Regulation And The Macroeconomy

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Abstract

This article uses the number of pages in the Code of Federal Regulations to investigate the empirical relationship between federal regulation and macroeconomic performance in the U.S. The analysis uses an aggregate production framework to study the co-movement of output and the factors of production that results from regulation. The use of cointegration methodology overcomes some shortcomings of traditional techniques. The results suggest that regulation generally is negatively related to aggregate economic performance in both the short run and the long run. Some specific areas of regulation are also found to have important long-run effects, some positive and some negative

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I. INTRODUCTION

The macroeconomic impact of government regulation has long been a hotly debated topic among politicians. Empirical studies of regulation's impact on the economy, however, have only recently appeared in the economics literature. One reason for the long-standing lack of attention among economists is the inherent difficulty in measuring the extent of regulation in the economy.

A recent study by Dawson and Seater (2006) overcomes this obstacle by presenting a time-series measure of federal regulation in the U.S. and relating this measure to macroeconomic variables of interest[1].

Dawson and Seater's measure of regulation displays growth in regulation for most years since 1949. However, there is great variation in the growth rate over time, and this variation is shown to be related to the temporal movement in macroeconomic variables including output, total factor productivity, labor services, capital services, and private investment. For example, Granger-causality tests indicate unidirectional Granger causality from regulation to most of the macro variables considered. In addition, reduced-form regressions relating regulation to the various measures of aggregate economic performance indicate that regulation added over the last 50 years has reduced aggregate output substantially, both by shifting the level of output down and by reducing output's trend rate of growth. Regulation is also found to affect total factor productivity and the factors of production, thus suggesting that regulation affects the allocation of resources in the economy. Finally, the effects of changes in regulation are found to be spread over time, thus altering the dynamic adjustment paths of all variables.

This paper extends the analysis of Dawson and Seater in two ways. First, an aggregate production function framework is used which allows the co-movement of output and the factors of production to be related to regulation in a single-equation model. This approach differs from the analysis of Dawson and Seater, where regulation is related to each of the various macro variables individually (i.e., a different reduced-form regression is estimated for each macro variable). Second, the time-series (stationarity) properties of the underlying variables are exploited to uncover the short- and long-run relationships between regulation and aggregate economic performance using cointegration methodology. This technique avoids several potential problems associated with the standard regression analysis used in many of the existing studies of regulation and allows a more complete analysis of the underlying areas of regulation.

The paper is organized as follows. Section II briefly reviews the measure of federal regulation in the U.S. proposed by Dawson and Seater. Section III presents a simple model of aggregate production that relates regulation and economic performance, provides some preliminary evidence based on traditional regression analysis, and exposes some potential problems with this approach. Section IV discusses the time-series properties of the underlying variables and their implications for empirical analysis, and uses cointegration methodology to complete the empirical analysis. The last section concludes.

II. MEASURING REGULATION: A BRIEF REVIEW

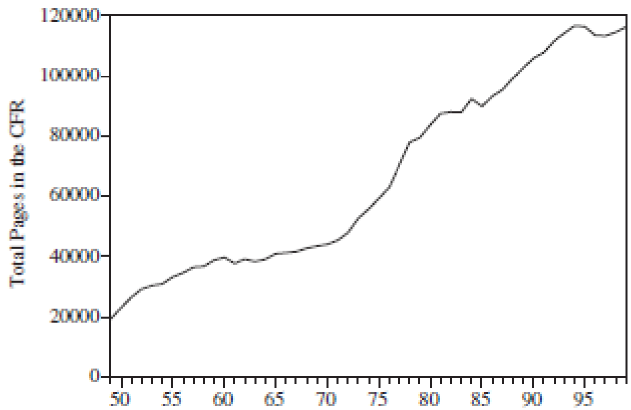
The measure of federal regulation in the U.S. used in this paper is taken from Dawson and Seater (2006). The measure is the number of pages in the *Code of Federal Regulations* (hereafter, CFR). The CFR is the U.S. government publication that prints all federal regulations in existence during a given year. This section provides a brief discussion of the CFR and the measure of regulation extracted from it. For a more complete discussion, see the Appendix in Dawson and Seater. Full details on the construction of the CFR measure are provided in Dawson (2000).

The CFR was first published in 1938. It was divided into 50 'titles', each of which pertains to a major division of regulation, such as agriculture, banking, environment, labor, shipping, etc. The structure of 50 titles continues today. The second complete edition of the CFR was published in 1949. Between 1938 and 1949, annual supplements to the CFR were published, listing changes in regulations. Because of the way the annual supplements were done, it is difficult to use them to update the 1938 edition of the CFR to obtain annual page counts. After 1949, the annual supplements were replaced by 'pocket' supplements, which were done differently than the annual supplements. In addition, updated versions of entire titles were published with increasing frequency after 1949. The pocket supplements together with the intermittent title revisions make it possible to construct fairly accurate annual page counts for the CFR between 1949 and 1969. Since 1969, the entire CFR has been revised annually, so annual page counts can be obtained directly.

Counting pages in the CFR to measure regulation obviously has limitations (e.g., it cannot capture the vigor of enforcement), but it is reasonable to believe that the number of pages of printed regulation is an indicator of the extent of regulation. Federal law requires that all federal regulations be printed in the CFR; if there were no regulations reported in the CFR, there would be no federal regulation, suggesting a positive correlation between the CFR page count and the amount of regulation. Other studies have proposed measures of regulation based on page counts (or similar) in the *Federal Register* and *U.S. Code*[2]. However, these publications include information other than regulations. Thus, the measure offered by Dawson and Seater is a more accurate measure of regulation, and also covers a much longer time span than these alternatives[3].

Figure 1 shows the time series for the total page count of the CFR from 1949 to 1999 as reported in Dawson and Seater. Regulation grows almost all the time, but its growth rate varies a great deal. Periods of negative growth are infrequent, and, when negative, the magnitude of the growth rate always is small. High growth rates occur in the 1970s, even though that period saw important deregulation in transportation, telecommunications, and energy. Clearly, any deregulation that did occur in those industries is more than offset by increased regulation in other areas, as Hopkins (1991) has noted. The behavior of the regulatory series is equally interesting during the 1980s, when the Reagan administration promoted deregulation as a national priority. Although the growth in the number of pages in the CFR slows during the 1980s, a decrease in total pages occurs only in one year, 1985. The 1990s witnessed the largest reduction in pages of regulation in the history of the CFR, when three consecutive years of decline are recorded. This coincides with the Clinton administration's ‘reinventing government’ initiative which boasted of reduced regulation in general and a reduction in the number of pages in the CFR in particular.

Figure 1. Federal Regulation in the U.S., 1949–1999



Source: Dawson and Seater (2006)

III. MODEL, PRELIMINARY EVIDENCE, AND POTENTIAL PROBLEMS

This section provides a brief outline of the model used to study the relationship between regulation and macroeconomic performance, and then presents some empirical evidence that serves as an initial reference point for the analysis that follows in the next section of the paper.

3.1. The Model

The empirical analysis in the remainder of the paper is based on a simple model of aggregate production. Let aggregate private-sector output, Y_t, be determined by the production technology

$$Y_t = A_t f(N_t, K_t), \tag{1}$$

where N_t represents aggregate employment of labor services and K_t represents the flow of services from the stock of private capital. A_t is an index of total factor productivity or Hicks-neutral technical change which is assumed to be a function of aggregate shocks, Z_t, and government regulation, R_t; i.e.,

$$A_t = A(Z_t, R_t). \tag{2}$$

By assuming a generalized Cobb-Douglas form for the aggregate production function and taking natural logarithms, (1) can be rewritten as

$$y_t = a_t + e_N n_t + e_K k_t, \tag{3}$$

where lower-case letters denote logarithms of their upper-case counterparts and e_i represents the elasticity of output with respect to factor i=N, K. If the technology (1) exhibits constant returns to scale over the inputs N_t and K_t, then $e_N+e_K= 1$[4]. Under this assumption, (3) can be written as

$$(y_t - k_t) = a_t + e_N(n_t - k_t). \tag{4}$$

If we make explicit reference to the factors affecting productivity, a_t, as described in (2), we can derive an empirical specification that is useful for testing the effects of government regulation on aggregate economic activity. This specification is taken from (4) under the assumption that the implicit function (2) can be expressed as a log-linear relation of the determinants of total factor productivity; namely,

$$(y_t - k_t) = \alpha + \beta z_t + \theta(n_t - k_t) + \sum_{j=0}^{J} \omega_j (r_{t-j} - k_{t-j}) + \in_t \, . \tag{5}$$

where $\in_t$ is a disturbance term. The regulation measure enters the equation as the regulation-to-capital ratio, (r_t−k_t), to maintain consistency with the other level variables in the model. Up to J lags of the regulation measure are included, as regulatory change may affect economic activity over an extended period of time. From a theoretical standpoint, it is unclear whether the regulation parameters ω_j are positive or negative. Different types of regulations may have different affects on production, some positive and some negative, thus leaving the anticipated impact of the aggregate regulation variable ambiguous. This, ultimately, is an empirical issue, which is the focus of this paper.

The empirical analysis throughout the paper utilizes annual data from the U.S. The measure of regulation (r) is the CFR measure used by Dawson and Seater (2006) over the period 1949 to 1999, as discussed in Section II[5]. Data on private business output (y), hours of labor services (n), and private capital services (k) are prepared by the U.S. Department of Labor and reported in the *Monthly Labor Review*[6]. Output is real output in the private business sector, which is gross domestic product less output produced by the government, private households, and non-profit institutions. Labor 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. Capital is the service flows of equipment, structures, inventories, and land, computed as a Tornqvist aggregate of capital stocks using rental prices as weights. The capacity utilization rate in the manufacturing sector of the economy (cu), published in the *Federal Reserve Bulletin*, is used as a proxy for z.

3.2. Preliminary Evidence

This subsection provides a summary analysis of the relationship between regulation and macroeconomic performance. OLS estimates of equation (5) are reported in *Table 1*. Five lags of the regulation variable are included to capture the adjustment of economic activity over time to changes in regulation (i.e., J= 5 in equation (5) above)[7]. Estimation of the model includes a correction for first-order serial correlation in the error process, which is sufficient to eliminate any evidence of serial correlation up to lag 12 in the residuals based on the Breusch-Godfrey serial correlation LM test. The estimates reported in the first two columns of *Table 1* are the sum of current and lagged coefficients on the regulation variables, $\sum_{j=0}^{J} \hat{\omega}_j$, along with F-statistics for the significance of the sum. The first row of the table uses the measure of aggregate regulation (i.e., total pages in the CFR), while the remaining rows consider specific areas of regulation (pages in the individual titles of the CFR). Note that each row of *Table 1* reports a separate estimate of equation (5). Thus, the analysis of specific areas of regulation involves the estimation of separate regressions, each using the individual titles of the CFR in turn (rather than jointly estimating the impact of each title simultaneously in a single equation). Further discussion of this approach is provided below.

Table 1

Estimation of Equations (5) and (6) 1949–1999

Regulation measure	OLS estimation of (5)		DOLS estimation of (6)	
	$\sum_{j=0}^{J}\hat{\omega}_{I}$	*F*-test	$\hat{\gamma}$	*t*-test
Complete *CFR*	− 0.2392	7.52**	− 0.2680	− 2.08**
Title 7: Agriculture	0.0365	0.12	0.0906	1.40
Title 8: Aliens and Citizenship	0.0107	0.06	− 0.1096	− 1.40
Title 12: Banks and Banking	− 0.0661	0.64	− 0.0035	− 0.05
Title 13: Business Credit	0.0149	0.50	0.0894	3.88**
Title 15: Commerce	− 0.0539	3.10*	− 0.1149	− 3.82**
Title 16: Commercial Practices	− 0.0190	0.07	0.0160	0.13
Title 17: Commodity and Securities Exchange	− 0.0571	1.03	− 0.2181	− 1.75*
Title 18: Conservation of Power	0.0021	0.002	0.1486	1.77*
Title 19: Customs Duties	− 0.0832	1.48	− 0.3444	− 2.93**
Title 20: Employee's Benefits	− 0.1230	3.12*	− 0.2536	− 2.35**
Title 21: Food and Drugs	− 0.0742	0.80	0.1623	2.04**
Title 22: Foreign Relations	− 0.1175	4.57**	− 0.3326	− 7.19***
Title 23: Highways	− 0.0061	0.18	− 0.0419	− 2.24**
Title 24: Housing Credit	− 0.0656	34.53***	− 0.0897	− 12.24***
Title 26: Internal Revenue	0.0179	0.04	0.74891	3.59***
Title 28: Judicial Administration	− 0.0378	0.93	0.2115	2.95**
Title 29: Labor	− 0.0847	3.18*	− 0.0314	− 0.30
Title 30: Mineral Resources	− 0.1068	8.62**	− 0.2433	− 5.01***
Title 31: Money and Finance: Treasury	− 0.0498	1.97	− 0.0758	− 0.71
Title 33: Navigation and Navigable Waters	− 0.1024	2.72	− 0.1026	− 0.83
Title 36: Parks and Forests	− 0.0593	1.82	− 0.2516	− 5.60***
Title 37: Patents and Copyrights	− 0.0788	2.92*	− 0.3114	− 7.57***
Title 38: Pensions, Bonuses, and Veteran's Relief	− 0.0735	1.29	− 0.3416	− 4.54***
Title 40: Protection of the Environment	0.0388	0.90	− 0.0131	− 1.15
Title 41: Public Contracts	0.0072	0.35	0.0237	1.70
Title 42: Public Health	− 0.0531	4.54**	− 0.1530	− 3.10**
Title 43: Public Lands: Interior	0.0129	0.07	− 0.2106	− 2.80**
Title 45: Public Welfare	− 0.0111	0.21	0.0431	1.19
Title 46: Shipping	0.0157	0.04	0.0766	0.82
Title 47: Telecommunications	− 0.0427	0.35	− 0.1162	− 0.91
Title 49: Transportation and Railroads	− 0.1007	3.55*	− 0.1702	− 1.79*
Title 50: Wildlife and Fisheries	− 0.0713	13.45***	− 0.1568	− 14.63***

Notes: *F*-test is the *F*-statistic for the null hypothesis that the sum of current and lagged coefficients on the regulation variable in equation (5) equals zero. $J = 5$ in the estimation of (5); estimates include a correction for first-order autocorrelation in the error process. *t*-test is the *t*-statistic for the null hypothesis that the parameter γ in equation (6) equals zero. $k = 3$ in the estimation of (6); *t*-statistics include a non-parametric correction for serial correlation. The estimation for Title 40 is limited to 22 observations because environmental regulations were not assigned to Title 40 until 1971.
*,**, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

The results in the first row of *Table 1* report a statistically significant negative relationship between output per unit of capital and the aggregate regulation-capital ratio[8]. A one percentage point increase in the regulation-capital ratio is associated with a combined 0.24 percentage point reduction in the productivity of capital over the five-year adjustment period considered here. Turning now to the individual areas of regulation, the results suggest that some areas of regulation are important and some are not. The current and lagged impact of regulation in Titles 15 (commerce), 20 (employee benefits), 22 (foreign relations), 24 (housing credit), 29 (labor), 30 (mineral resources), 37 (patents and copyrights), 42 (public health), 49 (transportation), and 50 (wildlife and fisheries) are found to be significantly related to output per unit of capital. For each of these areas, the estimated impact is negative. The estimated size of the impact differs across these areas, ranging from a 0.05 percentage point decrease to a 0.12 percentage point decrease in capital productivity for each one percentage point increase in the regulation-capital ratio over a five-year period. Not surprisingly, each of these individual effects is estimated to be smaller than the 0.24 percentage point effect estimated for the aggregate measure of regulation in row one of the table. Looking across the list of areas that are found to be significantly related to economic activity, there is no rationale for explaining why these particular areas of regulation are significant and others are not. It is easy, for example, to imagine that labor regulations or transportation regulations negatively impact output. But, it is also easy to imagine that many of the areas not found to be significant could be related to growth, either positively or negatively. Ultimately, determining which areas of regulation are significantly related to growth is simply an empirical issue.

3.3. Potential Problems

In closing the discussion of the OLS results reported in *Table 1*, note that the perspective of modern dynamic economics questions the validity of this approach. First, the levels of aggregate time series are often found to be nonstationary, possibly making them unsuitable for use in standard regression analysis. Second, there are questions about the appropriate estimation technique given the possible presence of multicollinearity and omitted variables bias. Further discussion of the nonstationarity issue is deferred to the next section. The potential for the omitted variables problem, as it applies to the study of regulation and the macroeconomy in particular, is described further here.

Recall that *Table 1* reports separate estimates of the model in equation (5) by using each of the individual titles of the CFR in separate regressions. The objective of this approach is to determine which specific areas of regulation have an impact on the aggregate economy. However, there is a problem with this approach. Namely, the page counts of the various titles of the CFR are highly correlated with one another. The mean correlation among page counts of the individual titles is 0.60, with an even higher median of 0.77. The maximum correlation is 0.99, and the minimum correlation is −0.76. Such high correlations imply that including just one type of regulation in a statistical analysis is likely to be misleading because of this collinearity and the consequent omitted variables problem[9].

The collinearity problem is even more severe when addressing the issues of macroeconomic dynamics. The correlations among the individual titles discussed above are all contemporaneous. For analyzing time-series behavior, the dynamic relations among various types of regulation are also important. Granger-causality tests can be used to show the intertemporal dependence of one series on another after accounting for the first series' dependence on its own lagged values. As an example of the kind of dependence that can exist between different titles of the CFR, Granger-causality tests were conducted for Title 16 (Commercial Practices) and Title 29 (Labor Relations). The Granger-causality tests show that the page counts of those titles both Granger-cause and are Granger-caused by the page count of the other title. Similar results are found for most of the other titles of the CFR. These results show that there are temporal orderings in the statistical relations among the types of regulation and provide strong evidence that a time-series analysis restricted to a subset of regulations is likely to suffer from serious omitted variables bias.

In closing, note that the forgoing discussion has important implications for the approach used in many of the existing studies of regulation. Most studies rely on measures of specific areas of regulation, such as regulation of entry, labor regulations, or regulation of a particular industry (such as transportation). This reliance, of course, is primarily due to the inherent difficulties in measuring total regulation. If the objective is to estimate the impact of total regulation (as in this study), the high correlations among the different areas of regulation might actually be considered good news – because they suggest that a subset of regulations may capture the behavior of aggregate regulation. Indeed, in a recent study, Nicoletti et al. (2001, p. 43) interpret their indicators of regulation as 'a proxy for the overall regulatory policies followed by OECD countries over the sample period'. Examination of the data, however, shows this hope to be ill-founded. Nicoletti et al.'s measure spans 1978–1998 and shows a 66% decline over that period. As it turns out, subsets of CFR titles corresponding to Nicoletti et al.'s measure behave similarly over that period. For example, Titles 23 (Highways), 46 (Shipping), and 49 (Transportation) of the CFR encompass regulation of air transport, railways, and road freight, one of Nicoletti et al.'s regulation groups. The page counts of these titles drop from a total of 8,400 in 1978 to 8,261 in 1998, thus exhibiting behavior which is qualitatively similar to Nicoletti et al.'s measure. Nevertheless, the page count of the whole CFR displays the opposite behavior, rising 47% over the 1978–1998 period. Therefore, subsets of regulation are not reliable proxies for total regulation.

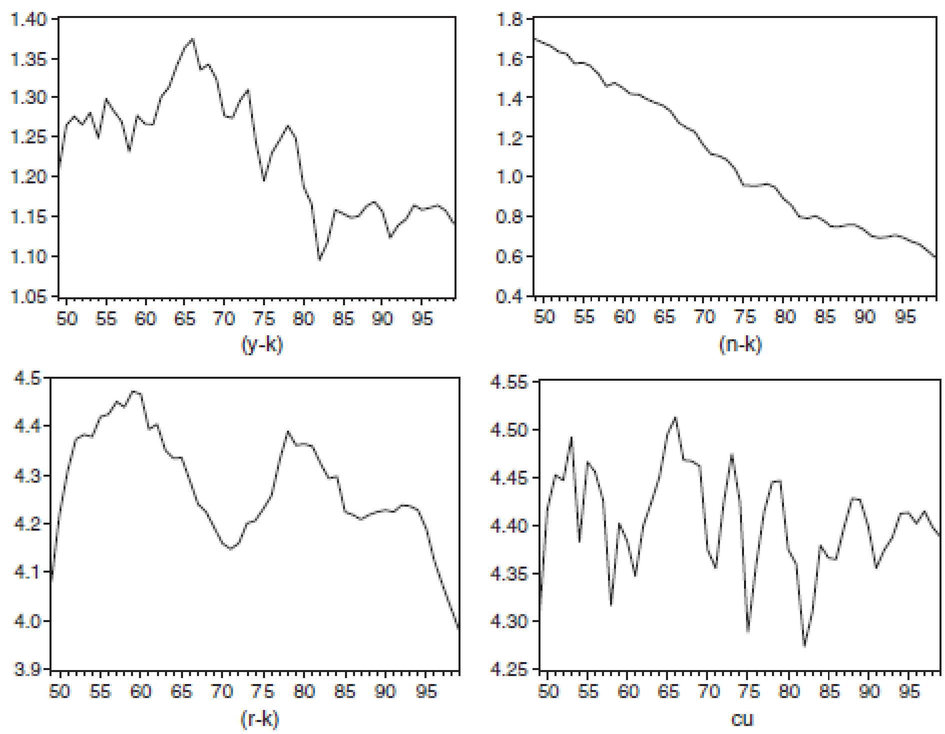
IV. COINTEGRATION ANALYSIS

As discussed above, a number of potential pitfalls exist with the use of standard regression analysis. One concern is the failure to account for the time-series properties of the variables used in the analysis. In particular, standard regression analysis may be inappropriate if the time series are found to be nonstationary. A second problem pertains to omitted variables bias, which occurs when important variables are left out of the empirical specification. Such a problem was shown to exist when specific areas of regulation are used individually in the analysis. Failure to address these problems could skew statistical inference when standard OLS techniques are used, resulting in inconsistent estimates of how a change in regulation affects the economy. This section presents an alternative approach, based on the theory of cointegration, which can address these difficulties.

4.1. Estimating Long-Run Trends

It is well known in the macroeconomics literature that many macro variables contain a stochastic trend, and that conventional estimation techniques do not take into account the implications of this type of nonstationarity. It is not surprising, then, that standard Dickey-Fuller tests indicate the null hypothesis of a unit root cannot be rejected for the variables ($y-k$), ($n-k$), and ($r-k$)[10]. Empirical analysis such as that presented in the previous section may not be appropriate in the presence of nonstationary variables, since findings of statistical significance may be spurious. We now present an alternative approach for measuring the effects of regulation – based on the theory of cointegration – which takes into account the nonstationarity properties of the underlying data[11].

Figure 2. Plots of Raw Data Used in Analysis



The concept of cointegration is illustrated using the model described above, which provides the empirical specification given in equation (5). However, the cointegration methodology is not conditional on any particular theoretical model and is robust to a variety of departures from the framework presented above. Equation (5) is repeated here for convenience:

$$(y_t - k_t) = \alpha + \beta z_t + \theta(n_t - k_t) + \sum_{j=0}^{J} \omega_j (r_{t-j} - k_{t-j}) + \epsilon_t \; . \tag{5}$$

The goal is to estimate the parameters ω_j. First, the appropriate estimation technique must account for the time-series (nonstationarity) properties of the variables in (5). Recall from above that conventional unit root tests indicate the variables ($y-k$), ($n-k$), and ($r-k$) are nonstationary. Similar tests indicate, however, that the first differences of these variables $\Delta(y-k)$, $\Delta(n-k)$, and

Δ(*r*−*k*), are stationary. In other words, the variables (*y*−*k*), (*n*−*k*), and (*r*−*k*) are said to be first-order integrated, or *I*(1). If the error term ∈ in (5), on the other hand, is stationary, or *I*(0), then the variables (*y*−*k*), (*n*−*k*), and (*r*−*k*) are said to be cointegrated. That is, the variables in (5) are individually trending (i.e., nonstationary), but they share a common long-run trend while deviating from each other only in the short run. Intuitively, we expect this result; otherwise, the variables (*y*−*k*), (*n*−*k*), and (*r*−*k*) would be found to drift unrealistically away from one another.

Johansen (1988, 1991) provides a test for cointegration as well as the number of distinct cointegrating relationships (vectors) among a set of variables. The results of Johansen tests reported in *Table 2* support the hypothesis that (*y*−*k*), (*n*−*k*), and (*r*−*k*) are cointegrated, which suggests that the error term, in (5) is in fact stationary. The finding of cointegration is important for several reasons relating to the estimation of the relationship between regulation and macroeconomic performance. First, notice that the error term in (5) will typically be both serially correlated and correlated with the regressors (*n*−*k*) and (*r*−*k*). While serial correlation is straightforward to address in conventional econometric techniques, correlation between the error term and the regressors leads to inconsistent parameter estimates when the variables in (5) are not cointegrated. When the variables are cointegrated, however, OLS estimation of the cointegrating parameters – or cointegrating vector – is robust to the presence of this type of correlation. This property results because ∈ (error term) is stationary while the regressors are individually nonstationary. There may be some transitory correlation between the error term and the regressors, but the long-run correlation must be zero since trending variables must eventually diverge from stationary ones. Thus, the finding of cointegration among the variables in (5) suggests we can obtain accurate estimates of the long-run relationship among these variables.

Table 2

Johansen Cointegration Tests $(y - k)$, $(n - k)$, and $(r - k)$

	λ-Max		Trace	
H_0: h =	Test statistic	90% C.V.	Test statistic	90% C.V.
Lags in VAR model: $k = 1$				
0	44.98	13.39	53.70	26.70
1	8.72	10.60	8.72	13.31
2	0.004	2.71	0.004	2.71
Lags in VAR model: $k = 2$				
0	27.29	13.39	37.01	26.70
1	8.13	10.60	9.72	13.31
2	1.59	2.71	1.59	2.71
Lags in VAR model: $k = 3$				
0	20.15	13.39	31.66	26.70
1	9.71	10.60	11.51	13.31
2	1.80	2.71	1.80	2.71
Lags in VAR model: $k = 4$				
0	18.23	13.39	29.88	26.70
1	8.27	10.60	11.65	13.31
2	3.38	2.71	3.38	2.71

Notes: The cointegration tests assume a p-dimensional VAR model with k lags, where p is the number of stochastic variables among which the investigator wishes to test for cointegration. The 8-max statistic tests the null hypothesis of h cointegrating relationships against the alternative of $h + 1$ cointegrating relationships. The trace statistic tests the null hypothesis of h cointegrating relationships against the alternative of $p = 3$ cointegrating relationships. The test assumes a linear trend in the data and a constant in the cointegrating relationship. The results also hold under the assumption of no trend in the data and a constant in the cointegrating relationship.

A second desirable property that results from similar reasoning is that the estimation of cointegrated systems is robust to a wide range of underlying theoretical models. Consistent estimates of the cointegrating relationship among the variables in (5) can be obtained even if there are omitted explanatory variables that are correlated with the regressors. In other words, as long as the variables in (5) are cointegrated, we can consistently estimate the parameters of that long-run relationship. This property is particularly important in light of the discussion in the previous section regarding the high correlation between individual titles of regulation and the consequent omitted variables problem. Thus, cointegration analysis can be used to identify which specific areas of regulation are important at the macroeconomic level and reliable estimates of each area's impact can be obtained. We now turn to the empirical procedure for estimating these relationships.

The logic of the discussion above requires the presence of a single cointegrating vector linking ($y-k$), ($n-k$), and ($r-k$). The results of the Johansen ‘Trace’ test reported in *Table 2* suggest that the hypothesis of a single cointegrating vector is in fact consistent with the data. Therefore, we can proceed with the estimation of the cointegrating vector using single-equation techniques[12]. As noted, standard OLS estimation will produce consistent estimates of the cointegrating vector. However, statistical inference cannot be carried out using conventional standard errors; a correction for serial correlation is necessary.

We use the dynamic OLS (DOLS) procedure suggested by Stock and Watson (1993), as described in Hamilton (1994, p. 608), to estimate the cointegrating relationship between the variables of interest. This procedure specifies a single equation of the form:

$$(y_t - k_t) = \alpha + \pi(n_t - k_t) + \gamma(r_t - k_t) + \sum_{i=-k}^{k} \pi_i \Delta(n_{t+i} - k_{t+i}) + \sum_{i=-k}^{k} \gamma_i \Delta(r_{t+i} - k_{t+i}) + \in_t^* \tag{6}$$

where Δ is the first-difference operator and, $\in_t^*$ is related to $\in_t$ such that $\in_t^* = \in_t - \sum_{i=-k}^{k} \pi_i \Delta(n_{t+i} - k_{t+i}) - \sum_{i=-k}^{k} \gamma_i \Delta(r_{t+i} - k_{t+i})$. Equation (6) is estimated by OLS, with leads and lags of the first differences of the right-hand-side variables included to eliminate the effects of regressor endogeneity on the distribution of the OLS estimator. A non-parametric correction for serial correlation is required for the *t*-statistics; see Hamilton (pp. 610–611) for details. This procedure provides consistent estimates of the cointegrating vector $\{1, -\pi, -\gamma\}$ and the corrected *t*-statistics can be compared to standard *t*-tables.

Equation (6) appears, at first glance, to be very similar to equation (5) estimated in the previous section. There are, however, some noteworthy differences. Unlike equation (5), equation (6) contains leads and lags of the first differences of all right-hand-side variables. Equation (5) includes lags of the level of the regulation variable only. Thus, the estimates of the regulation parameter from equation (5) are the sum of the coefficients on the current and lagged levels of regulation, in order to capture the long-run impact of regulation when there are adjustment lags. By contrast, the estimation of the single parameter γ in equation (6) measures the long-run impact of regulation. Likewise, equation (5) includes the capacity utilization rate, *cu*, as an explanatory variable to proxy for aggregate shocks, *z*, in order to account for short-run economic fluctuations around the trend relationship. Equation (6), however, does not include a proxy for *z*, and leads and lags are included simply to eliminate the effects of regressor endogeneity on the distribution of the least squares estimator. Intuitively, equation (6) is specified to estimate only the cointegrating relationship among ($y-k$), ($n-k$), and ($r-k$) in the long run. By contrast, equation (5), as estimated in *Table 1*, implicitly models both the long-run parameters and the adjustment of the economy to changes in regulation over the short run. It is reasonable to suppose that a procedure – such as the estimation of equation (6)– that separates these two steps will provide more accurate estimates of the long-run trend relationship.

To facilitate comparison with previous results, the DOLS estimates of γ from equation (6) are reported alongside the estimated regulation parameters from equation (5) in *Table 1*. The DOLS estimation uses k= 3[13]. The corrected *t*-statistics are also reported. In the first row of the table, the aggregate measure of regulation is used. The results suggest a negative relationship between regulation and output per unit of capital over the long run. The size of the impact is estimated to be slightly larger than in the analysis of the previous section – a one percentage point increase in the regulation-capital ratio causes nearly a 0.27 percentage point decrease in output per unit of capital, compared to a 0.24 percentage point decrease estimated in the previous section.

In the remaining rows of *Table 1*, the individual titles of regulation are used in the analysis. Again, each row reports a separate application of the DOLS procedure, each using the individual titles of the CFR in turn. Recall, however, that the cointegration analysis is not subject to the omitted variables problem discussed in the previous section. Of the 32 areas of regulation considered, 22 are found to have a statistically significant long-run impact on aggregate economic activity[14]. Only 10 such areas were found in the previous section. Additional areas of regulation found to be important using the present analysis include Titles 13 (business credit), 17 (commodity and securities exchange), 18 (conservation of power), 19 (customs duties), 21 (food and drugs), 23 (highways), 26 (internal revenue), 28 (judicial administration), 36 (parks and forests), 38 (pensions, bonuses, and veterans relief), 41 (public contracts), and 43 (public lands). In each case where a title is found to be statistically significant in both analyses, the size of the estimated impact is larger using the cointegration analysis. The largest negative impact is associated with Title 19, with a −0.34 percentage point impact. This title was not found to be statistically significant in the estimation of (5). Only one title was found to be significant in the estimation of (5), but not in the present analysis – Title 29 (labor).

Interestingly, several areas of regulation are estimated to have a positive effect on the economy. These include Titles 13, 18, 21, 26, 28, and 41. It is certainly reasonable to suppose that regulations relating to the judicial system (Title 28) might have such an effect, insofar as these regulations promote the enforcement of property rights and contracts. Admittedly, it is more difficult to explain how regulations relating to internal revenue (Title 26) might have a positive effect. The largest positive impact is associated with Title 26, with a 0.75 percentage point impact. This title was not found to be statistically significant in the estimation of (5).

Before closing the discussion of the cointegration results, it is important to assess the robustness of these results. The robustness issue is especially important in light of the empirical nature of the relationship between regulation and macro performance (i.e., given the lack of a theoretical prediction regarding regulation's effect on the economy). One simple test for robustness involves splitting the sample into two sub-periods to see if the results from the whole sample also hold for the sub-samples[15]. To accomplish this test, the 1949–1999 sample period used in the analysis above is split into two equal periods: 1949–1975 and 1976–1999. Johansen tests indicate the presence of a single cointegrating vector among the variables ($y-k$), ($n-k$), and ($r-k$) during these sub-periods under assumptions similar to those used in *Table 2* (using total pages in the CFR as the measure of regulation). Applying the DOLS procedure to each of these sub-samples also provides evidence consistent with that for the whole sample. Specifically, total regulation (total pages in the CFR) is found to be negatively related to aggregate economic performance. For the 1949–1975 period, the estimated coefficient on regulation is −0.4347 (with an adjusted *t*-statistic of −9.36); for the 1976–1999 period, the estimated coefficient on regulation is −0.3776 (−12.62). In fact, these estimated impacts of regulation (and the *t*-statistics) are larger than those for the whole sample (as reported in the first row of *Table 1*). Thus, the results do not appear to be dependent on the sample period considered in the analysis.

Another simple way to test for robustness involves changing the empirical specification to see if the results with respect to regulation are affected. Since it is possible that the regulation measure could be capturing some aspect of government activity in the economy other than regulation itself, an obvious choice would be to introduce a new variable that captures government activity into the specification to determine if the statistical significance of the regulation variable is affected. Along these lines, a measure of government capital is added to the specification in (6). Specifically, the specification in (6) is augmented to include the variable ($g-k$) along with k leads and lags of $\Delta(g-k)$, where g is the natural logarithm of government capital measured as federal, state, and local government equipment and structures (fixed nonresidential government capital) excluding military equipment and structures (obtained from the Bureau of Economic Analysis). Johansen tests indicate the presence of a single cointegrating vector among the variables ($y-k$), ($n-k$), ($g-k$), and ($r-k$) under assumptions similar to those used in *Table 2*. Applying the DOLS procedure to the expanded specification provides evidence that regulation is negatively related to economic performance even when government capital is included in the model. The estimated coefficient on the regulation variable (total pages in the CFR) is −0.3580 (with an adjusted t-statistic of −9.30). Again, this estimated impact (and t-statistic) is even larger than the results reported in the first row of *Table 1*. Thus, the results appear to be robust to this change in the empirical specification. This result is not surprising since, as discussed above, one of the properties of the cointegration methodology is its ability to provide consistent parameter estimates of the cointegrating vector even when there are omitted variables that are correlated with the regressors. The foregoing test for robustness also demonstrates this important property.

In summary, the cointegration analysis generally confirms most of the results from the OLS analysis presented in the previous section. However, the cointegration analysis suggests an even larger negative impact of aggregate regulation on the economy over the long run. The results also suggest a larger impact from those specific areas of regulation found previously to be significant, and suggest that some additional areas of regulation are significantly related to economic performance – some positive and some negative. Taken together, the results suggest an important impact of regulation on the macroeconomy. These results are robust to splitting the sample period in half and adding a measure of government capital to the empirical specification.

4.2. Estimating Short-Run Dynamics

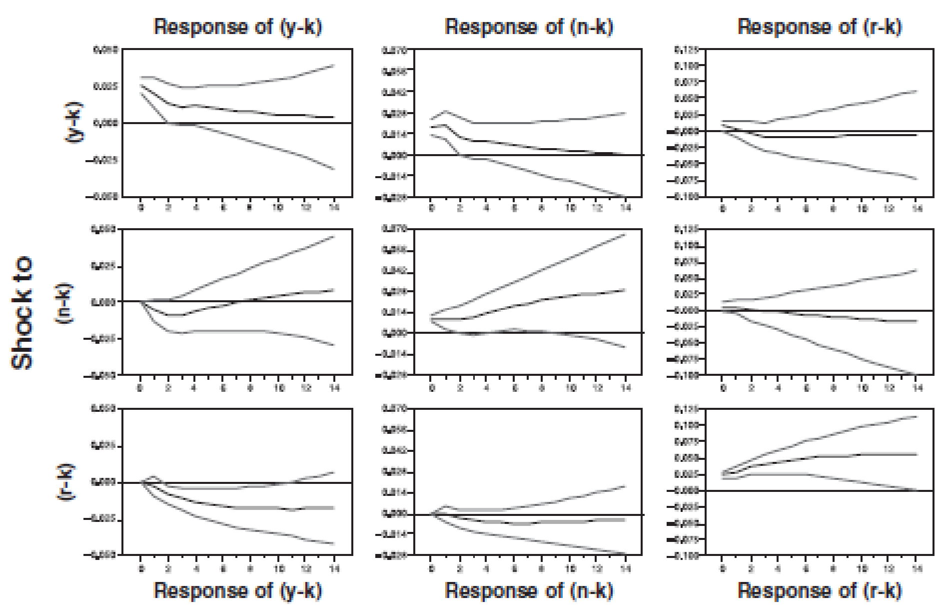
To discuss the short-run dynamics implied by the relationship between regulation and the macroeconomy, consider a model that imposes the long-run (cointegrating) relationship estimated above while also allowing for temporary divergences from this trend. The model takes the form

$$\Delta \mathbf{x}_t = \mu + \delta[(y_{t-1} - k_{t-1}) - \hat{\pi}(n_{t-1} - k_{t-1}) - \hat{\gamma}(r_{t-1} - k_{t-1})] + \sum_{j=1}^{k} \Phi_j \Delta \mathbf{x}_{t-j} + e_t, \tag{7}$$

where Δx is the vector of first differences {Δ(y−k), Δ(n−k), Δ(r−k)}′. The parameters $\hat{\pi}$ and $\hat{\gamma}$ are the previously estimated cointegrating coefficients for (y−k), (n−k), and (r−k). The parameters μ, δ, and Φ govern the short-run dynamics. This restricted vector autoregression (VAR) specification is referred to as the error-correction representation of the system. For any set of cointegrated variables, the error-correction representation is the appropriate VAR for describing the short-run dynamics among the variables in that set.

To examine the dynamic response of output to a shock in the regulation variable, a k= 2 version of the error-correction model (7) is estimated over the period 1949–1999[16]. Note that the cointegrating vector obtained from the DOLS analysis above is imposed in the estimation of (7). Rather than report the individual parameter estimates, it is customary to study short-run dynamics using the impulse response functions and variance decompositions of the model variables. *Figure 3* shows the matrix of impulse response functions when the aggregate measure of regulation is used in the analysis. The two-standard-deviation error bands are also shown for the responses. These graphs can be used to determine the length of time over which a change in regulation typically affects aggregate economic activity. The lower left graph in the figure shows the response of output per unit of capital to a one-standard-deviation shock in the regulation variable. Over the first two years following the shock, the change in regulation has virtually no effect on the economy; the standard-error bands are initially wide enough that the response cannot be considered more than noise. By contrast, over a horizon of 2–11 years, there is a statistically significant negative impact on output.

Figure 3. Impulse Responses



Another perspective on the economy's dynamic response to a regulation shock can be gained using variance decompositions. The variance decompositions for ($y-k$) are reported in *Table 3*. These variance decompositions provide the percentage of the j-year ahead mean-squared forecast error in ($y-k$) due to innovations in the other model variables. The more interesting information is found at longer horizons, where the interaction among the model variables has sufficient time to become felt. *Table 3* reports that the importance of regulation in explaining the variation in output increases over time. At five years out, nearly 20% of the variation in ($y-k$) is attributable to regulation; at a horizon of 15 years, more than half of the variation in ($y-k$) is explained by the regulation variable.

Table 3

Variance Decompositions for $(y - k)$

Horizon $j =$	Standard error	Percentage of variance attributable to:		
		$(y - k)$	$(n - k)$	$(r - k)$
1	0.0242	100	0	0
2	0.0316	96.6	2.9	0.5
3	0.0358	86.3	8.0	5.6
4	0.0395	77.2	10.4	12.4
5	0.0430	70.4	10.1	19.6
6	0.0463	64.7	9.0	26.4
7	0.0493	59.3	7.9	32.8
8	0.0523	54.3	7.2	38.6
9	0.0551	49.7	6.9	43.3
10	0.0579	45.7	7.2	47.1
11	0.0606	42.0	7.9	50.1
12	0.0633	38.7	9.0	52.3
13	0.0658	35.9	10.2	53.9
14	0.0684	33.3	11.6	55.1
15	0.0708	31.1	13.0	55.9

Notes: Variance decompositions describe the percentage of the forecast error in $(y - k)$ due to other variables in the model during the last j years. Results obtained from the estimation of the error-correction model (7) using $k = 2$ lags and the aggregate measure of regulation over the period 1949–1999. Percentages may not add to 100 due to rounding.

The error-correction model can also be estimated using the individual areas of regulation. Although the results are not reported, impulse response analysis generally suggests that individual areas of regulation do not have important short-run effects. Variance decompositions can be used to indicate which individual areas may be related to short-run behavior, and these include Titles 15 (19% at a 15-year horizon), 17 (19%), 20 (22%), 29 (17%), 31 (18%), 33 (28%), 42 (39%), and 47 (30%). We interpret these result as suggesting that these areas of regulation are most closely related to the economy's short-run behavior. It may also be that these specific areas of regulation do not have a large enough impact to be felt at the aggregate level, thus providing the statistically negligible effects from the impulse response analysis. However, it is reasonable to suppose that these areas of regulation may have important effects on particular sectors of the economy where their impact would be most evident. Ultimately, this is an empirical issue which we do not address here.

V. CONCLUSION

This paper uses a time series which consistently measures federal regulatory activity in the U.S. to investigate the empirical relationship between regulation and macroeconomic performance. The analysis builds on previous studies of this relationship by (1) using a single-equation aggregate production function model which describes how regulation affects output in the economy, and (2) using empirical techniques based on cointegration to address some potential problems in the estimation. Preliminary empirical evidence based on simple regression techniques indicate that regulation – both aggregate measures of regulation as well as some specific areas of regulation – may be significantly related to macroeconomic performance. When more advanced statistical techniques based on cointegration analysis are used, evidence of a long-run trend (cointegrating) relationship between output, capital, labor, and regulation is found. The empirical results indicate that regulatory activity has a significantly negative impact on aggregate economic performance in the U.S. The finding that regulation is important in determining long-run aggregate economic outcomes is further supported by an analysis of area-specific regulations. The evidence suggests that 22 out of 32 areas of regulation have significant long-run effects, some negative and some positive.

Estimation of an error-correction model, which takes the cointegrating relationship between regulation and the other model variables as given, allows an analysis of the time horizon over which regulation affects economic performance. Impulse response analysis indicates that a shock in the overall level of regulation negatively impacts economic activity over a horizon of 2–11 years. Variance decompositions predict that regulation accounts for over half of the forecast error in output at a horizon of 15 years. The impact of area-specific regulations seems less noticeable on the aggregate economy in the short run, although variance decompositions suggest some areas may be related to short-run fluctuations.

Although the results contained herein apply directly to the effects of regulation in the postwar U.S. economy, the application to other economies and other times is transparent. Regulatory activity which affects the behavior of economic agents has implications which can be measured at the aggregate level. Unfortunately, from a policy perspective, economic theory cannot predict how regulation at the micro-level translates into complex, dynamic adjustment of the economy at the macro-level. Empirical estimates of the economy's response to regulation, therefore, are a crucial part of effective policymaking.

In closing, we note that many benefits of regulation may not be measured in economic terms. Thus, finding a negative economic effect of regulation should not be taken to mean that regulation imposes a net welfare cost on society. Such a finding does establish, however, a standard which the benefits of regulation must exceed in order for it to pass the usual cost-benefit analysis.

FOOTNOTES

1. A number of other recent studies relate regulatory effects to macroeconomic concerns. For example, using OECD data, Nicoletti and Scarpetta (2003) find that product regulation that creates barriers to entry reduces industry-level multifactor productivity growth. Alesina et al. (2003) find that such regulation reduces industrial investment. Djankov et al. (2002) construct a measure of regulation of entry in 85 countries and relate it to several country characteristics, such as the amount of corruption or the type of government. In a series of empirical papers by World Bank economists, Kaufmann, Kraay, and Zoido-Lobaton (1999, 2002) and Kaufmann, Kraay, and Mastruzzi (2003) study the ability of 'perceived government effectiveness', one component of which is regulation, to explain cross-country differences in per capita income. All of these studies, however, use regulation data in cross-sections or panels of countries which include little or no time dimension, thus making the analysis of macroeconomic dynamics difficult or impossible. We complement this body of evidence by using a strict time-series approach.

2. See, for example, Friedman and Friedman (1979), Becker and Mulligan (1999), and Mulligan and Shleifer (2003).

3. Goff (1996), in his pioneering work on regulation at the macroeconomic level, uses factor analysis to construct a clever composite measure of regulation, one component of which is the number of pages in the CFR. It spans almost as long a period as the Dawson and Seater (2006) measure, and it attempts to capture elements of enforcement vigor. Its main limitation is that, being a factor analysis construct, its meaning is unclear.

4. The constant returns to scale assumption is consistent with the data used in the analysis below. OLS estimation of (3) with a correction for first-order serial correlation provides an F-statistic of 1.21 (p-value = 0.2772) for the null hypothesis that $e_N+e_K= 1$.

5. Although the CFR measure dates back to 1938, starting the sample in 1949 follows the standard practice of excluding the World War II period from the analysis, and also discards the period 1938–1949 during which there were no revisions in the *CFR*.

6. Historical data on these variables are available at http://www.bls.gov/mfp.

7. The lag length $J= 5$ was chosen using a 'general to specific' approach beginning with a maximum of 10 lags and sequentially eliminating the last lag when statistical significance at the 10% level was not achieved.

8. Although not reported in *Table 1*, the estimated coefficients on the other independent variables in the model are generally statistically significant and of the expected sign across all equations reported in the table. Detailed results are available upon request.

9. High correlations among individual titles also causes multicollinearity problems in an analysis where all of the individual titles are included in a single regression equation. Multicollinearity problems aside, the large number of titles leaves too few degrees of freedom for such an analysis to provide any meaningful results. Dawson and Seater (2006) explore this possibility

and conclude that the low degrees of freedom – which causes large standard errors and prevents the inclusion of lagged regulation – introduces sufficient biases in the estimation that no determination of which titles are statistically significant can be made.

10. Test results are available upon request. The aggregate measure of regulation is used for the variable *r* in this test and throughout the following discussion. The series *cu* is stationary in levels according to this test. Plots of the series are provided in *Figure 2*.

11. Recent developments in the time series econometrics literature suggest that conventional unit root tests fail to reject the null hypothesis of a unit root too often when the true data generating process is in fact trend stationary with a break in the intercept and/or slope of the trend funcion – that is, when the series is ‘trend-break stationary’. To explore this possibility, three separate tests for trend-break stationarity were conducted on each of the series in the model using the methodology of Zivot and Andrews (1992), Vogelsang and Perron (1998), and Sen (2003). The results consistently indicate no statistically significant structural breaks in the series; that is, the unit-root null hypothesis could not be rejected for any of the series. This finding of nonstationarity among the variables in the model further supports the use of the cointegration methodology in the analysis that follows.

12. A finding of three distinct cointegrating vectors would indicate that the variables in the three-dimensional system are stationary in levels, and that estimation in levels (as in the estimation of equation (5) in the previous section) is appropriate. The finding of a single cointegrating vector thus further supports the use of the cointegration approach to estimating the relationship between the variables in the system.

13. The results are generally not sensitive to choosing different values for *k*.

14. Cointegration tests analogous to those in *Table 2* indicate the presence of a single cointegrating relationship among ($y-k$), ($n-k$), and the individual titles of regulation, with the possible exception of Titles 15, 22, 31, 33, 38, and 46. For these titles, interpretation of the DOLS results is somewhat tenuous.

15. It is difficult to consider more than two sub-samples or shorter sub-samples because of the inherent degrees-of-freedom problems.

16. The results are not sensitive to different values of *k*.

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