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Regulation and Productivity Growth: Are We in a New Productivity Slowdown?

John W. Dawson
Appalachian State University

Abstract

This paper updates the empirical evidence on the role of federal regulation and taxes in the well-known productivity slowdown of the 1970s, based on revised and extended data on federal regulation and marginal tax rates through 2016 in the U.S. The analysis uses a time-series model derived from endogenous growth theory with regulation and taxes as policy variables. Co-movement among the policy variables and productivity growth—during both the slowdown and the subsequent recovery—suggests regulation may have played a role. Tax effects are small and statistically insignificant. The updated results also suggest a new productivity slowdown is underway, since the early-2000s, and that regulation may once again have something to do with it.

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Contact: John W. Dawson - dawsonjw@appstate.edu.
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1. Introduction

In their study of regulation and macroeconomic performance in the U.S., Dawson and Seater (2013) proposed that regulation and taxes might have played a role in the well-known "productivity slowdown" of the 1970s. Their empirical analysis covers the period 1949-2005. Recent updates in their time-series measures of regulation and taxes now allow an extension of the analysis through 2016. This paper presents the updated empirical results on the role of regulation and taxes in the productivity slowdown.[1]

The updated results suggest the link between regulation and the productivity slowdown—as well as productivity's recovery following the slowdown—may be closer than previously thought. Specifically, rapid growth in regulation during the 1960s and 70s has an increasingly negative effect on productivity's trend during the slowdown. This result differs from the original estimate of regulation's effect provided by Dawson and Seater. In addition, the extended sample uncovers a new slowdown in productivity's trend beginning in the early 2000s and continuing through 2016. The updated results suggest regulation may also play a role in this new productivity slowdown. Moreover, the extension to 2016 provides additional data points that reduce the risk of over-fitting in the model used by Dawson and Seater, thus increasing confidence in the estimates provided by the model.

The paper is organized as follows. The next section briefly describes the data updates and extensions through 2016 that make the current analysis possible. Section 3 briefly describes the empirical methodology. Section 4 presents and discusses the updated empirical results. The final section concludes.

2. Data

Dawson and Seater's (2013) original analysis uses the number of pages in the *Code of Federal Regulations* (hereafter, CFR) to measure the extent of regulation in the U.S. Dawson (2019b) extends the CFR page-count series through 2016 and provides a discussion of the series' behavior during the extended period. Figures 1 and 2 show the extended page-count series and its growth rate, respectively. Figure 2 indicates rapid growth in pages of regulation beginning in the early-1960s through the late-1970s, followed by a decline during the 1980s through the mid-1990s. Growth then rises slightly from the late-1990s through the mid-2000s and then begins a

[1]A more recent study by Coffey, McLaughlin, and Peretto (2020), which is similar in spirit to Dawson and Seater (2013), includes a sample through 2012. However, they estimate the effect of regulation on GDP rather than productivity explicitly. Their estimate of regulation's effect is a 0.8 percentage-point decline in annual output growth, which is about half of Dawson and Seater's estimate of about 2 percentage points. In an update of Dawson and Seater's original estimate, Dawson (2019b) estimates a 1.4 percentage-point decline in annual growth over the extended 1949-2016 period. The smaller estimate by Coffey *et al*. may be due to their shorter sample period, which starts in 1977 due to their use of the RegData series on regulatory restrictions instead of the page-count series used by Dawson and Seater (2013) and Dawson (2019b) that starts in 1949. Smaller estimates may also result from the use of the RegData measure of regulation; see Dawson (2019b) for additional details. See Al-Ubaydli and McLaughlin (2015) for additional information on RegData. This paper focuses exclusively on regulation's effect using total factor productivity rather than GDP as the dependent variable.

very gradual decline around 2005 (the end of Dawson and Seater's sample period) through 2016. By 2016, growth in pages of regulation is approaching historical lows.[2]

Figure 1
CFR Page-Count Series, 1949-2016

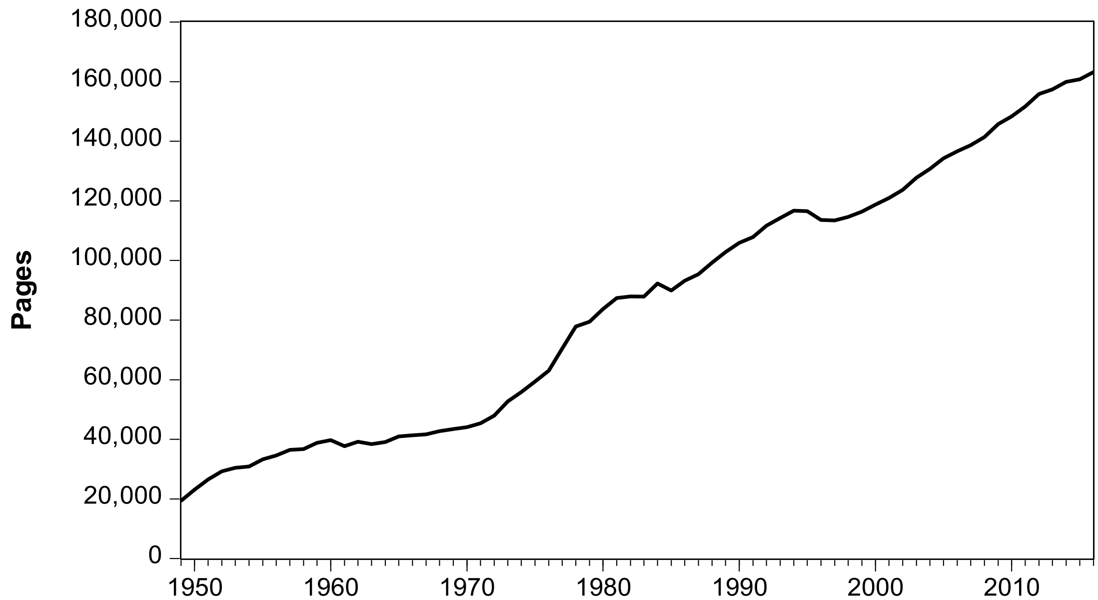
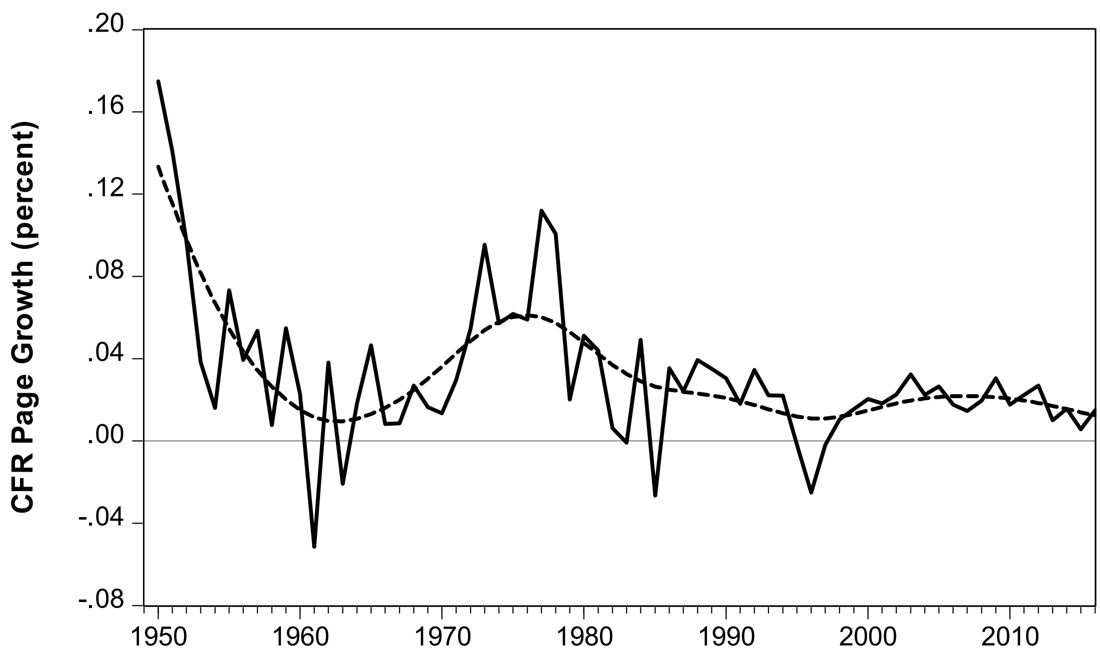


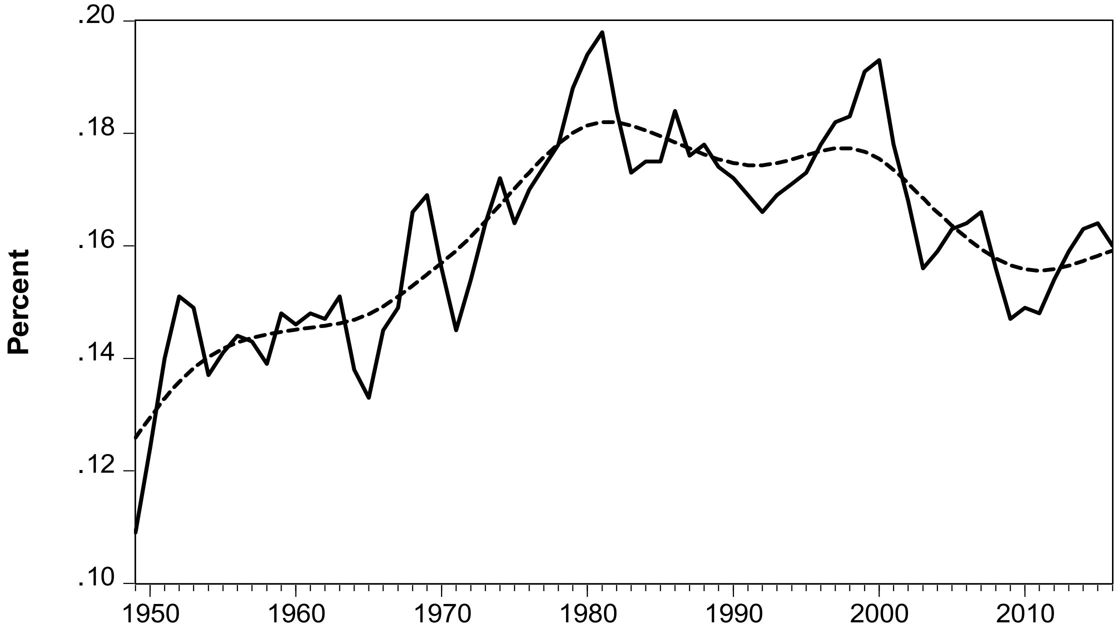
Figure 2
Growth in the CFR Page-Count Series, 1949-2016



[2]Figure 2 and the remaining figures in the paper include "smoothed" (H-P filtered) series, but all the analysis that follows uses the raw data only. The smoothed series illustrate general trends in the data, which often are obscured by the high-frequency variation of the raw series. For convenience, an Appendix provides scatterplots of the raw data.

Dawson and Seater's model also includes taxes as a policy variable. Their measure of taxes is the average marginal effective tax rate, including both the individual income tax and the Social Security tax, from Stephenson (1998) with revisions and updates through 2016 by Dawson (2019a). Figure 3 shows the marginal tax rate series over the 1949-2016 period. Taxes rose during much of the period shown in Figure 3, peaking around 1980. Then tax rates declined during the 1980s, rose during the 1990s, declined during the 2000s, and then began to rise again after the Great Recession through the mid-2010s.

Figure 3
Average Marginal Tax Rate, 1949-2016



The dependent variable of interest here is total factor productivity (TFP), defined as the Solow residual from a Cobb-Douglas production function assuming a capital share of 30%. That is, $TFP = \log(Y) - 0.3\log(K) - 0.7\log(N)$, where Y is output, K is physical capital, and N is labor. The underlying data for the construction of the *TFP* series is from the Bureau of Labor Statistics.[3] Real output (Y) is output in the private business sector, which is gross domestic product less output produced by the government, private households, and non-profit institutions. Capital (K) is service flows of equipment, structures, inventories, and land, computed as a Tornqvist aggregate of capital stocks using rental prices as weights. Labor (N) is hours worked by all persons in the private business sector, computed as a Tornqvist aggregate of hours of all persons using hourly compensation as weights.

Figure 4 shows the growth rate of the *TFP* series. TFP growth is declining at the start of the sample, but that seems to be an artifact of the leverage the first point in the sample has on the initial part of the smoothed series. Ignoring that episode, then TFP really starts falling in the mid-1960s, stops falling in the early-1980s, grows slowly through the 1980s and 90s, and then begins a sustained slowdown beginning in the early 2000s through the end of the period shown. The falling growth rate between about 1965 and 1980 is the well-known "productivity

[3]Downloaded from https://www.bls.gov/mfp/special_requests/mfptablehis.xlsx on February 13, 2019.

slowdown." Comparing the smoothed series in Figure 4 with those in Figures 2 and 3 indicates that the productivity slowdown coincides with the period of rapid growth in both regulation and the marginal tax rate—with turning points that match closely in all three series. Moreover, the general rise in productivity growth following the slowdown lasting through the 1980s and 90s coincides with a period of declining tax rates and slowing regulatory growth. Figure 5 combines the smoothed series from Figures 2-4 to provide a closer look at the co-movement in the trends of these variables.

Figure 4
Growth in Total Factor Productivity, 1949-2016

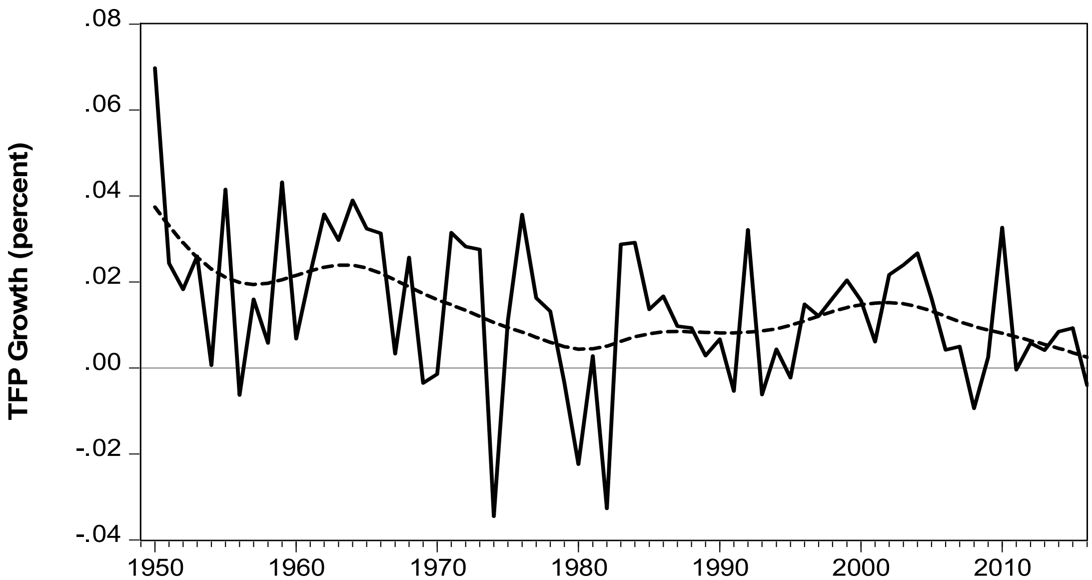
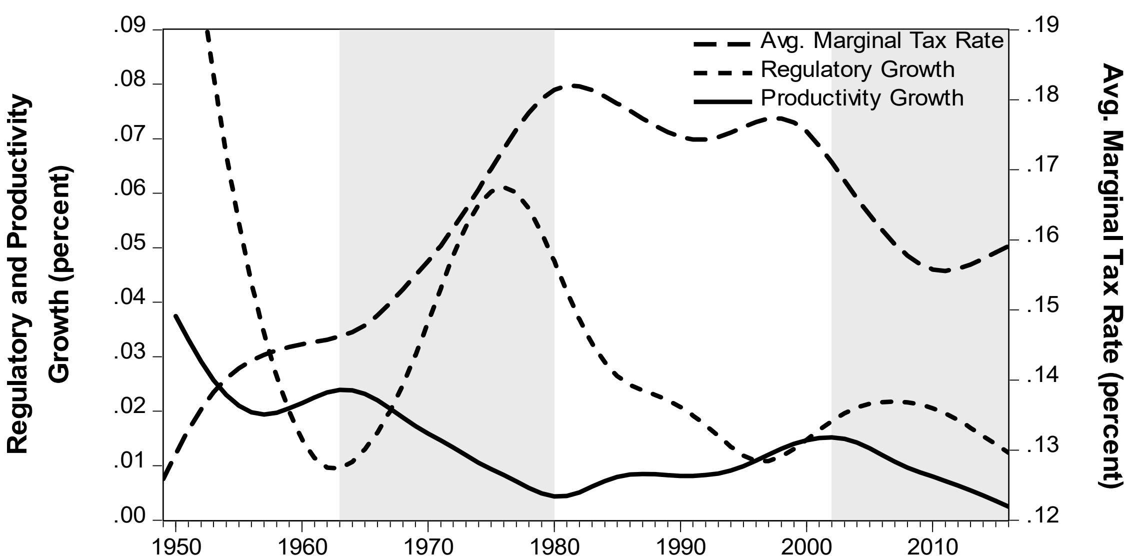


Figure 5
Trends in Regulatory Growth, Tax Rates, and Productivity Growth (Smoothed series; Periods of productivity slowdown shaded)



3. Methodology

This section uses the updated CFR page-count and marginal tax rate series to estimate the effects of regulation and taxes on total factor productivity. The model and analysis are the same as in Dawson and Seater (2013), with the sample period extended through 2016.

Dawson and Seater derive their regression model from the second-generation endogenous growth model proposed by Peretto (2007). Peretto's model provides a solution for final goods (Y) of the general form $Y = A(\bullet)e^{B(\bullet)t}C(\bullet)$, where $A(\bullet)$ is an intercept term, $B(\bullet)$ is the trend, and $C(\bullet)$ is a cycle effect. The arguments of the functions A, B, and C are subsets of the model parameters and various tax rates. Dawson and Seater adapt this general-form solution for their study of regulation by including a measure of regulation as an argument in these functions. Peretto's model does not include regulation, so closed-form solutions for $A(\bullet)$, $B(\bullet)$, and $C(\bullet)$ are not available. Instead, Dawson and Seater use quadratic approximations for these functions including current and lagged values of the regulation and tax variables.

Dawson and Seater's final estimating equation is

$$TFP_t = \alpha + \left[\beta + \sum_{j=0}^{J_1^R} \gamma_j^R R_{t-j} + \sum_{j=0}^{J_2^R} \delta_j^R R_{t-j}^2 + \sum_{j=0}^{J_1^T} \gamma_j^T T_{t-j} + \sum_{j=0}^{J_2^T} \delta_j^T T_{t-j}^2\right] t + \sum_{j=0}^{J_3^R} \omega_j^R r_{t-j} + \sum_{j=0}^{J_3^T} \omega_j^T \tau_{t-j} + u_t, \quad (1)$$

where the dependent variable, *TFP*, is total factor productivity, as defined above; R is regulation; T is the marginal tax rate; r is the natural log of R; τ is the natural log of T; α, β, γ_j, δ_j, and ω_j are constants to be estimated; J_i are lag lengths; and u is a log-normally distributed residual.

To interpret the empirical results, it is useful to recognize that regulation can have two kinds of effects on TFP's trend in this model: a uniform shift in the trend (a *trend-intercept* effect) and time-varying breaks in the trend (*trend-linear* and *trend-quadratic* effects). The trend-intercept effect is calculated as $\beta_R \Sigma \omega_j^R$, where β_R is the trend in regulation. The trend-linear and trend-quadratic effects are determined by the γ_j^R and δ_j^R coefficients. In addition to these effects on TFP's trend, regulation can also have cyclical effects, as determined by the ω_j^R coefficients. Similar effects can be obtained for taxes as determined by the analogous coefficients pertaining to taxes along with the underlying trend in taxes, β_T.[4]

Estimation of (1) is by the dynamic ordinary least squares (DOLS) procedure suggested by Saikkonen (1992) and Stock and Watson (1993) to provide an asymptotically efficient estimator in a cointegrated system. The DOLS procedure augments the estimating equation in (1) with

[4]For additional details on the derivation of equation (1) from endogenous growth theory and the interpretation of the various coefficients in the estimating equation, see Section 4 in Dawson and Seater (2013). Dawson and Seater also estimate equations analogous to (1) for physical capital, labor services, and real output as dependent variables, but attention is restricted here to total factor productivity as the dependent variable. See Dawson (2019b) for the latest evidence using real output as the dependent variable and Dawson (2019c) for the capital and labor inputs.

$$\sum_{j=-p}^{q} \mu_j^R \Delta r_{t+j} + \sum_{j=-p}^{q} \mu_j^T \Delta \tau_{t+j} \quad (2)$$

to eliminate the feedback in the cointegrating system. Standard OLS estimates of the coefficients from the augmented regression are consistent, but the usual *t*- and *F*-statistics must be re-scaled using an estimate of the long-run variance of the DOLS residuals. See Hamilton (1994, pp. 608-612) for a description of this non-parametric correction for serial correlation. The μ_j coefficients on the leads and lags in (2) are of no practical interest and thus are not reported. The lag lengths J_i on the regulation and tax variables in (1) and the appropriate number of lags p and leads q in (2) are chosen using a search procedure to find a lag structure that minimizes the Schwarz–Bayes Criterion (SBC).[5]

To ensure that the DOLS procedure for estimating a cointegrating system is appropriate in this setting, the variables in (1) are pre-tested for stationarity. The DF-GLS (Elliott *et al*. 1996) test cannot reject the unit-root null hypothesis in any of the model variables at the 5% level.[6] However, conventional unit-root tests often fail to reject the unit-root null when there is a break in the trend function under the stationary alternative hypothesis. Thus, we consider the unit-root test proposed by Zivot and Andrews (1992) which assumes a break in both intercept and trend at an unknown, endogenously determined time. The Zivot–Andrews test also fails to reject the unit-root null for all of the variables. These results suggest the model variables are individually nonstationary and the DOLS procedure for estimating a cointegrating system is appropriate.[7] Finally, to examine the sensitivity of the policy variables (*R* and *T*) to the dependent variable (*TFP*), Granger-causality tests are performed. The results indicate no causality running from the dependent variable to either of the policy variables, a finding that is consistent with econometric exogeneity of the policy variables.

Before turning to the results from the DOLS estimation of (1) in the next section, it is worthwhile to acknowledge that estimating models with a large number of parameters using a relatively small number of observations runs a risk of over-fitting the model. Dawson and Seater's search procedure includes the potential for estimating up to 46 parameters. Fortunately, the best-fit models reported in their study include far fewer parameters. For example, their best-fit specification for TFP over the 1949-2005 period includes 23 parameters. Moreover, the best-fit specification reported below for the 1949-2016 period is even simpler, with only 15 parameters. Extending the sample to 2016, which provides 11 additional data points, further reduces the risk of over-fitting. This is another important contribution of the updated analysis.

4. Results

Table I reports the best-fit model estimate for total factor productivity over the 1949-2016 period. We first discuss the effects of regulation and then turn to the tax effects later in this

[5]See Dawson and Seater (2013) for additional details on the search procedure.
[6]The DF-GLS test includes an intercept and trend. The test results discussed here are not reported, but are available from the author upon request.
[7]Testing directly for cointegration is also possible, but the available tests have low power or are inconsistent with the underlying theory. Thus, Dawson and Seater (2013) proceed with the assumption of cointegrated variables. See additional details in Dawson and Seater.

section. The model reported in Table I is identical to the best-fit model in Dawson and Seater in terms of variables included and lag structure of the regulation variables. While the model structure is the same, however, the regulation coefficients in Table I have different magnitudes than those reported in Dawson and Seater. This implies different estimates of regulation's effect on TFP.

The estimate of regulation's trend obtained from estimating $r_t = \alpha_R + \beta_R t + \nu_t$ is $\beta_R = 0.0294$ and the estimate of ω_0^R from Table I is −0.116, thus suggesting a trend-intercept effect of $\beta_R \Sigma \omega_j^R = -0.0034$. This suggests a uniform reduction in TFP's trend due to regulation, but the size of this negative effect is small. Taking into account the trend-linear and trend-quadratic effects suggested by the γ_j^R and δ_j^R coefficients reported in Table I, regulation's total effect on TFP's trend is shown in Figure 6. The effect is negative throughout the sample period, but increases in regulation cause this negative effect on TFP's trend to turn increasingly negative from the mid-1960s through about 1980—that is, during the productivity slowdown. The average value of regulation's negative effect on TFP's trend for the 1949-2016 period is −0.01, or about half the average value of −0.0195 reported by Dawson and Seater for 1949-2005. In addition, the pattern of regulation's effect in the extended sample differs markedly from that reported by Dawson and Seater, with increases in regulation during the productivity slowdown coinciding with a rapid increase in the negative effect on TFP's trend. Dawson and Seater's original estimate suggests the opposite effect during the slowdown (see their Figure 9), thus the new evidence suggests an even closer relationship than previously reported between the rapid increase in regulation and slowing productivity growth during this period. Regulation's negative effect tempers somewhat with slowing regulatory growth in the 1980s and 90s, but then turns increasingly negative again in the mid-2000s, coinciding with the new productivity slowdown late in the sample.

Figure 6
Total Effect of Regulation on TFP's Trend

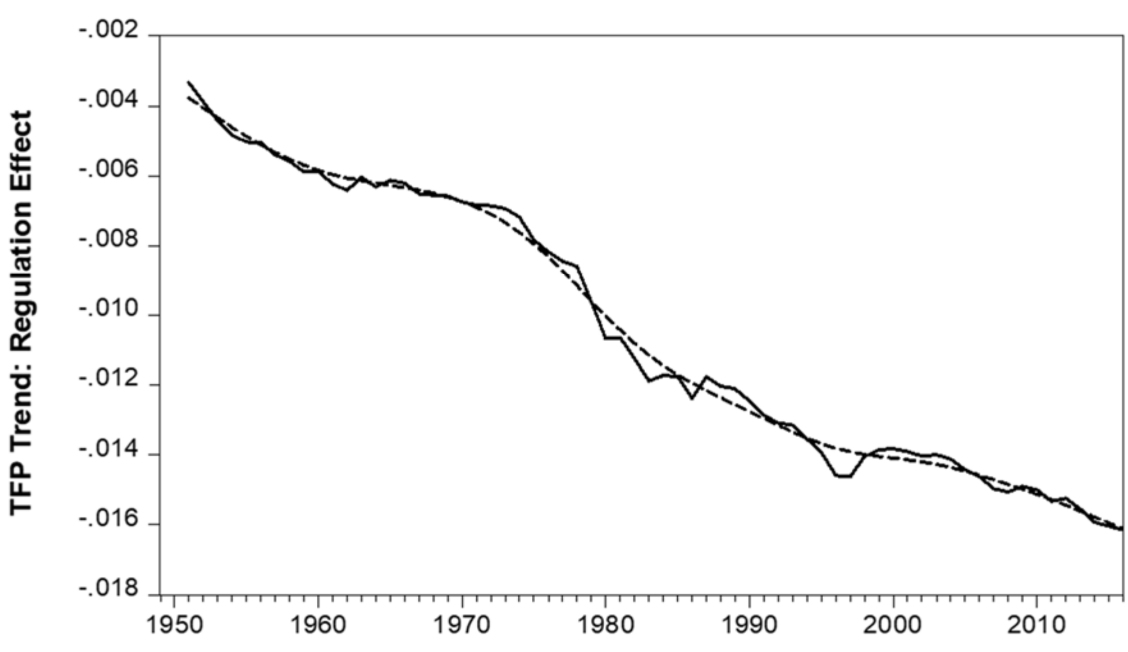


Table I
Model Estimates for Total Factor Productivity, 1949-2016

$$TFP_t = \alpha + \left[\beta + \sum_{j=0}^{J_1^R} \gamma_j^R R_{t-j} + \sum_{j=0}^{J_2^R} \delta_j^R R_{t-j}^2 + \sum_{j=0}^{J_1^T} \gamma_j^T T_{t-j} + \sum_{j=0}^{J_2^T} \delta_j^T T_{t-j}^2\right] t + \sum_{j=0}^{J_3^R} \omega_j^R r_{t-j} + \sum_{j=0}^{J_3^T} \omega_j^T \tau_{t-j} + u_t$$

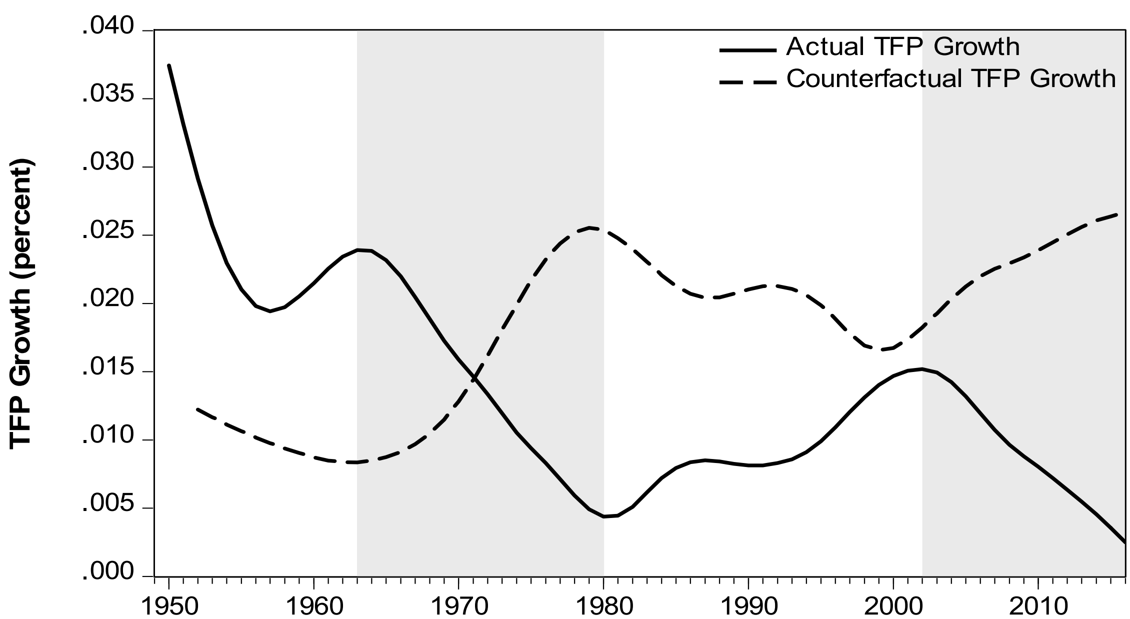
γ_0^R	−2.31E-08 (−0.262)
γ_1^R	2.16E-08 (0.180)
γ_2^R	−1.70E-07 (−1.549)
δ_0^R	−4.34E-13 (−2.246)
ω_0^R	−0.116 (−1.261)
ω_0^T	0.148 (0.999)
ω_1^T	−0.226 (−1.806)
$\beta_R\Sigma\omega_j^R$	−0.0034
$\beta_T\Sigma\omega_j^T$	−0.0002
$\Sigma\gamma_j^R$ {*F* test: $\Sigma\gamma_j^R = 0$} [p-value]	−1.72E-07 {12.733} [0.001]
$\Sigma\omega_j^T$ {*F* test: $\Sigma\omega_j^T = 0$} [p-value]	−0.078 {0.182} [0.672]
α	8.136 (12.126)
β	0.032 (9.452)
p, q	3, 3

Notes: Estimation by DOLS includes p lags and q leads of Δr_t and $\Delta\tau_t$ whose coefficient estimates are not reported. Only parameter estimates included in the best-fit model are reported. Numbers in parentheses (.) are *t*-statistics corrected for serial correlation using the non-parametric procedure described in Hamilton (1994, 608-612) and may be compared to standard *t* tables. Numbers in braces {.} are *F*-statistics corrected in a similar manner and may be compared to standard *F* tables. Numbers in brackets [.] are p-values. The value of β_R is 0.0294 and the value of β_T is 0.002863. *Source*: Author's calculations.

Regulation also has cycle effects in this model. The combined trend and cyclical effects of regulation can be obtained by constructing the counterfactual series which shows the level of TFP had regulation remained at its 1949 level. Figure 7 shows the smoothed actual and counterfactual TFP series.[8] The counterfactual series indicates that productivity growth would have increased sharply from the mid-1960s until about 1980 without the negative influence of increases in regulation after 1949. Instead, regulatory growth coincides with a slowdown in actual productivity growth during this time—the infamous productivity slowdown. After that, counterfactual productivity growth subsides absent the slowing regulatory growth that occurred during the 1980s and 90s. Thus, slower regulatory growth during this time coincides with the recovery in actual productivity growth.

The evidence in Figure 7 also indicates a distinct role of regulation in the new productivity slowdown that is currently underway, as the counterfactual series begins to rise in the late 1990s. Once again, actual productivity growth exhibits just the opposite behavior during this period. This coincides with increasing regulatory growth beginning in the late-1990s through the late-2000s (see the smoothed regulatory growth series in Figure 5). Although regulatory growth begins to rise just ahead of the current productivity slowdown, the growth rate of regulation is noticeably slower than during the original productivity slowdown. It therefore appears that regulation can play a role in slowing productivity growth without the rapid growth in regulation witnessed during the productivity slowdown of the 1970s.

Figure 7
Actual and Counterfactual TFP Growth Assuming Regulation Remained Constant at 1949 Level (Smoothed series; Periods of actual TFP slowdown shaded)

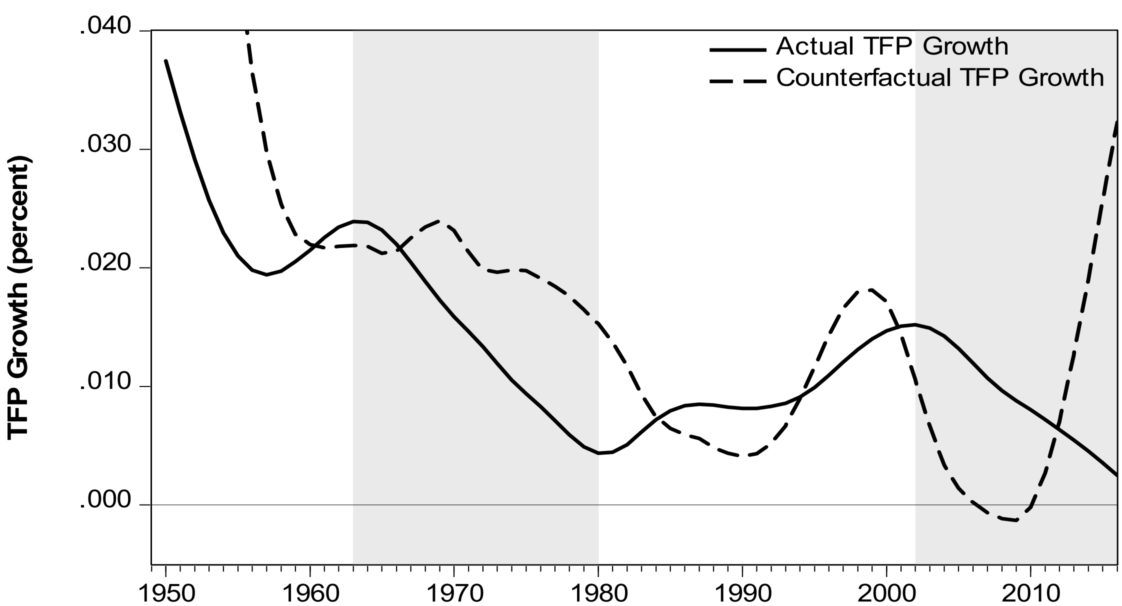


[8]See Dawson and Seater (2013), in particular their footnote 19, for details on the construction of the counterfactual series.

The recent study by Coffey *et al*. (2020) offers a possible explanation for the new association between regulation and productivity growth. They argue that the effect of a growing regulatory regime is *cumulative* in nature—that is, "the effect of government intervention on economic growth is not simply the sum of static costs associated with individual interventions" (Coffey *et al*., p. 5). Mandel and Carew (2013) originally framed this idea in the context of regulation: "For each new regulation added to the existing pile, there is a greater possibility for interaction, for inefficient company resource allocation, and for reduced ability to invest in innovation. The negative effect on US industry of regulatory accumulation actually compounds on itself for every additional regulation added to the pile" (Mandel and Carew, p. 4). If regulation has such a cumulative effect, then years of regulatory build-up may eventually take a toll—such as the current slowdown in productivity growth—even as current regulatory growth remains slow by historical standards. To be clear, our model and metric of regulation may not explicitly capture such a cumulative effect, but the occurrence of a slowdown in a time of muted growth in regulation is at least prima facie evidence that such an effect could be at work.

Taxes may also play a role in explaining TFP growth. On the tax side, the best-fit model reported in Table I is much simpler in terms of variables included and lag structure than the original model reported by Dawson and Seater. Indeed, only two tax coefficients—ω_0^T and ω_1^T—are reported in Table I, while Dawson and Seater's best-fit model includes seven tax variables. Figure 8 plots the smoothed actual and counterfactual TFP growth series obtained by holding the marginal tax rate at its 1949 level. Here, the counterfactual series generally trends closely with actual productivity growth. This indicates the effect of regulation clearly dominates that of taxes in explaining trends in productivity growth.

Figure 8
Actual and Counterfactual TFP Growth Assuming Taxes Remained Constant at 1949 Level
(Smoothed series; Periods of actual TFP slowdown shaded)

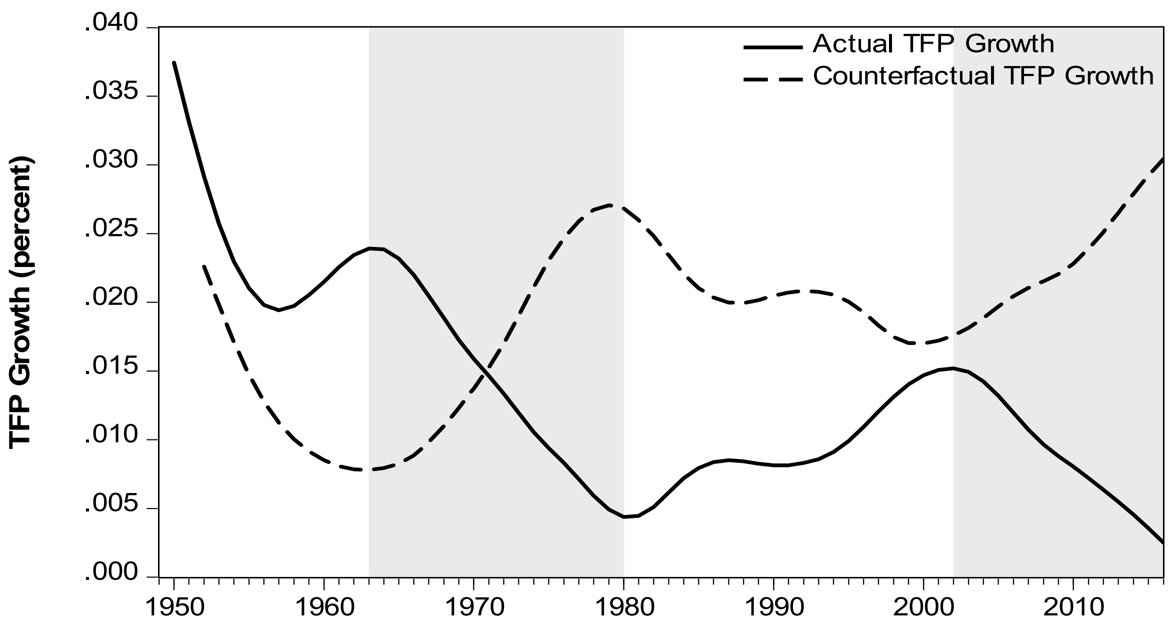


The only exception to the general conclusion that regulation's effect is dominant occurs late in the sample period—during the current productivity slowdown—when the counterfactual series turns sharply higher beginning in 2010 even as actual productivity growth continues to fall. This coincides with an increase in the marginal tax rate beginning around the same time (see Figure 3). Combining the results from Figures 7 and 8 thus suggests the current productivity slowdown began with increasing regulatory growth in the late-1990s and early-2000s and continued with increasing tax rates in the 2010s.

The results in Table I confirm the general conclusion of a small tax effect, as no trend-linear (γ_j^T) and trend-quadratic (δ_j^T) tax terms appear in the best-fit model and the sum of the ω_i^T terms are insignificantly different from zero. Dawson and Seater also found statistically insignificant tax effects in their model for TFP. The finding of small and insignificant tax effects is not surprising given that the tax measure included in the model is a measure of individual income and Social Security taxes. Personal tax rates should most directly distort labor supply decisions, but the construction of TFP differences out the contribution of labor to output. Thus, the effect of taxes is implicitly controlled for in the TFP series. See Dawson (2019c) for a closer look at the role of taxes and regulation on the labor and capital inputs individually.

Figure 9 shows the combined effects of regulation and taxes on TFP, plotting the smoothed actual and counterfactual TFP series obtained by holding both the level of regulation and the marginal tax rate at their 1949 levels. The pattern over time is similar to that shown in Figure 7, again confirming that regulation's effect dominates that of taxes in explaining the time path of TFP.

Figure 9
Actual and Counterfactual TFP Growth Assuming Regulation and Taxes Remained Constant at 1949 Levels (Smoothed series; Periods of actual TFP slowdown shaded)



5. Conclusion

This paper updates previous empirical estimates of the role of regulation and taxes in the infamous "productivity slowdown" that occurred from the mid-1960s until around 1980. The analysis uses a time-series model derived from endogenous growth theory along with recently updated data on the extent of federal regulation and marginal tax rates through 2016. The new estimates suggest that rapid growth in regulation beginning in the mid-1960s had an increasingly negative effect on productivity's trend during the slowdown—suggesting an even closer relationship between regulation and slowing productivity growth than previous results indicated. Combined trend and cycle effects clearly show that regulatory growth coincides with slowing productivity growth during the slowdown and that slower growth in regulation through the 1980s and 1990s coincides with the subsequent recovery of productivity growth. Regulation effects dominate tax effects both during and after the slowdown, with tax effects generally estimated to be small and statistically insignificant.

The updated analysis also indicates the onset of a new productivity slowdown beginning in the early-2000s. While growth in regulation has been historically slow in the period since this new slowdown began, the model for total factor productivity suggests regulation played a role—with the estimated effect of regulation turning increasingly negative and steadily increasing from the late-1990s onward. We speculate that the new productivity slowdown occurring during a period of relatively slow regulatory growth may reflect the cumulative nature of regulatory build-up over time, as has been suggested previously in the literature.

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Appendix: Scatterplots of Raw Data