlation tests are reported.
* Denoted significance at the 10% level.
** Denoted significance at the 5% level.
*** Denoted significance at the 1% level.

The estimates on population growth are positive, although not statistically significant. We also include regional dummy variables because it is possible that resources or regional policy may influence income disparities by the changing the competitive and comparative advantages across U.S. states. When factors of production are mobile, one location can draw production away from other locations and influence regional economic performance and the convergence process (Lall and Yilmaz, 2001). The negative coefficients for the West, Midwest, and South are not surprising, since these estimates are being compared to the high per-capita income level of the states from the Northeast (the base group excluded from the regression).

Growth theory stresses the importance of human capital to the income process so its exclusion from the baseline specifications may bias the coefficients on investment, population growth, energy intensity, and the regional-specific effects. We carry out robustness checks in columns (3) and (4) by exploring the effect of adding educational attainment as a proxy for human capital. In terms of magnitude, the presence of human-capital accumulation increases the impact of physical capital accumulation on income, while lowering the impact of population growth, energy intensity, lagged real GDP per capita, and the regional dummy variables on income. The results for investment, lagged real GDP per capita, and energy intensity with respect to renewable and nonrenewable energy are robust to controlling for human capital and remain statistically significant, and the population growth and energy intensity with respect to fossil fuels remains statistically insignificant. Once education is accounted for, only the West regional variable stays statistically significant. In both specifications, education is positive indicating that a ten percent increase in education results in an increase in per capita income between 1.1 to 1.43%, however human capital is only statistically significant at the margin with *p*-values equaling 0.165 and 0.10.

5.2. The convergence of energy intensity

Having established the link between total energy intensity and the level of per capita income, we next provide evidence on the convergence of energy intensity across U.S. states using measures of total renewable and nonrenewable energy and fossil fuel energy. To that end, we specify an empirical model for energy convergence that closely follows Eq. (2.15). Table 5 presents the results. As in the previous table, column one measures energy usage as total energy consumption, whereas column two measures usages as fossil fuel consumption.

The coefficients for initial energy intensity in both columns confirm the prediction of the theoretical model as highlighted by the statistically significant rates of convergence. The implied rates of convergence from both regressions are approximately equal to1%. The estimated levels of convergence in energy intensity are similar to the rates of convergence recently found within the literature (Csereklyei and Stern, 2015; Mulder and de Groot, 2012b; Liddle, 2010; Markandya et al., 2006). That is, these authors found the following estimates for the rates of convergence in energy intensity: Markandya et al. (2006) find a rate of 1.02% for group of Eastern European countries between the period 1992–2002; Liddle (2010) finds a rate of 1.06% for 111 international countries for the period 1990–2006; Mulder and de Groot (2012b) find a rate of 1.8% for 18 OECD countries for the period 1970–2005; and, Csereklyei and Stern (2015) find a range of estimated rates between 1 and 2% for a sample of 93 international countries for the period 1971–2010.

Based on the implied rate of convergence, the estimated half-life is approximately equal to 50 years for the total energy consumption specification (column 1) and is approximately equal to 87 years for the fossil fuel consumption (column 2) specifications, respectively. If one takes the average of both the total energy consumption (column 1) and fossil fuel consumption (column 2) specifications, the estimated half-life is approximately equal to 68.5 years. Intuitively, this estimated half-life implies that a shock to state-level energy intensity would take approximately 68.5 years to dissipate by one half. This estimated half-life of convergence may seem exceedingly long to the casual reader, especially for those persons who are accustomed to the more traditional economic growth literature, where an estimated convergence rate of 2% would yield an approximate half-life of 35 years. However, when compared to the other estimates of energy-intense convergence within the literature, our estimated half-life is more-or-less in line with the other studies. Particularly, based on the estimated rates of convergence identified above, the implied half-life for each study are as follows: Markandya et al. (2006)— 68 years (1.02% rate of convergence); Liddle (2010)— 65 years (1.06% rate of convergence); Mulder and de Groot (2012b)— 39 years (1.8% rate of convergence); and, Csereklyei and Stern (2015)— 46 years (based on implied 1.5% rate of convergence).

Our interpretation of the long half-life of energy intensity is that the structural change, to less energy-intense economies, occurring across U.S. states is a slow process through time. As the U.S. continues to transition to a more service-based economy (combined with energy efficient technological innovations), its energy needs will likely continue to decrease slowly over the next coming decades (Mulder and de Groot, 2012a). As an energy-intense industrial economy for the better part of two centuries, it seems intuitive then that it would take the U.S. economy a relatively long time to decrease its total energy consumption (which is reflected in our estimated one percent rate of convergence for energy intensity). Hence, if a shock occurs to U.S. energy intensity, it perhaps reasonable that it would take 68.5 years for the shock to dissipate in half.

In regards to our control variables, the investment share is positive (which is consistent with theory) and statistically significant. For the total energy specification in column 1, the coefficient on the investment share implies that a 10% increase in capital accumulation would lead to an approximate 0.4% increase in energy intensity. Similar to the previous tables, the population variable has a positive but statistically insignificant effect on energy intensity.

The regional indicator variables are used as a means of absorbing some of the unexplained variation across state energy intensity levels over the entire period of observation. The regional indicator for "Northeast" was treated as the base, leaving the regional indicators for the "West," "Midwest," and "South." Among these indicators, it is interesting to note that the regressions yielded negative coefficient estimates for the rest of the regions. These results do not necessarily indicate that these regions are converging at an absolute lower rate, but rather are converging at a lower rate relative to the Northeast (the base region). These findings are arguably due to the Northeast's lack of fossil fuel resources (outside of Pennsylvania) compared to the other census regions. For example, between 2012 and 2013 the following regions consumed more coal relative the Northeast's consumption over the same period: the Midwest consumed 600% more coal; the South consumed nearly 400% more coal; and, the West consumed 200% more coal (Energy Information Administration, 2015a). The large difference in coal consumption, between the West and Northeast regions, likely explains the relative large marginal effect and negative estimated coefficient on the West region in Table 5.

The estimated coefficient on the degree day variable is negative but statistically insignificant. The negative estimated coefficient is consistent with theory because an increase in degree days would imply an increase in energy demand (heating or cooling services); therefore, an increase in demand would imply an increase in energy intensity. However, our estimated rate of convergence implies that energy intensity is falling over the observation period, thus degree days are estimated to be inversely related (negative) with our observed trends in energy intensity.

6. Discussion and policy implications

Consistent with recent empirical observations of energy intensity in developed countries, we find strong evidence of convergence in energy intensity among a set of advanced economies (U.S. states). Our results, motivated in part by Csereklyei and Stern (2015), test a strong and weak version of the energy decoupling hypothesis. The strong hypothesis, as defined by Csereklyei and Stern (2015), predicts that economic growth has less of an effect on energy use as income increases over time. We did not test the effect of economic growth on energy (per se), but rather we investigated the effect of energy use on income growth. Based on our augmented definition of strong decoupling, we reject the hypothesis. That is, we find sufficient evidence to imply that energy plays a positive and statistically significant role in economic growth or convergence, which does *not* imply a strong decoupling between energy use and per capita economic growth in the U.S. This result is evidenced by the statistical significance of the energy variables in the economic growth models. In fact, based on the face value of the estimated coefficient on total energy consumption, a 1% increase in total energy consumption only increases per capita income by 0.02% , which is a positive but relatively small effect.

At the same time, we found strong evidence of convergence in energy intensity across U.S. states. Table 5 reports the parameter estimates for the energy intensity specification, where energy measures include total energy consumption (both renewable and nonrenewable) and total fossil fuel consumption (nonrenewable). The lagged energy intensity coefficient in both column (1) and column (2) is positive and statistically significant at the 1% level. The signs of the lagged dependent variable robustly suggest the existence of conditional convergence and confirm our models predictions that energy intensity slows down as energy grows towards its steady state. This last finding is our corollary to Csereklyei and Stern's (2015) definition of weak decoupling, which they define as a decline in energy use in wealthier countries over time. Similar to the findings of Csereklyei and Stern (2015), we fail to reject the hypothesis of weak decoupling as well.

Our findings are similar to the trends discussed by Rühl et al. (2012), who observed that global energy intensities seem to be converging to ever lower levels. They posited four drivers for the convergence in intensities: technology, resource endowments, economic structure, and fuel mix. In the words of the authors: (1) technological development improves the conversion of fuels and end use efficiency; (2) domestic energy resource availability lowers the price of energy and effects its usage; (3) the transition to a service-based economic structure lowers per capita energy consumption; and, (4) a diversified fuel mix tends to drive down energy intensity levels through time (Rühl et al., 2012). In the context of our study, we arguably controlled for the first three drivers and implicitly controlled for the last driver. That is, our empirical model contained an explicit variable for technological development, which we demonstrated was embedded in the very definition of energy intensity itself. The states' resource endowments were arguably captured by the explanatory variable pertaining to the level of energy resources, which we proxied with state-level energy consumption.

The third driver is relatively difficult to model in our neoclassical growth framework, but is arguably captured by the accumulation of capital process that we developed in the theoretical model. According to Rühl et al. (2012), the observed trends in energy intensity reflect well-known, stylized patterns of economic development. That is, as the economic structure transitions from energy-intensive industrial activities to less energy-intensive service activities, then energy use has a tendency to decline in lockstep with this transition process. Our theoretical model was able to capture this transition process by showing that the steady state level of economic growth is positively related to the share of capital in an economy's per capita income. Intuitively, an economy that engages in more industrial activities should require more capital accumulation, and the converse holds true as well — ceteris paribus, less industrial activity implies less capital accumulation (as reflected in the capital share parameter). Our empirical model, in turn, confirmed this hypothesis as the capital share parameter was found to be both positive and highly statistically significant in the convergence of energy intensity. Hence, as U.S. state economies transitioned from less industrial activities during our period of observation, we would expect the capital share parameter to capture this transition process.

For the sake of tractability, the fuel mix was not modeled explicitly in our theoretical growth framework. Arguably, the U.S. already possessed a relatively diverse fuel mix at the beginning of our period of observation, due to the existing rich energy endowment. The two oil crises in the 1970s impelled states to diversify their fuel mix further, which included introducing renewables into the mix. Our theoretical model did not account for this change in the fuel mix, but rather implicitly assumed that energy resources are homogenous by measuring all consumption in terms of the total heat content (BTUs) of the various sources. Nevertheless, we checked the robustness of our convergence analysis against different definitions or measures of energy resource consumption (total energy consumption versus fossil fuel consumption), in which we found remarkably similar results despite the defined differences.

Based on our estimated results, and our failure to reject the weak decoupling hypothesis, certain policy implications emerge for energy consumption and economic growth in the U.S. The first implication is based on our estimate of the implied rate of convergence in energy intensity. Specifically, we estimate the implied rate of convergence to be 1% (per year) for total energy consumption and fossil fuel energy consumption, a finding in line with Csereklyei and Stern (2015), Liddle (2010), and Csereklyei et al. (2016). The estimate, for total energy consumption, yields a half-life estimate approximately equal to 50 years. The half-life implies that if there is some gap between the initial observed level of energy consumption and its steady state level, then half of the initial gap will be eliminated in approximately 50 years.

These findings potentially could affect state-level renewable energy policies or portfolio standards, where states seek to diversify their energy resource portfolio, among other policy goals. Because our estimated rates of convergence have policy implications for long-run energy intensity, not necessarily short-run intensity, our findings do not suggest that states should pare back or forgo renewable portfolio standards (RPSs). On the contrary, such policy measures help an economy to deal with short-term adverse shocks to the energy sector. Furthermore, a RPS could arguably help a state economy to drive down its energy intensity trajectory into the future, which implies that a state would be even less vulnerable to future adverse energy shocks.

Lastly, and perhaps most importantly, our rejection of the strong decoupling hypothesis and failure to reject the weak decoupling hypothesis imply that state-level economic growth need not necessarily be constrained by resource availability. In other words, our findings imply that state-level economic growth and convergence are not highly dependent on energy resource use. Whereas, failure to reject the weak hypothesis suggests that energy use is declining as the U.S. economy continues to grow through time. This does not suggest that energy resource availability or prices will have no effect on the economy in the short run — in fact, short-run shocks to resources, such as a shortage in the crude oil supply, can have relatively large effects on a state economy. However, our estimated rates of convergence imply that any short-run shocks to energy usage should not necessarily create any long-lasting detrimental effects on the state's future economic growth trajectory.

Future research could benefit by expanding upon the current analysis. Our estimates were limited to a set of advanced economies, from which we were able to demonstrate well-founded observations of energy intensity and energy decoupling within a developed nation, but it is difficult to say if the same results would hold up among a set of developing economies. In other words, it would be interesting to examine the existence and rate of convergence in energy intensity among developing economies that have not fully transitioned to a service-based economic structure.

Appendix A. Textbook Solow model

Solow's (1956) model takes the rates of saving, population growth, and labor-augmenting technological progress as exogenous. The initial model contains two factors of production (inputs)—capital and labor. If one specifies a Cobb—Douglas production function (Mankiw et al., 1992), the output is determine at time t as follows

$$Y(t)=K(t)^{\alpha}\cdot(A(t)\cdot L(t))^{1-\alpha}\quad 0<\alpha<1, \tag{A.1}$$

where Y denotes output, K is physical capital, L is labor, and A is a labor-augmenting level of technology (Islam, 1995). The above specification assumes constant returns to scale in capital and labor; i.e., the output or production share elasticities (α and $1-\alpha$) sum to one. This implies that doubling both inputs will result in a doubling of output. Since population and technology are assumed to grow at exogenous rates n and g, they are defined as

$$\frac{\dot{L(t)}}{L(t)}=n\ \rightarrow\ L(t)=L(0)\cdot\exp\{nt\} \tag{A.2}$$

$$\frac{\dot{A(t)}}{A(t)}=g\ \rightarrow\ A(t)=A(0)\cdot\exp\{gt\}. \tag{A.3}$$

The notation above with the "dot" above the variable, indicates the derivative of the variable with respect to time. For example, $\dot{X}$ is equivalent to $\frac{dX}{dt}$. The two equations above imply that effective labor, defined as $A(t)\cdot L(t)$, grows (or more technically declines) exogenously at the rate of $n+g$.

For ease of interpretation, we can redefine the model's variables in intensive form as follows:

$$k(t)\equiv\frac{K(t)}{A(t)\cdot L(t)}$$
$$y(t)\equiv\frac{Y(t)}{A(t)\cdot L(t)},$$

where $k(t)$ denotes the stock of capital per effective unit of labor, $A(t)\cdot L(t)$, and $y(t)$ denotes the level of output per effective unit of labor. Given the Cobb–Douglas specification of production in Eq. (A.1), the function can be rewritten in intensive form as $y(t)=k(t)^{\alpha}$.

Next, Solow (1956) defines the equation of motion of capital formulation as follows:

$$\dot{k(t)}=I(t)-\delta\cdot k(t). \tag{A.4}$$

Eq. (A.4) implies that capital is growing in current investment, $I(t)$, but decreasing over time due to the depreciation, δ, of the current stock of capital. Solow assumes that a constant fraction of income, s, is dedicated toward investment, which is defined as $I(t)=s\cdot Y(t)$. Where the parameter s denotes the exogenously determined saving rate. Substituting this identity into the above equation, and rewriting it in intensive form, yields the following:

$$\dot{k(t)}=sy-\delta\cdot k(t). \tag{A.5}$$

Given that Eq. (A.4) is defined as capital per effective unit of labor, which is also growing at the rate of $n+g$, the equation of motion implies that the current level of capital is also growing at those exogenous rates, or:

$$\dot{k(t)}=s\cdot k^{\alpha}-(n+g+\delta)\cdot k(t). \tag{A.6}$$

In the above equation, we have also substituted the production function, in intensive form, for $y=f(x)=k^{\alpha}$. Eq. (A.6) implies that capital, k, converges to a unique steady-state value, k^{*}, over time, which is defined as (the steady-state is locally and globally stable provided that $\alpha<1$):

$$k^{*}=\left[\frac{s}{(n+g+\delta)}\right]^{1/1-\alpha}. \tag{A.7}$$

This equation implies that the steady-state level of capital is positively related to the savings rate and negatively related to the population growth rate.

Substituting the steady-state level of capital into the production function, and converting to natural logs, implies the following about the steady-state income per capita level:

$$\ln\left[\frac{Y(t)}{L(t)}\right]=\ln A(0)+g\cdot t+\left(\frac{\alpha}{1-\alpha}\right)\ln(s)-\left(\frac{\alpha}{1-\alpha}\right)\ln(n+g+\delta). \tag{A.8}$$

Mankiw et al. (1992) assume that the initial level of technology, $\ln A(0)$, which is an arbitrary constant, is defined by $\ln A(0)=\beta_0+\varepsilon$; where β_0 denotes a constant to be estimated via a regression analysis, and ε is a standard noise term. They then substitute this identity into Eq. (A.8), and redefine the parameters on each of the right-hand side variables (i.e., $\alpha/(1-\alpha)=\beta_i$)), to empirically test the steady-state income per capita level predicted by the model. Exploiting a cross-section of international countries, the authors find that the theoretical model performs exceeding well in explaining income per capita within the data.

Appendix B. Proof for the rate of convergence with the three-factor Solow growth model

From Eqs. (2.2)–(2.3) above we have:

$$\dot{k(t)} = s_k \cdot k(t)^\alpha \cdot e(t)^\beta - (n+g+\delta) \cdot k(t),$$
$$\dot{e(t)} = s_e \cdot k(t)^\alpha \cdot e(t)^\beta - (n+g+\delta) \cdot e(t).$$

In order to derive the rate of convergence we log-linearize around the steady state of both inputs. (This is basically a first-order Taylor series expansion around the steady state, but our notation will differ slightly from textbook definitions of a Taylor series expansion). If we totally differentiate the first equation of motion above then we derive (where we have omitted the time factor for the purposes of exposition):

$$\begin{aligned}\dot{k} - \dot{k}^* = & \dot{k} \\ & \approx \left(s_k \cdot \alpha \cdot (k^*)^{\alpha-1} \cdot (e^*)^\beta\right) dk + \left(s_k \cdot \beta \cdot (k^*)^\alpha \cdot (e^*)^{\beta-1}\right) de \\ & \quad - (n+g+\delta) dk \\ & \approx \left(\alpha \cdot \frac{(k^*)^{\alpha-1} \cdot (e^*)^\beta}{k(t)^\alpha \cdot e(t)^\beta} \cdot s_k \cdot k(t)^\alpha \cdot e(t)^\beta\right) dk \\ & \quad + \left(\beta \cdot \frac{(k^*)^\alpha \cdot (e^*)^{\beta-1}}{k(t)^\alpha \cdot e(t)^\beta} \cdot s_k \cdot k(t)^\alpha \cdot e(t)^\beta\right) de - (n+g+\delta) dk \\ & \approx \left(\alpha \cdot (g+n+\delta) \frac{e^*}{k^*}\right) dk + (\beta \cdot (g+n+\delta))\, de - (n+g+\delta) dk \\ & \approx ((\alpha-1) \cdot (g+n+\delta))\, \frac{dk}{k^*} + (\beta \cdot (g+n+\delta))\, \frac{de}{e^*} \\ & \approx ((\alpha-1) \cdot (g+n+\delta)) \cdot (\ln(k) - \ln(k^*)) \\ & \quad + (\beta \cdot (g+n+\delta)) \cdot (\ln(e) - \ln(e^*)). \end{aligned} \tag{B.1}$$

By symmetry, the log-linearization of energy capital around its steady state is defined as:

$$\begin{aligned}\dot{e} - \dot{e}^* = & \dot{e} \\ & \approx (\alpha \cdot (g+n+\delta)) \cdot (\ln(k) - \ln(k^*)) \\ & \quad + ((\beta-1) \cdot (g+n+\delta)) \cdot (\ln(e) - \ln(e^*)). \end{aligned} \tag{B.2}$$

The production function, in intensive form, is defined as $y = f(k,e) = k^\alpha \cdot e^\beta$, and its growth rate then is defined as

$$\frac{\dot{y}}{y} = \alpha \cdot \frac{\dot{k}}{k} + \beta \cdot \frac{\dot{e}}{e}. \tag{B.3}$$

Similarly, we can log-linearize around the steady state of output by totally differentiating the production function as follows:

$$\begin{aligned}\frac{y-y^*}{y^*} &= \alpha \cdot \left(\frac{k-k^*}{k^*}\right) + \beta \cdot \left(\frac{e-e^*}{e^*}\right) \\ (\ln(y) - \ln(y^*)) &\approx \alpha \cdot (\ln(k) - \ln(k^*)) + \beta \cdot (\ln(e) - \ln(e^*)). \end{aligned} \tag{B.4}$$

By substituting Eqs. (B.1) and (B.2) into Eq. (B.3), and using the identity defined in Eq. (B.4), the rate of convergence is defined as

$$\frac{d \ln y}{dt} = (\alpha + \beta - 1) \cdot (n+g+\delta) \cdot (\ln(y) - \ln(y^*)). \tag{B.5}$$

Appendix C. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.03.029.

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