The Demand for Capital Maintenance and Supply-Side Tax Policy

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August 14, 2024

Using novel micro data from Class I freight railroads, I show that capital maintenance is an economic decision with a price elasticity around two. This finding is most relevant in the context of supply-side capital tax policies. Under traditional capital theory, which typically assumes that investment is the only input to capital production and the demand for capital maintenance is perfectly inelastic and zero, tax cuts stimulate capital deepening directly through a decline in the user cost of capital. However, as long as maintenance is an economic decision, then capital tax cuts cause firms to substitute investment for maintenance because the tax code subsidizes maintenance at a rate determined by the marginal effective tax rate on capital. The resulting decline in maintenance substantially attenuates the effect of tax policy on the user cost of capital, which in turn makes the capital stock relatively inelastic to tax changes. I illustrate the quantitative consequences of this finding using the 2017 Tax Cuts and Jobs Act (TCJA). Calibrated to the empirical results, a neoclassical model with maintenance predicts output to rise about 60% as much as an otherwise identical model with demand for maintenance fixed inelasticially at zero. In the context of TCJA, this implies the cost of the maintenance-investment distortion is around 1% of GDP, which amounts to around $200B.

JEL-Classification: D21, D22, D25, H25

Keywords: Capital taxation, capital maintenance

*Massachusetts Institute of Technology, jpmejia@mit.edu. I am especially grateful to Martin Beraja and Jim Poterba for invaluable guidance. Additionally, Ricardo Caballero, Tomás Caravello, Janice Eberly, Joel Flynn, Jon Gruber, Pedro Martinez-Bruera, Ellen McGrattan, Chelsea Mitchell, Giuditta Perinelli, Karthik Sastry, Iván Werning and participants in numerous seminars provided helpful comments and discussions. This material is based upon work supported by the NSF under Grant No. 1122374 and is also generously supported by the George and Obie Shultz Fund.

1 Introduction

Perhaps the central issue in capital theory is the fact that capital is unobserved. To varying degrees of uncertainty, we observe what are presumably inputs into capital accumulation like investment, but it has historically been a source of controversy how to translate those observations into capital itself (Hayek 1935; Pigou 1941; Feldstein and Rothschild 1974).[1] Since the seminal work of Hall and Jorgenson (1967), economists have largely constrained themselves to single-input theories of capital production, particularly for understanding the effects of supply-side tax policy on the capital stock and economic growth (Lucas 1990). Under such theories, the tax elasticity of investment is a sufficient statistic for the tax elasticity of capital and through additional structural assumptions, the tax elasticities of output and welfare. For that reason, policymakers and economists alike focus almost exclusively on the tax elasticity of investment, using it as both a tool to motivate major reforms like the 2017 Tax Cuts and Jobs Act and to evaluate the effects of tax reform (Romer and Romer 2010). However, single-input theories are insufficient to understand the consequences of tax policy changes if other inputs to capital are differentially taxed and the elasticity of demand for their services is greater than zero. One such input is capital maintenance.[2] In this paper, I investigate the price elasticity of capital maintenance and the resulting implications for tax policy analysis when capital is produced with both maintenance and investment.

Maintenance expenditures are expensed costs on capital, labor, and intermediate inputs to restore, repair, or ensure continued productivity of existing capital. By contrast, traditional investment improves existing capital or purchases new capital.[3] On the margin, firms maintain capital to make it last longer at the cost of an additional unit of new investment. For example, Burlington Northern maintains its current locomotive engines until it becomes more cost-effective to replace them. The tax code distorts these allocations. While investment is typically subject to taxation, maintenance costs are fully expensed, creating a tax wedge. If the demand for maintenance is remotely price-elastic,

1. Although the early debates were about physical capital, modern discussions of intangibles have reawakened slumbering arguments over theory and measurement in capital theory. See, for example, Peters and Taylor (2017), Haskel and Westlake (2018), and McGrattan (2020).

2. There are, of course, many ways that firms can change their capital stocks beyond investment and maintenance. Albonico, Kalyvitis, and Pappa (2014) and Kabir, Tan, and Vardishvili (2023) along with an old macroeconomic literature give a role to utilization, while Goolsbee (1998b) highlights scrappage decisions. I focus on only maintenance and investment because of the differential tax treatment.

3. An alternative definition, which I favor, comes from Scott (1984): "Gross investment expenditures are aimed at improving, while maintenance expenditures are aimed at restoring, economic arrangements." This is an economic rather than an accounting definition and so does not map neatly into the tax code or accounting data and practice.

changes in the relative price of maintenance to investment can lead firms to substitute between them. Since the capital tax wedge affects this relative price, reductions in capital taxation may prompt firms to favor new investment over maintenance. This substitution effect suggests that the tax elasticity of capital could be much smaller than traditionally estimated, with correspondingly smaller effects on output and welfare.

Like many intangible expenditures, maintenance is a *hidden* investment because it is treated as an operating expense, which means it is difficult to observe in many standard data sources. In the data we have, maintenance looks large. In Canada, for instance, maintenance expenditures are about half the size of new investment in aggregate data. The question is decisively not whether firms maintain capital—they obviously do—but whether maintenance is price-elastic.[4] I shed light on this question with a novel dataset of maintenance and investment behavior from Class I freight railroads. Every year, large railroads are required to file independently audited granular reports on their assets and operating expenses with the Surface Transportation Board. As part of that, railroads report a detailed breakdown of their expenditures on what is maintained (locomotives and freight cars) and how it is maintained (through labor, materials, and external services). Railroads also report both quantities and prices for a wide array of different capital goods. This provides an ideal and unique environment to study the elasticity of demand for maintenance; no other dataset, to my knowledge, provides such granular detail on assets, maintenance, and investment. As a first exercise, I regress the log maintenance rate on the log relative price of maintenance to investment for two capital types across seven firms from 1999-2023. The coefficient is identified through variation in the relative price of maintenance across firms and capital types driven by variation in exposure to tax policy and the labor component of maintenance expenditures. This yields an elasticity around 2, significantly larger than the neoclassical benchmark of zero. The result holds up across a wide array of robustness exercises within freight railroads.

It is natural to wonder how well a result from railroads extends to the rest of the economy. I test this using industry data from the Statistics of Income (SOI), which is a representative sample of corporate tax returns within around fifty industries. This dataset allows for two tests of the theory. First, I directly measure the maintenance elasticity of demand using an identification strategy from the investment literature. Following a

4. In single-input theory, the demand for maintenance is perfectly inelastic and zero. Alternatively, one may think of maintenance, as Poterba (1984) does, as perfectly inelastic but positive. In that sense, maintenance simply scales up with more capital and is like a depreciation cost. Lumpy investment and durable consumption theories often include maintenance as an intermediate expenditure between purchases of new capital goods (Bachmann, Caballero, and Engel 2013). However, the choice there is not economic; agents simply expend some constant maintenance rate. Moreover, maintenance is solely included to keep the drift rate of the capital stock low so that investment is sufficiently lumpy.

methodology in the tradition of Cummins, Hassett, and Hubbard (1994) and best exemplified by Zwick and Mahon (2017), I use cross-sectional variation in exposure to exogenous tax policy changes to identify the maintenance elasticity. This is possible because each tax return contains line items for both book capital and maintenance. Second, theory implies that untaxable firms should not adjust their maintenance behavior in response to changes in tax policy. Because the SOI breaks down its sample into taxable and untaxable firms, we can directly test this. The maintenance elasticity for taxable firms is remarkably similar in these data to the one obtained using freight rail data, while the maintenance elasticity is zero for untaxable firms.

What matters, however, is not merely that the price elasticity is statistically significant, but that it is economically significant. I show this quantitatively in the context of supply-side tax policy. Typically, tax policy analysis around reforms is done both empirically and quantitatively. Empirical analysis tends to revolve around the tax elasticity of investment. Using data from Compustat, I show that standard regressions of investment on tax policy suffer from omitted variable bias if they do not account for maintenance. All such regressions are built on a particular theory of investment, in this case a single-input theory. When the demand elasticity is two, the investment elasticity is underestimated by around 25%. This argument is analogous to the one made by Goolsbee (1998a), which argued that similar regressions omitting investment prices implicitly assume perfectly competitive markets for investment goods. In that sense, there are no "model-free" investment regressions. Structural (or quantitative) tax analysis likewise orbits around the tax elasticity of investment in both the short run and the long run. I show that this is quantitatively problematic for both dynamic and long-run predictions about tax reforms using the 2017 Tax Cuts and Jobs Act as an example. In both cases, I use the neoclassical model as a foil.

First, I show that dynamic analyses of the capital stock diverge under the standard neoclassical model from those obtained from the NGM augmented with maintenance. This indicates that the standard perpetual inventory model is a poor approximation for the capital stock even in the short run. In a second step, I use the neoclassical analysis of TCJA from Barro and Furman (2018) as a foil. Their careful quantitative analysis relies entirely on the user cost of capital to predict that the long-run effect of the reform would lead to a 2% increase in output per capita. I show that an otherwise identical model with maintenance would instead predict an increase in output of only 1.2%. This is observationally equivalent to halving the capital share in the standard neoclassical model.

In sum, despite a firm argument from McGrattan and Schmitz Jr. (1999) that maintenance is "too big to ignore," the channel is rarely accounted for in theoretical, empirical, or quantitative tax policy analysis. Indeed, all of the main tax policy analysis models from the government, think tanks, and academia entirely ignore maintenance when predicting the likely growth and welfare effects of policy (Auerbach et al. 2017). Of course, such models miss out on many parts of reality and by virtue of being models, that is a feature rather than a bug. This paper, with simple theory, empirics, and quantification, aims to convince tax policy researchers of all stripes that including a small adjustment for capital maintenance is worth it.

Literature. This paper connects to a theoretical literature which deviates from the Hall and Jorgenson (1967) tradition by making elements of user cost endogenous to tax policy. Although Feldstein and Rothschild (1974) laid early groundwork with their analysis of optimal capital replacement decisions, McGrattan and Schmitz Jr. (1999) inaugurated a small but robust theoretical literature on the importance of endogenous capital maintenance. That paper develops a homogeneous capital model of maintenance and investment, with maintenance expenditures pinned down by the relative price of maintenance to investment and provides the original insight that depreciation is endogenous to tax policy. Several other papers build on McGrattan and Schmitz Jr. (1999) in the areas of public capital maintenance (Kalaitzidakis and Kalyvitis 2004, 2005; Dioikitopoulos and Kalyvitis 2008), cyclical fluctuations (Albonico, Kalyvitis, and Pappa 2014), and investment theory (Boucekkine, Fabbri, and Gozzi 2010; Kabir, Tan, and Vardishvili 2023). My contribution is a parsimonious theoretical framework grounded in the McGrattan and Schmitz Jr. (1999) neoclassical model that provides a simple sufficient statistic approach to estimating the maintenance demand elasticity and its quantitative effects.[5]

I also contribute to an empirical literature documenting the economic relevance of capital maintenance. To date, most papers have relied on aggregate data from the Canadian Annual Capital Expenditures Survey because there are very few high-quality data sources. For example, Albonico, Kalyvitis, and Pappa (2014) develop parametric estimates of the cyclical elasticities of maintenance and depreciation using this source, while McGrattan and Schmitz Jr. (1999) document the cyclical properties of maintenance with the Hodrick-Prescott filter. Angelopoulou and Kalyvitis (2012) estimate an aggregate Euler equation with endogenous depreciation. Other papers use cross-sectional data. Kabir,

5. There has been significant theoretical work linking utilization to depreciation (Greenwood, Hercowitz, and Huffman 1988; Justiniano, Primiceri, and Tambalotti 2010) and utilization and maintenance together to depreciation (Boucekkine, Fabbri, and Gozzi 2010; Kabir, Tan, and Vardishvili 2023). While undoubtedly correct and important that utilization plays a role in the depreciation of capital and utilization is endogenous, I focus solely on maintenance in this paper because it more clearly isolates the theoretical channel I am interested in and is clearly differentially taxed from investment, while utilitzation is less clear.

Tan, and Vardishvili (2023) use maintenance data from Indian firms to document capital misallocation and Kalyvitis and Vella (2015) estimate the productivity effects of infrastructure maintenance expenditures for U.S. states. I expand on these studies by building a novel maintenance and investment dataset using financial filings from Class I freight railroads.[6]

Additionally, there is a rich literature that indirectly documents capital maintenance as an economic choice. Goolsbee (1998b) examines factors affecting the decision to retire airplanes. Retirement directly relates to maintenance because, rather than maintain an old airplane, a firm simply invests in a new one. Focusing on an investment tax credit for a 13 year-old Boeing 707, Goolsbee finds that moving the investment tax credit from zero to 10% increases the probability of retirement from 9% to 12%. Relatedly, Goolsbee (2004) convincingly argues that the quality elasticity of capital with respect to the cost of capital is around 0.5%, where quality is roughly measured with maintenance expenditures per unit of capital. Moreover, my empirical estimates relate to work from Bitros (1976) and Grimes (2004), which study the relationship between maintenance and capital expenditures in the freight rail industry and documents that they are intertemporally substitutable, which is a key part of the theory in this paper. Additionally, economists have documented a clear connection between maintenance and depreciation in the housing literature. For example, Knight and Sirmans (1996) study the effect of maintenance on housing depreciation and find that poorly maintained homes depreciate significantly faster than their well-maintained counterparts, while Harding, Rosenthal, and Sirmans (2007) find that housing depreciates about 0.5 percentage points less per year after accounting for maintenance.

x**Roadmap.** In Section 2, I develop a theoretical framework to analyze capital maintenance. Section 3 documents the empirical elasticity of demand for maintenance. In Section 4, I show why accounting for maintenance matters for tax policy analysis. Section 5 concludes.

6. In industrial organization, Rust (1987) and Harris and Yellen (2023) study maintenance but do not study the price elasticity directly.

2 Transmission of Capital Tax Policy with Capital Maintenance

This section develops a simple model of capital maintenance and investment.[7] Suppose that maintenance contributes to capital accumulation through the following variation on the law of motion for capital:

$$K_{t+1} = (1 - \delta + g(x_t) + h(m_t))\, K_t. \tag{1}$$

Here, $m_t \equiv \frac{M_t}{K_t}$ is the maintenance rate, $x_t \equiv \frac{X_t}{K_t}$ is the investment rate, and δ is an exogenous depreciation rate. Modern capital theory, which is oriented toward generating testable empirical and quantitative relationships, typically assumes $g(x_t)$ is a weakly concave function and $h(m_t) = h'(m_t) = 0$. In that case, given some initial level of capital K_0, it is clear that the level of capital at any point in time is a function only of previous investment choices. In that sense, there is no longer any room for other margins of adjustment to capital. On the other hand, this paper emphasizes instead that, as long as the demand for maintenance is price-elastic, the sequence of capital stocks is a function of choices about both maintenance and investment. That conclusion encompasses earlier work from McGrattan and Schmitz Jr. (1999), Kabir, Tan, and Vardishvili (2023), and a number of other papers, which assume that maintenance can affect capital through a depreciation technology given by $h(m_t) = -\delta(m_t)$, where $\delta(m_t)$ is typically strictly decreasing and strictly convex. I weaken those restrictions by instead placing the following assumption on the investment and maintenance technologies.

Assumption 1. *$g(x_t)$ and $h(m_t)$ are weakly concave functions.*

Under Assumption 1, maintenance is a viable tool for changing the capital stock in the same way that investment is. The extent to which maintenance or investment is a better technology for changing the capital stock depends on their relative concavities. If, as is a standard assumption, investment enters linearly in (1) and maintenance does too, then they are perfect substitutes. Although a long literature tells us about the concavity of $g(x_t)$ at various horizons (Caballero 1994; Hassett and Hubbard 2002; Zwick and Mahon 2017), we do not know much about $h(m_t)$. Ultimately, the shape of $h(m_t)$ depends on the elasticity of demand for maintenance in a way that will become clear shortly.

Given (1), a firm intent on choosing a sequence of optimal maintenance expenditures

7. Appendix A contains a more traditional neoclassical model of profit maximization to arrive at the same results.

would equate the marginal benefit of maintenance with its marginal cost. The marginal benefit is that maintenance contributes slightly more to capital accumulation, which is captured by $h'(m)$. The marginal cost is a unit of foregone investment, which is determined by the relative price of maintenance to investment. Letting p^m denote the pre-tax price of maintenance, p^x the pre-tax price of investment, and considering the steady state decision, the firm equates marginal benefit with marginal cost exactly when

$$h'(m) = \frac{p^m(1-\tau)}{p^x}, \tag{2}$$

where τ is the marginal tax on capital. Because maintenance is tax deductible while investment is not, it is as if tax policy subsidizes maintenance relative to investment. Inverting $h'(m)$ yields the demand for the maintenance rate, while integrating $h'(m)$ yields $h(m)$. Hence, as long as $h'(m) > 0$, the decision to maintain is economic rather than technical. The more elastic demand is, the closer to linear the maintenance technology $h(m)$ is. This implies that if we learn about the elasticity of demand for maintenance, we can learn about the shape of $h(m)$.

Incorporating maintenance leads to an additional element in the standard Jorgensonian user cost of capital, namely that an additional unit of capital must be maintained at price p^m. In steady state, with a linear $g(x)$ and a concave production function $F(K)$, firms invest until the marginal product of capital equals the user cost Ψ:

$$F_K = \Psi = \frac{p^x}{1-\tau}\left(r^k + \delta - h(m) + h'(m)m\right), \tag{3}$$

where p^x is the price of investment, r^k is the discount rate, τ is the marginal effective tax rate on capital, and m is the optimally chosen maintenance rate given the relative price. (3) is a generalization of the Hall and Jorgenson (1967) user cost; under the extreme case $h'(m) = 0$, it is exactly the traditional user cost. When $h'(m) = 0$, a tax cut causes firms to demand more capital—through investment—up to a point determined by the curvature of $F(K)$. In this case, the user cost is increasing monotonically in the tax rate, so the tax semi-elasticity of user cost is simply

$$\varepsilon_\Psi = \frac{1}{1-\tau}.$$

If, on the other hand, $h'(m) > 0$, then there is substitution between investment and maintenance when taxes change. From (2), an increase in τ causes the demand for maintenance to rise, which puts a countervailing force on user cost.

Proposition 1. *When $h'(m) > 0$, the tax semi-elasticity of user cost is given by*

$$\varepsilon_{\Psi} = \frac{1}{1-\tau} - \frac{m(\tau)}{\widetilde{\Psi}}, \tag{4}$$

where

$$\widetilde{\Psi} \equiv r^k + \delta - h(m(\tau)) + (1-\tau)m(\tau)$$

is the pre-tax user cost.

Given a particular tax rate, the level of demand for the maintenance rate demand determines the extent to which maintenance offsets the traditional force in tax policy analysis. As the maintenance share of the pre-tax user cost rises, the tax elasticity of user cost declines. Intuitively, that is because maintenance is the endogenous part of user cost. As the constant component $r^k + \delta$ goes to zero, maintenance dominates the user cost expression, which means that tax policy can go in the *opposite* predicted direction. This result contradicts the theoretical result from House (2014) and Winberry (2021), which show that low-depreciation capital goods like structures are more tax-elastic. In the maintenance framework, low depreciation capital goods are *more* tax-elastic because maintenance is relatively more important.

To give some more intuition, suppose that the demand for maintenance is constant elasticity and parameterized by an elasticity parameter $\omega \geq 0$ and a level parameter $\gamma \geq 0$.

Example 1. *If the demand for maintenance is given by $m = \gamma(1-\tau)^{-\omega}$, then*

$$h(m) = \frac{\gamma^{1/\omega}}{1-1/\omega} m^{1-1/\omega}.$$

With $\gamma = 0$, it is simply the standard neoclassical investment theory. $\omega > 0$ is the interesting case and yields two economically interesting properties about the role of maintenance in capital accumulation. First, ω characterizes the elasticity of substitution between investment and maintenance in the production of capital. As $\omega \to \infty$, $h(m)$ becomes linear in the maintenance rate. This makes maintenance and investment perfect substitutes for producing capital. Second, ω characterizes returns to scale in maintenance. If $\omega < 1$, then there are decreasing returns. This yields an $h(m)$ conceptually equivalent to the restrictions imposed by McGrattan and Schmitz Jr. (1999), which require maintenance to only slow the depreciation of capital but not add to its stock. If $\omega > 1$, there are increasing returns to scale in maintenance. This makes maintenance *subtract* from the user cost of capital on net. Indeed, increasing returns to maintenance can make tax policy have the opposite predicted effect on capital accumulation as a single-input theory would predict by making the user cost decrease.

A numerical example suffices to show the importance of maintenance. Suppose output is given by $F(k) = k^{\alpha}$, where $k = K/L$ is the capital-labor ratio. In Figure 1, I plot steady-state user cost and the resulting capital-labor ratio for values of $\omega = \{0, 0.5, 3\}$ with the remaining parameters set such that initial user cost and the capital-labor ratio are the same when $\tau = 0$. Clearly, as ω rises, which is equivalent to the endogenous response of maintenance becoming stronger, the effect of tax policy on capital accumulation wanes precisely because the user cost of capital becomes relatively inelastic. Indeed, as tax rates rise sufficiently high, user cost can even decline as firms substitute away from maintenance toward investment.

Clearly, the preceding analysis presents a problem for traditional single-input tax policy analysis. When inputs to capital accumulation are differentially taxed, the resulting effect of a tax change on capital accumulation are exceedingly difficult to predict without knowing the elasticity of demand for maintenance. I address that subsequently.

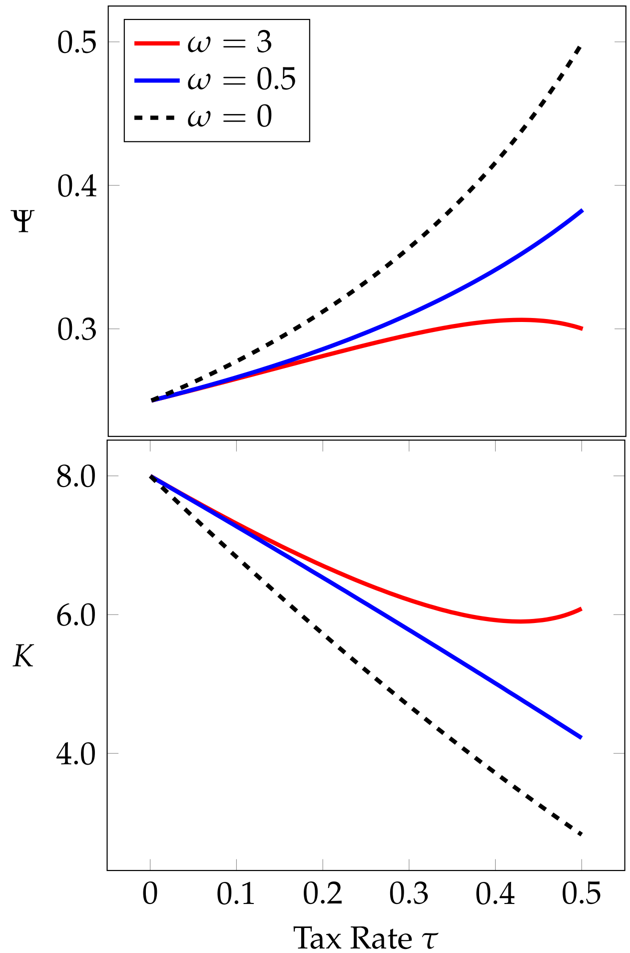


Figure 1: Comparing user costs and capital-labor ratios for differing values of ω. Given ω and γ, constant parameters are set such that user cost is the same at the undistorted steady state. I set $\alpha = 0.4$ for this exercise.

3 Testing Endogenous Maintenance

The testable implication of the model is whether maintenance rates respond to relative prices. Under the standard model of investment, maintenance expenditures should be completely invariant to changes in the relative price of maintenance. This section tests that hypothesis with data from Class I freight rail in the United States.

3.1 Estimation Strategy and Data

I use variation between firms and capital types over time to determine whether increases in the relative price of investment alter the maintenance intensity. To do that, I construct a novel dataset of maintenance and investment expenditures for Class I freight railroads using their financial filings with the Surface Transportation Board. Only freight rail and airlines are required by law to provide detailed data on their maintenance and repair expenditures. I focus on the former because its maintenance activities are significantly less regulated by the government than the airline industry's. This study follows up on Bitros (1976) and Grimes (2004), which also study the determinants of maintenance policy using freight rail data, but without the objective of studying its response to relative prices.

By regulation, any freight railroad with revenue exceeding $250 million must file an annual R-1 report with the Surface Transportation Board. The R-1 report can be thought of as a much more granular version of a 10-K filed by a publicly traded corporation. For example, it contains hundreds of line items for individual types of operating expenditures that would normally be summarized in one or two in a 10-K. It also details the size and composition of its property, plant, and equipment in value and quantities, its trackage by state, taxes paid, capital expenditures, and so on. Most importantly, it contains detailed data on maintenance expenditures by capital type as well as how those expenditures were allocated to labor and parts, both internally and externally. Every data item is independently audited by a third party firm like PwC or KPMG.

With that in mind, freight rail is an ideal setting to study maintenance decisions. Its capital stock is almost entirely physical and made up of a mix of rolling stock (locomotives and freight cars) and fixed plant. Since 1980, it has largely deregulated and since the mid-1990s, the industry has settled into a stable competitive equilibrium with around seven large companies carrying most of the United States' freight traffic: CSX Industries, Burlington Northern & Santa Fe, Union Pacific, Norfolk Southern, Kansas City Southern, Soo Line, and Grand Trunk, which is operated by the Canadian National Railway. All of these railroads own their tracks and equipment and have faced relatively little financial trouble over the past 25 years. I focus on how maintenance responds to relative prices in those seven companies from 1999-2023.

Each R-1 report contains about twenty different "schedules" which correspond to different information about the railroad. For example, Schedule 410 has several hundred line items on different operating expenses broken down by labor and material cost. These expenditures are largely maintenance on different aspects of railway operations from tracks to rail ties to electrical systems, and so on. For this paper, I maintain a narrow focus on freight cars and locomotives because they are easiest to identify in the data.

Theory suggests we require, at minimum, a maintenance rate and a relative price. I use Schedule 410 Line 202 for locomotive maintenance and Schedule 410 Line 221 for freight car maintenance. These expenditures are the only ones which clearly and directly affect only locomotives and freight cars, respectively. I use Schedules 330 and 335 to construct the denominator of the maintenance rate. Conveniently, the R-1 breaks down property, plant, and equipment into approximately forty different categories, which allows me to isolate which ones are locomotives and freight cars. By comparison, there is no way to distinguish equipment from structures in Compustat. I use the net stock of each capital type in book value as the denominator for the maintenance rate. Because the whole point of this paper is that the net stock of capital is constructed incorrectly with a linear perpetual inventory method, I later construct an alternative capital stock and repeat the same analysis in Section 3.5. I also use Schedules 330-335 to extract information on gross investment rates and retirements, which are the other main variables in the analysis.

The main independent variable of interest is the after-tax relative price of maintenance to investment:

$$P_{i,j,t} = \frac{p^m_{i,j,t}(1-\tau_{i,t})}{p^x_{j,t}},$$

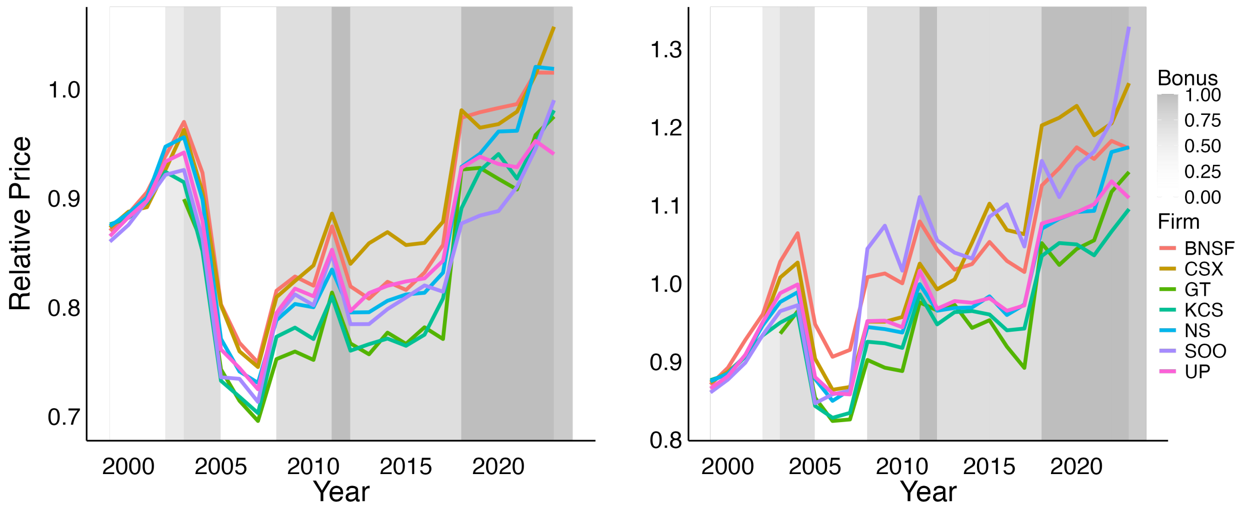
where $p^m_{i,j,t}$ is the pre-tax maintenance price of capital good j for firm i at time t. Because of restrictions on data availability, only the pre-tax price of maintenance varies by firm type, whereas tax rates vary by firm and investment prices by capital type. I construct each as follows:

1. **Price of investment.** The price of investment does not vary by firm, only by capital type. It is simply the BLS's producer price index for locomotives and freight cars.

2. **Tax term.** The tax term varies by firm but not by capital type because rolling stock are taxed at the same rate. However, there is variation between firms because firms vary in their geographic area and hence their exposure to state tax policy. R-1 Schedule 702 details the mileage of track by state for each firm. I use that information to construct a weighted tax term. I extend the dataset of Suárez Serrato and Zidar (2018) to construct the tax term through 2023.

3. **Price of maintenance.** The price of maintenance is a weighted average of labor and material costs. Labor costs are firm-specific and come from each firm's Wage Form A&B filed with the Surface Transportation Bureau. The materials cost index is from the Bureau of Labor Statistics. I weight each input with the cost share from Schedule 410, which breaks down maintenance expenditures by labor cost and materials for both locomotives and freight cars.

Putting items 1-3 together, relative prices may vary between firms and capital types for three reasons. First, because firms differ in their geographic concentration, they also vary in their exposure to state-level tax policy differences. Second, because capital types differ in their maintenance labor intensities, maintenance prices differ between capital types. Third, investment prices differ for locomotives and freight cars. Putting that together, there is variation between capital types and firms in their exposure to relative price changes. I plot that variation in Figure 2.



(a) Freight Cars

(b) Locomotives

Figure 2: The relative price of maintaining freight cars (left) and locomotives (right). The degree of shading corresponds to the strength of bonus depreciation.

I rely on exactly that variation between firms and capital types in their exposure to relative prices to help identify the coefficient β in the panel regression

$$\log m_{i,j,t} = \alpha_i + T_t + \kappa_j + \beta \log P_{i,j,t} + \text{Controls} + \epsilon_{i,j,t}, \tag{5}$$

where $m_{i,j,t}$ is the firm i and capital type j maintenance rate at time t, α_i is a firm fixed effect, κ_j T_t is a time fixed effect, κ_j is a fixed effect for capital type j, $P_{i,j,t}$ is the relative price. The log-log specification is to accommodate a constant elasticity demand function.

3.2 Reduced Form Results

In Table 1, I present estimates of (5), where standard errors are clustered by firm. I cluster by firm because firms probably coordinate maintenance decisions across capital types. Column (1) contains the baseline relationship between the maintenance rate and the relative price. The relationship is statistically significant, negative, and large. A one percent increase in the relative price of maintenance to investment corresponds to a two percent decrease in the maintenance rate. In Appendix B.1, I present corresponding results for a linear-linear model, which is similarly statistically significant and large in magnitude.

	Dependent variable: $\log m_{i,j,t}$			
	(1)	(2)	(3)	(4)
$\log(P_{i,j,t})$	-2.101	-2.245	-1.847	-0.676
	(0.808)	(0.422)	(0.536)	(0.223)
Age		-1.902	-1.864	-0.833
		(0.590)	(0.591)	(0.323)
$\log x_{i,j,t}$			0.058	0.009
			(0.017)	(0.018)
$\log m_{i,j,t-1}$				0.778
				(0.067)
N	342	342	342	328
FE: Type	X	X	X	X
FE: Year	X	X	X	X
FE: Firm-Type	X	X	X	X

Table 1: Results for regressing a the log maintenance rate on the log relative price. Standard errors are clustered by firm.

Column (2) adds age as a covariate, where age is proxied with the ratio of net to gross capital book. A larger value for age corresponds to younger capital because less of it has depreciated. The coefficient on age is similar in magnitude and significance to the coefficient on price for both functional forms. Since a larger value for age corresponds to younger capital, it is sensible that the coefficient is negative. Column (3) adds the investment rate. This yields a puzzling result because it appears to be weakly complementary with the maintenance rate. However, that disappears after controlling for autocorrelation in the maintenance rate in column (4). Indeed, there is no relationship after controlling for past maintenance. The strong degree of autocorrelation in maintenance indicates that a large share of maintenance is required, which lends some credence to the traditional view of maintenance.

After accounting for the dynamic relationship between maintenance and prices in column (4), the coefficients are relatively stable across specifications within each functional relationship. The log relationship indicates that a one percent increase in the price of maintenance corresponds to a 2-3 percent decline in the maintenance rate. For comparison, the tax semi-elasticity of the investment rate is generally between 0.5 and 1 (Hassett and Hubbard 2002), while other studies have found values about twice as large (Zwick and Mahon 2017).

	Dependent variable: log $M_{i,j,t}$		
	(1)	(2)	(3)
log $P_{i,j,t}$	-0.695	-0.370	-0.394
	(0.353)	(0.111)	(0.114)
log $M_{i,j,t-1}$		0.885	0.888
		(0.021)	(0.022)
log $X_{i,j,t}$			-0.003
			(0.005)
N	342	328	328
FE: Firm	X	X	X
FE: Year	X	X	X
FE: Type	X	X	X

Table 2: Regression of the log-level of maintenance on the relative price for freight rail Standard errors clustered by firm.

Table 2 tests the maintenance elasticity in levels. The model does not make an unconditional prediction about the sign of the coefficient on price. If there are decreasing returns, then the level of maintenance should increase with the relative price because the corresponding increase in investment should more than compensate for the decline in maintenance. With increasing returns, the opposite is true. Across specifications, the coefficient on price is significantly negative and economically large. In particular, the price elasticity in column (3), which controls for autocorrelation in the level of maintenance, is about 3.5. This is half the size of the estimated price elasticity of investment in Zwick and Mahon (2017).

Altogether, the results reject the traditional view that maintenance does not respond to relative prices. Because the price elasticity is greater than one, this also means that the results agree that there are increasing returns to maintenance. In that case, maintenance *adds* to the capital stock rather than simply slowing its decline. It also means that the elasticity of substitution between maintenance and investment is theoretically positive, although it appears to be null in this data. From Figure 1, that means there is a point at which tax changes have the opposite effect on the user cost of capital, capital stock, and output than standard theory would predict.

On the other hand, there are significant concerns with endogeneity, external validity, and measurement error in the capital stock. I address each subsequently.

3.3 Endogeneity of Relative Prices

A key issue in the preceding analysis is the endogeneity of the relative price of maintenance. This subsection addresses that within the freight rail data. The following subsection addresses the external validity of the estimates with national industry-level while also using tax shocks as instruments to identify the maintenance elasticity.

There are three components to the relative price: a price for maintenance, a price for investment, and a tax term. The price of maintenance is made up of both the a firm-specific labor cost index and a material cost index which does not vary by firm. On average, the labor share of maintenance costs is approximately 40%. Figure 10 shows the average labor share over the sample period. Although labor shares vary across firms and capital types, there is very little variation in the labor cost index itself. That is largely because freight railroads are heavily unionized, which also means that wages are sticky and exogenous to maintenance demand shocks because they grow at a rate determined by macro price indices. However, the maintenance materials cost index is plausibly endogenous precisely because many materials are specific to the freight rail industry. Similarly, the price of investing in locomotives or freight cars is likely endogenous. Although the industry is global and so are the suppliers, U.S. freight rail is a large player in the industry as a whole and it is probably not true that they are price takers. Altogether, this suggests an instrumental variables approach is necessary to correct for endogeneity.

I use three different instruments for the relative price, each of which has its own pros and cons.

1. **Oil shocks.** Känzig (2021) creates a long time series of monthly oil news shocks. I take the annual average of these for the sample period. Because freight rail primarily runs on diesel and is a major hauler of many types of oil, oil shocks affect both the price of maintaining freight rail and investing in freight rail, but do not affect the maintenance rate. The issue is that oil shocks are common across railroads and so I replace the time fixed effect with a year trend and industry controls. The industry controls are for freight rail productivity growth, the rail cost adjustment factor, and real output growth. The Surface Transportation Board (STB) provided the first two. The rail cost adjustment factor is adjusted for productivity growth by the STB.

2. **Tax shocks.** Tax policy is exogenous to freight rail and affects maintenance only through the relative price. The reasoning is similar to the traditional public finance literature on tax policy as a natural experiment in, for example, Cummins, Hassett, and Hubbard (1994) and Zwick and Mahon (2017). However, there is no variation in tax rates between capital types and little across firms despite the fact that variation in trackage location leads to variation in tax rates. Figure 11 shows tax rates by firm over the sample period. Because of the little cross-sectional variation, I again omit a time fixed effect and instead rely on a time trend and industry controls. I first regress the maintenance rate on the tax term directly and second as an instrument for the pre-tax relative price.

3. **Lagged relative price.** In principle, the lagged relative price should only affect the maintenance rate through price autocorrelation. I also use the twice-lagged relative price as an instrument for the current relative price. The key benefit to using lagged prices is that it allows us to use time fixed effects.

Table 3 reports results for each of the specifications discussed in 1-3. The results are similar to those in the main specification for the log-log relationship. Although some are only borderline statistically significant, they are all economically significant to the same degree as the original regressions. Appendix 3.3 contains additional results for the linear specification and the same for maintenance in levels. The results again correspond to those in the main specification.

	Dependent variable: $\log m_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
$\log P_{i,j,t}$	-1.644	-1.662		-2.431	-3.218
	(0.920)	(0.400)		(0.990)	(1.435)
$1-\tau_{i,t}$			-1.194		
			(0.219)		
N	316	316	316	328	314
Instrument	Oil	Tax Rate		$\log P_{i,j,t-1}$	$\log P_{i,j,t-2}$
F-test	16.6	33.1		1272.4	453.3
Industry Controls	X	X	X		
FE: firm	X	X	X	X	X
FE: type	X	X	X	X	X
FE: year				X	X

Table 3: Instrumental variables results for regressing the log maintenance rate on a measure of the relative price. The first column uses oil shock as an instrument for the log relative price. The second uses taxes as a shock for the *pre-tax* relative price. Every regression with instruments reports the Cragg-Donald F-statistic.

3.4 External Validity

It is natural to suspect that results on freight rail may not translate particularly well to the economy as a whole. After all, freight rail is a physically intensive and mature industry for which maintenance may be more important than others. In this subsection, I provide evidence using industry tax data from the Internal Revenue Service's (IRS) Statistics of Income (SOI) that the results hold up across the economy.

Corporations report a large number of operating expenses and balance sheet items as line items on their tax forms to the IRS. The SOI samples across those tax returns to provide summary measures of each line item at a roughly three-digit NAICS level going back to 1998 and through 2020. This is the only economy-wide collection of maintenance data at an annual frequency in the United States. I use Tables 12 and 13 I use Tables 12 and 13 of the SOI's Corporate Reports in combination with variation in tax policy exposure by industry over time to estimate the price elasticity of maintenance demand.

I take maintenance, investment, and book capital stock data from the SOI corporate reports from 1998-2020 from Table 12 and Table 13. This excludes filings made with Forms 1120S, 1120-REIT, and 1120-RIC. Table 12 has all corporate filings, while Table 13 only summarizes firms with positive net income. Using both tables together, I obtain corresponding data for firms which go untaxed. This is important because theory says that the tax wedge should only matter for taxable firms. Industries vary in their exposure to tax policy because they differ in their production technologies. Some industries use more structures, while others use more equipment. The end result, due to differential capital taxation, is that marginal effective tax rates vary widely by industry. This fact lies at the center of a literature on identifying the effects of tax policy on investment going back to Cummins, Hassett, and Hubbard (1994) in the past to modern studies from Zwick and Mahon (2017). Building on this literature, I leverage the BEA's fixed asset data to create a panel of capital-weighted marginal effective tax rates by industry. Because the number of SOI industries fluctuates over time but is always weakly larger than the number of BEA industries, I map the SOI industries into BEA industries for consistency and use the latter as a unit of observation. There are fifty such industries and 49 after I exclude the financial sector. Appendix C contains summary statistics.

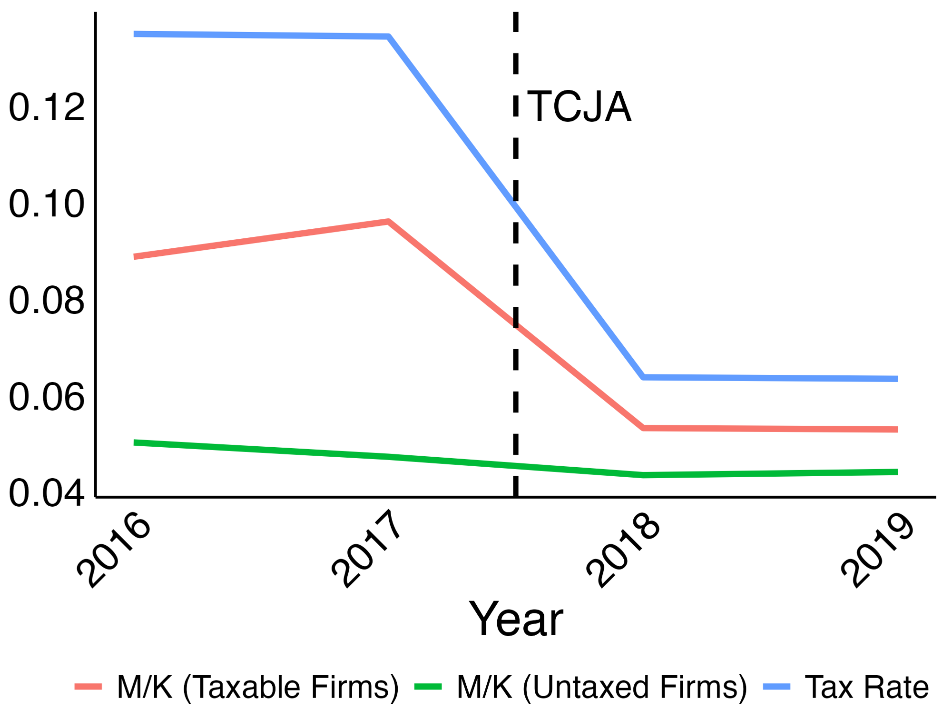


Figure 3: The average maintenance rate of taxable firms and untaxable firms plotted against the average marginal tax rate from the SOI sample. Untaxable firms had negative net income. The dashed line depicts the 2017 Tax Cuts and Jobs Act (TCJA), which passed toward the end of 2017.

Figure 3 plots the average maintenance rate of taxable and untaxable firms from 2016-

2019. I also plot an indicator for when the 2017 Tax Cuts and Jobs Act (TCJA) passed. TCJA, passed in late 2017 and taking effect in 2018, is one of the largest postwar tax reforms, involving a move toward 100% bonus depreciation for certain types of equipment and a cut in the corporate tax rate from 35% to 21%. While the maintenance rate for untaxable firms appears invariant to the large drop in the average marginal tax rate, the maintenance rate for taxable firms appears to drop nearly one-for-one with the tax rate.

We can go beyond visuals to show the effects of tax policy changes on maintenance rates. Since the tax wedge is a key determinant of the relative price of maintenance, I use variation in that tax wedge from 1998-2020 to identify the coefficient in

$$\log m_{j,t} = \alpha_j + T_t + \log\left(1 - \tau_{j,t}\right) + \text{Controls} + \epsilon_{j,t}. \tag{6}$$

There was a great deal of policy variation in the relevant window.[8] Bonus depreciation, which allows firms to expense a larger share of certain equipment investment expenditures immediately and hence is a tax cut, began following 9/11 and has largely existed intact up to the present. House and Shapiro (2008) and Zwick and Mahon (2017) show that this had a substantial effect on the investment decisions of industries and firms with more exposure to that tax policy. Later, the 2017 Tax Cuts and Jobs Act (TCJA) constituted the largest tax reform in postwar history with both a corporate rate cut and an expansion of bonus depreciation. Kennedy et al. (2023) and Chodorow-Reich et al. (2023) show that the tax cut had a large and significant effect on corporate investment. I show the same for maintenance using similar regression specifications as for freight rail. The main difference is that the SOI does not have a measure of gross investment and net investment is occasionally negative, so I do not take a log transformation of the investment rate.

I give the results for the log-log specification in Table 3.4.[9] The coefficient on the log tax term for taxable firms is in columns 1-3 and untaxable firms in 4-6. Whereas the coefficient on the log tax term is around -2.75 for taxable firms, it is centered at zero for untaxable firms.[10] This result is useful for four reasons. First, columns 1-3 give demand elasticities of a similar magnitude and significance as in the freight rail results. Second, the tax term is a result of exogenous policy variation, which means it decisively resolves the endogeneity problem. Third, because the result only applies to taxable firms, it confirms that the driving force for the result is the distortion. It is difficult to show this for

8. I detail how I create $\tau_{j,t}$ in Appendix D. It is largely the same procedure as previous iterations of cross-sectional tax policy analysis from, for example, House and Shapiro (2008).

9. I show the corresponding results for the linear-linear model and the level cases in Appendix C.

10. The dynamic specification in column 3 yields a coefficient around -2.5 because the autocorrelation of the maintenance rate is 1/3.

freight rail because Class I freight railroads are generally profitable. Finally, Table 3.4 confirms that the results are not limited to freight rail and are indeed an economy-wide phenomenon.

	Dependent variable: $\log m_{j,t}$					
	Taxable Firms			Untaxable Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1-\tau_{j,t})$	-2.912	-2.516	-1.665	0.010	0.004	0.000
	(1.128)	(1.003)	(0.732)	(0.093)	(0.100)	(0.067)
$x_{j,t}$		-0.052	-0.056		-0.002	-0.002
		(0.021)	(0.025)		(0.001)	(0.001)
$\log m_{j,t-1}$			0.340			0.371
			(0.098)			(0.070)
N	1071	1012	1005	1070	1009	1003
FE: Industry	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X

Table 4: Regression results of the maintenance rate on the tax term along with additional controls. Standard errors are clustered by BEA industry. The investment rate is net investment scaled by the net capital stock.

However, there are two potential issues with the data in this subsection. I give a detailed discussion of both in Appendix C.1. Briefly, there is a measurement error in the magnitude of the maintenance expenditure because it is likely the SOI only reports external maintenance expenditures rather than the sum of internal and external maintenance expenditures. This happens because firms place internal maintenance expenditures under similarly tax deductible wages rather than maintenance. Applying estimates from the more granular freight rail data, tax rates and the share of externally purchased services do not appear to be systematically related. Hence, if we can extrapolate from freight rail to the economy as a whole, then measurement error in maintenance does not affect the coefficient on the tax term in Table 3.4. Second, the capital stock is likely measured incorrectly; I discuss this source of bias in Section 3.5. Third, the estimates in Table 3.4 implicitly assume a perfectly competitive supply curve for the supply of investment and maintenance. Goolsbee (1998b) shows that this is not a correct assumption. Applying his estimates implies that the elasticities in Table 3.4 should be magnified by approximately 1.4.

3.5 Measurement Error in Capital Stocks

The key source of measurement error in the main specification is the capital stock, which is the denominator for the maintenance rate. Throughout, I have used the net book capital stock, which is formed from the perpetual inventory method according to $K_{t+1} = K_t (1 - \delta) + X_t$.[11] On the other hand, the whole point of this paper is that precisely because maintenance is price-elastic, it is incorrect to apply the standard perpetual inventory method. Instead, capital stocks should be formed according to (1).

I correct for bias with an iterative structural approach. The idea is to take an initial guess for the parameters in the function $h(m_t)$ and use that to iterate forward an initial capital stock using observed maintenance levels and capital expenditures. Using that synthetic capital stock, I rerun the regression (5) without controls until the estimated parameters converge. For both the log-log and linear-linear cases, we cannot recover the level parameter, and so we are really estimating the elasticity parameter for the former and the slope parameter for the latter. I use the estimates in column (1) of Table 1 as initial guesses. In both cases, I calibrate the remaining parameters such that the maintenance rate is 5% when $P = 1$. I also set $\delta = 10\%$ in line with the estimate for rolling stock in Baldwin, Liu, and Tanguay (2015).

Figure 4 compares the coefficients on the bias-corrected series to the original coefficients. While the absolute value of the coefficient in the log-log specification shrinks to approximately 1.6, the coefficient on the linear-linear specification rises moderately to 0.5. In both cases, there is very little practical economic or statistical difference between parameter estimates.

Although the coefficients turn out to be fairly similar, the capital stocks do not. Figure 5 compares the resulting synthetic capital stock series to the one used in the main specifications for both freight cars and locomotives. Each series takes a simple sum over firm capital stocks within each capital type for the synthetic series K_t^S and divides by the original capital stock K_t^O. The left-hand panel uses the linear-linear specification while the right-hand panel is the log-log. In both cases, the synthetic capital stock series is substantially smaller than the original by the end of the sample, reaching around 40-50% as large for the linear specification and 60-70% for the log specification. The constant elas-

11. There is no need to worry about aggregating over capital types because there is a separate capital stock and depreciation rate for each type of capital.

ticity functional form attenuates the effect of large changes in maintenance while linear demand does not, which leads to the large difference between the two.

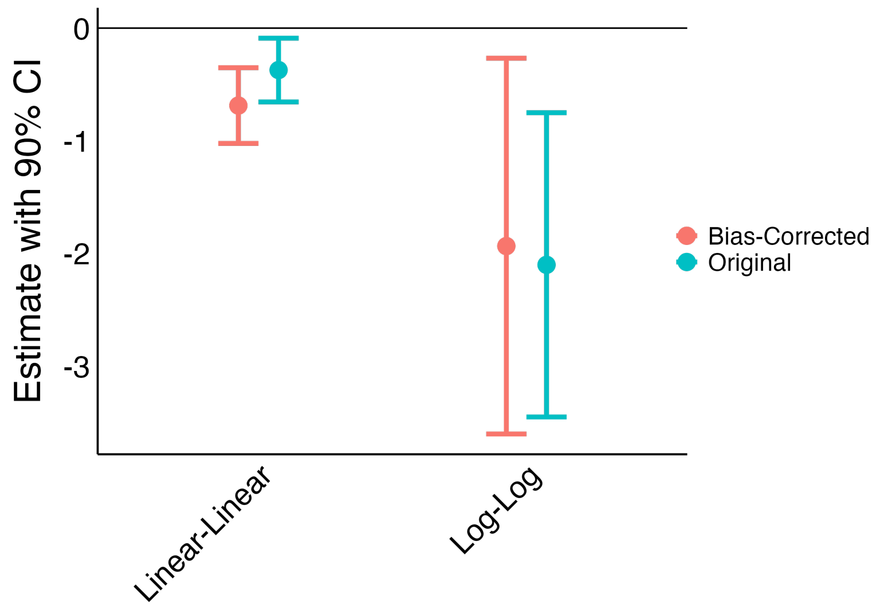
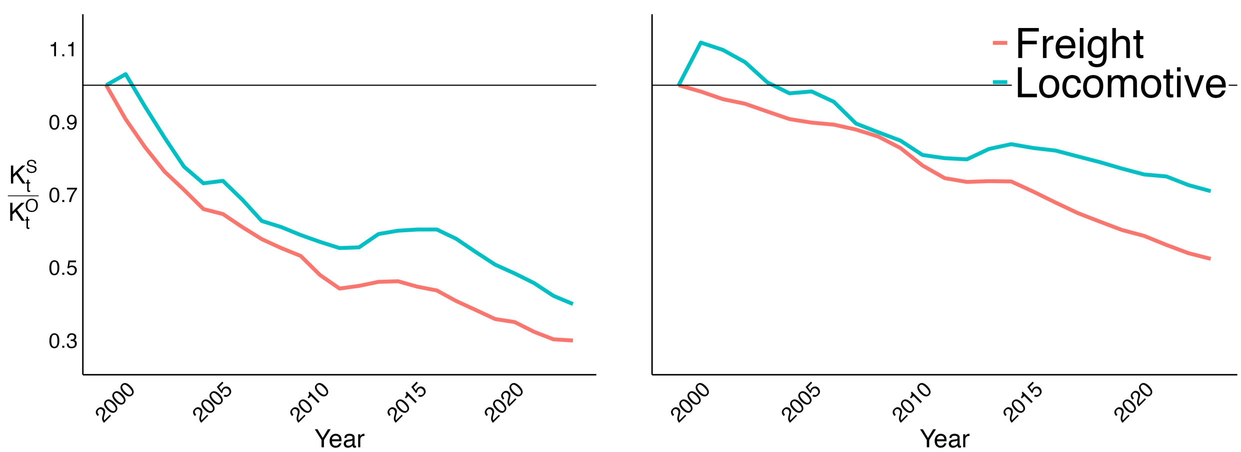


Figure 4: Bias-corrected coefficients compared to baseline estimates. The bias correction comes from creating a synthetic capital stock given each $h(m)$ and iterating over parameters until the estimates converge.



(a) Linear Demand

(b) Constant Elasticity Demand

Figure 5: Comparing the synthetic capital stock for freight and locomotives to the original. The synthetic capital stock K_t^S is the sum over firms within capital types at year t, while K_t^0 is the same for the book value used in the baseline estimates. Panel (a) uses the linear-linear specification and Panel (b) is the log-log specification.

3.6 Dynamic Effects

The results for freight rail and the SOI indicate that the demand for maintenance is neither perfectly inelastic nor zero. This opens the question of the dynamic stability of the coefficient. It could be the case that price changes temporarily induce firms to change maintenance behavior despite the fact that the price changes are themselves more persistent, which would indicate that the model is likely misspecified. From Figure 2, relative price changes for freight rail seem to be persistent. Similarly, tax changes have been persistent throughout the 21st century aside from the occasional lapse in bonus depreciation.[12] To address this question, I run local projections of the same specifications used for the static regressions for the freight rail and SOI data. In particular, I run

$$\log m_{i,j,t+h} = \alpha_i + T_t + \kappa_j + \beta_h \log P_{i,j,t} + \epsilon_{i,j,t} \tag{7}$$

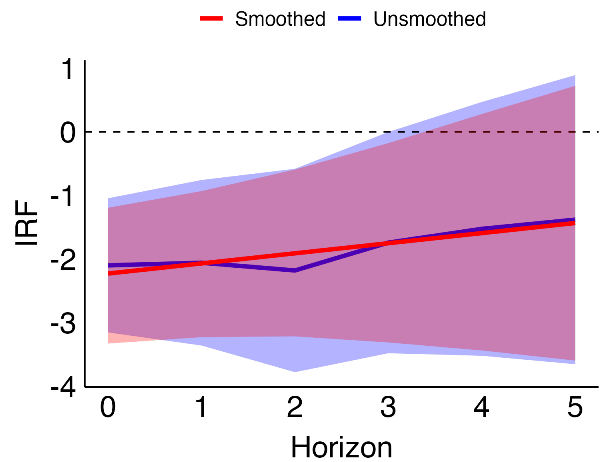
for the freight rail data and

$$\log m_{i,t+h} = \alpha_i + T_t + \beta_h \log(1 - \tau_{i,t}) + \epsilon_{i,j,t} \tag{8}$$

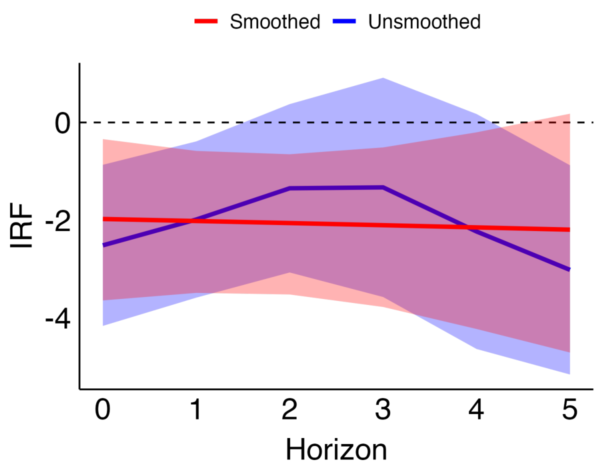
for the SOI data. I run each regression for up to $h = 5$ years after a shock. Again, I cluster the freight rail data by firm and the SOI data by industry. Figure 6 plots the results for the baseline specification. The top panel plots the impulse response to a price shock for the maintenance rail data. The bottom left panel plots the impulse response to a tax shock for taxable firms and the right panel for untaxable firms in the SOI data. The red line plots an impulse response function from a smoothed local projection from Mejia (2024) and the blue line is a standard panel local projection.

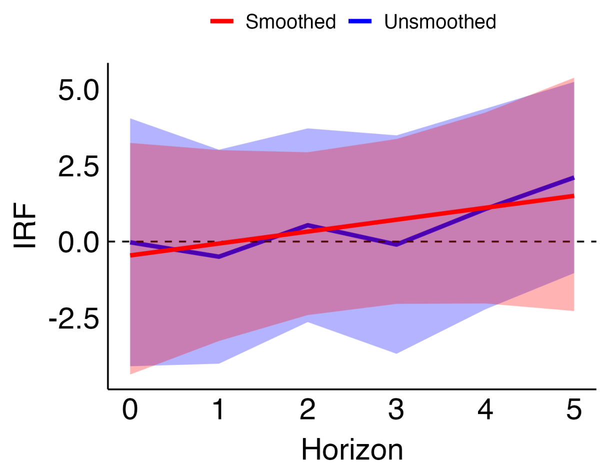
For both the freight rail and SOI data, the coefficient is stable and significant across multiple years. In particular, taxable firms in the SOI show no decline in the maintenance rate five years out from a shock, whereas there is some attenuation from freight rail. At the same time, the statistical significance declines because the sample size gets substantially smaller for each horizon, particularly for the freight rail data. As a check, the coefficient on untaxed firms remains zero at all horizons.

12. Figure 13 in the appendix plots the sequence of coefficient from a regression of the relative price of maintenance on its lags for freight rail and tax policy.



(a) Freight Rail IRF





(b) SOI: Taxable Firm IRF

(c) SOI: Untaxed Firm IRF

Figure 6: Impulse responses of the log maintenance rate to a unit increase in the log relative price of maintenance. The regressions are simply dynamic versions of the static specifications, where the impulse response is the sequence of coefficients β_h on the price shock from horizons $h = 0, \ldots, 5$.

4 The Maintenance Channel and Tax Policy Analysis

Structural and empirical tax policy analysis tend to revolve around a single parameter: the tax elasticity of investment. In single-input models, that parameter is either exactly or approximately a sufficient statistic for the tax elasticity of capital and output. That is no longer true when the price elasticity of maintenance is greater than zero, a condition which is strongly supported in the data. In this section, I explore the implications of a positive price elasticity of maintenance for both empirical and structural tax policy analysis.

4.1 Empirical Analysis

Economists use tax reforms as natural experiments to determine the tax elasticity of investment. Among many others, recent examples on bonus depreciation include House and Shapiro (2008), Kitchen and Knittel (2011), and Zwick and Mahon (2017), while similar work on TCJA includes Kennedy et al. (2023) and Crawford and Markarian (2024). The empirical focus on investment follows from the standard single-input model, in which taxes lower the user cost of capital, leading to capital deepening and ultimately output growth through increased demand for investment. In such models, the tax elasticity of investment *is* the tax elasticity of capital. Indeed, when evaluating the medium-run and long-run consequences of TCJA, Chodorow-Reich et al. (2023) state explicitly that their empirical estimates of the tax elasticity of investment map directly into the tax elasticity of capital:

> We start with a (nearly) "model-free" quantification. Column (1) of Table 6 reports the steady state partial equilibrium change in domestic capital (or equivalently investment), computed as the capital-weighted fitted values using the regressions (p. 39).

This is *not* to pick on their careful work, but merely to highlight that the empirical investment demand elasticity is typically viewed as sufficient for evaluating the consequences of tax policy changes. However, investment regressions are generally not model-free and usually does not claim to be.[13] Indeed, since the pioneering work of Summers (1981) and Cummins, Hassett, and Hubbard (1994), investment regressions have typically followed from a model specification. For example, regressions of some measure of investment on the tax term $1/(1-\tau)$ follow directly from the observation that the tax semi-elasticity of user cost is the tax term. Similarly, regressions of investment on the user cost of capital rely on a particular model of investment.

If there is more than one input to capital production, then simply regressing investment on a tax term or user cost suffers from omitted variable bias because it fails to account for substitutability between maintenance and investment. This is a direct result of Proposition 1, which suggests that the true exposure of investment to tax policy must account for maintenance. The insight is analogous to the lesson of Goolsbee (1998a), which emphasizes that the supply of investment goods is not perfectly competitive, so one cannot simply regress investment on a tax term and omit prices. In the same way

13. The description of the regressions as "model-free" in Chodorow-Reich et al. (2023) is curious because they build an elegant extension of Hall and Jorgenson (1967) to model the multinational provisions of TCJA with the express purpose of mapping their regressions into a model.

that regressing investment on a tax term alone assumes perfect competition in the supply of investment goods, so too does omitting maintenance imply a particular model of capital production. In that sense, there are no "model-free" analyses of tax policy.

To show how much the omitted variable bias matters in the context of capital maintenance, I use firm-level data from Compustat together with industry-level tax policy variation. The exercise is to compare the coefficient of a standard regression which ignores maintenance with a regression that accounts for it through a constant-elasticity maintenance demand function for a grid of values for the demand elasticity ω. *Ex ante*, the direction of the omitted variable bias is not obvious. Although accounting for maintenance reduces the tax elasticity of user cost, which would make the coefficient larger, it also may make the coefficient smaller if maintenance severs the relationship between investment and the user cost. This is entirely plausible for large values of the maintenance elasticity, which would push the tax elasticity of user cost toward zero. The regression is

$$\log X_{i,t} = \alpha_i + T_t + \beta_x \left(\frac{1}{1-\tau_{j,t}} - \frac{m(\tau_{j,t})}{\widetilde{\Psi}_{i,t}} \right) + \varepsilon_{i,t}, \tag{9}$$

where α_i is a firm fixed effect and T_t is a year fixed effect. The coefficient β is pinned down by exogenous variation in tax policy across industries. The tax policy variable is the industry-j marginal effective tax rate for firm i. I discuss construction in Appendix D, but it is largely the same as in House and Shapiro (2008) and Zwick and Mahon (2017) except over a longer time span. The data are from 1973-2022 and cover 20,612 firms. Maintenance demand is pinned down by two parameters: a level parameter and an elasticity parameter: $m = \gamma(1-\tau)^{-\omega}$ For every value of the elasticity parameter, I set the level parameter γ by multiplying the mean industry maintenance rate from the SOI by the maxim value of the capital tax rate in the data for firm i. This ensures a conservative value for γ. I set the remainder of the pre-tax user cost by using the industry-specific depreciation rate from the BEA and using a common discount rate of 0.15.

Figure 7 plots the coefficient β_x for varying levels of the maintenance elasticity from $\omega = 0$ to $\omega = 15$. The red line label "NGM" is the investment elasticity when not accounting for maintenance and the blue line labeled "NGMM" accounts for maintenance through the parameter ω. Standard errors are clustered by industry. For $\omega = 2$, which is the best estimate in this paper, the investment demand elasticity is underestimated by approximately 30%. There is some irony to the fact that accounting for maintenance enhances the tax elasticity of investment in a statistical sense while also diminishing its importance in an economic sense. For moderate values of ω, the investment elasticity is slightly underestimated, while it is a dramatic overestimate for larger values of ω. As ω

rises, the coefficient declines because the taxes have an increasingly small effect on the user cost, which means it can explain considerably less of the variation in investment demand.

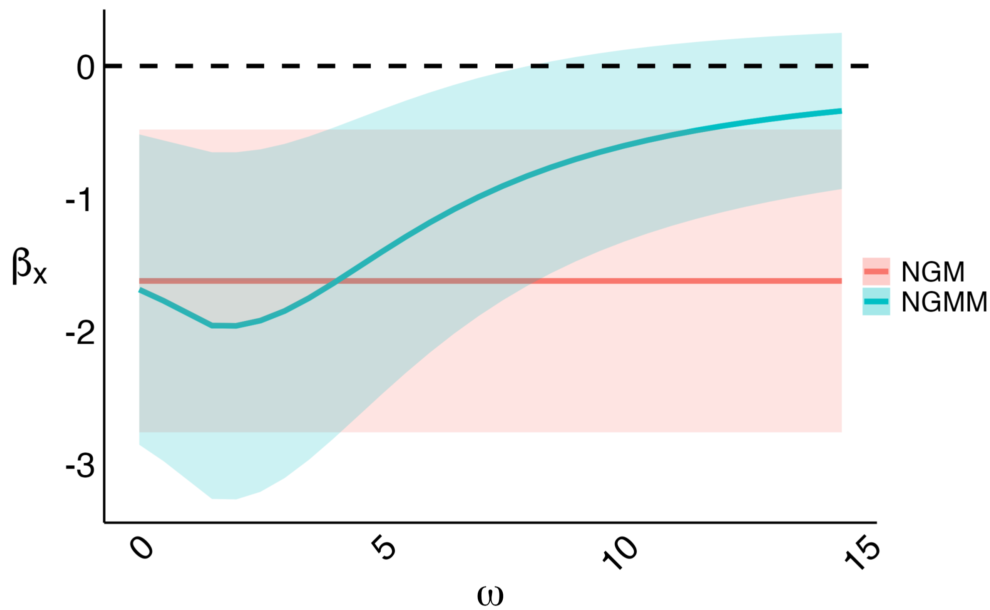


Figure 7: Estimated investment demand elasticity under the NGM-implied tax semi-elasticity of user cost and the NGMM-implied tax semi-elasticity of user cost for varying values of ω. Standard errors are clustered by industry and data are from 1973-2022.

The curvature in Figure 7 depends on the parameters. If $\widetilde{\Psi}$ is larger, then the coefficient β_x would converge to zero more slowly because the maintenance share of user cost would be less important for the same values of ω. With that in mind, Figure 7 should be considered an illustration of the dangers of not accounting for maintenance when estimating the demand elasticity of its substitute in production and not necessarily a precise measure of the investment demand elasticity.

4.2 Structural Tax Policy Analysis

Quantitative models form the basis for both predicting the effects of proposed tax reforms and evaluating them *ex post*. They played a particularly large role in the robust debate around the 2017 Tax Cuts and Jobs Act. TCJA is among the largest tax reforms of the postwar era. It cut corporate tax rates from 35% to 21% and altered tax wedges between assets; lawmakers gave certain types of equipment 100% bonus depreciation and altered the cost of capital for different types of intangibles. 100% expensing entirely eliminated the tax wedge between maintenance and investment.[14] Although models disagreed to some extent on the effects of TCJA and varied in complexity from Barro and Furman's 2018 simple Ramsey model to the the Penn Wharton OLG model and the DSGE model from the Joint Committee on Taxation, they all have in common a single-input perpetual inventory equation with constant depreciation to iterate forward the capital stock (Auerbach et al. 2017). The central contention of this paper is that such models are unlikely to make accurate predictions about the likely effects of tax policy changes on output or growth if they rely on single-input capital theories when the exact policy they study changes the margin of substitution between two inputs to capital accumulation. I illustrate this using the a comparison between the NGM and the NGMM in two steps. First, I compare the dynamic predictions of the NGM with investment adjustment costs to an otherwise identical NGMM after feeding in a sequence of marginal capital tax rates calibrated from TCJA. Second, I use the Barro and Furman (2018) analysis of the TCJA as a foil to compare long run predictions, changing only the law of motion for capital from their model to reflect the one in this paper.

Dynamics

Under TCJA, only the provision for the corporate rate change is permanent, whereas the expensing components for equipment sunset after 2026. There is 100% bonus depreciation on equipment until 2022.[15] After that, it declines by 20 percentage points per year until sunsetting entirely. At the same time, corporations must amortize R&D expenditures beginning in 2022. This leads to interesting time variation in capital tax rates. In this subsection, I use a simple neoclassical model to highlight the differing dynamic predictions for capital accumulation between the NGM and the NGMM following the passage of TCJA. I focus on a simple model to prominently highlight the differences between a model with and a model without maintenance.

In this subsection, I focus on homogeneous capital to illustrate the mechanism. Consider a firm which produces with Cobb-Douglas technology according to $Y_t = k_t^{\alpha}$, where $k_t = K_t/L_t$ is in intensive form. To model dynamics, I use the investment adjustment cost function from Christiano, Eichenbaum, and Evans (2005). Capital accumulates according

14. At the same time, policymakers introduced new measures to combat profit shifting from tax havens abroad. For a full description of the various changes, see CEA (2018) and Gale et al. (2018).

15. Bonus depreciation allows firms to deduct an extra percentage of their investment expenditures every year. Usually, firms are allowed to deduct from gross income a certain percentage of their investment according to guidance from the IRS. Let the net present value of these deductions be denoted as z_t. If the bonus depreciation percentage is θ, then the effective present value of depreciation deductions is $\tilde{z}_t = \theta + (1-\theta)\, z_t$. See House and Shapiro (2008), Kitchen and Knittel (2011), and Zwick and Mahon (2017) for detailed empirical analysis of bonus depreciation.

to

$$K_{t+1} = X_t \left(1 - \frac{\phi}{2}\left(\frac{X_t}{X_{t-1}} - 1\right)^2\right) + K_t\left(1 - \delta + \mathbb{1}\left(\frac{\gamma^{1/\omega}}{1-1/\omega} m_t^{1-1/\omega}\right)\right), \tag{10}$$

where the indicator function is equal to one for the NGMM and zero otherwise. I ignore the household sector in the interest of parsimony and focus exclusively on a representative firm in partial equilibrium.

I use Barro and Furman (2018) and Chodorow-Reich et al. (2023) to calibrate the models. I use the latter's estimate of the investment price elasticity to calibrate ϕ. Barro and Furman (2018) set $\alpha = 0.38$ and a discount rate of $r^k = 0.082$. In the NGM, I set $\delta = 0.085$ because that is the capital share-weighted average of depreciation rates in Barro and Furman (2018). I set δ in the NGMM to match the initial user cost of capital in the NGM given $\gamma = 0.05$ and $\omega = 2$, which implies $\delta \approx 0.1445$. Finally, I feed in a sequence of capital tax rates for corporations from 2017-2026, when TCJA sunsets.

Figure 8 plots the evolution of the capital-labor ratio from 2017-2050. The dynamics between the standard neoclassical model and the NGMM plus maintenance are quite different. Capital grows faster and significantly more under the NGM before returning to a more moderate steady state as the TCJA provisions sunset. On the other hand, capital in the NGMM grows considerably less before the TCJA provisions sunset, which means that the sunsetting does not actually matter very much.

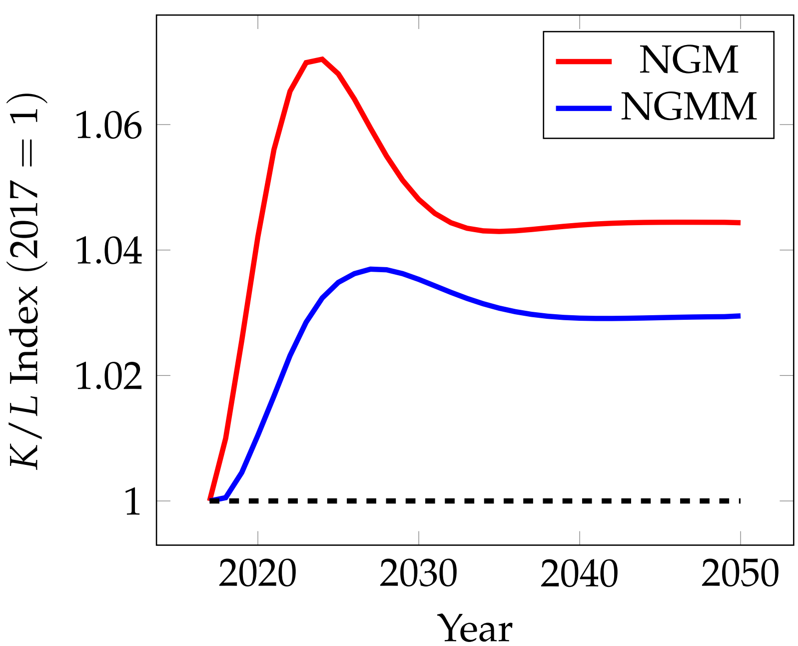


Figure 8: Capital-labor ratio in the NGM and NGMM given a sequence of tax rates from the 2017 Tax Cuts and Jobs Act.

Evidently, there is a significant amount of model misspecification when focusing on one capital input rather than two. This provides some context to Chodorow-Reich et al. (2023) and Zeida (2022), which are the two most prominent *ex post* structural analyses of the dynamics of capital following TCJA. Although both models are far more complex than the simple one here, they both predict increases in the domestic capital-labor ratio to a quantitatively similar degree as the NGM in Figure 8. As a result, they both similarly miss out on the complex dynamics implied by accounting for maintenance, which suggest that capital is far less tax elastic than in their models.

Aside from the mere difference in dynamics, Figure 8 is important because it highlights the danger in relying on empirical investment elasticities to calibrate quantitative models. Chodorow-Reich et al. (2023) use a static elasticity to calibrate the evolution of capital following TCJA, but this is clearly insufficient. Indeed, given the evidence in Section 3.6 that relative price changes have enduring effects on maintenance intensity, it is not informative to simply extrapolate the dynamics of capital accumulation based solely on an investment elasticity estimate. For precisely that reason, long-run estimates will be similarly uninformative. I explore that in the following subsection.

Long Run Analysis

I expand on the previous model to replicate the Barro and Furman (2018) estimates of the long-run effects of TCJA. That paper models long-run effects using a neoclassical model with five capital types: equipment, structures, R&D, intellectual property, and other types of intellectual property. Their analysis revolves around the steady-state user cost of capital, which is given for each type i by

$$MPK_i = \Psi_i = \frac{1-\lambda_i \tau^c}{1-\tau^c}\left(r^k + \delta\right), \tag{11}$$

where MPK_i is the steady-state marginal product of capital, λ_i is the expensing rate for capital type i, τ^c is the corporate tax rate, r^k is the discount rate, and δ is a constant depreciation rate. Barro and Furman discipline the demand for capital using a calibrated Cobb-Douglas production function for both a corporate and a pass-through sector. (11) forms the basis for all quantitative tax policy models. Differences emerge between model predictions about capital accumulation solely from adjustment costs, restrictions on debt, or crowding out. In the final case, the discount rate may be modeled as endogenous to tax policy.

Barro and Furman model a variety of different assumptions on (11), but almost universally, their analysis yields promising results for the TCJA, predicting large increases in the capital-labor ratio and, as a direct consequence, significantly higher output per capita. Their approach amounts to simply computing the analytical steady state under different capital tax policies while implicitly assuming that the demand for maintenance is perfectly inelastic and zero. I focus on bringing maintenance into their environment. Since the Barro-Furman model is simply the neoclassical growth model, denote it as "NGM" and the NGM plus maintenance as the "NGMM" Under constant-elasticity demand for maintenance the user cost of capital becomes

$$MPK_i = \Psi_i = \frac{1-\lambda_i \tau^c}{1-\tau^c}\left(r^k + \delta - \frac{\gamma_i^{1/\omega}}{\omega - 1} m_i^{1-1/\omega}\right), \tag{12}$$

where $m_i = \gamma_i \left(\frac{1-\tau^c}{1-\lambda_i \tau^c}\right)^{-\omega}$ is pinned down by tax policy. Let $1-\tau \equiv \frac{1-\tau^c \lambda}{1-\tau^c}$. Proposition 1 yields an easy comparison between the two models.

Corollary 2. *With one capital type and Cobb-Douglas production parameterized by α, the tax semi-elasticity of the capital-labor ratio is given by*

$$\varepsilon_k = -\frac{1}{1-\alpha}\left(\frac{1}{1-\tau} - \frac{m(\tau)}{\widetilde{\Psi}}\right) \tag{13}$$

and the tax semi-elasticity of output per capita is given by

$$\varepsilon_y = -\frac{\alpha}{1-\alpha}\left(\frac{1}{1-\tau} - \frac{m(\tau)}{\widetilde{\Psi}}\right). \tag{14}$$

Clearly, if $\omega = 0$, then the tax elasticities of capital are the same in the NGM and the NGMM. But as γ and ω rise, that is no longer true.[16] This is the same logic as Proposition 1. Our goal is to compare the predicted change in the user cost of capital, the capital to labor ratio, and the resulting change in the output to labor ratio between the NGM and NGMM. I focus on the baseline "law as written" scenario for TCJA and ignore debt incurred by firms.

To compare the NGM to the NGMM, I calibrate the baseline user cost to be the same

16. With more than one capital type, the proportional change in the capital-labor ratio is given by

$$\frac{\Delta(K_i/L)}{K_i/L} = -\frac{1}{1-\sum_i \alpha_i}\left[\left(1 - \sum_{j\neq i}\alpha_j\right)\frac{\Delta\Psi_i}{\Psi_i} + \sum_{j\neq i}\alpha_j \frac{\Delta\Psi_j}{\Psi_j}\right].$$

From Corollary 2, the elasticity will be smaller for each capital type in the NGMM. Indeed, even if the change in user cost is the same in both models for one capital type, the proportional change will be smaller in the capital-labor ratio will be smaller in the NGMM as long as at least one other capital type has an active maintenance channel.

in both models prior to TCJA. Following the estimates in Section 3, I apply a maintenance demand function with $\gamma = 0.05$ and $\omega = 2$. This is a conservative demand function; it implies that the maintenance rate is 0.05 when the relative price is equal to one. For freight rail, which I argue has a more comprehensive measure of maintenance than the SOI data, it would be far too low. Nevertheless, we have no evidence on maintenance demand for different types of capital and so I simply use a common and conservative demand function across all capital types. Given that, I set the constant parameters $R_i = r^k + \delta_i$ for each capital type such that the baseline user cost is the same in the NGM and the NGMM. R_i is typically larger in the NGMM than the NGM because maintenance subtracts from user cost. See Barro and Furman (2018) for the full "law as written" calibration. The most important elements are a decline in the corporate tax rate from 38% to 27% and elimination of full expensing for R&D expenditures.[17] Note that the law as written scenario sunsets full expensing for equipment.

Table 5 presents the resulting change in user costs for both corporate and passthrough business following TCJA. The top panel is corporate business and the bottom panel is passthroughs. The first column contains a baseline user cost common to both the NGM and the NGMM. The next two columns contain the percent change in the user cost and capital-labor ratio for each type of capital under the NGM and the following two for the NGMM. For structures, the percent change in user cost is more than twice as high for the NGM than the NGMM, while the difference is smaller for equipment and intellectual property. The reason for that follows from the calibration of the R_i in the NGMM. Since user cost is lower for structures, R_i must be set correspondingly lower. In that case, the maintenance share of user cost is larger, which means that it dominates when taxes change. By comparison, maintenance is a relatively small part of other IP, so the difference in user costs is correspondingly smaller.

17. The Barro-Furman calibration of corporate tax rates accounts for state and federal taxes.

	Baseline UCC	NGM %Δ UCC	NGM %Δ K/L	NGMM %Δ UCC	NGMM %Δ K/L
Corporate Business					
Equipment	0.190	-4.09%	+7.20%	-2.80%	+ 4.24%
Structures	0.143	-11.5%	+14.6%	-4.46%	+5.90%
Residential Structures	0.153	-11.5%	+14.6%	-4.91%	+6.35%
Intellectual Property	0.188	+7.89%	-4.78%	+5.97%	-4.54%
Other IP	0.305	-3.50%	+6.61%	-2.83%	+4.27%
%ΔK/L		+8.19%		+3.77%	
%ΔY/L		+3.11%		+1.43%	
Passthrough Business					
Equipment	0.187	+0.12%	-0.80%	+0.08%	-0.48%
Structures	0.139	+0.35%	-1.02%	+0.12%	-0.51%
Residential Structures	0.148	+0.35%	-1.03%	+0.13%	-0.53%
Intellectual Property	0.188	+14.3%	-14.9%	+9.98%	-9.38%
Other IP	0.302	+0.10%	-0.78%	+0.10%	-0.50%
%ΔK/L		-1.78%		-1.04%	
%ΔY/L		-0.68%		-0.40%	

Table 5: Effects of TCJA in the NGM and NGMM. The top panel depicts the change in the user cost of capital and capital-labor ratio within the NGM and the NGMM given a common baseline user cost of capital for corporate businesses. The bottom panel does the same for passthrough businesses. See Barro and Furman (2018) for calibrated parameters.

In the corporate sector, the NGM predicts a capital-labor ratio and an output-labor ratio more than twice as large as the NGM. An equivalent way to summarize the result is that the NGMM is observationally equivalent to the NGM with a capital share that has been halved. In the passthrough sector, the change in user cost for most capital types is driven by a small increase in the personal income tax rate. But the sum of these differences in the NGMM yields a total change in the capital-labor ratio that is about 60% as large as in the NGM.

Figure 9 puts together the changes in the corporate and passthrough sectors into an aggregate change in the output-labor ratio. Barro and Furman calibrate the model such that 6.8% of passthroughs switch to the corporate sector in the long run; I keep that assumption. In total, the NGMM predicts that TCJA would increase the output-labor ratio about 55% as much as the NGM suggests it would. This is a significant difference and requires no frictions to arrive there.

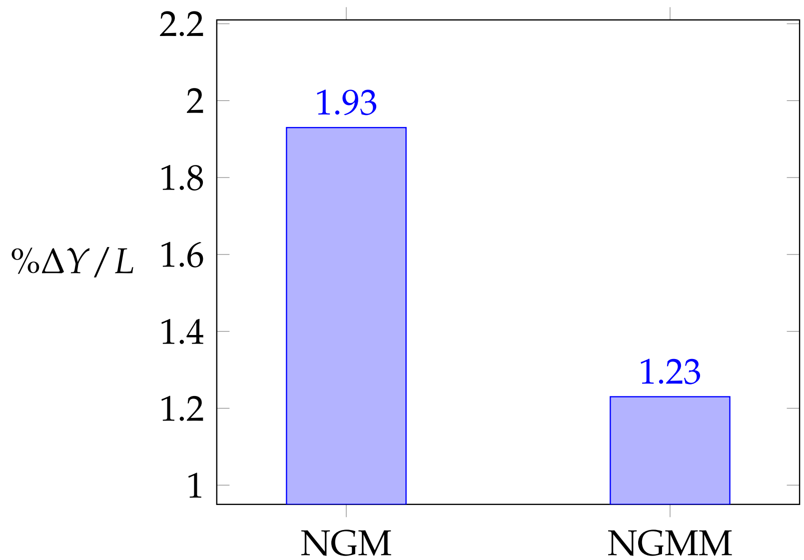


Figure 9: Increase in steady-state per capita output (productivity) in the NGM and the NGMM.

Given the simplicity of both the NGM and the NGMM in this setting, it is difficult to empirically validate which is closer to the truth. If we assume a convergence rate of 5%, then the output-labor ratio would reach 40% convergence by 2027. This amounts to an increase in the per capita growth rate of about 0.08% per year for the NGM model and 0.05% in the NGMM. In the following subsection, I detail why it is difficult to empirically evaluate the productivity and capital deepening effects of TCJA without accounting for maintenance.

5 Concluding Remarks

In this paper, I discuss the theoretical, empirical, and quantitative relevance of accounting for endogenous maintenance in the context of capital tax policy. I provided a parsimonious and flexible framework for evaluating the likely consequences on the short-run and long-run impacts on allocations of maintenance, investment, and capital for heterogeneous capital. Additionally, I provided two novel sources of evidence on the price elasticity of maintenance. First, I put together an entirely new dataset on the maintenance and investment behavior of Class I freight railroads using financial filings from the Surface Transportation Board. Second, I leveraged maintenance data from corporate tax returns at the industry level from the IRS. These sources agree that the maintenance demand elasticity is plausibly around one. Quantitatively, this indicates a tax elasticity of the capital stock about half as large as we would predict using a single-input neoclassical model. In other words, accounting for maintenance yields a significantly lower tax elasticity of output and capital than the standard model without imposing any frictions.

Arguably, the key limitation to this study relates precisely to other types of "hidden" investment like intangibles (Crouzet et al. 2022) and sweat equity (Bhandari and McGrattan 2021). Depreciation is made up of two components: obsolescence and physical wear and tear. The type of maintenance in this paper only addresses the latter and not the former because it is entirely about physical capital. However, the majority of the capital stock is arguably intangible (Bhandari and McGrattan 2021), which means that its depreciation is largely obsolescence and hence has little to do with this paper's concept of maintenance.[18] As a result, this study only speaks to the physical capital stock, which is a small share of the total capital stock. However, both quantitative and empirical tax analyses continue to focus almost exclusively on tangible capital. Tax policy models from the Joint Committee on Taxation, the Penn Wharton Budget Center, the Congressional Budget Office, the Tax Foundation and many other workhorse models for tax policy analysis focus largely on tangible capital. This signals that there is utility in measuring tangible capital maintenance properly even if it has to be scaled down in importance by the extent to which intangibles are more significant.

More work needs to be done by economists on rigorously evaluating the empirical maintenance demand curves by capital type, which requires, in turn, that government agencies take a more active role in making maintenance data available to them. Given the groundwork laid here and in prior work by McGrattan and Schmitz Jr. (1999) and Goolsbee (2004), the case for public finance and macroeconomists to undertake these studies is, I think, too big to ignore.

18. Exercise of market power would have large effects on depreciation of this kind of capital and in that sense, could be thought of as maintenance.

References

Albonico, Alice, Sarantis Kalyvitis, and Evi Pappa. 2014. "Capital maintenance and depreciation over the business cycle." *Journal of Economic Dynamics and Control* 39 (February): 273–286. ISSN: 01651889. https://doi.org/10.1016/j.jedc.2013.12.008.

Angelopoulou, Eleni, and Sarantis Kalyvitis. 2012. "Estimating the Euler Equation for Aggregate Investment with Endogenous Capital Depreciation." *Southern Economic Journal* 78, no. 3 (January): 1057–1078. ISSN: 0038-4038. https://doi.org/10.4284/0038-4038-78.3.1057.

Auerbach, Alan J. 1983. "Corporate Taxation in the United States." *Brookings Papers on Economic Activity* 2.

Auerbach, Alan J., Itai Grinberg, Thomas Barthold, Nicholas Bull, W. Gavin Elkins, Pamela Moomau, Rachel Moore, Benjamin Page, Brandon Pecoraro, and Kyle Pomerleau. 2017. "MACROECONOMIC MODELING OF TAX POLICY." *National Tax Journal* 70, no. 4 (December): 819–836. ISSN: 0028-0283. https://doi.org/10.17310/ntj.2017.4.06.

Bachmann, Rüdiger, Ricardo J. Caballero, and Eduardo M. R. A. Engel. 2013. "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model." *American Economic Journal: Macroeconomics* 5, no. 4 (October): 29–67. ISSN: 1945-7707. https://doi.org/10.1257/mac.5.4.29.

Baldwin, John, Huju Liu, and Marc Tanguay. 2015. " An Update on Depreciation Rates for the Canadian Productivity Accounts." *The Canadian Productivity Review.*

Barro, Robert J., and Jason Furman. 2018. "The macroeconomic effects of the 2017 tax reform."

Bhandari, Anmol, and Ellen R McGrattan. 2021. "Sweat Equity in U.S. Private Business*." *The Quarterly Journal of Economics* 136, no. 2 (March): 727–781. ISSN: 0033-5533. https://doi.org/10.1093/qje/qjaa041.

Bitros, George C. 1976. "A Statistical Theory of Expenditures in Capital Maintenance and Repair." *Journal of Political Economy* 84, no. 5 (October): 917–936. ISSN: 0022-3808. https://doi.org/10.1086/260490.

Boucekkine, R., G. Fabbri, and F. Gozzi. 2010. "Maintenance and investment: Complements or substitutes? A reappraisal." *Journal of Economic Dynamics and Control* 34, no. 12 (December): 2420–2439. ISSN: 01651889. https://doi.org/10.1016/j.jedc.2010.06.007.

Brazell, David W., Lowell Dworin, and Michael Walsh. 1989. "A History of Federal Tax Depreciation Policy." May.

Caballero, Ricardo J. 1994. "Small Sample Bias and Adjustment Costs." *Review of Economics and Statistics* 76 (1): 52–58.

CEA. 2018. *Economic Report of the President.* Technical report.

Chodorow-Reich, Gabriel, Matthew Smith, Owen Zidar, and Eric Zwick. 2023. "Tax Policy and Investment in a Global Economy."

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy." *Journal of Political Economy* 113, no. 1 (February): 1–45. ISSN: 0022-3808. https://doi.org/10.1086/426038.

Crawford, Steven, and Garen Markarian. 2024. "The effect of the Tax Cuts and Jobs Act of 2017 on corporate investment." *Journal of Corporate Finance* 87 (August): 102619. ISSN: 09291199. https://doi.org/10.1016/j.jcorpfin.2024.102619.

Crouzet, Nicolas, Janice Eberly, Andrea Eisfeldt, and Dimitris Papanikolaou. 2022. *A Model of Intangible Capital.* Technical report. Cambridge, MA: National Bureau of Economic Research, August. https://doi.org/10.3386/w30376.

Cummins, Jason G., Kevin A. Hassett, and R. Glenn Hubbard. 1994. "A Reconsideration of Investment Behavior Using Tax Reforms as Natural Experiments." *Brookings Papers on Economic Activity* 2:1–74.

Dioikitopoulos, Evangelos V., and Sarantis Kalyvitis. 2008. "Public capital maintenance and congestion: Long-run growth and fiscal policies." *Journal of Economic Dynamics and Control* 32, no. 12 (December): 3760–3779. ISSN: 01651889. https://doi.org/10.1016/j.jedc.2008.04.001.

Feldstein, Martin S., and Michael Rothschild. 1974. "Towards an Economic Theory of Replacement Investment." *Econometrica* 42 (3): 393–424.

Gale, William G., Hilary Gelfond, Aaron Krupkin, Mark J. Mazur, and Eric Toder. 2018. *Effects of the Tax Cuts and Jobs Act: A Preliminary Analysis.* Technical report. Tax Policy Center (Urban Institute and Brookings Institution).

Goolsbee, Austan. 1998a. "Investment Tax Incentives, Prices, and the Supply of Capital Goods." *The Quarterly Journal of Economics* 113, no. 1 (February): 121–148. ISSN: 0033-5533. https://doi.org/10.1162/003355398555540.

———. 1998b. "The Business Cycle, Financial Performance, and the Retirement of Capital Goods." *Review of Economic Dynamics* 1, no. 2 (April): 474–496. ISSN: 10942025. https://doi.org/10.1006/redy.1998.0012.

———. 2004. "Taxes and the quality of capital." *Journal of Public Economics* 88, nos. 3-4 (March): 519–543. ISSN: 00472727. https://doi.org/10.1016/S0047-2727(02)00190-1.

Gormsen, Niels, and Kilian Huber. 2022. "Discount Rates: Measurement and Implications for Investment."

Greenwood, Jeremy, Zvi Hercowitz, and Gregory Huffman. 1988. "Investment, Capacity Utilization, and the Real Business Cycle." *American Economic Review* 78 (3): 402–417.

Grimes, George Avery. 2004. "Recovering Capital Expenditures: The Railroad Industry Paradox." PhD diss., University of Illinois at Urbana-Champaign. https://railtec.illinois.edu/wp/wp-content/uploads/pdf-archive/DissertationText-39-Final.pdf.

Hall, Robert E., and Dale Jorgenson. 1967. "Tax Policy and Investment Behavior." *American Economic Review* 57:391–414.

Harding, John P., Stuart S. Rosenthal, and C.F. Sirmans. 2007. "Depreciation of housing capital, maintenance, and house price inflation: Estimates from a repeat sales model." *Journal of Urban Economics* 61, no. 2 (March): 193–217. ISSN: 00941190. https://doi.org/10.1016/j.jue.2006.07.007.

Harris, Adam, and Maggie Yellen. 2023. "Decision-Making with Machine Prediction: Evidence from Prediction Maintenance in Trucking."

Haskel, Jonathan, and Stian Westlake. 2018. *Capitalism without Capital: The Rise of the Intangible Economy.* Princeton University Press. ISBN: 9780691175034.

Hassett, Kevin A., and R. Glenn Hubbard. 2002. "Tax Policy and Business Investment," 1293–1343. https://doi.org/10.1016/S1573-4420(02)80024-6.

Hayek, Friedrich A. 1935. "The Maintenance of Capital." *Economica* 2 (7): 241–276.

House, Christopher L, and Matthew D Shapiro. 2008. "Temporary Investment Tax Incentives: Theory with Evidence from Bonus Depreciation." *American Economic Review* 98, no. 3 (May): 737–768. ISSN: 0002-8282. https://doi.org/10.1257/aer.98.3.737. https://pubs.aeaweb.org/doi/10.1257/aer.98.3.737.

House, Christopher L. 2014. "Fixed costs and long-lived investments." *Journal of Monetary Economics* 68 (November): 86–100. ISSN: 03043932. https://doi.org/10.1016/j.jmoneco.2014.07.011.

Jorgenson, Dale W., and Kun-Young Yun. 1991. *Tax Reform and the Cost of Capital.* Oxford University Press, August. ISBN: 0198285930. https://doi.org/10.1093/0198285930.001.0001.

Justiniano, Alejandro, Giorgio E. Primiceri, and Andrea Tambalotti. 2010. "Investment shocks and business cycles." *Journal of Monetary Economics* 57, no. 2 (March): 132–145. ISSN: 03043932. https://doi.org/10.1016/j.jmoneco.2009.12.008.

Kabir, Poorya, Eugene Tan, and Ia Vardishvili. 2023. " Does Marginal Product Dispersion Imply Productivity Losses? The Case of Maintenance Flexibility and Endogenous Capital User Costs."

Kalaitzidakis, Pantelis, and Sarantis Kalyvitis. 2004. "On the macroeconomic implications of maintenance in public capital." *Journal of Public Economics* 88, nos. 3-4 (March): 695–712. ISSN: 00472727. https://doi.org/10.1016/S0047-2727(02)00221-9.

———. 2005. ""New" Public Investment and/or Public Capital Maintenance for Growth? The Canadian Experience." *Economic Inquiry* 43, no. 3 (July): 586–600. ISSN: 00952583. https://doi.org/10.1093/ei/cbi040.

Kalyvitis, Sarantis, and Eugenia Vella. 2015. "PRODUCTIVITY EFFECTS OF PUBLIC CAPITAL MAINTENANCE: EVIDENCE FROM U.S. STATES." *Economic Inquiry* 53, no. 1 (January): 72–90. ISSN: 0095-2583. https://doi.org/10.1111/ecin.12136.

Känzig, Diego R. 2021. "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements." *American Economic Review* 111, no. 4 (April): 1092–1125. ISSN: 0002-8282. https://doi.org/10.1257/aer.20190964.

Kennedy, Patrick J, Christine Dobridge, Paul Landefeld, and Jacob Mortenson. 2023. *The Efficiency-Equity Tradeoff of the Corporate Income Tax: Evidence from the Tax Cuts and Jobs Act.* Technical report.

Kitchen, John, and Matthew Knittel. 2011. "Business Use of Special Provisions for Accelerated Depreciation: Section 179 Expensing and Bonus Depreciation, 2002-2009." *SSRN Electronic Journal,* ISSN: 1556-5068. https://doi.org/10.2139/ssrn.2789660.

Knight, John R., and C.F. Sirmans. 1996. "Depreciation, Maintenance, and Housing Prices." *Journal of Housing Economics* 5, no. 4 (December): 369–389. ISSN: 10511377. https://doi.org/10.1006/jhec.1996.0019.

Lucas, Robert E. 1990. "Supply-Side Economics: An Analytical Review." *Oxford Economic Papers* 42 (2): 293–316.

McGrattan, Ellen R. 2020. "Intangible capital and measured productivity." *Review of Economic Dynamics* 37 (August): S147–S166. ISSN: 10942025. https://doi.org/10.1016/j.red.2020.06.007. https://linkinghub.elsevier.com/retrieve/pii/S1094202520300466.

McGrattan, Ellen R., and James A. Schmitz Jr. 1999. "Maintenance and Repair: Too Big to Ignore." *Federal Reserve Bank of Minneapolis Quarterly Review,* no. Fall, 213.

Mejia, Jackson. 2024. "Smooth Local Panel Projections."

Peters, Ryan H., and Lucian A. Taylor. 2017. "Intangible capital and the investment-q relation." *Journal of Financial Economics* 123 (2): 251–272. ISSN: 0304405X. https://doi.org/10.1016/j.jfineco.2016.03.011.

Pigou, A. C. 1941. "Maintaining Capital Intact." *Economica* 8, no. 31 (August): 271. ISSN: 00130427. https://doi.org/10.2307/2549333.

Poterba, James M. 1984. "Tax Subsidies to Owner-Occupied Housing: An Asset-Market Approach." *The Quarterly Journal of Economics* 99, no. 4 (November): 729. ISSN: 00335533. https://doi.org/10.2307/1883123.

Romer, Christina D, and David H Romer. 2010. "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks." *American Economic Review* 100 (3): 763–801.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica* 55, no. 5 (September): 999. ISSN: 00129682. https://doi.org/10.2307/1911259.

Scott, Maurice. 1984. “Maintaining Capital Intact.” *Oxford Economic Papers* 36:59–73.

Suárez Serrato, Juan Carlos, and Owen Zidar. 2018. “The structure of state corporate taxation and its impact on state tax revenues and economic activity.” *Journal of Public Economics* 167 (November): 158–176. ISSN: 00472727. https://doi.org/10.1016/j.jpubeco.2018.09.006.

Summers, Lawrence H. 1981. “Taxation and Corporate Investment: A q-Theory Approach.” *Brookings Papers on Economic Activity* 1:67–127.

Winberry, Thomas. 2021. “Lumpy Investment, Business Cycles, and Stimulus Policy.” *American Economic Review* 111, no. 1 (January): 364–396. ISSN: 0002-8282. https://doi.org/10.1257/aer.20161723.

Zeida, Teegawende H. 2022. “The Tax Cuts and Jobs Act (TCJA): A quantitative evaluation of key provisions.” *Review of Economic Dynamics* 46 (October): 74–97. ISSN: 10942025. https://doi.org/10.1016/j.red.2021.08.003.

Zwick, Eric, and James Mahon. 2017. “Tax Policy and Heterogeneous Investment Behavior.” *American Economic Review* 107, no. 1 (January): 217–248. ISSN: 0002-8282. https://doi.org/10.1257/aer.20140855. https://pubs.aeaweb.org/doi/10.1257/aer.20140855.

A Model

Although the theory in the paper is stylized, we can derive the same equilibrium starting from a more traditional theory of the firm. Suppose that a firm produces with capital K and labor L according to a concave production function $F(K_t, L_t)$. Every period, it chooses how much to maintain M_t its existing capital or invest in new capital X_t subject to the law of motion

$$K_{t+1} = K_t \left(1 - \delta + h(m_t) + g(x_t)\right). \tag{A.1}$$

The firm chooses a sequence of maintenance, investment, and labor to maximize the net present value of its dividends

$$d_t = (1 - \tau_t^c)\left(F(K_t, L_t - p_t^m M_t - w_t M_t) - (1 - \tau_t^x)\, p_x X_t.\right. \tag{A.2}$$

Letting λ_t denote the Lagrange multiplier, the equilibrium conditions are

$$w_t = F_L\left(K_t, L_t\right) \tag{A.3}$$

$$g'(x_t) = \frac{1}{\lambda_t}\left(1 - \tau_t^x\right) p_t^x \tag{A.4}$$

$$h'(m_t) = \frac{1}{\lambda_t}\left(1 - \tau_t^c\right) p_t^m \tag{A.5}$$

$$\begin{aligned} \lambda_t(1 + r^k) = {} & (1 - \tau_{t+1}^c) F_K(K_{t+1}, L_{t+1}) \\ & + \lambda_{t+1}\left(1 - \delta + h(m_t) - h'(m_t) m_t + g(x_t) - g'(x_t) x_t\right) \end{aligned} \tag{A.6}$$

Combining the optimality conditions for maintenance and investment yields

$$h'(m_t) = \frac{1 - \tau_t^c}{1 - \tau_t^x} \frac{p_t^m}{p_t^x} g'(x_t)$$

As long as $g'(x_t) = 1$, we recover (2) from the main text since $1 - \tau_t \equiv \frac{1-\tau_t^c}{1-\tau_t^x}$. It is standard to assume $g(x_t)$ is linear in the long run, although many make the same assumption for empirical work. Ambiguity about the shape of the $g(x_t)$ function is why I include the investment rate as an explanatory variable in the main regressions. Suppose that $g(x_t)$ is linear in the long run. Then we recover the user cost of capital from the main text:

$$\Psi = \frac{r^k + \delta - h(m)}{1 - \tau} + m. \tag{A.7}$$

Proof of Proposition 1. Suppose an inverse to $h'(m)$ exists. Since $h(m)$ is concave, the maintenance rate is increasing in the tax rate. Define a new function $m(\tau)$ which defines demand for maintenance as a function of the tax rate. Then the user cost is given by

$$\Psi = \frac{r^k + \delta - h(m(\tau)) + (1-\tau)m(\tau)}{1-\tau}. \tag{A.8}$$

Define the numerator of (A.8) as

$$\widetilde{\Psi} \equiv r^k + \delta - h(m(\tau)) + (1-\tau)m(\tau).$$

Then the tax semi-elasticity is given by

$$\begin{aligned} \varepsilon_\Psi &= \frac{\left(-h'(m(\tau))m'(\tau) - m(\tau) + (1-\tau)m'(\tau)\right)(1-\tau) + \widetilde{\Psi}}{(1-\tau)^2} \frac{1-\tau}{\widetilde{\Psi}} \\ &= \frac{1}{1-\tau} - \frac{m(\tau)}{\widetilde{\Psi}}. \end{aligned} \tag{A.9}$$

B Freight Rail

Group	Variable	Mean	10th Percentile	Median	90th Percentile	Count
Freight	Age	0.646	0.518	0.616	0.845	171
	$m_{i,j,t}$	0.177	0.055	0.127	0.377	171
	$P_{i,j,t}$	0.857	0.757	0.857	0.964	171
	$x_{i,j,t}$	0.062	0.002	0.039	0.130	171
Locomotives	Age	0.692	0.593	0.661	0.806	171
	$m_{i,j,t}$	0.138	0.048	0.113	0.251	171
	$P_{i,j,t}$	0.995	0.870	0.973	1.147	171
	$x_{i,j,t}$	0.127	0.025	0.082	0.256	171

Table A1: Summary statistics for variables from R-1 financial statements.

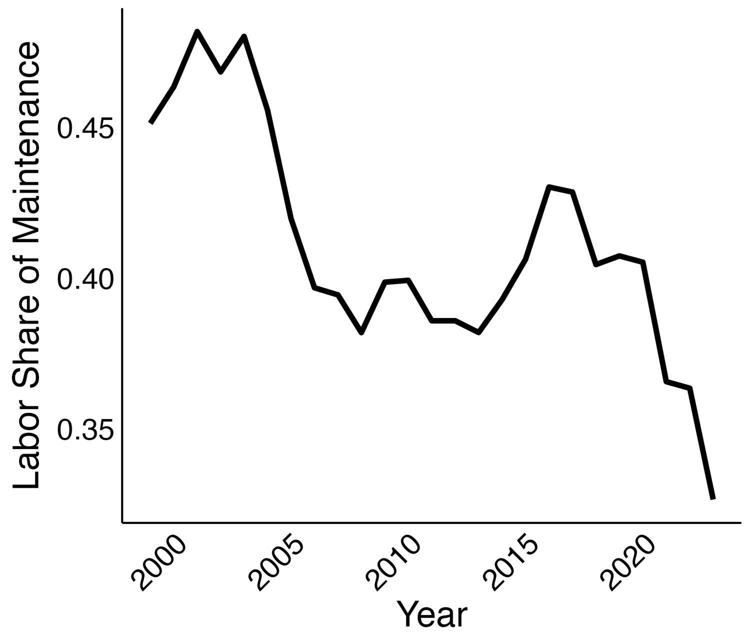


Figure 10: Average labor share of maintenance costs by year from 1999-2023. Computed by adding up all labor maintenance costs and dividing by total maintenance costs. The remainder is material costs.

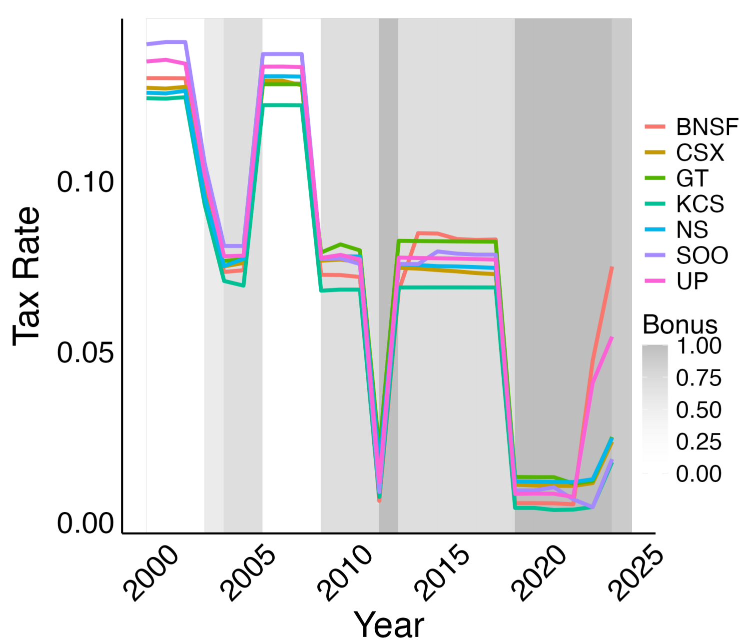


Figure 11: Tax rates by Class I freight rail firm from 1999-2023. Tax rates are computed by taking a weighted average of state tax rates based on miles of trackage operated by firm.

B.1 Linear Model

	Dependent variable: $m_{i,j,t}$			
	(1)	(2)	(3)	(4)
$P_{i,j,t}$	-0.372	-0.438	-0.381	-0.133
	(0.169)	(0.088)	(0.090)	(0.063)
Age		-0.444	-0.420	-0.228
		(0.110)	(0.122)	(0.090)
$x_{i,j,t}$			0.204	0.132
			(0.064)	(0.132)
$m_{i,j,t-1}$				0.650
				(0.117)
N	342	342	342	328
FE: Type	X	X	X	X
FE: Year	X	X	X	X
FE: Firm-Type	X	X	X	X

Table A2: Results for regressing the maintenance rate on the relative price of maintenance. The top panel takes a logarithmic transformation of the maintenance rate and the relative price, while the bottom panel is linear. Standard errors are clustered by firm.

	Dependent variable: $m_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
$P_{i,j,t}$	-0.190	-0.315		-0.397	-0.479
	(0.192)	(0.122)		(0.225)	(0.349)
$1 - \tau_{i,t}$			-0.215		
			(0.059)		
Year Trend	-0.005	-0.005	-0.005		
	(0.003)	(0.001)	(0.001)		
ΔTFP_t	-0.080	-0.019	-0.170		
	(0.193)	(0.113)	(0.096)		
$\Delta \log \text{GDP}_t$	-0.284	-0.268	-0.246		
	(0.198)	(0.271)	(0.231)		
$\log \text{RCAF}_t$	0.107	0.100	0.099		
	(0.040)	(0.059)	(0.058)		
N	316	316	316	328	314
Instrument	Oil	Tax Rate		$\log P_{i,j,t-1}$	$\log P_{i,j,t-2}$
F-test	15.7	30.5		1214.6	486.2
FE: firm	X	X	X	X	X
FE: type	X	X	X	X	X
FE: year				X	X

Table A3: Instrumental variables results for regressing the maintenance rate on a measure of the relative price. The first column uses oil shock as an instrument for the relative price. The second uses taxes as a shock for the *pre-tax* relative price. Every regression with instruments reports the Cragg-Donald F-statistic.

C SOI

I report summary statistics for the primary variables in the SOI in Table A4. The data for untaxed firms comes from subtracting the relevant figures for taxable firms in Table 13 from the corresponding figures for *all* firms in Table 12. The distribution of maintenance rates in Table A4 is quite low relative to the best data we have. Canada is the only country with good national data on maintenance and it has typically been the centerpiece of studies on maintenance (McGrattan and Schmitz Jr. 1999). However, the national maintenance rate in Canada is close to 12%, whereas the maintenance rate here is closer to 5%. That can be partially but not fully explained by the fact that depreciation rates in Canada are roughly twice as high as in the United States (Baldwin, Liu, and Tanguay 2015). A secondary explanation is that it is quite difficult to track maintenance expenditures. Only airlines and freight rail are required to meticulously track maintenance expenditures independently of other types whereas other industries do not have the same incentive. It could easily be the case that a large share of maintenance expenditures go under labor cost or some other part of costs of goods sold. From the perspective of the firm, it is irrelevant how such expenditures are allocated because they are not regulated at all and are tax deductible regardless.

Variable	Mean	10th Percentile	Median	90th Percentile	Count
$1 - \tau_{j,t}$	0.863	0.791	0.860	0.931	1071
Taxable Firms					
$m_{j,t}$	0.051	0.018	0.038	0.100	1071
$x_{j,t}$	-0.131	-0.610	0.049	0.468	1071
Age	0.463	0.342	0.459	0.591	1071
Untaxable Firms					
$m_{j,t}$	0.049	0.013	0.036	0.094	1071
$x_{j,t}$	-0.156	-0.644	0.025	0.455	1071
Age	0.495	0.364	0.486	0.653	1071
year	2008.580	2000.000	2008.000	2018.000	1071

Table A4: Summary statistics for the SOI.

Regression results for the linear-linear model are in Table A5. The results here do not line up as well with the freight rail results as they do in the log-log case, but are still significant for most specifications. Adding age as a covariate makes the tax term insignificant.

	Dependent variable: $m_{j,t}$					
	Taxable Firms			Untaxable Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
$1-\tau_{j,t}$	-0.145	-0.122	-0.072	0.025	0.019	0.007
	(0.073)	(0.065)	(0.042)	(0.109)	(0.117)	(0.077)
$x_{j,t}$		-0.003	-0.003		-0.002	-0.002
		(0.001)	(0.001)		(0.001)	(0.001
$m_{j,t-1}$			0.456			0.371
			(0.056)			(0.070)
N	1071	1012	1005	1070	1009	1003
FE: Industry	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X

Table A5: Linear Regression results of the maintenance rate on the tax term. Standard errors are clustered by BEA industry. The investment rate is net investment scaled by the net capital stock.

I report regression results for all firms in the SOI in Table A6.

	Dependent variable:					
	$\log m_{j,t}$			$m_{j,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1-\tau_{j,t})$	-2.363	-2.166	-1.014			
	(1.271)	(1.178)	(0.586)			
$1-\tau_{j,t}$				-0.085	-0.074	-0.033
				(0.064)	(0.063)	(0.021)
$x_{j,t}$		-0.117	-0.166		-0.006	-0.007
		(0.050)	(0.038)		(0.002)	(0.003)
$\log m_{j,t-1}$			0.613			
			(0.097)			
$m_{j,t-1}$						0.703
						(0.034)
Num.Obs.	1117	1066	1059	1117	1066	1059
FE: Industry	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X

Table A6: Linear Regression results of the maintenance rate on the tax term. Standard errors are clustered by BEA industry. The investment rate is net investment scaled by the net capital stock.

Table A7 shows the maintenance elasticity in levels for the SOI data. The coefficient is negative but not significant for taxable firms. Because the theory is about the maintenance rate rather than maintenance in levels, it is ex ante ambiguous what the sign should be. If there are decreasing returns to maintenance intensity, then the sign should be positive because in that case maintenance and investment are complements in *levels*. If there are increasing returns, then the sign should go the other way.

	Dependent variable: $\log M_{j,t}$	
	SOI	
	Taxable Firms	Untaxable Firms
$1 - \tau_{j,t}$	-1.587	2.883
	(1.369)	(2.533)
$\log M_{j,t-1}$	0.527	0.443
	(0.098)	(0.063)
N	1005	1003

Table A7: Regression of the log-level of maintenance on the tax term for the SOI data. The SOI regressions have two-way fixed effects. Standard errors are clustered by BEA industry.

C.1 Bias in the SOI Maintenance Coefficient

Measurement Error in the Maintenance Rate

There is likely a substantial amount of measurement error in the SOI measure of maintenance. Maintenance and repairs can be done internally by teams employed by the firm or externally through contracted work. Oftentimes the latter is part of an original purchase agreement for a piece of equipment. The issue here is whether internal maintenance services are assigned to maintenance in the SOI or not, and I suspect that the answer is "no" for two reasons. First, internal maintenance can be assigned to other, similarly tax deductible categories. For example, the wages paid to workers may be billed to wages rather than maintenance. Outside of freight rail and a select couple of other industries, firms are not required to keep close track of what is maintenance and what is not, so there is no incentive for firms to actually make the proper category assignment. This leads to a significant underestimate of the actual quantity of maintenance. For example, take the SOI industry containing freight rail: Air, Freight, and Water Transportation Services. In the SOI data, the maintenance rate is only approximately 5% on average, while it is nearly three times higher in the far more granular freight rail data which takes close account of how to assign expenditures properly. Figure 12 plots the share of externally purchased services.

The SOI maintenance measurement error only matters if the proportion of purchased maintenance services systematically varies with tax policy. If the share of external maintenance declines when taxes increase, then the coefficient on the tax term is biased down-

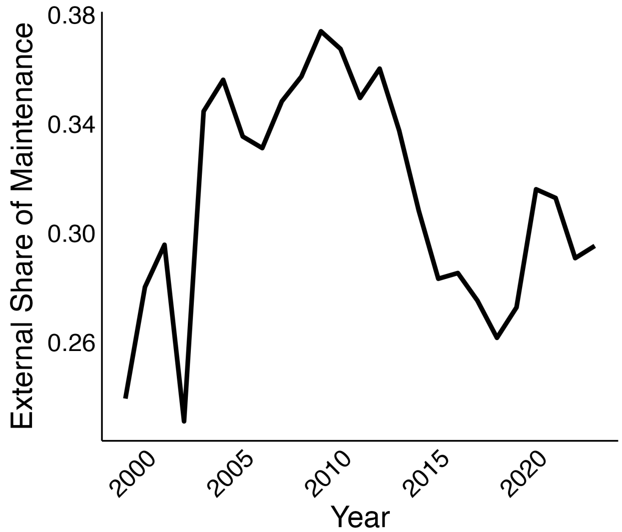


Figure 12: Share of external services in total maintenance expenditures for Class I freight rail. Taken as the sum of external expenditures by year divided by the sum of total maintenance expenditures.

ward. The easiest test for this is to regress the share of external maintenance on tax policy using the freight rail data. Table C.1 does exactly that. Because there is not enough variation between firms in tax policy, I use industry controls and a time trend. Column (1) indicates that there is a strong systematic relationship between the tax rate and the share of external services. However, Column (2) indicates that, after controlling for the lagged share of external services, this relationship goes away. The strength of the autocorrelation indicates a large degree of persistence in the share of external services by firm and type. From Column (2), I interpret the degree of autocorrelation as indicating that the bias is not important after accounting for the lagged expenditure share.

	Dependent variable: External Service Share$_{i,j,t}$	
	(1)	(2)
$\tau_{i,t}$	-0.281	-0.048
	(0.062)	(0.085)
External Service Share$_{i,j,t-1}$		0.929
		$(6.16e^{-8})$
N	315	312
Industry Controls	X	X
FE: firm	X	X
FE: type	X	X

Table A8: Regression of the external maintenance service share on the tax rate for freight rail. Tax rates only vary by firm and not by capital type. Industry controls are a cost index from the Surface Transportation Board, the GDP growth rate, and freight rail productivity growth.

Omitted Variable Bias

Recall that the simplest version of the first-order condition for maintenance equates the marginal benefit of maintenance to the after-tax relative price of maintenance to investment:

$$h'(m) = \frac{p^m (1-\tau)}{p^x}.$$

In the SOI data, we do not have a credible way to estimate either p^m or p^x by industry. Instead, the implicit assumption is that changes in tax policy do not affect the pre-tax relative price, and so taking logs on both sides simply makes the error term swallow the relative price. Under that assumption, I would have to claim that the supply curves for maintenance and investment are flat. Goolsbee (1998b) shows that the slope of the investment supply curve is close to one. If we presume that maintenance prices are stickier than investment prices, then the coefficient on the tax term is biased downward in absolute value.

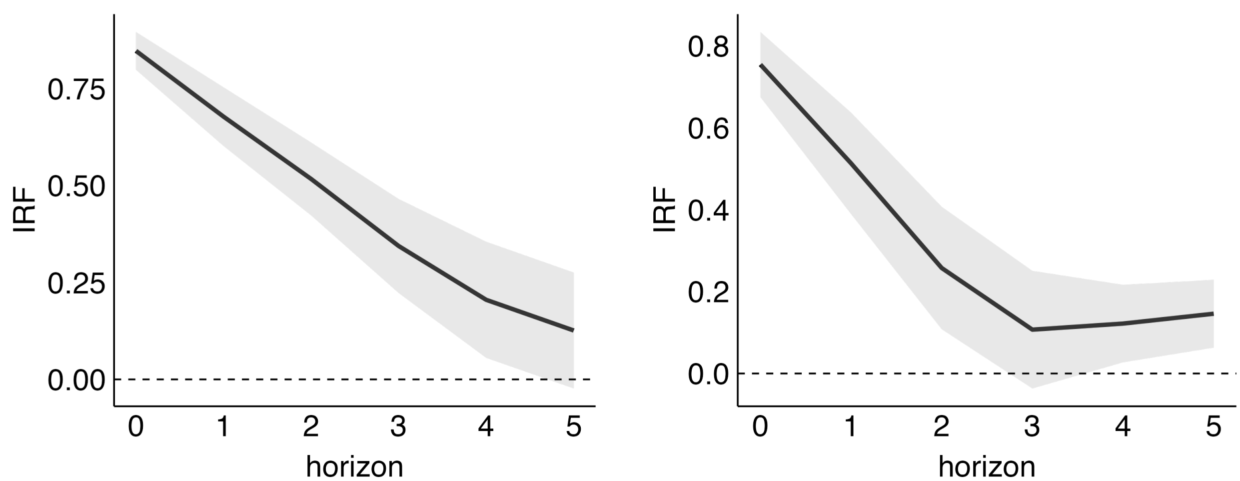
We can directly apply the estimates of Goolsbee (1998b). That paper estimates that approximately 60% of the incidence of tax policy goes to buyers of capital, 30% to suppliers, and 10% to the wages of capital producers. If we assume some symmetry in the wages of capital *maintainers* and capital producers, then we can use the corresponding relationship to adjust the relative price following a tax change. In particular, suppose the labor share of maintenance is typically around 0.4. That is true in the freight rail data. Applying his estimates implies that if the pre-tax relative price of maintenance is 1, it would decline to approximately 0.68 following a percentage point cut in the marginal tax rate.[19] Consequently, if the tax rate declines by 1 pp, then the actual decline in the relative price of maintenance is closer to 0.68. On average, that implies the price elasticity is underestimated by approximately 40% in the SOI data.

C.2 Price Dynamics

Figure 13 plots the dynamic evolution of the relative price following a unit increase. The left panel is for freight rail and is the result of the regression

$$\text{Log Relative Price}_{i,j,t} = \alpha_i + \kappa_j + T_t + \beta_h \text{Log Relative Price}_{i,j,t-h} + \varepsilon_{i,j,t},$$

where $h = 1, \ldots, 6$. The same regression is run on the right panel for tax policy in the SOI data, but using industry and year fixed effects.



(a) Freight rail price persistence

(b) Tax policy persistence (SOI)

Figure 13: The left panel plots the persistence of the log relative price of maintenance for freight rail and the right does the same for log tax policy. Each regression plots the coefficient on lagged relative price for 1-6 years out. The freight rail contains year, firm, and type fixed effects, while the tax policy data from SOI includes industry and year fixed effects.

19. Given a 1 p.p. tax cut, Goolsbee estimates that the price of an investment good rises by approximately 5%. About 20% of that price rise is driven by an increase in wages. Hence $(0.4 \times 0.1 + 0.6 \times 0.05)/0.5 = 0.68$.

D Tax Policy Construction

Toward creating a database of industry marginal effective tax rates (METR) on corporate capital, I combine data from the BEA and the IRS to follow the methodology of House and Shapiro (2008). Tax rates may differ between industries because there are differences in how assets are taxed and the mix of assets owned by industries may differ. Consequently, as long as we know who owns which assets and the tax rates on those assets, we can construct an industry-specific marginal effective tax rate. The Fixed Asset Tables from the BEA are convenient for this purpose for two reasons. First, Section 2 of the Fixed Asset tables contains data on 36 physical assets which are relatively easy to map to tax policy, make up the vast majority of physical investment, and can be categorized as either equipment or structures. I focus on these assets over the period 1971-2021, which spans the Asset Depreciation Range (ADR) System from 1971-1981, the Accelerated Cost Recovery System (ACRS) from 1982-1986, and the Modified Accelerated Cost Recovery System from 1987-2021. Second, the underlying detailed estimates for nonresidential investment can be mapped from BEA industries into three-digit NAICS codes. The BEA provides a bridge for this purpose.

There are three steps to constructing industry-specific marginal effective tax rates:

1. Calculate asset-specific marginal effective tax rates $\tau_{i,t}$ for asset i.
2. For each industry j, compute asset weights $\alpha^a_{i,j,t}$.
3. Putting Steps 1 and 2 together, compute the industry-specific tax rate as

$$\tau_{j,t} = \sum_{i=1}^{N} \alpha_{i,j,t} \tau_{i,t}$$

   where there are N types of capital and $\sum_{i=1}^{N} \alpha_{i,j,t} = 1$.

I go through each step in turn.

Asset-Specific Tax Rates

Define the asset-specific METR as

$$\tau^a_{i,t} = 1 - \frac{1 - \tau^c_t}{1 - \mathrm{ITC}^a_{i,t} - z^a_{i,t}\tau^c_t}, \tag{A.10}$$

where τ^c_t is the corporate tax rate, $\mathrm{ITC}_{i,t}$ is the investment tax credit on asset i, and $z_{i,t}$ is the net present value of tax depreciation allowances on asset i. Hence there are three components for each asset. First, the corporate tax rate τ_t^c is straightforward to obtain. Second, the investment tax credit $\text{ITC}_{i,t}$ is slightly more difficult. Investment tax credits vary substantially by asset type but have been irrelevant since the Tax Reform Act of 1986. I take the ITC for each asset from House and Shapiro (2008), who study the effects of bonus depreciation on investment across the same 36 assets from the BEA that I use to construct this database. They originally obtained data on the ITC from Dale Jorgenson.

$z_{i,t}$ is more difficult and requires some level of judgment. Suppose an asset has allowable depreciation $D_{i,t}^a$ and define $d_{i,t}^a$ as the share of the asset's allowable depreciation under tax law each period. This is nontrivial because companies are allowed to use different methods of depreciation. For each asset j, I define the present value of depreciation allowances as

$$z_{i,t}^a = \sum_{t=0}^{\infty} \left(\frac{1}{1+r^k} \right)^t d_{i,t}^a.$$

I assume that $r^k = 0.06$. While this assumption is clearly not innocuous, it is comparable to some of the recent literature. This is the same discount rate as in Chodorow-Reich et al. 2023, but is lower than in Barro and Furman (2018) and Gormsen and Huber (2022). Earlier literature on tax policy from the 1980s (see, e.g., Auerbach (1983) and Jorgenson and Yun (1991)) tends to use lower discount rates. $z_{i,t}$ varies both across assets and between tax eras. I discuss each era in chronological order. I relied heavily on Brazell, Dworin, and Walsh (1989) for understanding each era.

ADR (1971-1981. The ADR period marked a simplification from the earlier Bulletin F period, where there were hundreds of asset classes. However, the ADR period was still more complex than the tax rules that would follow. Most assets were depreciated according to standards that were industry-specific, which makes it challenging to map them to modern BEA tables. However, because the BEA asset categories are relatively broad and the ADR-recommended live lengths are similar among the assets that would go in each category, I simply assign the most common median life length within each category. Because the life length determination requires some judgment, there is surely some degree of error. For equipment, I assume firms follow a double declining balance method, while structures use straightline depreciation. I use the Treasury publication "Asset Depreciation Range System" published in 1971 to assign life lengths.

ACRS (1982-1986). The ACRS simplified the ADR into eight asset classes and significantly decreased depreciation lives. I assigned each BEA asset into its a class using IRS publication 534 and used the double-declining balance method for all assets.

MACRS (1987-Present). The Tax Reform Act of 1986 changed depreciation schedules and got rid of the ITC while retaining much of the simplicity of the ACRS era. House and Shapiro (2008) map each asset to a corresponding depreciation table in IRS Publication 946. I use their matching scheme and assumptions about which depreciation method firms use. For example, most equipment is depreciated with the double-declining balance method, while structures are often depreciated with the straightline method. Using the House-Shapiro mapping scheme, it is straightforward to compute $z_{i,t}$. However, the U.S. government has allowed firms to take bonus depreciation on certain types of capital investment. Defining θ_t as the allowable bonus depreciation in year t, let the net present value of tax depreciation allowances be

$$\tilde{z}^a_{i,t} \begin{cases} \theta + (1-\theta_t) z^a_{i,t} & \text{if eligible} \\ z^a_{i,t} & \text{if ineligible,} \end{cases} \tag{A.11}$$

where $\tilde{z}^a_{i,t}$ takes the place of $z^a_{i,t}$ in equation A.10. At various points, $\theta = 1$ for some assets, so the marginal effective tax rate is zero. Conveniently, House and Shapiro (2008) also map whether or not each BEA asset is eligible for bonus depreciation, so I use their mapping.

Weights

To get the industry-asset weights $\alpha_{i,j,t}$ within each major asset category, I use the underlying detail data from the BEA Fixed Asset Table. Each BEA industry has a matrix of assets for nominal investment, real investment, and historical and current-cost net capital stocks and depreciation. I use capital weights from the current year to determine weights on each asset for each industry. That is,

$$\alpha_{i,j,t} = \frac{k^a_{i,j,t}}{K^a_{j,t}},$$

where $k_{i,j,t}$ is stock of capital type i from industry j and $K_{j,t}$ is the total capital stock in year t by industry j in the corresponding major asset category. I restrict attention to the 36 assets I obtain METRs for. Of course, I could have also used stocks as weights or previous year investment flows or some rolling average of investment flows. The results are largely similar regardless.

Putting together weights weights and marginal tax rates, the marginal effective tax rate on industry j is

$$\tau_{j,t} = \sum_{i=1}^{36} \alpha_{i,j,t} \tau_{i,t}.$$

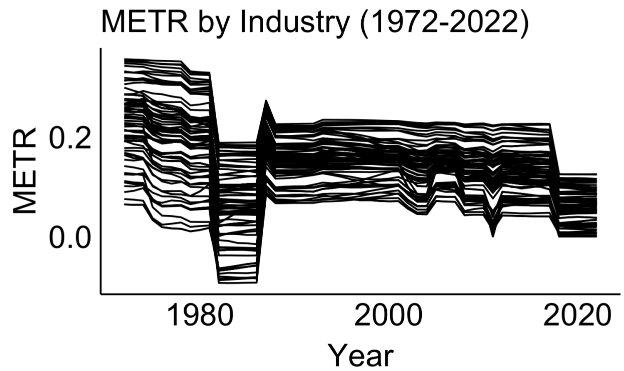


Figure 14: Marginal effective tax rates for NAICs industries from 1971-2022.

Using the BEA-NAICS bridge, we then have prices and tax rates for each three-digit NAICS industry. I plot the time series of tax rates for each industry in Figure 14.