Why Tax Cuts Don't Boost Capital as Much as We Predict: The Maintenance Margin

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Standard models overstate how much business tax cuts raise capital because they overlook maintenance. Firms adjust capital through both investment in new assets and maintenance of old ones, but the tax code treats these margins differently: maintenance is fully expensed while investment is capitalized. Using newly digitized freight railroad regulatory filings and IRS industry data, I quantify how this asymmetry alters tax policy transmission through two channels. First, the user cost of capital is a weighted average of investment and maintenance costs. I find the maintenance share is 25-60%, and because this share is already tax-shielded through full expensing, aggregate effects on capital, output, and wages are 30-40% smaller than standard predictions. Second, when investment becomes relatively cheaper, firms substitute away from maintenance, raising depreciation and breaking the one-to-one mapping between investment and capital inherent to typical models of investment. I estimate a maintenance demand elasticity of 3-4, implying the capital elasticity is roughly two-thirds the investment elasticity. For the 2017 Tax Cuts and Jobs Act, these parameters imply about $240 billion less corporate capital after ten years compared to standard predictions.

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1 Introduction

Policymakers use corporate tax cuts and investment subsidies to stimulate capital accumulation, which leads to higher output and wages (Romer and Romer 2010). The predicted effectiveness of such policies rests on a particular transmission mechanism: by reducing the user cost of capital, tax cuts encourage firms to invest more, which increases the capital stock. In practice, we evaluate this mechanism by estimating how much investment responds to tax reform (Hassett and Hubbard 2002; Zwick and Mahon 2017; Kennedy et al. 2023). Since workhorse investment models (e.g., Hall and Jorgenson (1967)) imply that the tax elasticity of investment *is* the tax elasticity of capital, we can directly map the observed change in investment to capital, and with additional assumptions, to output and wages (Chodorow-Reich et al. 2025). However, an overlooked yet practically important margin interrupts the transmission of tax cuts to capital, and the mapping of investment into capital: *maintenance of existing capital*.

In practice, maintenance is quantitatively large and important for tax policy. Firms spend considerable resources maintaining and repairing existing capital, which slows economic depreciation. Across industries, maintenance expenditures are 25-60% of the user cost of capital—often rivaling or exceeding investment in new capital. Yet tax policy treats these two margins of capital adjustment asymmetrically. Maintenance expenditures are fully expensed against current income, like wages or materials. By contrast, investment in new capital is typically capitalized and deducted through tax depreciation schedules over many years. This differential treatment means that when policymakers introduce investment incentives—such as bonus depreciation or investment tax credits—they are stimulating only one margin of capital adjustment while leaving the other largely unaffected. I show this asymmetry attenuates tax policy effects through two mechanisms: a scale effect operating through the level of maintenance, and a substitution effect operating through its elasticity.

Theoretical Mechanisms. Consider first how investment incentives affect the scale of capital accumulation. In standard models with fixed depreciation, the cost of capital is simply the cost of purchasing new assets—the familiar (Hall and Jorgenson 1967) user cost of capital. But the true cost of capital services includes both the initial purchase and the ongoing cost of maintaining assets over their lifetime. The effective cost of capital services is therefore a weighted average of the cost of new capital (which responds to investment incentives) and the cost of maintenance (which does not, since maintenance is already fully expensed). When policymakers introduce investment subsidies, only one component of this weighted average falls. I call this a *capital preservation effect*. The scale response is therefore smaller than standard models predict, with the magnitude of attenuation equal to the maintenance share of user cost. Standard models implicitly assume this share is zero.

Beyond the capital preservation effect, investment incentives also create a relative price distortion. By reducing the cost of new capital while leaving maintenance costs unchanged, they make replacement relatively cheaper than preservation. If maintenance demand is elastic, then firms will substitute away from maintenance and toward investment. Consequently, economic depreciation rises. This *input substitution effect* means that gross investment overstates net capital accumulation because more of the observed investment must now offset higher depreciation rather than expand the capital stock. The magnitude of this wedge depends on the elasticity of maintenance demand. If demand is more elastic, then firms cut maintenance sharply when it becomes relatively expensive, depreciation rises, and the gap between observed investment and capital accumulation rises.

Maintenance Demand in the Data. The theoretical mechanisms depend critically on two parameters. First, the capital preservation effect requires knowing the *level* of maintenance relative to the user cost of capital. McGrattan and Schmitz Jr. (1999) points out that this is plausibly quite large in Canada, but it remains relatively underexplored in the United States. Second, the input substitution effect depends on the *elasticity* of maintenance demand. Goolsbee (1998b) shows that the decision to *replace* capital is price-sensitive, but we lack a direct estimate of the demand elasticity.[1] A central contribution of this paper is to provide a unified estimate of a maintenance demand function using two disparate sources of data and identification strategies. One is precisely detailed at the firm-asset level, while the other is aggregated industry data, but together they tell a unified story about maintenance demand.

My first source of data comes from the regulatory filings of large freight railroads. Class I freight railroads, which are roughly defined to be those with revenue over $1 billion, are required to submit detailed accounts of their financial and real activities with the Surface Transportation Board. I hand-collect and digitize these going back several decades. Although each filing is an unparalleled window into the maintenance and investment behavior of firms at the asset level, they have not been used in economics since Bitros (1976). I observe the quantity and value of each firm's locomotives and freight cars, what they spend on maintaining them, and how much of that maintenance was done internally rather than contracted out. To study maintenance demand, I focus on a period from 1999 to 2023.[2]

1. Goolsbee (1998b) provides important precedent for the mechanism I study. He shows that airlines effectively increase their depreciation rates by retiring planes more quickly in response to investment subsidies. Though his setting scrappage and resale rather than maintenance decisions, the economic insight is the same: investment incentives can endogenously raise depreciation, breaking the standard one-to-one mapping from investment to capital. In a putty-clay model with vintages, his replacement effect is formally equivalent to the endogenous depreciation I model through maintenance.

2. Before the late 1990s, there was considerable regulatory upheaval and consolidation in the freight rail industry.

Three facts emerge. First, maintenance is large: the maintenance share of user cost averages 60%, implying standard user cost formulas overstate tax responsiveness by a factor of 2.5. Second, maintenance spending typically exceeds investment in new assets. Third, 65% of maintenance is performed in-house, with labor costs accounting for 40%—variation I exploit for identification.

To identify the maintenance demand elasticity, I construct a Bartik-style instrument that leverages variation in the geographic distribution and labor composition of maintenance costs by firm. By interacting pre-determined, firm-specific maintenance labor cost shares with plausibly exogenous state-level shocks to maintenance wages, this strategy isolates cost-driven shifts in the relative price of maintenance from unobserved firm-level demand shocks. The analysis yields a maintenance demand elasticity of approximately four. Crucially, this response is driven entirely by adjustments to in-house maintenance, while outsourced maintenance services do not respond. This divergence provides evidence for causality, as it confirms the instrument is isolating a supply-side cost shock rather than a confounding demand shock, which would likely cause both maintenance margins to move in tandem.

Nevertheless, freight rail assets may not be representative of capital more broadly, and the firm-level analysis cannot capture any general equilibrium. To partially address both concerns, I turn to industry-level corporate tax returns from the Internal Revenue Service's Statistics of Income (SOI), which covers the corporate sector. The data allow for external validity on an economy-wide basis and cover any within-industry general equilibrium effects like capital reallocation, but fall short of capturing any economy-wide general equilibrium effects.

The SOI data validate the elasticity parameter, but not the level effect. In the SOI, the maintenance share of user cost is less than half as large as in the R-1 data, and it is only half as large as new investment in levels. However, the demand elasticity is remarkably stable. Following the empirical *investment* literature (Zwick and Mahon 2017; Curtis et al. 2021), I exploit quasi-experimental variation in industries' exposure to major investment incentives—namely bonus depreciation and the 2017 Tax Cuts and Jobs Act. Because industries differ in their capital composition, these national tax policies create differential, plausibly exogenous shocks to the after-tax price wedge between new investment and maintenance. This approach, which implicitly nets out capital reallocation within broad industries, produces an estimated demand elasticity of approximately three, which is indistinguishable from the railroad estimate. Moreover, the demand elasticity is only positive for taxable firms, which is exactly what theory predicts.

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This makes it difficult to study. Maintenance behavior may differ if firms expect to be acquired, and part of my data only begin in the late 1990s. See (Saunders 2003) for a history of the period.

Aggregate Implications. The empirical findings—positive and elastic maintenance demand—alter both how we should interpret tax policy evidence and the predicted macroeconomic effects of tax reform.

My empirical findings have first-order implications for how we interpret evidence on tax policy. The standard approach in public finance estimates investment elasticities and treats them as equivalent to capital elasticities, implicitly assuming a one-to-one correspondence between investment and capital accumulation (Hartley, Hassett, and Rauh 2025; Chodorow-Reich et al. 2025). But accounting for maintenance breaks this correspondence. When investment incentives alter relative prices, firms substitute away from maintenance, raising depreciation endogenously. The same observed investment response therefore corresponds to a smaller capital response: a portion of gross investment now simply replaces capital that depreciates faster rather than expanding the productive stock. I derive a closed-form correction showing that the capital elasticity is approximately two-thirds the investment elasticity when maintenance parameters take their empirically estimated values.[3] This substantial wedge—driven by the maintenance margin—matters for both policy analysis and for models calibrated to match investment moments. Indeed, my empirical estimates imply that the elasticity of capital with respect to tax changes is roughly two-thirds the investment elasticity, and that the aggregate effects of corporate tax cuts are 30–40% smaller than standard models predict.

The two mechanisms also imply smaller macroeconomic effects than standard models predict. The capital preservation effect operates through the level of maintenance: when maintenance accounts for 25-60% of user cost (as I find empirically), investment incentives reduce total capital costs by only 40-75% as much as standard models predict. The steady-state capital stock therefore rises proportionally less, with correspondingly attenuated effects on output and wages. The input substitution effect reinforces this attenuation along the transition path. Because elastic maintenance demand breaks the one-to-one mapping between gross investment and net capital accumulation, matching observed investment responses requires higher adjustment costs in models with maintenance than in standard models. This slows convergence to the new steady state, meaning growth effects within policy-relevant horizons—such as the ten-year budget window used for tax scoring—are even smaller than the steady-state haircut alone would suggest.

To quantify these forces, I embed the estimated maintenance function into a general equilibrium model calibrated to the U.S. economy, following the framework of Chodorow-Reich et al. (2025). I use the level of demand for maintenance from the SOI, and calibrate the elasticity by combining the R-1 and SOI estimates. Simulating the TCJA, I compare outcomes to an otherwise

3. The capital preservation effect also implies that standard investment regressions suffer from omitted variable bias: because maintenance costs are tax-shielded, the measured change in user cost overstates the true change, causing the estimated coefficient to be biased downward. I provide corrections for both channels.

identical model without maintenance, isolating the haircut maintenance imposes. The results confirm the first-order importance of the maintenance margin. Across a variety of model closures, including those that account for general equilibrium effects through wages, interest rates, and maintenance prices, the ten-year responses of macroeconomic aggregates are about 50–70% as large as the standard framework, a gap that accounts for a roughly $240 billion overestimation of corporate capital identified at the outset.

Related Literature. This paper relates to four main strands of literature.

First, this paper refines the literature on multiple margins of capital adjustment by showing that the tax distortion between maintenance and investment is a first-order concern. The closest paper is McGrattan and Schmitz Jr. (1999). To my knowledge, theirs is the only other paper that explicitly studies the maintenance-investment distortion in the tax code. While their foundational work focused on input substitution, I show that the capital preservation effect is first-order, with larger and more direct consequences for the user cost of capital. Importantly, I also illustrate how to map theory into empirics to interpret maintenance data and show how maintenance matters for tax scoring. Other papers, including Kabir, Tan, and Vardishvili (2024), Boucekkine, Fabbri, and Gozzi (2010), and Albonico, Kalyvitis, and Pappa (2014) study maintenance and capital utilization in non-tax settings. I abstract from utilization because reallocation between investment and maintenance is itself second-order for capital accumulation, and accounting for utilization would require modeling indirect effects of indirect effects.[4] Finally, Feldstein and Rothschild (1974) and Cooley, Greenwood, and Yorukoglu (1997) study how tax policy influences capital replacement decisions in vintage capital settings. Although their models are substantially different, their points are broadly similar: tax cuts may reduce the value of existing capital relative to newer vintages and therefore lead to faster replacement.

Second, my paper relates to a literature documenting the empirical relevance of maintenance for capital. There is a large literature documenting the determinants and effects of maintenance decisions for residential housing (Knight and Sirmans 1996; Harding, Rosenthal, and Sirmans 2007; Hernandez and Trupkin 2021).[5] On the firm side, there is some evidence of tax cuts inducing firms replacing old, high-maintenance capital with younger capital, lower-maintenance capital. For example, Goolsbee (1998b) shows that airlines retire their airplanes more quickly when tax

4. My analysis focuses on maintenance of private capital. Kalaitzidakis and Kalyvitis (2004), Kalaitzidakis and Kalyvitis (2005), and Dioikitopoulos and Kalyvitis (2008) study the empirical and theoretical characteristics of public capital maintenance.

5. The investment-maintenance distortion goes the other way in the housing tax code. Whereas improvements are deductible from the capital gains tax basis, maintenance is not, which creates a distortion in favor of the former. There is no direct evidence of the importance of that margin, but Cunningham and Engelhardt (2008) and Shan (2011) show that the 1997 Taxpayer Relief Act, which lowered the capital gains tax, increased housing mobility, which is akin to increasing the renewal rate of housing.

policy makes it favorable to buy new ones. Similarly, Goolsbee (2004) shows that firms buy capital with lower maintenance requirements following tax cuts. Some studies—which abstract from tax distortions—rely on maintenance data from India (Kabir, Tan, and Vardishvili 2024; Kabir and Tan 2024) or Canada (Albonico, Kalyvitis, and Pappa 2014; Angelopoulou and Kalyvitis 2012), but none, to my knowledge, estimate a maintenance demand function at all or using data from the United States. This lack of direct evidence has forced prior models to rely on assumptions. My work provides the first empirical estimate of the U.S. maintenance demand function, offering a necessary parameter to correctly model capital dynamics.

Third, the results provide a universal adjustment factor for the quantitative tax reform literature. The user cost of capital is the primary transmission channel for business tax policy in virtually all modern frameworks, whether they incorporate a variety of complications such as explicit demographics (PWBM 2019), heterogeneous capital (Barro and Furman 2018), heterogeneous firms (Sedlacek and Sterk 2019; Zeida 2022), lumpy adjustment (Winberry 2021), financial frictions (Occhino 2023), or global tax considerations (Chodorow-Reich et al. 2025). Because my key mechanisms directly alter this user cost, the haircut I identify in a neoclassical model should apply similarly in these richer settings. Fundamentally, maintenance acts as a powerful dampening force on the central channel of capital taxation, regardless of other model features.

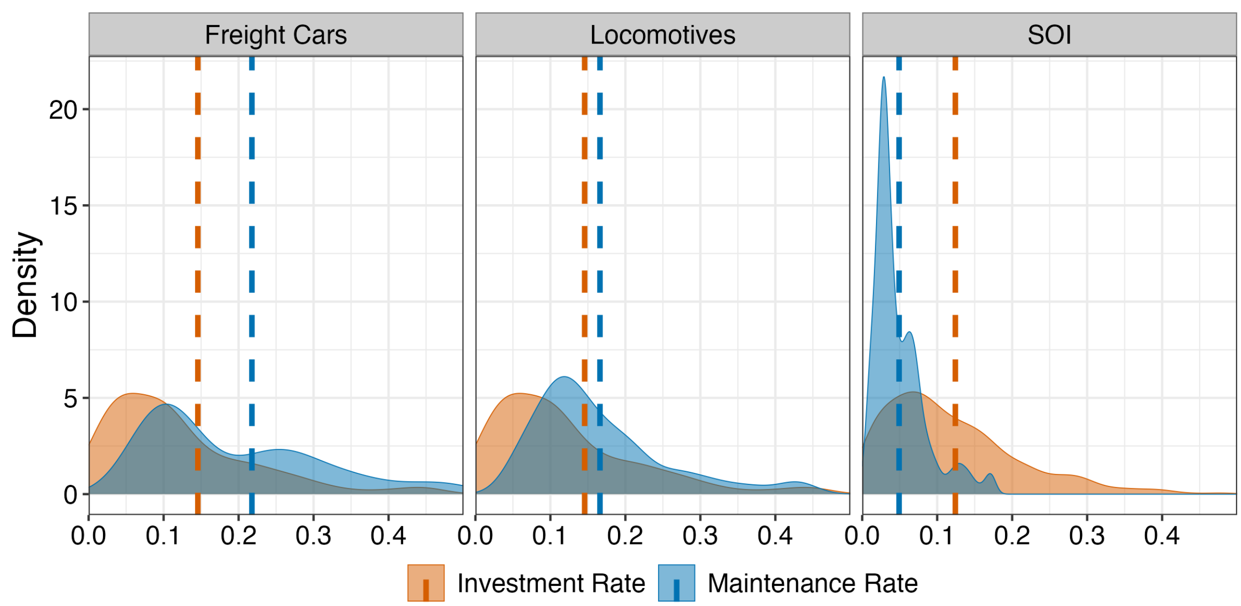
Finally, my paper connects to an extensive literature in public finance on tax incentives and investment. Since Hall and Jorgenson (1967) and Summers (1981), a large literature has used theoretical models to guide investment regressions. The result, from Hassett and Hubbard (2002), is a consensus estimate of the tax elasticity of investment around -0.5 to -1, which has been confirmed in recent years by Zwick and Mahon (2017), Kennedy et al. (2023), Chodorow-Reich et al. (2025), and Hartley, Hassett, and Rauh (2025). My theoretical results, which highlight the divergence between capital and investment elasticities, imply that accounting for maintenance magnifies the coefficients on these regressions for two reasons. First, the input substitution effect creates an additional margin of adjustment for capital, so investment in new capital is necessarily more elastic. Second, the capital preservation effect means the cost of capital moves by less, which implies the coefficient on the cost of capital must be larger to explain the observed quantity response. Combining my theoretical closed-form bias correction with the empirical demand function suggests standard investment elasticities are underestimated by one-third.

Roadmap. Section 2 presents brief institutional background on the maintenance-investment distinction. Section 3 gives a simple neoclassical model of maintenance, which I then take to the data in Sections 4–5. I return to the theory in Section 6, where I discuss and derive results on the aggregate and empirical implications of positive and elastic maintenance demand. Section 7 shows the importance of the theory by embedding the estimated maintenance demand function into a quantitative model of the Tax Cuts and Jobs Act. Section 8 concludes.

2 Maintenance vs. Investment

Firms engage in a wide range of activities to change the capital stock, from routine maintenance of existing capital to full replacement. Those activities are distinguished by maintenance, which preserves or restores capital services without improving quality, and investment, which creates or upgrades capital. For example, a ground shipping company may make its vehicle fleet live longer through diligent attention to routine maintenance like oil changes or proactively changing the tires early to avoid worse damage through a highway tire blowout. By contrast, investment would be purchasing an entirely new fleet of vehicles or replacing the engine in an existing vehicle. Thus, the key distinction between investment and maintenance is that the former adds new capital to the stock, while the latter simply keeps old capital around for longer in its existing quality. This distinction is not merely semantic. It maps directly to firm expenditures and how the tax code treats them.

Figure 1: Density plots for maintenance and investment rates

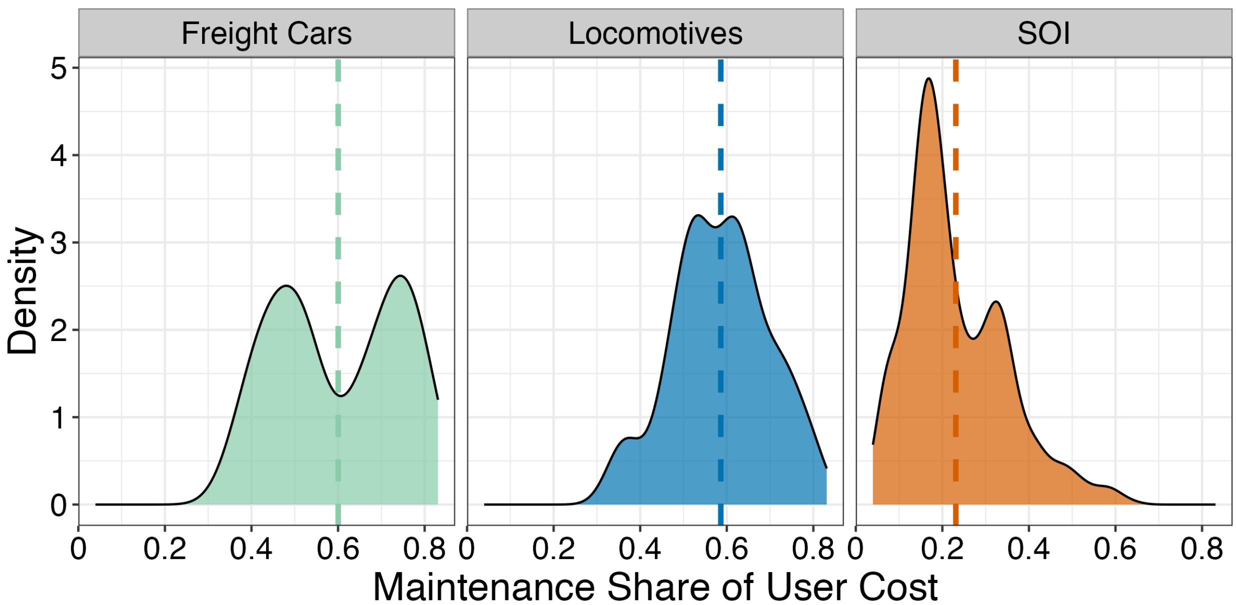


Note: Each density plot is constructed with beginning of period book capital in the denominator. The dashed lines are mean maintenance and investment rates. The rolling stock data span from 1999-2023, with 172 observations per asset type. There are 1116 observations in the SOI data, covering 49 major industries from 1999-2021.

Before turning to tax rules, it is useful to establish magnitudes. How large is maintenance, relative to investment? Figure 1 plots the distribution of maintenance and investment rates—measured as shares of beginning-of-period book capital—across two major railroad asset types and across all major industries from the Statistics of Income (SOI). I describe the underlying data in detail in Section 4, but include this preview here to illustrate the economic importance of maintenance expenditures. In each case, maintenance rates are substantial, suggesting that firms allocate considerable resources toward preserving existing capital, on the same order of magnitude as investment.

While maintenance rates establish that firms spend substantially on preserving capital, the economically relevant measure for tax policy is the maintenance share of user cost—the fraction of total capital costs devoted to maintenance rather than purchasing and financing new capital. This share, derived formally in Section 3, directly measures how much of the cost of capital is insulated from investment-specific tax reforms.

Figure 2: Density plots for the maintenance share of user cost (unadjusted)



Note: The dashed lines are mean maintenance shares, which are 23% (SOI), 60% (Freight Cars), and 58.6% (Locomotives). The maintenance share is calculated as $1 - \tau) \cdot p^M \cdot m$ divided by total user cost. See Appendix B for detailed construction.

Figure 2 plots the distribution of the maintenance share of user cost. The results are striking: in the aggregate SOI data, maintenance accounts for about 25% of the user cost of capital, while for railroad rolling stock, that share is more than double, at nearly 60%. Because maintenance is already fully expensed, this large fraction of capital costs is insulated from investment-specific tax reforms—making the differential tax treatment a first-order policy concern.

The tax code reinforces the distinction between maintenance and investment through differential treatment under Sections 162 and 263 of the Internal Revenue Code. In general, maintenance is immediately deductible as an operating expense, while investment must be capitalized and depreciated over time. That matters for a firm deciding whether to invest an extra dollar in new capital or spend the dollar on maintaining existing capital. Letting τ^c denote the firm's tax rate, the after-tax cost of maintenance is $1 - \tau^c$ because it is deductible. On the other hand, a new capital expenditure must be depreciated over time.[6] Let z denote the net present value of the depreciation deductions, and c denote any additional investment incentives like investment tax credits. The after-tax cost of investment is $1 - \tau^c z - c$. This implies a wedge in the maintenance-investment decision given by

$$\text{Wedge} = \frac{\text{After-tax Cost of \$1 of Maintenance}}{\text{After-tax Cost of \$1 of Investment}} = \frac{1 - \tau^c}{1 - \tau^c z - c}. \quad (1)$$

Appendix Figure A.1 discusses in detail how the wedge varies by asset and over time. In Section 3, I discuss the economics of the wedge, while Section 5 shows how it empirically maps into substitution between maintenance and investment.

3 A Simple Model of Capital Maintenance

Section 2 established two foundational facts: maintenance is a large and economically significant component of capital costs, with a user cost share of 25-60%, and the tax code creates a policy wedge by treating it asymmetrically from investment. Following McGrattan and Schmitz Jr. (1999), which first embedded maintenance in a neoclassical model with taxes, this section now builds a formal model to analyze the consequences of these facts. The model formalizes two key mechanisms through which maintenance alters the transmission of tax policy to the real economy. First, a capital preservation effect dampens the scale response to investment incentives. Second, an input substitution effect breaks the one-to-one mapping between investment and capital. I then derive an empirical specification for estimating the maintenance demand elasticity.

3.1 Firm Problem

Time is discrete and there is no uncertainty. A representative firm produces output $Y_t = F(K_t)$ as a weakly concave function of capital. It purchases new capital at price p_t^I and maintenance services at price p_t^M, both elastically supplied. Investment plays its standard role of adding to the capital stock linearly. However, maintenance reduces the economic depreciation rate through a

6. Firms cannot easily game this distinction because routine maintenance expenditures typically fall below a *de minimis* safe-harbor threshold, while capital improvements do not, and established case law enforces consistent application of the rules. For example, in the 2003 court case *FedEx Corp. v. United States*, FedEx disputed whether \$66M worth of expenditures on maintaining existing aircraft engines in 1993 should be considered maintenance or investment. The question decided ten percent of their tax bill for that year.

technology $\delta(m_t)$, where $m_t \equiv M_t/K_t$ is the maintenance rate. I assume $\delta'(m) < 0$ and $\delta''(m) > 0$: additional maintenance slows depreciation, but with diminishing returns. Capital therefore evolves according to

$$K_{t+1} = (1 - \delta(m_t))\, K_t + I_t. \tag{2}$$

One can think of capital services as being produced by two distinct inputs: investment and maintenance. In the canonical putty-putty homogeneous capital model, capital is only produced by investment, and there is no real choice to the firm between inputs. The only way to disinvest is by allowing capital to depreciation. Here, firms can choose to add to the capital stock in two ways and have a technology which can effectively destroy capital.

The firm faces three tax provisions. Maintenance expenditures are fully deductible against current income at rate τ_t^c, while investment must be capitalized and depreciated over time, yielding a present value of deductions $z_t\tau_t^c$ per dollar invested. Additionally, there is an investment subsidy c_t. The firm chooses investment, maintenance, and capital to maximize the present value of after-tax cash flows:

$$\max_{I_t, M_t, K_{t+1}} \sum_{t=0}^{\infty} \left(\frac{1}{1+r^k}\right)^t \left\{ \left(1 - \tau_t^c\right) \left[F\left(K_t\right) - p_t^M M_t\right] - \left(1 - z_t\tau_t^c - c_t\right) p_t^I I_t \right\} \tag{3}$$

subject to equation (2). This leads to two optimality conditions, which together summarize the effects of maintenance on the tax policy transmission mechanism.

3.2 The Capital Preservation Effect

The firm's optimal capital choice equates the marginal product with the user cost of capital. In steady state, this condition is:

$$F_K = \underbrace{\frac{p^I\left(1 - \tau^c z - c\right)}{1 - \tau^c}\left(r^k + \delta(m)\right)}_{\text{Investment Component}} + \underbrace{p^M m}_{\text{Maintenance Component}} \equiv \Psi^{\text{NGMM}}. \tag{4}$$

This expression reveals the capital preservation effect. The total cost of capital services has two components: the tax-adjusted cost of purchasing and financing new capital (first term), and the after-tax cost of maintaining existing capital (second term). Investment incentives—such as increases in z through bonus depreciation—reduce only the first component. The second component is unaffected because maintenance is already fully expensed and therefore tax policy has no direct effect on it.

Define the maintenance share of user cost as $s_m \equiv \frac{p^M m(1-\tau^c)}{\Psi^{\text{NGMM}}}$. This share, which Section 2 showed is 25-60%, governs the magnitude of the capital preservation effect. Because this fraction of the user cost is fully expensed, it does not respond to investment incentives like z or c. Investment incentives therefore produce a smaller scale effect, as the firm's optimal choice of capital services scales down relative to a standard model by a magnitude directly proportional to s_m.

For comparison, the standard user cost without maintenance is

$$\Psi^{\text{NGM}} = \frac{p^I \left(1 - \tau^c z - c\right)}{1 - \tau^c} \left(r^k + \delta\right), \tag{5}$$

which implicitly assumes $s_m = 0$, so all components of the cost of capital are sensitive to tax policy. This variant, originally derived by Hall and Jorgenson (1967), is regularly employed in both theoretical (Chodorow-Reich et al. 2025) and empirical work (Hartley, Hassett, and Rauh 2025).

3.3 The Input Substitution Effect

The firm chooses maintenance to equate its marginal benefit (reduced depreciation) with its marginal cost (foregone investment). This yields the optimal maintenance condition:

$$-\delta'(m) = \frac{p^M}{p^I} \frac{1 - \tau^c}{1 - \tau^c z - c} \equiv \frac{p^M}{p^I}(1 - \tau), \tag{6}$$

where $1 - \tau \equiv (1 - \tau^c)/(1 - \tau^c z - c)$ is the marginal tax wedge—precisely the wedge introduced in Section 2.

This is the input substitution effect. When investment incentives increase z, they reduce $(1 - \tau)$—the relative price of maintenance to investment—making maintenance relatively more expensive. Firms respond by substituting toward investment and away from maintenance. If maintenance demand is elastic ($\omega > 0$), this substitution raises the depreciation rate $\delta(m)$ endogenously, so that more gross investment must offset faster depreciation rather than expanding net capital. The magnitude of this substitution, and thus the wedge between investment and capital responses, is determined entirely by the elasticity ω.

To make this operational, I assume an isoelastic depreciation technology:

$$\delta(m) = \delta_0 - \frac{\gamma^{1/\omega}}{1 - 1/\omega} m^{1-1/\omega}, \tag{7}$$

where $\delta_0 > 0$ is baseline depreciation, $\omega > 1$ governs the curvature (higher ω = more elastic demand), and $\gamma > 0$ shifts the level. This specification is decreasing and convex, ensuring diminishing returns to maintenance, and delivers a tractable maintenance demand function.

Proposition 1 (Maintenance Demand)**.** *Under isoelastic depreciation technology, the maintenance* *demand function is*

$$m = \gamma \left(\frac{p^M}{p^I} \frac{1 - \tau^c}{1 - \tau^c z - c} \right)^{-\omega}. \tag{8}$$

The parameter ω is the price elasticity of maintenance demand, and γ determines its level.

A higher elasticity ω amplifies the input substitution effect: when investment becomes relatively cheaper, firms cut maintenance more sharply, depreciation spikes more dramatically, and the wedge between investment and capital widens. The elasticity ω—which I estimate in Section 5—therefore governs the magnitude of this effect.

Empirical Maintenance Demand. Suppose there is cross-sectional data on maintenance intensity and relative prices and all units exhibit constant-elasticity demand:

$$m_{i,t} = \gamma \left[\frac{p^M_{i,t}(1-\tau_{i,t})}{p^I_{i,t}} \right]^{-\omega} \times \exp(u_{i,t}), \tag{9}$$

where $u_{i,t}$ captures shocks to maintenance beyond the wedge, for example unanticipated breakdowns or weather events, productivity shifts in upkeep methods, or measurement error. I interpret ω as a behavioral elasticity that reflects both tax and non-tax motives for maintenance. The term $u_{i,t}$ absorbs changes in other determinants of maintenance, including regulatory compliance, reliability concerns, utilization smoothing, and firm-specific operating conditions. The theory requires only that maintenance reduces depreciation with diminishing returns; the empirical design asks how relative after-tax prices shift this schedule. With two-way fixed effects, a log transformation yields

$$\log m_{i,t} = \underbrace{\alpha_i + \lambda_t}_{=\log \gamma} - \omega \, \log\!\left[\frac{p^M_{i,t}(1-\tau_{i,t})}{p^I_{i,t}} \right] + u_{i,t}, \tag{10}$$

where $\tau_{i,t}$ captures unit-specific variation in tax treatment (e.g., firm-level tax rates in the railroad data, or industry-level policy exposure in the SOI data). If $u_{i,t}$ is mean zero and orthogonal to the relative price (conditional on fixed effects and controls), it is possible to identify the common elasticity ω from within-unit, over-time variation in the after-tax wedge and then recover γ. The central empirical task of the next sections is to estimate the maintenance demand function—both its level (γ), which determines s_m at the prevailing equilibrium, and the elasticity (ω), which governs the input substitution effect.

4 Data

This section introduces two novel sources of maintenance data for the United States. First, I digitize regulatory filings from Class I freight railroads spanning 1999-2023, providing firm-asset level detail on maintenance expenditures, capital stocks, and input costs. To my knowledge, this is the first use of R-1 data in modern economics since Bitros (1976). Second, I construct industry-level measures from IRS Statistics of Income (SOI) corporate tax returns covering 1999-2019. While the SOI has been used to study investment (e.g., Zwick and Mahon (2017)), this is the first application to maintenance. Together, these datasets provide complementary evidence: the railroad data offer precision and detailed variation in firm behavior, while the SOI provides economy-wide coverage.

4.1 R-1 Data from the Surface Transportation Board

Class I freight railroads—defined as having revenue exceeding $1 billion—account for about 40% of U.S. freight transportation. Following industry consolidation in the 1980s and early 1990s, the sector has consisted of approximately seven large firms in stable competitive equilibrium since the late 1990s.[7] By regulation, these firms must file annual R-1 reports with the Surface Transportation Board (STB). These reports detail the size and composition of firms' capital in value and quantities, trackage by state, taxes paid, capital expenditures, and maintenance expenditures broken down by capital type and input source (materials, labor, or purchased services). Reports are independently audited and provide an unparalleled window into firm capital structure and maintenance behavior. The data span 1999-2023.

For this paper, I maintain a narrow focus on freight cars and locomotives. These assets offer two advantages for studying maintenance demand. First, maintenance activities and associated prices can be straightforwardly identified in the data, whereas this is not true for other capital types. Second, track maintenance is strictly regulated by the Federal Railroad Administration, while locomotive and freight car maintenance faces considerably less regulatory constraint. This provides meaningful variation in firm maintenance choices, which is essential for identification.

The main measure of the maintenance rate is the ratio of maintenance expenditures to lagged book capital. I also construct two alternative metrics: a physical maintenance rate (maintenance expenditures per horsepower for locomotives or per freight ton capacity for freight cars), and separate internal and external maintenance rates. The distribution of maintenance rates for both asset types appears in Figure 1.

7. The seven firms are CSX, Burlington Northern & Santa Fe, Union Pacific, Norfolk Southern, Kansas City Southern, Soo Line, and Grand Trunk (operated by Canadian National Railway). I end the sample in 2023 due to subsequent industry consolidation.

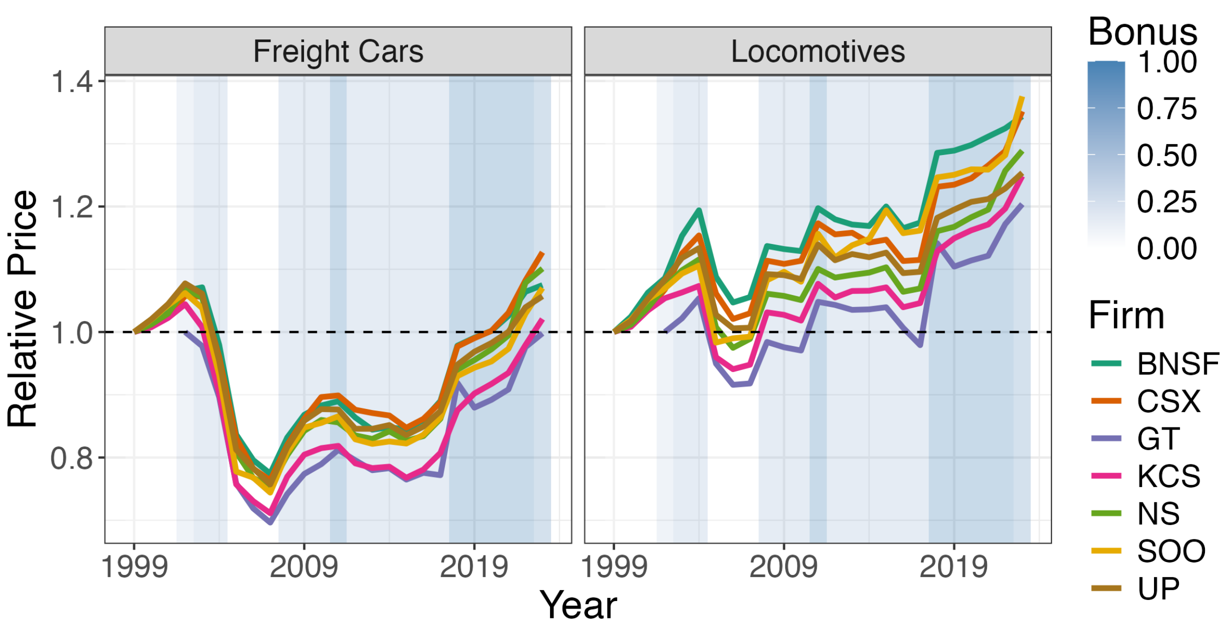
Next, I construct firm- and asset-specific relative prices as

$$P_{i,j,t} = \frac{p^M_{i,j,t}}{p^I_{j,t}} \frac{1-\tau_{i,t}}{1-\tau_{i,t} z_t}, \tag{11}$$

where $p^M_{i,j,t}$ is the pre-tax maintenance price of capital good j for firm i at time t, $p^I_{j,t}$ is the investment price of asset j, and $\tau_{i,t}$ is the firm-specific tax rate. Due to data availability, only the pre-tax price of maintenance varies by firm and capital type, whereas tax rates vary by firm and investment prices by capital type. Tax rates do not vary between assets because the IRS places locomotives and freight cars in the same depreciation category. Further details on data construction and summary statistics are in Appendix B.1.

Figure 3 plots the after-tax relative price of maintenance to investment for all Class I railroads since 1999. The price of maintaining locomotives has persistently increased since 2000, while the pattern is more U-shaped for freight cars. Background shading indicates periods of bonus depreciation, which reduced the relative price of investment and thus increased the maintenance-investment wedge. However, since all equipment here is in the same tax category, there is no variation between assets or across firms.

Figure 3: After-tax relative price of maintenance to investment



Notes: I construct the after-tax relative price of maintenance to investment as described in the main text and in Appendix B.1. Background shading is for bonus depreciation.

4.2 Industry Data from the Statistics of Income

The IRS Statistics of Income (SOI) aggregates corporate tax returns into industry-level samples at approximately the three-digit NAICS level. This is the only economy-wide collection of maintenance data at annual frequency in the United States. Corporations report maintenance expenditures and book capital as line items on their tax forms, which the SOI aggregates across firms within industries. I use SOI data from 1999-2019, aggregating to 49 industries to correspond with Bureau of Economic Analysis (BEA) classifications.[8] For some analyses, I separate the sample into taxable firms (those with positive net income) and non-taxable firms.

The SOI maintenance rate—the ratio of maintenance expenditures to lagged book capital—is noisier than the R-1 measure for two reasons. First, because labor expenditures appear as a separate line item on tax forms, reported maintenance largely reflects spending on materials and external services, understating total maintenance costs.[9] Second, the capital stock denominator uses tax depreciation schedules to construct book capital, which may not accurately reflect economic capital stocks. Despite these measurement issues, the resulting maintenance rates are similar to those observed in aggregate Canadian data.[10] Figure 1 plots the distribution of SOI maintenance rates across industries and years.

Because there is no easily identifiable measure of relative prices at the industry level, my identification strategy for the SOI data relies on the policy wedge defined in equation 1. I construct asset-specific wedges for every BEA asset using the mapping from assets to the tax code in House and Shapiro (2008). I then aggregate the asset-specific wedges into a capital-weighted industry-specific wedge, where the weights reflect each industry's capital composition. Industries with more equipment-intensive capital structures face larger policy-driven changes in the maintenance-investment wedge when investment incentives vary.[11]

Figure 4 plots the distribution of industry-specific wedges over time. Tax reforms throughout the 2000s—particularly expansions of bonus depreciation—tended to reduce the wedge proportionally more for equipment-intensive industries, while structures-intensive industries saw little change until the TCJA in 2017. There is significant variation in the incentive to substitute between maintenance and investment over time, which is exactly what I require to estimate the elasticity of maintenance demand.

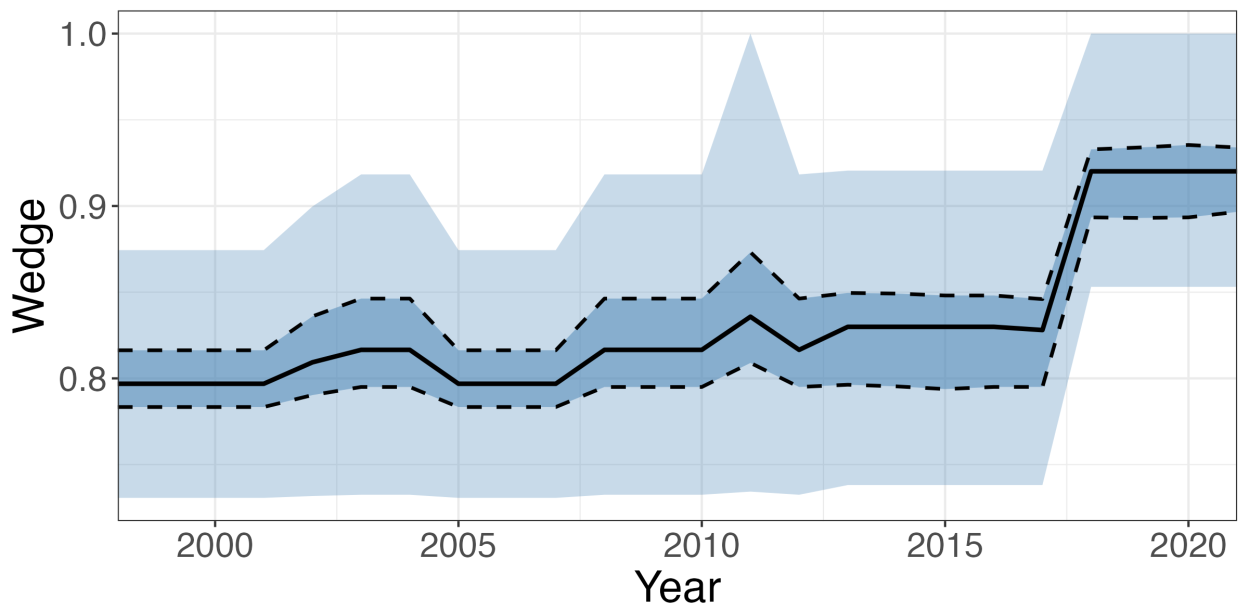
8. I exclude filings made with Forms 1120S, 1120-REIT, and 1120-RIC, and remove the financial sector. See Appendix B.2 for details on the SOI-BEA industry mapping and why I use the BEA definition.

9. The labor cost share in maintenance is typically 30-45%. Appendix B.2 discusses a potential correction and shows that the main results of this paper are conservative as a result

10. See Appendix Figure B.5 for a comparison.

11. Appendix B.2 provides details on asset-level wedge construction and capital weighting.

Figure 4: Distribution of industry-specific wedges over time



Notes: Every line is a quartile of the industry-specific wedge defined in the main text.

With these two complementary data sources in hand—detailed firm-level variation from railroads and broad industry coverage from the SOI—I now turn to estimating the maintenance demand function.

5 The Maintenance Demand Function

Section 3 showed that maintenance alters tax policy transmission through two mechanisms: a capital preservation effect (governed by the maintenance share s_m) and an input substitution effect (governed by the elasticity ω). This section estimates both parameters using complementary evidence from railroad data (firm-level variation in relative prices) and industry data (variation in tax policy exposure). The railroad estimates provide precise identification of the elasticity but reflect partial equilibrium responses at the firm level. The industry estimates capture any within-industry general equilibrium effects but are less precise due to measurement error in maintenance and capital stocks.

5.1 Evidence from Freight Railroads

I estimate the maintenance elasticity using locomotives and freight cars owned by seven Class I railroads from 1999-2023. Let $P_{i,j,t}$ denote the firm i by asset j by year t after-tax relative price of maintenance to investment defined in Section 4. The basic regression specification estimates the maintenance elasticity of demand ω with

$$\log m_{i,j,t} = \alpha_{ij} + \lambda_t - \omega \log P_{i,j,t} + \text{Controls} + u_{i,j,t}, \tag{12}$$

where α_{ij} is a firm-by-capital type fixed effect and λ_t is a time fixed effect. The coefficient ω is identified by leveraging variation in relative prices within each firm-capital type over time, with fixed effects controlling for all time-invariant characteristics and common temporal shocks. I cluster standard errors by firm and year to account for correlation in maintenance decisions between capital types within firms.

Identification Strategy. The relative price $P_{i,j,t}$ is likely endogenous. If firms experiencing higher maintenance demand also have systematically higher input costs or choose different factor mixes, then OLS estimates will be biased. Unobserved firm-level supply shocks could simultaneously affect maintenance intensity and input prices. Similarly, regional economic expansions might raise both wages and freight demand, leading firms to defer maintenance to maximize utilization.

To address this endogeneity, I construct a shift-share instrument that isolates exogenous variation in maintenance costs:

$$Z_{i,j,t} = \frac{\text{Labor}_{i,j,t-2}}{\text{Internal Maintenance}_{i,j,t-2}} \sum_{s=1}^{S} \frac{\text{Rail Miles}_{i,t,s}}{\text{Rail Miles}_{i,t}} W_{s,t}. \tag{13}$$

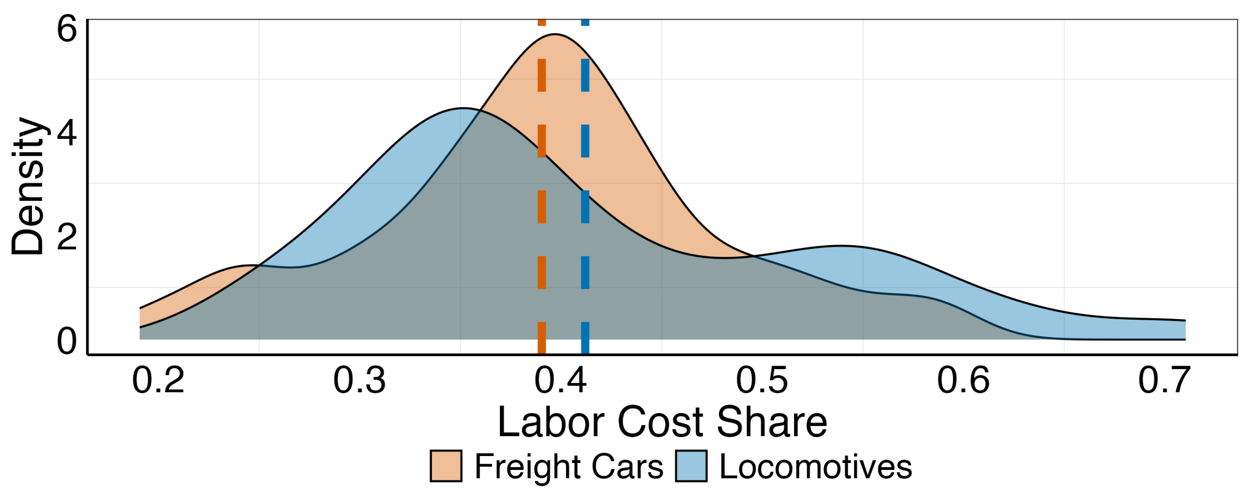
The instrument has two components. The *shares* capture each firm's cost structure: the labor cost share of internal maintenance, lagged two years to ensure pre-determination. Firms that rely more heavily on internal labor are more exposed to wage movements. The *shifts* are state-level wage indices for maintenance occupations (BLS SOC code 49-0000), weighted by each firm's geographic footprint. These state wages reflect broad labor market conditions—tightness, cost of living, unionization—that are plausibly orthogonal to individual railroads' maintenance needs.

Why focus on internal rather than total maintenance? This choice serves both a practical and a diagnostic purpose. Practically, external maintenance is typically contracted in advance with predetermined service agreements, often negotiated at equipment purchase. These contracts make external maintenance inflexible in the short run, so any price-driven adjustment occurs primarily through the internal margin. More importantly, the internal-external distinction provides a test of the exclusion restriction. If the instrument isolates cost-side shocks (shifting the price of in-house labor) we should observe: (i) large quantity responses for internal maintenance where firms can flex, (ii) near-zero responses for external maintenance where contracts are sticky, and (iii) firms substituting toward external when internal wages rise. By contrast, if the instrument were capturing demand shocks—such as utilization spikes that simultaneously raise maintenance needs and local wages—both internal and external quantities would move together. I show below that the data strongly support the cost-side interpretation.

The instrument follows the "many exogenous shifts" approach of Borusyak, Hull, and Jaravel (2024). The shifts, which occur at a broad state-level wage category across 49 states over 25 years, are numerous and plausibly orthogonal to firm-asset maintenance decisions. Railroad maintenance facilities are geographically dispersed based on network structure and historical infrastructure, not chosen to minimize current labor costs. The shares, comprised of geographic footprints and cost structures, are persistent and pre-determined. Together, these deliver variation in relative maintenance prices orthogonal to unobserved demand or supply shocks at the firm-asset level.

Figure 5 plots the distribution of labor cost shares by asset type, showing substantial variation both within and between firms over time. The first stage has the correct sign and exceeds the usual $F > 10$ threshold using the Montiel-Olea and Pflueger (2013) F test, but the inference that follows is robust to weak instruments. Additionally, the instrument satisfies standard exclusion restrictions. Appendix Figure C.1 shows that lagged maintenance rates are not predicted by $Z_{i,j,t}$, indicating no anticipation effects. Appendix Figure C.2 shows that labor cost shares are orthogonal to lagged maintenance rates, relative prices, and asset age, confirming that the shares are not correlated with pre-period predictors of maintenance.

Figure 5: Internal Labor Cost Share for Rolling Stock



Note: The figure plots the winsorized density of labor cost shares for locomotives and freight cars from R-1 reports.

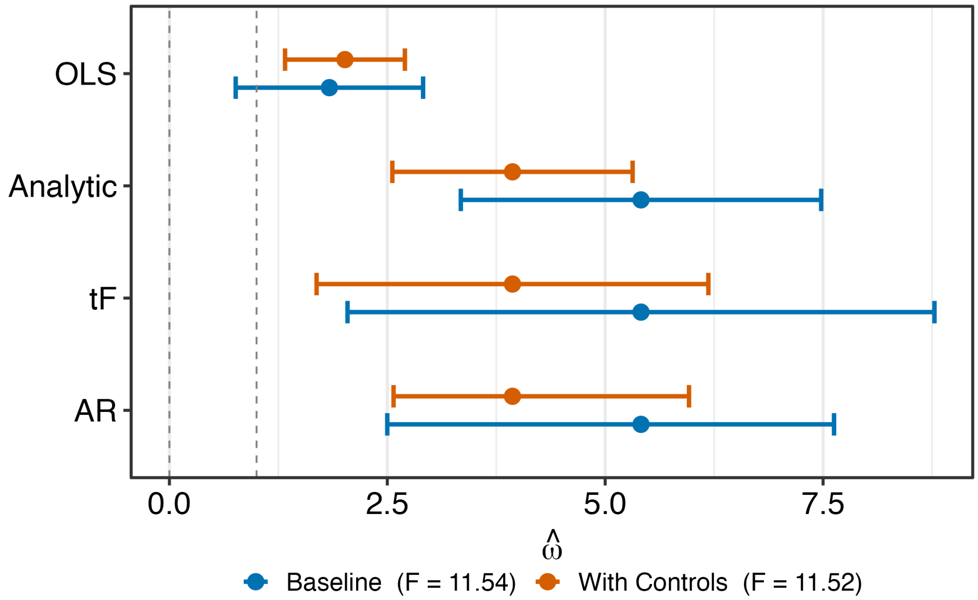
To address remaining confounders, I include several controls that target potential violations of the exclusion restriction at both the shift and unit level. At the shift level, the primary concern is that local economic conditions might simultaneously affect freight demand, wages, and maintenance intensity. For example, a regional boom could increase demand for rail services (raising utilization and deferring maintenance), tighten local labor markets (raising wages), and increase freight revenues simultaneously. To address this, I construct each firm's demand exposure as a weighted average of state-level GDP growth, using track miles in each state as weights. This variable captures how aggregate demand shocks in a railroad's service territory affect its operations, allowing me to isolate wage variation orthogonal to local business cycles.

At the unit level, I control for capital age (proxied by the ratio of net to gross book capital) because older capital requires more maintenance and may also have different exposure to local labor market condition since older equipment might be maintained at older facilities in regions with different wage dynamics. I also include firm-specific linear time trends to absorb gradual changes in firm operations, technology adoption, or management practices that might correlate with both maintenance intensity and geographic wage exposure. For example, if a firm is gradually shifting its maintenance operations to lower-wage regions over time, the firm trend absorbs this smooth reallocation, ensuring identification comes from within-firm year-to-year variation in the instrument rather than secular trends.

These controls, combined with firm-asset and time fixed effects, create a demanding specification: identification requires that conditional on a firm's persistent maintenance practices, common national shocks, smooth firm-specific trends, local demand conditions, and capital vintage, the instrument provides variation in maintenance costs orthogonal to unobserved maintenance needs.

Results. Figure 6 presents estimates of equation (12). The baseline OLS estimate yields a point estimate near 2. Instrumenting for relative prices produces a substantially larger elasticity: the TSLS point estimate is approximately 3.5. Because the instrument is only moderately strong (F $\approx$ 11), I follow Lee et al. (2022) and Lal et al. (2024) and compute 95% confidence intervals by inverting the Anderson and Rubin (1949) and tF statistics. While wider than analytic intervals, both easily reject $\omega = 0$ and $\omega = 1$. It is important to reject $\omega = 1$ so that returns to scale are decreasing in maintenance. For comparison, the tax 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).

Figure 6: R-1 maintenance demand elasticity with 95% confidence interval



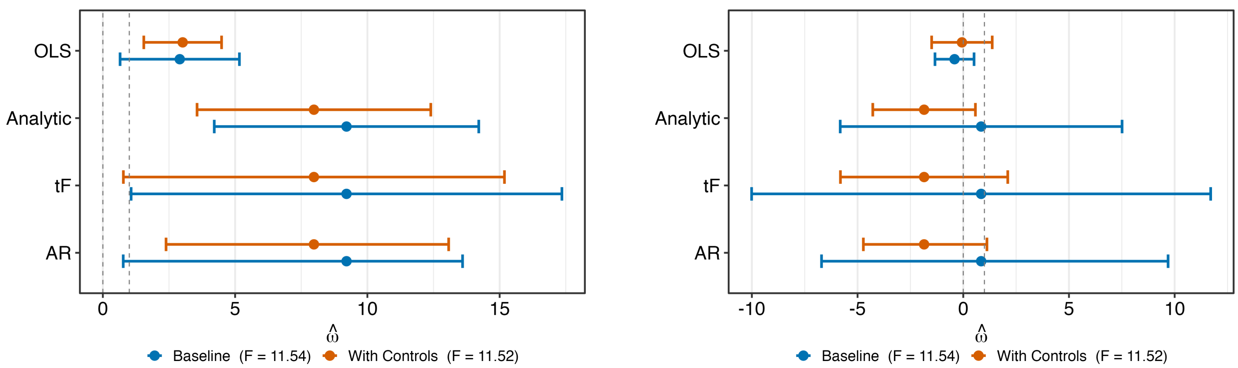
Note: This figure plots the point estimates and result for estimating (12). The blue lines contain no controls, while the orange lines control for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13). Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

Robustness and Validation. I now present two types of evidence supporting the baseline results: first, a test of the exclusion restriction using the internal-external maintenance split; second, a summary of additional robustness checks detailed in Appendix C.1.

Internal vs. External Maintenance: Testing the Exclusion Restriction. The preceding results aggregate all maintenance into a single input. Examining internal and external maintenance separately provides a powerful test of whether the instrument isolates cost-side variation or captures correlated demand shocks. The instrument shifts the cost of internal maintenance performed by the firm's own employees through state-level wage movements. If this successfully isolates supply-side shocks, it leads to sharp predictions. Internal maintenance is flexible: firms can reallocate labor, adjust schedules, or defer maintenance when costs rise. External maintenance is typically contracted in advance with predetermined service agreements, typically negotiated at equipment purchase, and involves vendors with limited capacity. A valid cost-side shock therefore predicts: (i) large quantity responses for internal maintenance where firms can flex, (ii) minimal responses for external maintenance where contracts are sticky, and (iii) substitution in sourcing mix toward external when internal becomes more expensive. These predictions would not hold under alternative interpretations. If the instrument captured demand shocks, for example, regional booms simultaneously raising maintenance needs and wages, both internal and external maintenance would move together and the sourcing mix would remain stable. The asymmetry predicted by the cost-side interpretation provides a falsifiable test.

Figures 7a and 7b re-estimate equation (12) separately for internal and external maintenance. The contrast is stark. Internal maintenance exhibits an elasticity nearly double the pooled estimate, reaching approximately 7, with confidence intervals easily rejecting both zero and unit elasticity. External maintenance shows an elasticity statistically indistinguishable from zero across all specifications.

Figure 7: Maintenance demand elasticity with 95% confidence intervals



(a) Internal maintenance demand elasticity (b) External maintenance demand elasticity

Note: Each panel plots the point estimates and results for estimating (12). The blue lines contain no controls, while the orange lines control for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13). Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

This pattern strongly supports the exclusion restriction. The instrument generates precisely the asymmetric response a cost shifter predicts: large adjustment on the flexible internal margin, no adjustment on the sticky external margin. The pattern is difficult to reconcile with demand confounds. The internal estimate of $\omega \approx 7$ likely provides an upper bound on the structural elasticity. Any residual demand-side correlation would attenuate the elasticity toward zero, so observing such a large elasticity despite potential attenuation suggests maintenance demand is highly price-sensitive where firms have flexibility.

Additional Robustness Checks. Appendix C.1 provides extensive additional validation. I show that the first stage is strong across multiple instrument specifications (Table C.1). The appendix also presents robustness checks using physical capital stocks rather than book values (Figure C.3), alternative instruments using national wage indices (Figure C.4), different lag structures for the labor shares (Figure C.5). Across all specifications, the large negative elasticity remains, indicating the result is not an artifact of any particular modeling choice.

I also provide checks with dynamic specifications. When controlling for lagged maintenance, the short-run elasticity is smaller, but the long-run elasticity remains at approximately 3.5 (Appendix Figure C.6), consistent with the steady-state interpretation from theory. However, local projections in Figure C.7 indicate that the response of maintenance is immediate but also displays persistence. Firms reduce upkeep on impact, and the effect deepens for two to three years before attenuating. This pattern is consistent with some adjustment frictions, such as planning lags or a stock-of-disrepair channel, that make the full reallocation of resources away from maintenance gradual rather than instantaneous.

5.2 Maintenance in the SOI

The railroad estimates reflect firm-level responses. In general equilibrium, firms may reallocate capital: when investment incentives make new capital attractive, firms cutting maintenance may sell used equipment to other firms rather than scrapping it. If buyers maintain this capital more intensively, the aggregate decline in maintenance will be smaller than the firm-level response. Appendix F.1 formalizes how this reallocation dampens the aggregate elasticity.

To estimate something closer to an aggregate elasticity, I turn to industry-level SOI data. The unit of observation—an industry-year covering 49 broadly defined industries—is sufficiently aggregated that within-industry capital reallocation is largely netted out. This assumes capital sales following tax cuts remain within industries, plausible for specialized capital (oil rigs) but less so for general-purpose capital (rental cars). Nevertheless, the SOI provides the only economy-wide evidence on maintenance and allows assessment of whether firm-level elasticities translate to the aggregate.

Identification Strategy. Identification comes from cross-sectional variation in industry exposure to tax policy changes. Industries differ in capital composition: some rely heavily on equipment eligible for accelerated depreciation, others on structures. This creates differential exposure to two major types of reforms. First, bonus depreciation varied from 0% to 100% between 2002-2023, with larger effects on equipment-intensive industries (House and Shapiro 2008; Zwick and Mahon 2017; Garrett, Ohrn, and Suárez Serrato 2020). Second, the 2017 Tax Cuts and Hobs Act increased bonus to 100% and cut the corporate rate from 35% to 21%, creating variation across industries (Kennedy et al. 2023; Chodorow-Reich et al. 2025). There is substantial evidence that both kinds of reforms boosted investment.

I estimate:

$$\log m_{i,t} = \alpha_i + \lambda_t - \omega \log\left(\frac{1-\tau_t^c}{1-\tau_t^c z_{i,t}}\right) + \text{Controls} + \varepsilon_{i,t}, \tag{14}$$

where α_i is an industry fixed effect and λ_t is a time fixed effect. Since τ_t^c is common across industries, the key choice is how to weight capital types in $z_{i,t}$)

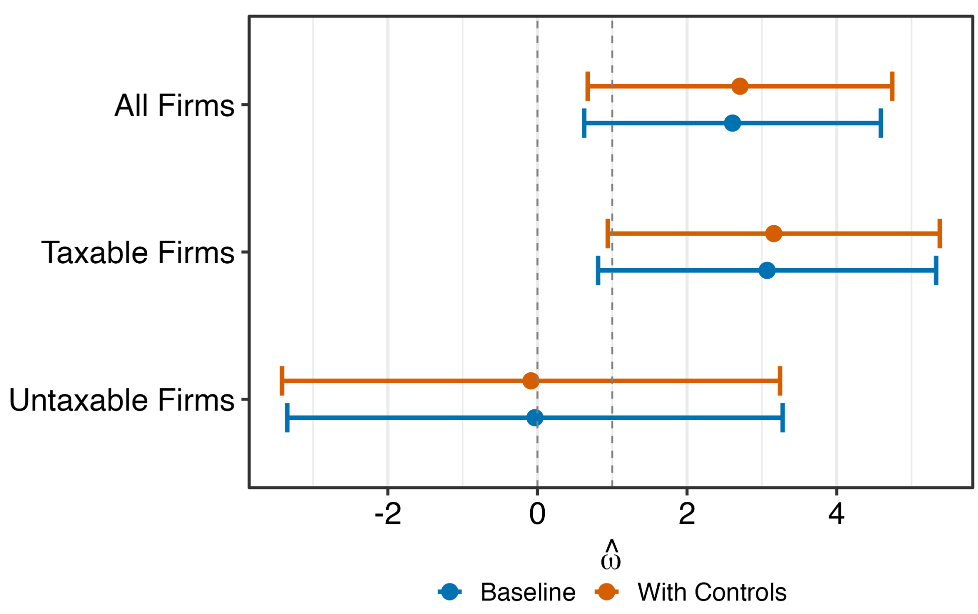
An investment-weighted scheme is standard in investment elasticity studies (e.g., (Zwick and Mahon 2017)). In those studies, z is constructed by taking a weighted average of recent investment flows. This captures the elasticity for recently acquired assets. However, maintenance applies to the entire installed capital base, not just recent purchases, making investment weights conceptually misaligned. In other words, firms do not need to maintain recently acquired assets, only older ones, so it is wrong to use investment weights. I use a capital-weighting scheme instead by weighting each asset by its average capital stock over pre-reform years. This captures the economically relevant margin: how maintenance responds to user cost changes for existing capital. Appendix Figure C.9 validates this choice: the maintenance demand elasticity is indistinguishable for an investment-weighted scheme.

The primary assumption is that the industry-by-year level policy variations are independent of other industry-by-year shocks that could simultaneously affect maintenance rates. These shocks might simultaneously influence both the implementation of tax policies and maintenance behaviors within industries, violating the assumption that policy variations are independent of other industry-year level factors. For example, policy around Covid-19 would plausibly not meet this criteria. Without adequately controlling for these time-varying confounders, the estimated relationship between tax policy and maintenance rates could be confounded by these unobserved influences. Toward mitigating that, I include broad linear and quadratic industry trends at the two-digit NAICS level.

Results. Figure 8 shows estimates of (14) for three groups: all firms, taxable firms, and untaxable firms. The top row of each group is a simple regression of the log maintenance rate on the log tax term, while the second column includes a control for the age of capital proxied by the ratio of gross to net book capital, and both include linear and quadratic trends for two-digit NAICS industries. Controlling for age accounts for the fact that older capital may require more maintenance. Compared to the partial equilibrium R-1 coefficient, the SOI general equilibrium coefficient is only about 60% as large. Although I reject the null hypothesis of perfectly inelastic maintenance demand, I fail to reject the null of unit elasticity. The gap between the SOI and freight rail estimates suggests some reallocation between firms following tax cuts, resulting in a smaller decline in aggregate maintenance than observed at the micro level. However, that conclusion must be tempered by the fact that there is some omitted variable bias introduced by the omission of a pre-tax price of maintenance in the SOI regression.

In the aggregate, some reallocation seems to be taking place and resulting in maintenance dampening. Since do not actually observe capital sales are not in the data, I partially test for that by splitting the sample into firms with positive net income ("taxable") and untaxable firms. The mapping is rough because some of the firms in the taxable sample have positive net operating losses, so they are not actually taxable. In principle, maintenance should rise for untaxable firms and decline for taxable firms following a tax cut if the model is correct. The middle two rows and bottom two rows of Figure 8 show demand elasticity estimates together with 95% confidence intervals. The maintenance demand elasticity increases to around three and becomes more statistically significant, which is quite similar to the partial equilibrium estimate in Figure 6. On the other hand, the untaxable elasticities are centered at zero. Thus, interpreted as either a placebo test for the theory or more broadly as reflecting reallocation, the sample split provides sound evidence in favor of the hypotheses advanced in Section 3.

Figure 8: Maintenance demand elasticity with 95% confidence interval



Note: This figure plots the point estimates and result for estimating (14). All estimates have two-way fixed effects together with linear and quadratic trends in two-digit NAICS codes. Orange lines control for the age of the capital stock. All standard errors are clustered by industry. The top estimate is for the All Firm sample, while the bottom two groups of estimates split the SOI into a taxable and an untaxable sample and re-runs (14) individually for each.

Robustness and Validation. Appendix C.2 presents extensive robustness checks. Results are unchanged when ending the sample in 2013, before SOI sampling methodology changes (Figure C.8). Using BEA capital stocks instead of SOI book capital yields similar though less precise estimates (Figure C.10). As noted above, using investment-weighted $z_{i,t}$ yields $\omega \approx 0$ (Figure C.9), confirming maintenance responds to the installed base rather than recent purchases. Testing for selection effects shows the elasticity is homogeneous across industries regardless of equipment intensity(Figure C.11).[12] The interaction between equipment intensity and the wedge is statistically insignificant and quantitatively small, ruling out the concern that differential bonus exposure correlates with pre-existing elasticity differences.

Local projections show maintenance responds essentially contemporaneously to policy changes (Figure C.12). Industries cut maintenance in the same year the wedge falls, with little persistence in subsequent years. This immediate adjustment contrasts with the gradual adjustment in the railroad data. It likely reflects the nature of identification: discrete policy reforms can be acted upon immediately, while cost shocks may require staggered operational adjustments. Since the SOI captures policy-relevant dynamics, subsequent quantitative exercises use the implied immediate response from these estimates.

5.3 Interpreting the Elasticities: Wage Endogeneity

Having estimated maintenance demand elasticities from two complementary sources, I now address a key interpretive question: do these reflect structural demand elasticities, and to what extent are they attenuated by general equilibrium price effects?

The preceding analysis implicitly treats p^M and p^I as policy invariant. Although a classic result from Goolsbee (1998a) shows that investment supply is upward sloping, newer evidence (House and Shapiro 2008; House, Mocanu, and Shapiro 2017; Basu, Kim, and Singh 2021) indicates that investment-good prices did not respond to tax policy changes during the 2000s, largely due to increased foreign competition. That invariance is less plausible for maintenance. Because labor is a key maintenance input and wages rise after tax cuts (Fuest, Peichl, and Siegloch 2018; Kennedy et al. 2023), p^M is plausibly endogenous to policy. If maintenance prices rise while investment-good prices remain constant, the pre-tax relative price p^M/p^I increases, working against the substitution induced by the tax wedge.

If maintenance supply is upward-sloping, tax policy affects both quantities and prices. When investment incentives reduce the after-tax cost of new capital, firms substitute away from maintenance, reducing demand for maintenance inputs. Simultaneously, the tax cut raises aggregate

12. Koby and Wolf (2020) point to important theoretical reasons to worry about heterogeneous selection effects of bonus. Low-depreciation equipment is the most effected by bonus *and* the most price-sensitive. That same concern does not appear to be important here.

demand and wages, increasing maintenance costs. These offsetting forces mean the estimated elasticity reflects an equilibrium response that combines demand and supply effects.

Let $\varepsilon_s > 0$ denote the elasticity of maintenance supply. With upward-sloping supply, shocks to the wedge partly move p^M, so estimating the regressions in Sections 5.1 and 5.2 recovers an *equilibrium* elasticity:

$$\omega_{\text{eq}} = \frac{\omega}{1 + \omega/\varepsilon_s}, \tag{15}$$

which satisfies $|\omega_{\text{eq}}| < |\omega|$ for any finite ε_s.[13] In absolute value, the regression coefficient understates the structural demand elasticity. How does this affect interpretation in each setting?

R-1 Railroads. In the railroad panel, the concern is that local wage movements may co-move with unobserved maintenance needs, rendering p^M partly endogenous. If wages rise precisely when firms need more maintenance, the instrument would be contaminated by demand shocks rather than isolating cost shifts. I address this concern in three ways.

First, the shift-share instrument isolates cost-side variation by interacting lagged, pre-policy maintenance labor shares with external state-level wage shocks. This design shifts the price of in-house labor rather than capturing demand for maintenance services. The shares are predetermined (lagged 2-3 years), and the shifts come from broad state labor market conditions plausibly orthogonal to individual railroad maintenance needs. Second, the specifications include firm-asset fixed effects, firm-specific trends, and year fixed effects, along with controls for local economic activity and capital age. These absorb slow-moving co-trends between wages and maintenance intensity. Third, and most importantly, I separate internal and external maintenance. Recall from before that internal maintenance drives the whole margin. This sharp asymmetry is precisely what a cost-shift design predicts: large responses on flexible margins, no response on sticky margins. Crucially, if the instrument captured demand shocks rather than cost shocks, one would expect both internal and external quantities to move together. A utilization spike or maintenance backlog would increase demand for both types of services. A regional boom simultaneously raising maintenance needs and wages would affect all maintenance margins similarly. The observed divergence is difficult to reconcile with a demand confound and strongly supports the cost-side interpretation.

This internal-external split also clarifies the direction of any remaining bias. If some residual correlation between wages and unobserved maintenance needs survives the instrument and controls, it would attenuate the elasticity toward zero rather than inflating it. Demand shocks that simultaneously raise wages and maintenance would create positive correlation, biasing the

13. Let demand be $m = a(Qp^M)^{-\omega}$ with $Q \equiv (1-\tau)/(1-\tau z)$, and inverse supply $p^M = b\, m^{1/\varepsilon_s}$ with $\varepsilon_s > 0$. Substituting gives $m^{1+\omega/\varepsilon_s} = a(Qb)^{-\omega}$. Taking logs and differentiating w.r.t. $\ln Q$ yields $\frac{d \ln m}{d \ln Q} = -\frac{\omega}{1+\omega/\varepsilon_s} \equiv -\omega_{\text{eq}}$, hence $\omega_{\text{eq}} = \omega/(1+\omega/\varepsilon_s) < \omega$ for finite ε_s.

coefficient upward in absolute value. The fact that we observe such large elasticities despite this potential positive bias suggests the cost-shift design successfully isolates supply-side variation.

SOI Industries. In the industry panel, identification comes from demand shifters. This creates a different endogeneity concern. After a tax cut that makes investment more attractive, wages rise throughout the economy due to increased labor demand. Simultaneously, the after-tax price of investment falls due to bonus depreciation or lower corporate rates. The increase in p^M (through wage pass-through) and decrease in the after-tax price of investment work in the same direction: both increase the relative price of maintenance, pushing the estimated coefficient toward zero in absolute value. This is the opposite direction from the railroad concern. In the railroad setting, if wages proxy for demand, endogeneity would inflate the elasticity. In the industry setting, wage pass-through mechanically dampens the elasticity. The SOI estimate may therefore reflect an equilibrium response where the substitution effect induced by the tax wedge is partially offset by wage increases.

I address this concern in two ways. First, I absorb common wage movements with two-way fixed effects and flexible linear and quadratic industry trends. Identification relies on differential policy exposure across industries rather than aggregate co-movement between tax policy and wages. Equipment-intensive industries face larger wedge changes than structures-intensive industries when bonus depreciation varies, even though both face similar wage pressures. This cross-sectional variation provides identification net of common wage shocks. Second, the taxable versus untaxable split provides validation. Both groups face the same wage movements, so any correlation between wages and unobserved demand shocks should affect both equally. However, only taxable industries face the tax incentive to substitute away from maintenance, and only their maintenance intensity responds in the data.

If wage movements were confounding the estimates by proxying for demand shocks or industry trends correlated with maintenance behavior, I would expect similar responses across both groups. The sharp divergence indicates identification comes from differential tax exposure rather than common factors affecting all industries. This serves as a powerful placebo test: the policy variation only creates incentives for taxable firms, and only taxable firms respond.

Because I do not separately model p^M in the industry setting, I cannot decompose the equilibrium response into structural demand and supply components. I therefore label the SOI coefficient an equilibrium elasticity, acknowledging that wage pass-through plausibly dampens the response and makes it a lower bound on the structural elasticity. The taxable-firm estimate of $\omega \approx 3$, very close to the pooled railroad estimate, suggests the equilibrium and structural elasticities may not differ dramatically, though some attenuation likely remains.

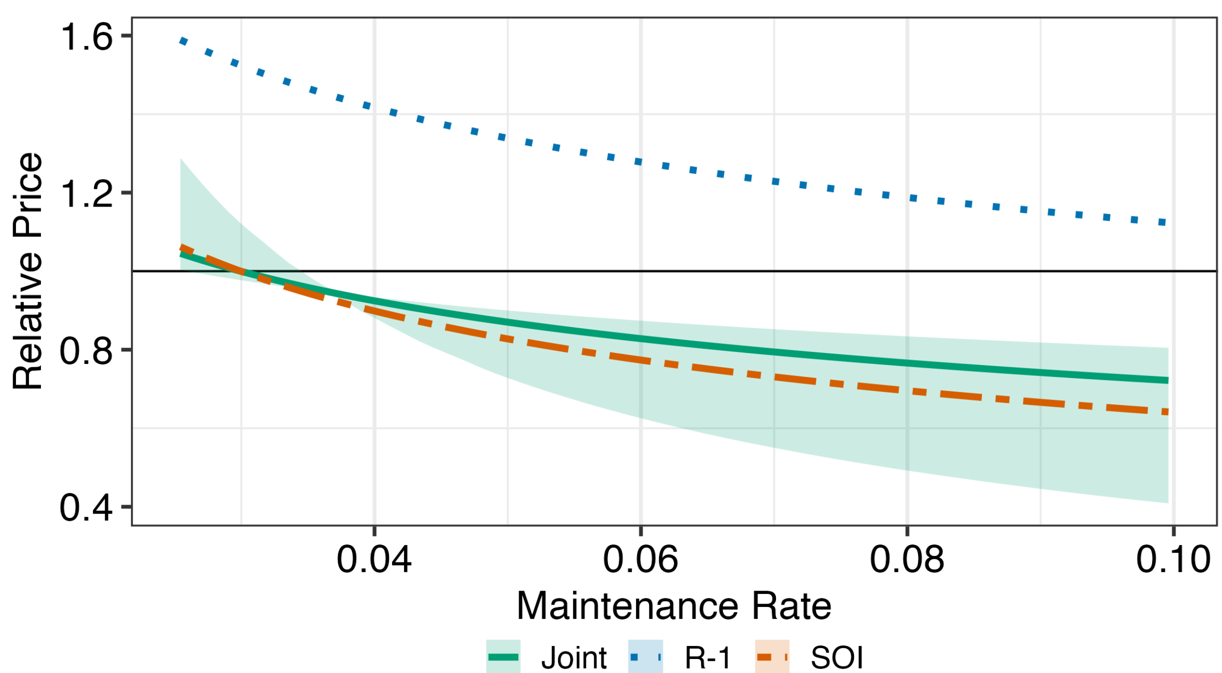
Interpretation and Range of Plausible Elasticities. Across both designs, any residual wage-related endogeneity that survives instruments, fixed effects, and trends operates to reduce the magnitude of the estimated elasticity. In the railroad panel, if wages partially proxy for unobserved maintenance needs despite the shift-share design, the elasticity would be biased toward zero. The internal-external asymmetry suggests this is not the dominant concern, but any remaining correlation would attenuate estimates downward. In the industry panel, wage pass-through mechanically works against the substitution effect, pushing coefficients toward zero by construction.

For policy counterfactuals, I combine these estimates into a single maintenance demand schedule of the form:

$$m = \gamma \left(\frac{p^M}{p^I} \frac{1-\tau^c}{1-\tau^c z} \right)^{-\omega}. \tag{16}$$

I use meta-analysis to pool estimates from both datasets, weighting by precision while allowing for heterogeneity across settings. From the railroad data, I include the baseline IV specification plus alternative instruments. From the SOI, I include all specifications except untaxable firms. The pooled elasticity is approximately 3.5, falling in the middle of the plausible structural range. I recover γ by inverting the demand function at the sample mean, which gives $\gamma \approx 0.03$.

Figure 9: Estimated Maintenance Demand Curve with 95% CI



Notes: The green curve is the pooled inverse-demand schedule combining estimates from R-1 and SOI data. The shaded band is the 95% confidence interval. The blue curve shows the railroad-only schedule; the orange curve shows the SOI-only schedule.

Figure 9 plots the resulting demand curve with a 95% confidence interval. The pooled curve (green) lies between the individual railroad and SOI curves but closer to the SOI, reflecting the meta-analysis weighting. This pooled demand schedule forms the foundation for subsequent counterfactual analysis of the 2017 Tax Cuts and Jobs Act. Appendix C.3 provides full details on the meta-analytic procedure, including gamma recovery via inverting the demand function at sample means, REML estimation, and covariance matrix construction.

6 Aggregate Implications of Maintenance Demand

Having established empirically that maintenance demand is both large and elastic, I now return to the model to derive the full theoretical consequences. This section builds on the microfoundations from Section 3 to derive new implications for aggregate variables, empirical measurement, and policy. These additional theoretical results provide the complete framework I will then take to a full quantitative simulation of the effects of the 2017 Tax Cuts and Jobs Act in the following section.

6.1 The Tax Elasticity of User Cost

In the standard neoclassical growth model with Cobb-Douglas production, a permanent tax shock propagates through the user cost of capital to other macro aggregates. In intensive form, the tax elasticities of capital, wages, and output are

$$\varepsilon_K = -\frac{1}{1-\alpha}\varepsilon_\Psi^{\text{NGM}} \quad \text{and} \quad \varepsilon_w = -\frac{\alpha}{1-\alpha}\varepsilon_\Psi^{\text{NGM}} \quad \text{and} \quad \varepsilon_Y = -\frac{\alpha}{1-\alpha}\varepsilon_\Psi^{\text{NGM}}, \tag{17}$$

where the tax elasticity of user cost is

$$\varepsilon_\Psi^{\text{NGM}} = \frac{\tau}{1-\tau}. \tag{18}$$

Perturbing the cost of capital by changing the tax rate τ therefore propagates to other variables exactly as in (17). How does that change when we add maintenance?

Recall from Section 3 that the user cost of capital includes an additive maintenance term. To simplify notation, let $p^I = p^M$ and suppose both inputs are elastically supplied. Let τ summarize the marginal effective tax rate and consider a small perturbation to τ. With maintenance, the generalized tax elasticity of user cost is

$$\boxed{\varepsilon_{\Psi}^{\text{NGMM}} = \underbrace{\frac{\tau}{1-\tau}}_{\substack{\text{NGM}\\ \text{Benchmark}}} \times \underbrace{\left(1 - \frac{m}{\Psi}\right)}_{\substack{\text{Capital Preservation}\\ \text{Effect}}} - \underbrace{\frac{\tau}{1-\tau}\left(\frac{\varepsilon_m}{\Psi}\left[\frac{\delta(m)\varepsilon_\delta}{1-\tau} + m\right]\right)}_{\text{Input Substitution Effect}}.} \tag{19}$$

Equation (19) decomposes the user cost elasticity into three components: the benchmark elasticity, a capital preservation effect, and an input substitution effect. I discuss each in turn.

Benchmark Elasticity. The first component of the first term in (19) is the benchmark tax elasticity of the user cost of capital from (18).

Capital Preservation Effect. The benchmark elasticity $\varepsilon_{\Psi}^{\text{NGM}}$ is given a haircut by the maintenance share of user cost. Since the lifetime cost of a unit of capital includes its upkeep costs and that upkeep is tax-deductible, only the remaining share is exposed to tax cuts. If maintenance dominated user cost, the user-cost elasticity would collapse to zero, and capital would not respond to taxes at all. Thus long-lived assets that also require heavy upkeep can be less tax-elastic than short-lived ones, reversing the standard "long-lived assets are more price-elastic" result in House (2014) and Koby and Wolf (2020).

Input Substitution Effect. Cutting taxes effectively makes new capital cheaper relative to maintaining old capital. Firms therefore reallocate dollars from maintenance toward investment, which mechanically raises depreciation. This effect is emphasized by McGrattan and Schmitz Jr. (1999). If maintenance demand were unit-elastic, the drop in m would exactly offset the rise in $\delta(m)$, leaving net user-cost sensitivity unchanged. With more elastic maintenance demand, depreciation moves a bit further against the shield (or with it), but this effect is generally small compared to the main tax-shield haircut.[14]

Proposition 2 (Attenuated Tax Elasticity)**.** *To first order, the sensitivity of the user cost of capital to a tax change is strictly smaller than in the benchmark neoclassical model.*

This immediately follows from equation (19) following the conclusion that input substitution is second-order. Proposition 2 establishes that the maintenance channel strictly dampens

14. To see why, note that the total derivative of user cost with respect to τ is

$$\frac{\mathrm{d}}{\mathrm{d}\tau}\Psi\big(\tau, m^*(\tau)\big) = \frac{\partial \Psi}{\partial \tau}\big(\tau, m^*(\tau)\big) + \frac{\partial \Psi}{\partial m}\big(\tau, m^*(\tau)\big) \cdot \frac{\partial m^*(\tau)}{\partial \tau}.$$

But by the first-order condition at the optimum $m^*(\tau)$, we have $\frac{\partial \Psi}{\partial m}\big(\tau, m^*(\tau)\big) = 0$.

the sensitivity of user cost to tax policy. This has immediate implications for evaluating investment incentives. Consider bonus depreciation, which effectively lowers z (the present value of depreciation allowances). In the benchmark model, this directly reduces user cost one-for-one through the term $(1 - \tau z)$ in the denominator. With maintenance, however, two offsetting forces arise. First, only the non-maintenance share of user cost actually responds to changes in z, scaling down the effect by $(1 - s_m)$. Second, as bonus makes investment relatively cheaper, firms reallocate spending away from maintenance, raising $\delta(m)$ and partially offsetting the initial user cost reduction. Together, these forces imply that the user cost elasticity with respect to bonus is considerably smaller than the benchmark model predicts.

The attenuated user cost elasticity in Proposition 2 maps directly to the key macro aggregates. As established in Equation (17), the elasticities of capital, output, and wages are all directly proportional to the user cost elasticity. It therefore immediately follows that these macro elasticities are also strictly smaller. Let s_m denote the maintenance share of user cost.

Corollary 1. *The tax elasticities of capital, output, and wages are strictly smaller in the maintenance model than in the benchmark model. In fact, the tax elasticities are marked down exactly by the maintenance share of user cost to first order. For any variable X, the tax elasticity is marked down by*

$$\varepsilon_X^{NGMM} = (1 - s_m)\varepsilon_X^{NGM}.$$

The proportional markdown in Corollary 1 provides a simple calibration device. In typical applications, the capital share $\alpha \approx 0.375$ (Barro and Furman 2018), implying $\alpha/(1 - \alpha) \approx 0.6$. This means the tax elasticity of wages and output is approximately 0.6 times the user cost elasticity in the benchmark model. If $s_m = 0.5$, the maintenance channel scales this down to $0.6 \times 0.5 = 0.3$. Observationally, this is equivalent to reducing the capital share from $\alpha = 0.375$ to $\alpha \approx 0.23$. Put differently, ignoring maintenance makes the economy appear twice as responsive to capital taxation as it actually is.

6.2 Implications for Measurement

A standard practice in the empirical investment literature is to infer capital elasticities directly from investment elasticities (Chodorow-Reich et al. 2025). In steady state with constant depreciation, $K = I/\delta$, so $\varepsilon_K = \varepsilon_I$. This identity justifies a common approach: estimate the causal effect of tax reform on investment using quasi-experimental variation, then translate that estimate directly into predictions for capital deepening, output growth, and wage increases. However, the maintenance margin breaks this mapping in two distinct ways. First, standard investment regressions are misspecified when they omit maintenance from user cost, understating the true investment elasticity. Second, even after correcting this omitted-variable bias, the investment and capital elasticities diverge when depreciation is endogenous. I address each problem in turn.

The first and most direct problem is that standard regressions are misspecified. The canonical investment regression estimates the causal effect of a change in the user cost of capital on some measure of investment:

$$f(I_{i,t}, K_{i,t-1}) = \beta \times g(\text{UCC}_{i,t}) + X_{i,t} + u_{i,t},$$

where $f(\cdot)$ and $g(\cdot)$ are transformations of investment and the user cost of capital, respectively, and $X_{i,t}$ is a vector of controls. Under standard mappings from investment to capital, and capital to other aggregates, a causal estimate of the tax elasticity of investment β is highly informative about the success of the reform.[15] Such regressions are misspecified if they omit the maintenance margin from user cost.

Corollary 2 (Omitted-Variable Bias in Standard Investment Regressions)**.** *Suppose the econometrician regresses investment on the user cost of capital but excludes maintenance. If maintenance demand is positive and elastic, the coefficient on user cost is biased downward. With constant-elasticity depreciation, a closed form exists and is given by*

$$\beta \approx \frac{\hat{\beta}}{1 - \frac{\gamma}{r^k + \delta_0 + \frac{\gamma}{1-\omega}}}, \tag{20}$$

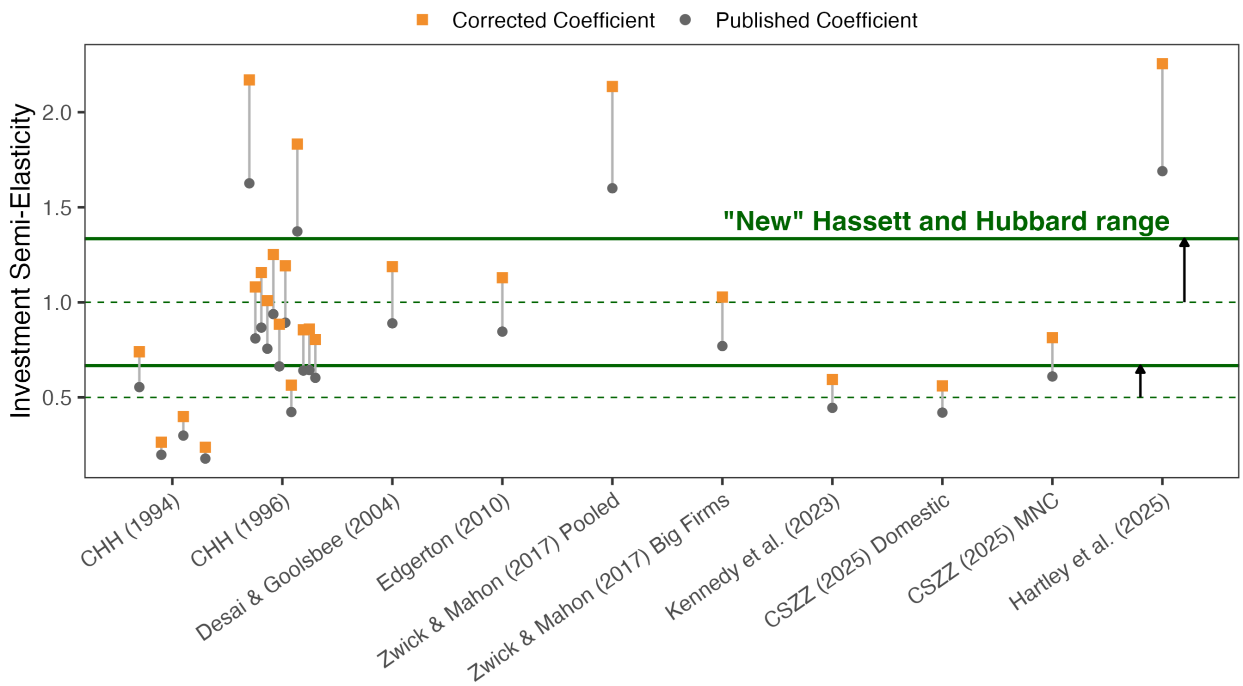
where β is the true investment elasticity. Proof: Appendix D.3.

Corollary 2 shows that, whenever maintenance demand is positive, standard regressions of investment on the textbook cost of capital understate the true gross investment response to tax changes. Thus, using observed investment responses to back out the aggregate effects of tax reforms is fundamentally misleading unless one also models maintenance behavior. Using the empirically estimated maintenance demand function, Figure 10 applies Corollary 2 to a broad swathe of studies from the investment literature. In general, the corrected estimates are about 35% larger than the published estimates. The lines in green plot what Hassett and Hubbard (2002) refer to as the "consensus range" for estimates in the literature; my correction similarly pushes the range upward.[16]

15. See, Cummins, Hassett, and Hubbard (1996), Desai and Goolsbee (2004), Edgerton (2010), and Hartley, Hassett, and Rauh (2025) for examples of this, among many others.

16. Note that as Chodorow-Reich (2025) argues, the coefficients in the figure are *not* investment elasticities.

Figure 10: Corrected Investment Coefficients from the Literature



Notes: This figure applies Corollary 2 to studies from the literature using the empirical maintenance demand function estimated in Section 5.2. I take most estimates in this figure from Chodorow-Reich, Zidar, and Zwick (2024). Note that CHH1994 stands for Cummins, Hassett, and Hubbard (1994), and similarly for the 1996 citation. CSZZ2025 stands for Chodorow-Reich et al. (2025). The correction factor is approximately 1.35.

The OVB correction, however, only fixes the *level* of the elasticity estimate. It does not address a second, deeper theoretical problem: even after correction, the tax elasticity of investment is not the same as the elasticity of capital if maintenance demand is elastic.

Corollary 3 (Investment-Capital Elasticity Gap)**.** *We can explicitly define steady-state investment in terms of tax rates as*

$$I(\tau) = \delta\left(m(\tau)\right) \times K\left(\tau, \delta(m(\tau)), m(\tau)\right),$$

from which it follows that

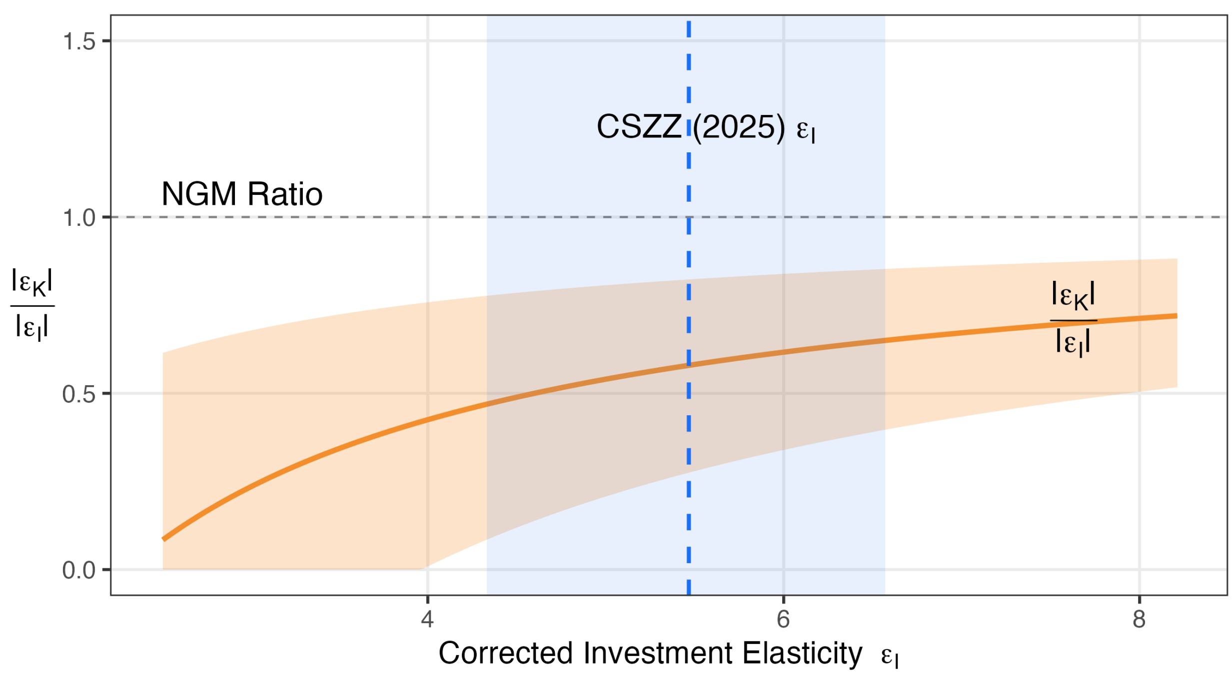
$$\varepsilon_I \approx \varepsilon_\delta + \varepsilon_K. \tag{21}$$

Corollary 3 establishes that the canonical neoclassical identity $\varepsilon_I = \varepsilon_K$ only holds when the tax elasticity of depreciation is zero. This requires either $\omega = 0$ (perfectly inelastic maintenance demand) or $\gamma = 0$ (no maintenance). The empirical estimates from Section 5 decisively reject both knife-edge cases. With $\omega \approx 3$ and positive maintenance intensity, depreciation rises substantially following tax cuts that make investment relatively cheaper. This creates a wedge: investment must rise more than capital to offset both the initial capital stock expansion and the induced increase in depreciation.

The intuition is straightforward. In the benchmark model with fixed depreciation, a 10% increase in the capital stock requires a 10% increase in investment to maintain the new steady state. With endogenous depreciation, a tax cut that raises capital by 10% also raises depreciation by, say, 5% (depending on ω and s_m). Investment must therefore rise by 15% to supply the additional capital and offset the faster depreciation. The investment response overstates the capital response.

Figure 11 visualizes the investment-capital elasticity gap, plotting the ratio $|\varepsilon_K|/|\varepsilon_I|$ as a function of the corrected investment elasticity. The orange curve shows the ratio using the estimated maintenance demand function; the shaded band is the 95% confidence interval incorporating parameter uncertainty from both ω and γ. The horizontal dashed line at one represents the benchmark model where $\varepsilon_I = \varepsilon_K$. The vertical dashed line shows a recent estimate of the tax elasticity of investment from Chodorow-Reich et al. (2025), corrected for omitted maintenance using Corollary 2.

Figure 11: Corrected Capital-Investment Elasticity Ratio



Notes: Using the first-order approximation to the tax elasticity of depreciation (Appendix D.2), this figure plots the corrected ratio of capital to investment elasticities along with a 95% confidence interval in orange. The vertical dashed line is an estimate of the tax elasticity of capital from Chodorow-Reich et al. (2025) corrected for maintenance using Corollary 2. The horizontal dashed line at one denotes the implied long-run ratio from standard investment models.

Three features stand out. First, the ratio is substantially below one across the entire plausible range of investment elasticities, confirming that the theoretical divergence is empirically large. Second, at the Chodorow-Reich et al. (2025) corrected investment elasticity, the implied capital elasticity is only about 60-65% as large. Third, the confidence band is fairly tight, indicating the gap is precisely estimated despite parameter uncertainty.

This has immediate implications for policy evaluation and scoring. When researchers estimate an investment elasticity and translate it directly into capital effects, they implicitly assume $\varepsilon_K = \varepsilon_I$. Figure 11 shows this assumption overstates capital responses by roughly 35-40%. Since output and wages are proportional to capital in the Cobb-Douglas case, the implied effects on aggregate income and labor earnings are similarly overstated. A reform that appears to boost long-run output by 3% in a benchmark model may actually boost output by only 2% once endogenous depreciation is accounted for.

Remark (Permanent Lift in the Investment Rate). In steady state $I/K = \delta(m)$. Since m falls when the after-tax price of new capital declines ($\partial m/\partial(1-\tau) < 0$), a tax cut raises $\delta(m)$. The result is a permanently higher gross investment rate and hence a younger average capital stock. Benchmark models with fixed depreciation cannot capture this vintage-age effect.[17]

Consider the neoclassical model as a contrast. There, the tax elasticity of investment is a sufficient statistic for partial equilibrium changes in capital and output because in steady state, $I = \delta K$. Hence the tax elasticities of investment and capital coincide, $\varepsilon_I = \varepsilon_K$. This one-for-one mapping is what allows the empirical literature—from the classic Hall-Jorgenson regressions to recent quasi-experiments such as from Zwick and Mahon (2017)—to translate an estimated "investment elasticity" directly into partial equilibrium predictions for capital deepening and output. The maintenance margin introduced next breaks that identity, enlarging the investment response but dampening the capital response, and therefore compels a re-examination of those standard empirical inferences.

Convergence and Scoring in the NGMM. The divergence between investment and capital elasticities has a further implication for dynamics. Because depreciation rises endogenously, the net capital accumulation from any given investment surge is smaller than in the benchmark model. Reconciling a large gross investment response with a dampened net capital response requires steeper adjustment costs.

17. Firms typically have an additional scrappage margin for adjustment, which is empirically important in the context of tax reform (Goolsbee 1998b). That is implicitly accounted for here by the fact that tax cuts stimulate firms to invest at a higher rate and shed old capital more quickly through higher depreciation. A vintage model would show this more explicitly, but the scrappage channel is captured by endogenous depreciation through elastic maintenance demand. In some sense, the demand elasticity for maintenance may be interpreted as a reduced form tax elasticity for the age distribution of capital. This would speak directly to the indirect evidence in Goolsbee (2004) that lower taxes induce firms to buy capital with lower maintenance costs.

The observed investment surge $\hat{\varepsilon}_I$ has two components: expansion of the capital stock *and* replacement of capital that now wears out faster. The net impulse pushing the capital stock equals $|\hat{\varepsilon}_I| - |\hat{\varepsilon}_\delta|$ after the depreciation drag is removed. To rationalize a large gross response driven by a smaller net force, the model must assume steeper adjustment frictions.

I formalize this using the quadratic capital adjustment cost specification standard in the tax literature (Summers 1981; Koby and Wolf 2020; Chodorow-Reich et al. 2025). Suppose we observe a tax elasticity of investment $\hat{\varepsilon}_I$. In the NGM, this implies an adjustment cost parameter $\phi_{\text{NGM}} = \frac{1}{\delta}|\hat{\varepsilon}_I|^{-1}$. In the NGMM, the implied adjustment cost parameter is:

$$\phi_{\text{NGMM}} \approx \frac{1}{\delta(m)} \frac{1}{|\hat{\varepsilon}_I| - |\hat{\varepsilon}_\delta|}. \tag{22}$$

See Appendix D.4 for the full derivation. Since $|\hat{\varepsilon}_\delta| > 0$, we have $\phi_{\text{NGMM}} > \phi_{\text{NGM}}$, implying slower convergence to steady state.

Slower convergence to a smaller steady state has direct implications for scoring tax reform. By statute, the Congressional Budget Office (CBO) scores tax reforms over ten-year windows, computing both a static score (assuming no behavioral changes) and a dynamic score (accounting for revenue feedback from growth effects). Since model convergence typically takes far longer than ten years, the transition path critically affects dynamic scores.

Corollary 4 (Dynamic Scoring in the NGMM)**.** *Consider a permanent tax cut scored over a ten-year window. Because the NGMM features slower convergence and a smaller steady-state capital stock than the NGM, the NGMM generates strictly less additional output and tax revenue over the scoring window. The dynamic score is therefore closer to the static score.*

This establishes that the maintenance channel substantially reduces estimated revenue feedback from investment incentives. Although economists emphasize the importance of dynamic scoring (Barro and Furman 2018; Elmendorf, Hubbard, and Williams 2024), incorporating the maintenance margin produces revenue projections closer to static scoring.

The theoretical results in this section establish that standard approaches systematically overstate policy effectiveness: investment regressions suffer from omitted-variable bias, corrected investment elasticities still overstate capital responses, and slower convergence reduces revenue feedback. To quantify these biases in a specific policy context, I now turn to a calibrated simulation of the 2017 Tax Cuts and Jobs Act.

7 Capital Maintenance and the 2017 Tax Cuts and Jobs Act

Theory has two key implications for the economics of capital maintenance, along with an implication for dynamic scoring of tax reform. First, when maintenance demand is positive, the resulting steady state capital, output, and wages are strictly smaller than predicted by an otherwise identical model without maintenance. Second the convergence rate is strictly smaller. Together, these imply that dynamic scores of tax reforms are closer to the conventional score than commonly understood. In this section, I illustrate the quantitative importance of each implication using the 2017 Tax Cuts and Jobs Act.

7.1 Model and Calibration

At its heart, the model is the same as in Section 3. Time is discrete and infinite. There are three sectors which produce output: corporate, non-corporate, and the government. The representative firm in each sector $i = c, nc$ produces a final output good $Y_{i,t}$ with identical Cobb-Douglas technology and discounts the future at rate r^k. The capital and labor inputs have respective shares α_K and α_L with $\alpha_K + \alpha_L \leq 1$. Aggregate output is given by

$$Y_t = \sum_{i \in \{c,nc,g\}} Y_{i,t}.$$

I normalize corporate productivity to one and discuss the calibration of non-corporate productivity below. To facilitate comparison with Chodorow-Reich et al. (2025), I use their calibrations of the discount rate, the capital share, and the labor share. To capture general equilibrium effects, one unit of inelastically supplied labor is allocated across sectors such that wages are equal between them.

Toward showing the distinction between the neoclassical growth model with maintenance (NGMM) and the standard neoclassical model (NGM), I set up two different laws of motion for capital and set the corresponding parameters such that both models start from the same steady state capital-labor ratio within each sector and the same initial divison of capital between sectors. Capital evolves according to (2) in the NGMM, while it has constant depreciation δ in the NGM. Initially, I assume there is no curvature in the supply curves of either maintenance or investment, which I relax later on. As a result, the maintenance intensity in the NGMM is driven solely by the tax wedge. To capture dynamics, both the NGM and the NGMM variants have capital adjustment costs paid in tax-deductible units of labor

$$\Phi(M_t, I_t, K_t) = \frac{\phi}{2}\left(\frac{I_t}{K_t} - \delta(m_t)\right)^2 K_t. \tag{23}$$

In the NGM variant, $\delta(m_t) = \delta$ since $m_t = 0$.[18] To get a fair comparison between the two models, some of the parameters—like ϕ—differ. I describe how subsequently.

NGMM Calibration. I calibrate (23) using the formula in (22) and use a constant-elasticity depreciation technology. The maintenance demand function estimate from Section 5.2 along with the initial tax rates pin down a point estimate for $\hat{m}$. To account for uncertainty, I use the demand function's variance-covariance matrix to take 5000 draws for ω and γ jointly. Next, for each draw, I set δ_0 and non-corporate productivity A_{nc} to jointly match the ratio of corporate to total capital of $K_c/K = 0.7$ and such that the NGMM's initial ratio of gross investment to private output equals 0.109, which is the pre-TCJA average physical investment rate in the National Income and Product Accounts.[19] The ratio of corporate to total capital comes from Chodorow-Reich et al. (2025). With those parameters, I apply first-order approximation to the tax elasticity of depreciation derived in Appendix D.2 to get $\hat{\varepsilon}_\delta$. Finally, to get $\hat{\varepsilon}_I$, I take the investment elasticity from Table 3, Column 3, Row 1 of Chodorow-Reich et al. (2025). I assume no covariance between the maintenance demand and investment demand elasticities and therefore propagate uncertainty about the elasticity estimate using the standard error estimates from Chodorow-Reich et al. (2025) by again taking 5000 draws. For every draw, I adjust the elasticity upward using Corollary 2. Putting those three ingredients together yields ϕ_{NGMM}. The resulting calibration implies a maintenance share of user cost $s_m \approx 0.22$ in the initial steady state, consistent with the SOI data shown in Figure 1 and the theoretical prediction that steady-state outcomes are marked down by approximately $(1 - s_m)$.

NGM Calibration. As a benchmark, I calibrate an otherwise identical model except that maintenance demand is inelastically zero. This entails two calibration changes. First, I set the constant depreciation rate δ such that the NGMM and the NGM have the same initial steady state capital-labor ratio in both sectors and the divison of capital between them is the same. Second, given that depreciation rate, I calculate ϕ_{NGM} using the unadjusted tax elasticity of investment from Chodorow-Reich et al. (2025). The idea is to calibrate adjustment costs as if the NGM is true, rather than adjust upwards as if the NGMM is correct. This yields a conservative difference in convergence rates.

Policy Reform. I set pre- and post-TCJA tax rates for both sectors following Chodorow-Reich et al. (2025). Following their approach, I assume that bonus depreciation is permanent and that the non-corporate sector did not see a change in marginal tax rates.[20] Given the reform, I compute

18. Note that this version of adjustment costs implies that maintenance instantaneously adjusts. I rely on capital adjustment costs because it allows for an easier comparison with Chodorow-Reich et al. (2025), which uses the same specification.

19. In particular, I divide the sum of non-residential investment in equipment and structures by gross domestic product less government expenditures in NIPA Table 1.1.5.

20. This is not actually what happened during TCJA because bonus was not permanent and the non-corporate

aggregate output growth by calculating

$$\frac{\Delta Y_{0,t}}{Y_0} = \sum_{i \in \{c,nc,g\}} c_i \frac{\Delta Y_{i,0,t}}{Y_{i,0}},$$

where c_i is the sectoral weight for corporates (c), noncorporates (nc), and government, respectively, and $\Delta Y_{i,0,t}/Y_{i,0}$ is the cumulative growth from year zero to t.

I propagate uncertainty from two sources: the maintenance demand function (via the variance-covariance matrix from Section 5) and capital adjustment costs. I hold all other parameters fixed, including the discount rate, capital share, labor share, and sectoral productivity levels. This approach differs from Chodorow-Reich et al. (2025), who show that propagating uncertainty across all structural parameters produces wide confidence intervals. I adopt the narrower approach for two reasons. First, it isolates uncertainty specifically attributable to the maintenance channel, which is the paper's focus. Second, it facilitates direct comparison: the NGM results exactly replicate Chodorow-Reich et al. when uncertainty is limited to adjustment costs alone. The trade-off is that the reported confidence intervals understate total uncertainty about TCJA's effects and should be interpreted as conditional on the broader calibration.

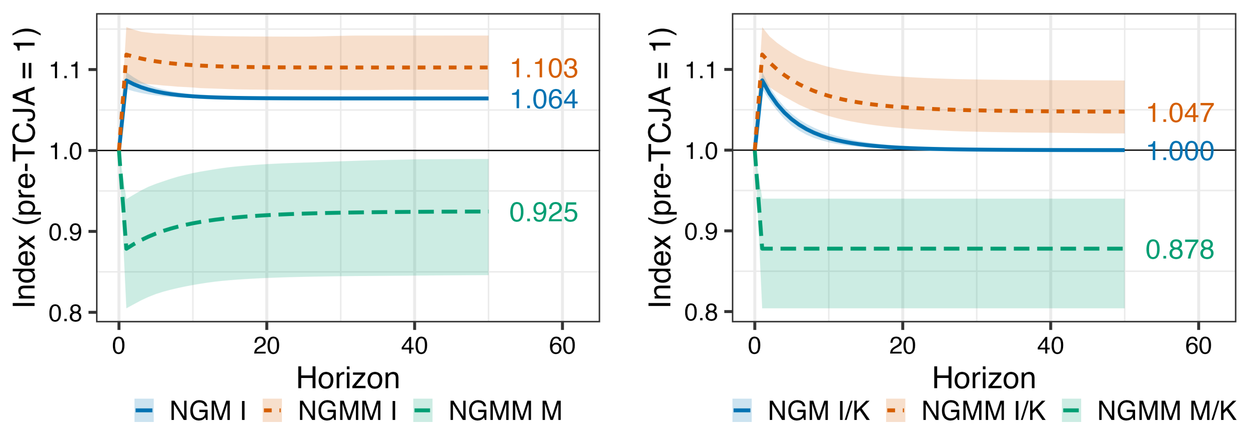
7.2 Aggregate Effects of TCJA

The Tax Cuts and Jobs Act cut capital taxes for corporations by around 3.4% on average. Figure 12 plots how that caused the *inputs* to capital to evolve following TCJA, along with 95% confidence intervals. The left panel plots the path of maintenance and investment in levels for both the NGM and the NGMM. In the NGM, investment rose by 6.4%, while it rose by 10.3% in the NGMM. This larger gross investment response reflects Corollary 3: standard regressions understate the true investment elasticity when maintenance is omitted from user cost. However, the larger investment response does not translate into proportionally larger capital accumulation. The decline in maintenance raises depreciation, so more of the gross investment flows toward replacement rather than expansion of the net capital stock. The right panel plots investment and maintenance as rates relative to capital. The key distinction between models is that the NGMM investment rate rises permanently—from the pre-TCJA baseline to 4.7% above–to offset the permanently lower maintenance rate. In contrast, the NGM investment rate increase is temporary, converging back toward the baseline as the capital stock adjusts. This reflects the theoretical result that endoge-

sector saw several large tax reductions. The goal is to demonstrate the aggregate effects of maintenance accounting rather than give a complete score for TCJA, and Chodorow-Reich et al. (2025) is the seminal aggregate analysis, so one can see the quantitative exercise as a comparison to their work rather than a complete description of TCJA. Given that, the magnitude of the pre- and post-TCJA tax rates for the corporate sector come from a capital-weighted average of the domestic block in Table E.10 of the same paper.

nous depreciation generates a permanent lift in the gross investment rate and a younger average capital stock.

Figure 12: The Effect of TCJA on Capital Inputs in the NGM and the NGMM



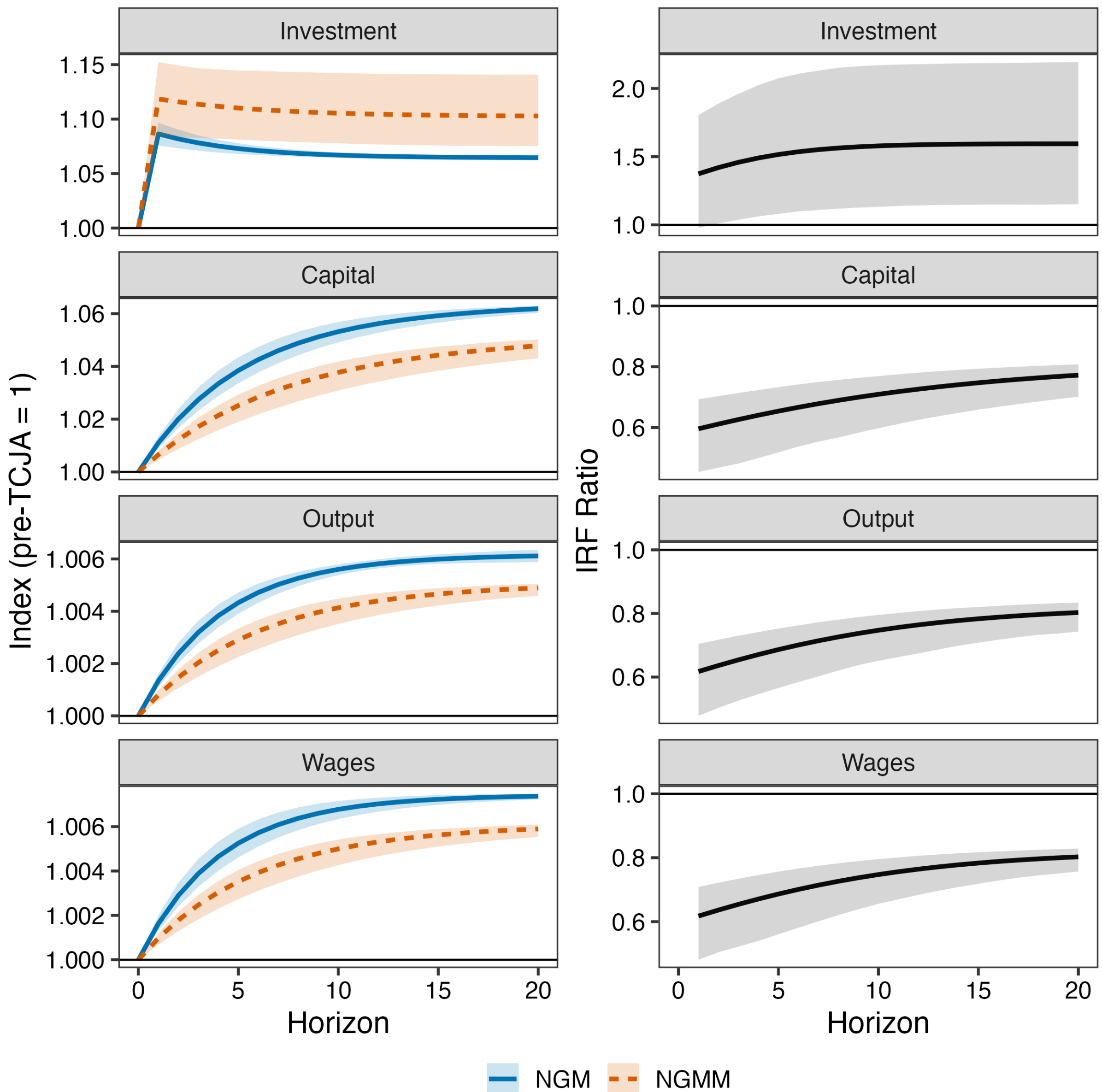
(a) Investment and Maintenance Levels

(b) Investment and Maintenance Rates

Notes: Panel (a) shows the response of domestic corporate investment and maintenance to TCJA in the NGMM (orange line with 95% CI) and the NGM (blue line). Panel (b) corresponding change in the maintenance and investment rates.

Figure 13 plots the aggregate effects of TCJA on investment, capital, output, and wages. The left panels display the path of each variable under both models with 95% confidence intervals; the right panels plot the ratio of NGMM to NGM responses. The figure quantitatively confirms the theoretical predictions from Section 6 in three ways. First, steady-state effects on capital, output, and wages are approximately 80% as large in the NGMM as in the NGM, with right-panel ratios converging to roughly 0.75-0.80 for all three variables. This validates Corollary 1. Second, the investment and capital responses diverge sharply in the NGMM, validating Corollary 3. In the NGM, both investment and capital rise by 6.4% in steady state, which replicates Chodorow-Reich et al. (2025). In the NGMM, investment rises by 10.3% while capital rises by only 2/3 that quantity, reflecting that gross investment must rise substantially to offset both capital expansion and faster replacement from reduced maintenance. Thus, the investment response visible to an econometrician substantially overstates the capital response relevant for output and wages. Third, convergence is markedly slower in the NGMM, validating Corollary 4. At the ten-year horizon, which is the statutory scoring window, the NGMM capital stock has reached only about 75% of the steady-state change, compared to roughly 85% in the NGM. This slower convergence reflects the higher implied adjustment costs ($\phi_{NGMM} > \phi_{NGM}$) required to reconcile the observed large gross investment response with a smaller net capital impulse after accounting for the depreciation drag.

Figure 13: The Effect of TCJA on Aggregate Outcomes



Notes: The left panel shows the response of aggregate variables to the TCJA in the NGMM (orange line) and the NGM (blue line). The right panel plots the ratio of IRFs. All lines are bootstrapped with a 95% confidence interval.

Together, these patterns illustrate that the maintenance channel operates through all three theoretical mechanisms identified in Section 6: the capital preservation effect dampens steady-state responses, the investment-capital elasticity gap means gross investment overstates capital accumulation, and slower convergence reduces growth along the transition path. The combination substantially alters the quantitative assessment of TCJA's macroeconomic effects.

7.3 Scoring TCJA

The quantitative difference in convergence rates between the NGMM and the NGM is materially important for the debate over how to score tax reform. Government bodies like the Congressional Budget Office and the Joint Committee on Taxation typically publish the budgetary and macroeconomic effects of tax reform at a ten-year horizon. Such "scores" are often static: they do not account for the changes in behavior engendered by the reform. For example, the static TCJA score would not account for the extra capital—and hence, extra output—resulting from the drop in the marginal effective tax rate on capital. By contrast, a "dynamic" score would account for the extra output resulting from behavioral changes.[21] Like static scores, dynamic scores are given for a ten-year window. As a result, the relevant metric for evaluating a reform is not the steady-state effects—which may take decades to reach—but the ten- or twenty-year marks along the convergence path.

Dynamic scores are only different from static scores to the extent that growth occurs. Since NGMM growth is minimal over the first ten years, the dynamic score is comparatively closer to the static score than in the NGM. To score the reform, I follow Barro and Furman (2018). For both the NGM and the NGMM, I adjust the Congressional Budget Office's (CBO) static output projections by feeding in a model-implid growth path. Taking as given the corporate revenue share of output projected by the CBO, the extra output generates additional tax revenue. I assess the contribution of each model by dividing the ten-year static cost of the bill by the amount of extra revenue generated through accounting for dynamic effects. The resulting figure is the percent of the bill's cost offset by extra revenue through additional output. If, for example, the dynamic offset is 100%, then the bill pays for itself. The results are in Table 1. Evidently, the bill does not pay for itself. In the NGM, about 7.5% of the static cost is offset by higher GDP, whereas the maintenance model offsets 5% of the static cost.

Given how little of the static cost is offset by either model—7.5% in the NGM and 5% in the NGMM—one interpretation is that investment-driven growth effects provide minimal self-financing for capital tax cuts, whether or not endogenous depreciation is accounted for. The maintenance channel reduces an already-small revenue feedback by approximately one-third. This does not render dynamic scoring irrelevant: dynamic scores inform distributional analysis, validate theoretical mechanisms, and guide timing of fiscal effects. However, it does suggest that for reforms primarily targeting investment incentives, the growth-induced revenue feedback may be too small to substantially alter fiscal projections. The maintenance channel makes this feedback even smaller.[22]

21. See Elmendorf, Hubbard, and Williams (2024) for a discussion of the debate over when and how to dynamically score tax reforms, among other types of legislation.

22. Nevertheless, the scoring exercise is not meant to score the tax reform in its entirety. I only look at the domestic

Table 1: Ten-Year Corporate Capital, Aggregate Output, and Scores

		$\Delta K_c/K_c$ (%)		$\Delta Y/Y$		Static-Score Offset	
		10Y	Ratio	10Y	Ratio	10Y	Ratio
GE	NGM	5.5	-	0.56	-	7.5	-
	NGMM	3.9	0.71	0.41	0.73	5.0	0.67
	NGMMP	4.1	0.75	0.44	0.79	5.3	0.71
GE w/CO	NGM	4.2	-	0.33	-	4.3	-
	NGMM	2.8	0.67	0.21	0.64	2.4	0.55
	NGMMP	2.9	0.69	0.22	0.67	2.6	0.60
PE	NGM	9.3	-	3.4	-	63.9	-
	NGM	7.0	0.75	2.5	0.74	38.6	0.60
PE w/CO	NGM	7.6	-	2.8	-	46.9	-
	NGM	5.2	0.73	1.9	0.71	26.4	0.56

Notes: Within each panel, the ratio is relative to the corresponding NGM model. The NGMMP denotes the model closure in which labor costs make up half of maintenance costs, so tax cuts induce a rise in the relative price of maintenance beyond that implied by the tax cut.

Table 1 presents ten-year outcomes for corporate capital accumulation, aggregate output growth, and the static-score offset, which is the percent of the reform's fiscal cost recovered through additional tax revenues from higher GDP.

Baseline Results (GE). In the baseline general equilibrium model, the NGM predicts corporate capital rises by 5.5% and aggregate output by 0.56% over ten years, offsetting 7.5% of the static cost through additional revenues. The NGMM predicts capital rises by 3.9% and output by 0.41%, offsetting only 5% of the static cost. The ratios are remarkably stable across all outcomes: NGMM responses are approximately 67-73% as large as NGM responses. This consistency reflects the theoretical structure: the maintenance share marks down all aggregates proportionally through the capital preservation effect, and slower convergence uniformly dampens all transition paths.

corporate tax and investment provisions, whereas other margins may be important. The static score for permanent bonus comes from Barro and Furman (2018).

Endogenous Maintenance Prices (NGMMP). The second row within each panel explores whether allowing the pre-tax price of maintenance to rise with wages—as discussed in Section 5.3—materially affects results. I assume labor comprises half of maintenance costs and compute the induced wage increase from the model's output expansion. Because maintenance has decreasing returns, the marginal reduction in maintenance costs more than offsets the increase in depreciation, but the quantitative difference from the baseline NGMM is minimal: the ratio of NGMM to NGM responses increases only from 0.67-0.73 to 0.69-0.79. This insensitivity confirms that wage endogeneity, while theoretically important for interpreting elasticity estimates, has limited quantitative impact on policy counterfactuals given the estimated parameter values.

Crowding Out (GE w/CO). The second panel incorporates fiscal crowding out. For each model, I compute the 2027 debt-GDP ratio implied by the TCJA's fiscal cost and the endogenous revenue feedback, then use Neveu and Schafer (2024) to calculate the increase in real interest rates from higher government debt. Higher interest rates reduce private investment, dampening capital accumulation. Crowding out affects both models, but exacerbates the difference between them: the NGMM offset falls to only 2.4% (compared to 5% without crowding out), while the NGM falls to 4.3% (compared to 7.5%). The larger proportional reduction in the NGMM reflects its slower initial growth: because the NGMM accumulates capital more gradually, it accumulates more debt over the ten-year window, generating larger crowding-out effects. The ratio of NGMM to NGM responses falls from 0.67-0.73 in the baseline to 0.55-0.67 with crowding out. Starting from a $17T baseline, the predicted difference in corporate capital between the NGMM and the NGM is about $240 billion.

Partial Equilibrium (PE). The final two panels assume perfectly elastic labor supply, removing general equilibrium wage effects. As expected, aggregate outcomes are substantially larger in this setting—the NGM offset rises to 63.9% without crowding out—but the ratio of NGMM to NGM responses remains similar, ranging from 0.60 to 0.75. This stability across closures reinforces that the maintenance channel operates primarily through the capital preservation effect (marking down steady states) and the depreciation drag (slowing convergence), both of which persist regardless of whether labor supply is elastic or inelastic.

Altogether, the results suggest that the maintenance channel is quantitatively important for analyzing the consequences of capital tax policy for capital accumulation, and hence for wages, productivity, and output. Although the NGM replicate those from Chodorow-Reich et al. (2025)—and therefore the haircuts I obtain apply to their results—the results extend to a broad array of models. In richer settings, the general equilibrium increase in domestic corporate capital accumulation is similarly large to the NGM and the channel is largely the same: capital accumulation via user cost reductions (Sedlacek and Sterk 2019; Zeida 2022). Maintenance may interact with capital in different ways in richer settings with more frictions, but fundamentally, the lesson for tax models of all kinds is simply that maintenance acts as a powerful dampening force regardless of frictions.

8 Concluding Remarks

In this paper, I establish that capital maintenance is a first-order margin for understanding how investment incentives transmit to aggregate outcomes. I provide a parsimonious and flexible framework for evaluating the consequences on the short-run and long-run impacts on allocations of maintenance, investment, and capital. Additionally, I construct an entirely new dataset on the maintenance and investment behavior of Class I freight railroads using financial filings from the Surface Transportation Board. Together with maintenance data from corporate tax returns, the evidence indicates that maintenance demand is large and elastic, with quantitatively large implications for tax reforms. Using a calibrated model of the 2017 Tax Cuts and Jobs Act, I show that accounting for maintenance reduces the ten-year capital, output, and revenue effects by approximately 25-30% relative to standard models.

The findings fundamentally revise how we interpret the empirical investment literature. Standard regressions understate investment elasticities by roughly 35% due to omitted-variable bias when maintenance is excluded from user cost (Corollary 2). However, even after correcting for this bias, the investment elasticity substantially overstates the capital elasticity when depreciation is endogenous (Corollary 3). The result is that studies estimating large investment responses to tax policy are correctly measuring gross investment but misinterpreting it as a one-for-one mapping into capital accumulation. The wedge between gross investment and net capital growth, driven by endogenous depreciation through the maintenance margin, is economically large and alters the quantitative assessment of policy effectiveness. These findings extend beyond the TCJA to any investment incentive that changes the relative price of new capital versus maintenance, including bonus depreciation, accelerated depreciation schedules, and corporate rate reductions across countries and time periods. 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 begin accounting for maintenance is too big to ignore.

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Appendices

A Institutional Background **51**

B Data **53**

B.1 R-1 Data Construction 53

B.2 SOI Data Construction 61

C Empirical Robustness and Identification Details **71**

C.1 R-1 Estimates 71

C.2 SOI Robustness Checks 78

C.3 Meta-Analysis Details 81

D Derivations for the Main Model **83**

D.1 Tax Elasticity of User Cost 83

D.2 The Tax Elasticity of Investment 84

D.3 Omitted Variable Bias in Investment Regressions 86

D.4 Adjustment Costs 88

D.5 Stability Under Cobb-Douglas Production 90

E Quantification **93**

F Model Extensions **95**

F.1 Capital Reallocation 95

F.2 Extension to Multiple Maintenance Inputs 99

G Additional Figures and Tables **101**

A Institutional Background

Once classified as an expenditure that must be capitalized, assets are slotted into one of eight lives under rules governed by the Modified Asset Cost Recovery System (MACRS)—three, five, seven, ten, fifteen, twenty, 27.5, or 39 years—which govern how quickly they may be depreciated; shorter class lives yield faster deductions and larger present-value tax benefits. Given a class life of T years and a discount rate r^k, the net present value of a dollar of deductions for a capital investment is

$$z = \sum_{t=0}^{T} \left(\frac{1}{1 + r^k} \right)^t d_t,$$

where d_t is the allowable deduction by the IRS in period t. Table A.1 shows typical assets and associated present value of deductions z for each class category, and Table A.2 works out the year-by-year tax consequences of spending a marginal dollar investing in a new seven-year asset versus maintaining an existing one.

Table A.1: MACRS Asset Lives and NPV of Depreciation Allowances z at a 6% discount rate

MACRS Asset Life (Years)	**Representative Examples**	z
3	Racehorses; special tools	0.9467
5	Automobiles; computers; office machinery	0.9038
7	Furniture; fixtures; general-purpose equipment; locomotives[23]	0.8645
10	Appliances; vessels; barges	0.8108
15	Land improvements; sewage treatment facilities; telephone poles	0.6942
20	Farm buildings; municipal sewers	0.6219
27.5	Residential rental property	0.5001
39	Nonresidential real property (commercial buildings)	0.3958

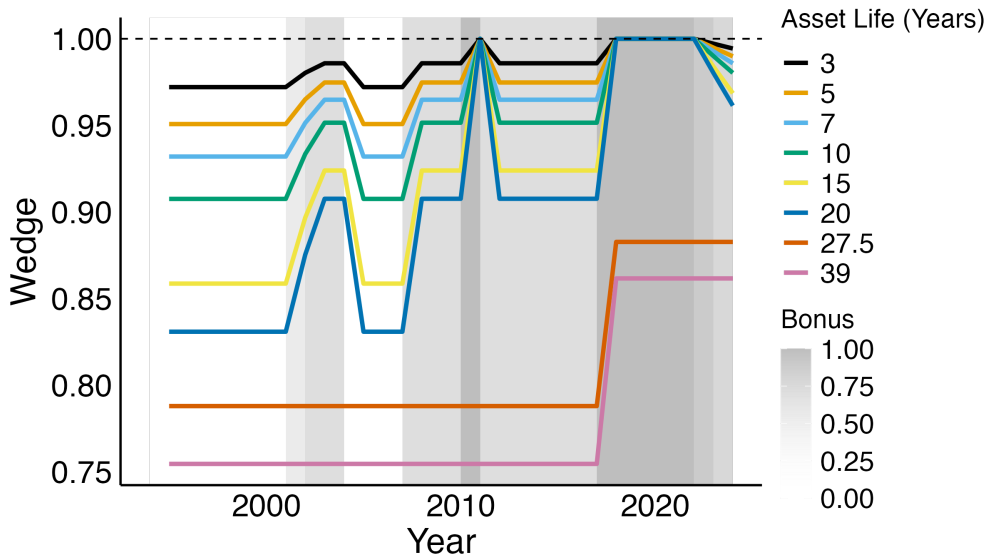
Table A.2: The Tax Treatment of Investment and Maintenance for a Seven-Year Asset

Year:	0	1	2	3	4	5	6	7	Total	z
Investment										
Deductions (000s)	142.9	244.9	174.9	124.9	89.3	89.2	89.3	44.6	1,000	
Tax benefit (τ = 35%)	50.0	85.7	61.2	43.7	31.3	31.2	31.3	15.6	350	0.86
Tax Benefit (PV)	50.0	80.9	54.5	36.7	24.8	23.3	22.0	10.4	302.6	
Maintenance										
Deductions (000s)	1,000	0	0	0	0	0	0	0	1,000	
Tax benefit (τ = 35%)	350	0	0	0	0	0	0	0	350	1.00
Tax Benefit (PV)	350	0	0	0	0	0	0	0	350	

Notes: This table adapts Table 1 from Zwick and Mahon (2017) to a seven-year MACRS schedule (8-year life with half-year convention and 200% declining balance until straightline becomes optimal). It includes year-by-year deductions, tax benefits, and present values using a 6% discount rate, and reports z, the PV factor per dollar of tax benefit.

Figure A.1 plots the wedge since 1995 for all MACRS assets. The wedge is largest for long-lived assets and with 100% bonus, the wedge vanishes for qualifying assets. Of course, some firms may elect not to claim bonus if they are not taxable because the deductions are worthless to them (Kitchen and Knittel 2011). Regardless, the wedge has varied considerably between asset types over time.

Figure A.1: The Maintenance-Investment Wedge for MACRS Assets



Notes: The wedge is defined in the main text as the ratio $(1 - \tau)/(1 - \tau\tilde{z})$, where $\tilde{z}$ is the net present value of depreciation allowances after accounting for bonus depreciation. I set the discount rate as $r = 0.06$.

B Data

B.1 R-1 Data Construction

Data Sources and Digitization

Class I freight railroads must file annual R-1 reports with the Surface Transportation Board (STB) under 49 CFR §1241. These reports follow the Uniform System of Accounts for Railroad Companies, which differs meaningfully from Generally Accepted Accounting Principles (GAAP). For example, railroads often use composite depreciation rates—group rates applied to classes of similar assets—which must be approved ex ante by the STB.

I hand-collected and digitized R-1 reports for all Class I railroads from 1999-2023. Reports are available directly from the STB website for years after 2012. For earlier years (1999-2011), I used Amazon Textract to extract the relevant data from PDF scans of physical filings. Each report is independently audited by major accounting firms (e.g., KPMG, PwC, Deloitte) and then reviewed by the STB, providing high data quality.

The reports contain dozens of detailed schedules. For this paper, I extract data from:

- **Schedule 410:** All components of maintenance expenditures come from Line 202 (Locomotives) and Line 221 (Freight Cars). This schedule also breaks down maintenance costs by materials, labor, and purchased services.

- **Schedules 330 and 335:** Investment expenditures and capital stocks for locomotives and freight cars
- **Schedule 702:** Miles of track by state (used for constructing geographic exposure weights)
- **Schedule 710:** Detailed capital inventories by asset type
- **Wage Form A&B:** Hourly wage rates for maintenance workers by occupation and firm

Sample Construction

My sample includes seven Class I railroads:

1. Burlington Northern & Santa Fe Railway (BNSF)
2. CSX Transportation
3. Norfolk Southern Railway (NS)
4. Union Pacific Railroad (UP)
5. Kansas City Southern Railway (KCS)
6. Soo Line Railroad (SOO)
7. Grand Trunk Western Railroad (GT)

These firms are geographically dispersed. Burlington Northern and Union Pacific dominate the western United States, with extensive networks covering the Great Plains and West Coast. CSX and Norfolk Southern operate primarily on the eastern seaboard and in the South. The Soo Line, Kansas City Southern, and Grand Trunk (operated by Canadian National Railway) have networks concentrated in the Midwest, with Kansas City Southern also serving the Southwest and Mexico.

The industry was highly fragmented prior to the Staggers Rail Act of 1980, which deregulated much of the industry. Throughout the 1980s and 1990s, extensive consolidation occurred through mergers and acquisitions. By the late 1990s, the industry had stabilized into the current seven-firm structure. I begin my sample in 1999 because: (1) the industry structure was stable by then, (2) some data elements in Schedule 410 are unavailable or inconsistent before this period, and (3) maintenance behavior may differ systematically during periods of anticipated merger activity. I end the sample in 2023 because Canadian Pacific Railway formally took control of both the Soo

Line and Kansas City Southern by 2024, fundamentally altering the competitive structure. Including post-merger years would conflate firm-level maintenance decisions with merger-related reorganization.

Institutional Background: The R-1 Reporting Requirement. The R-1 reporting requirement originates from the Interstate Commerce Commission (ICC), the predecessor to the STB. Prior to the 1990s, the ICC extensively used R-1 reports to regulate rate-setting through cost-of-service regulation. While the STB still maintains regulatory oversight and occasionally intervenes in rate disputes, its role has diminished substantially since deregulation. The detailed reporting requirements remain in place primarily for regulatory monitoring and dispute resolution, though the data are rarely used for academic research.

Maintenance Rate Construction

The primary maintenance rate is:

$$m_{i,j,t} = \frac{\text{Maintenance Expenditures}_{i,j,t}}{\text{Beginning Book Capital}_{i,j,t}}, \tag{A.1}$$

where i indexes firms, j indexes asset types (locomotives or freight cars), and t indexes years.

Maintenance expenditures come directly from Schedule 410, Line 202 for locomotives and Line 221 for freight cars. These lines capture all repair and maintenance activities and are broken down into whether the expenditures were for labor, materials, or external services. Beginning book capital is the prior year's ending value from Schedules 330 and 335. This timing ensures maintenance in year t responds to the capital stock at the start of year t, consistent with the theoretical model. I construct three alternative measures to check robustness:

Physical Maintenance Rate. To control for inflation and asset quality changes, I construct:

$$m^{\text{phys}}_{i,j,t} = \begin{cases} \frac{\text{Maintenance Expenditures}_{i,j,t}}{\text{Total Horsepower}_{i,j,t}} & \text{if } j = \text{locomotives} \\ \frac{\text{Maintenance Expenditures}_{i,j,t}}{\text{Total Freight Ton Capacity}_{i,j,t}} & \text{if } j = \text{freight cars} \end{cases} \tag{A.2}$$

Horsepower and freight ton capacity come from Schedule 710, which reports quantities and physical characteristics of equipment.

Internal vs. External Maintenance. Schedule 410 breaks down maintenance costs into three components:

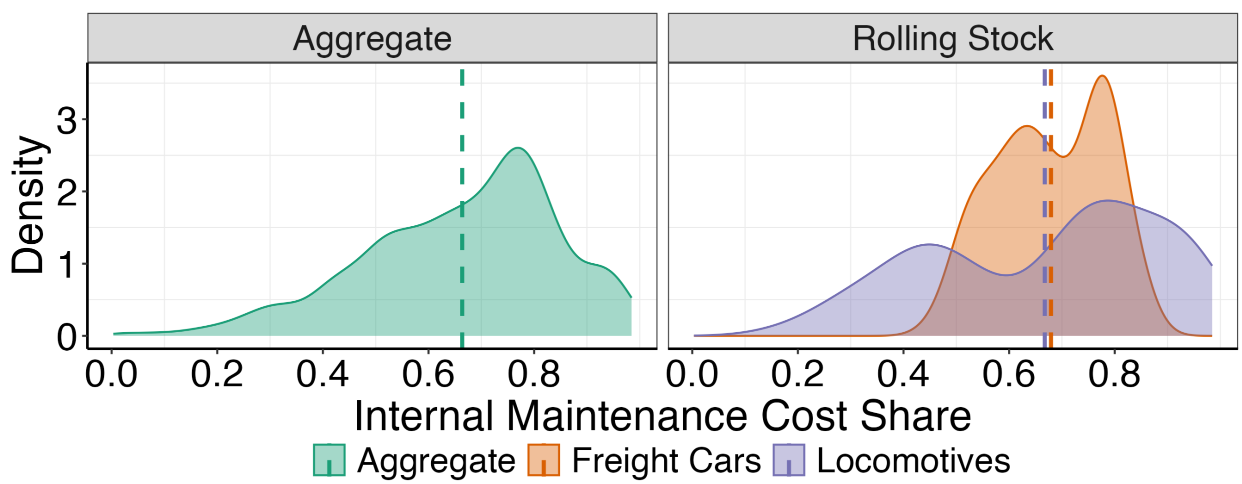
- Materials costs (e.g., replacement parts, lubricants, consumables)

- Labor costs (wages and benefits for railroad employees performing maintenance)
- Purchased services (maintenance contracted to outside vendors)

I define **internal maintenance** as the sum of materials and labor costs, and **external maintenance** as purchased services. This distinction is crucial for identification. Internal maintenance costs vary with local labor market conditions and firm-specific wage policies, while external maintenance costs reflect national market prices for specialized services. If maintenance demand is elastic, the adjustment will occur primarily through the internal margin in the short run, as external maintenance often involves predetermined contracts.

There is significant variability across firms in their internal maintenance practices. On average, approximately 65% of total maintenance is performed internally. However, this share varies considerably: some firms like Norfolk Southern perform nearly all locomotive maintenance in-house, while similarly sized competitors like CSX outsource around 70% of locomotive maintenance. Freight car maintenance tends to have less variability, perhaps because locomotives are more technically complex and require specialized expertise.

Figure B.1: Ratio of Internal Maintenance to Total Maintenance



Notes: The distribution of aggregate internal maintenance rates is constructed using Table 1 from the Statistics of Income, which encompasses all firms regardless of legal type, together with input-output tables from the BEA on purchases of equipment repairs from NAICS code 811 except housing services. For 2007, 2012, and 2017, I subtract payments to NAICS 811 from total maintenance expenditures after applying a labor cost correction. The distribution of the share of internal railroad equipment maintenance comes from dividing internal maintenance expenditures by total maintenance expenditures for all Class I freight railroads for locomotives and freight cars.

Relative Price Construction

The after-tax relative price is:

$$P_{i,j,t} = \frac{p^M_{i,j,t}}{p^I_{j,t}} \frac{1 - \tau_{i,t}}{1 - \tau_{i,t} z_t}. \tag{A.3}$$

I construct each component as follows:

Investment Price ($p^I_{j,t}$). The investment price varies by asset type but not by firm. I use BLS Producer Price Indices:

Freight Cars: Through 2016, I use BLS series PCU3365103365103Z ("Producer Price Index by Industry: Railroad Rolling Stock Manufacturing: Passenger and Freight Train Cars, New (Excluding Parts)"). For subsequent years, I splice this series with WPU14440102 ("Wholesale Price Index: Passenger and Freight Train Cars, New (Excluding Parts)"). The two series have a correlation of 0.98 in the overlapping period.

Locomotives: Through 2018, I use BLS series WDU1441 ("Wholesale Price Index: Locomotives"). The BLS discontinued this series in 2019 without a direct replacement. For 2019-2023, I construct a locomotive-specific price index by decomposing the broader rolling stock price index (WPU144) using investment shares from the R-1 data. Specifically, I calculate the locomotive share of total rolling stock investment for each year and construct a Tornqvist index that separates locomotive price movements from freight car price movements.

Maintenance Price ($p^M_{i,j,t}$). The pre-tax maintenance price is a firm-asset-time specific weighted average of input prices:

$$p^M_{i,j,t} = \alpha^{\text{labor}}_{i,j,t-1} \cdot w_{i,t} + \alpha^{\text{materials}}_{i,j,t-1} \cdot p^{\text{mat}}_t + \alpha^{\text{services}}_{i,j,t-1} \cdot p^{\text{serv}}_t, \tag{A.4}$$

where:

- $\alpha^{\text{labor}}_{i,j,t-1}$, $\alpha^{\text{materials}}_{i,j,t-1}$, and $\alpha^{\text{services}}_{i,j,t-1}$ are lagged cost shares for labor, materials, and purchased services from Schedule 410. I use lagged shares to avoid mechanical correlation between prices and quantities.

- $w_{i,t}$ is the firm-specific average hourly wage for rolling stock maintenance workers from Wage Form A&B filed with the STB. This form reports detailed wage information by occupation and skill level.

- p^{mat}_t is BLS series PCU33651033651054 ("Producer Price Index by Industry: Railroad Rolling Stock Manufacturing: Railway Maintenance of Way Equipment and Parts, Parts for All Railcars, and Other Railway Vehicles")

- p_t^{serv} is the Producer Price Index for equipment maintenance and repair services (BLS series PCU8111, available from 2007 forward)

For the external services component before 2007, I use the PPI for automotive repair and maintenance (BLS series PCU8111) as a proxy. This series is highly correlated (correlation = 0.94) with the equipment maintenance series in the overlapping period (2007-2023) and captures similar labor and parts cost pressures facing maintenance service providers.

The external cost component assumes a constant markup over time for maintenance services purchased from vendors. This is a simplifying assumption, but variation in external maintenance prices comes primarily from underlying input costs (parts and labor) rather than time-varying markups.

Tax Parameters. I construct firm-specific statutory tax rates ($\tau_{i,t}$) as:

$$\tau_{i,t} = \tau_t^{\text{federal}} + \tau_{i,t}^{\text{state}} - \tau_t^{\text{federal}} \cdot \tau_{i,t}^{\text{state}}, \tag{A.5}$$

where τ_t^{federal} is the federal corporate tax rate (35% before 2018, 21% thereafter) and $\tau_{i,t}^{\text{state}}$ is a revenue-weighted average state corporate tax rate.

The state component is calculated using the geographic distribution of each railroad's operations. Schedule 702 reports track miles by state for each firm. I use these track miles as weights to construct a firm-specific exposure to state corporate tax rates:

$$\tau_{i,t}^{\text{state}} = \sum_s \left(\frac{\text{Track Miles}_{i,s,t}}{\text{Total Track Miles}_{i,t}} \right) \cdot \tau_{s,t}^{\text{state}}, \tag{A.6}$$

where $\tau_{s,t}^{\text{state}}$ is the statutory corporate tax rate in state s at time t. I obtain state tax rates by extending the dataset of Suárez Serrato and Zidar (2016) through 2023.

The present value of depreciation allowances (z_t) varies over time due to changes in bonus depreciation and MACRS schedules. Following House and Shapiro (2008), I calculate:

- Both locomotives and freight cars are classified as MACRS 7-year property
- Bonus depreciation rates
- Discount rate: $r^k = 0.0713$ (industry average for NAICS 48 from Gormsen and Huber (2022))

Because the IRS places both asset types in the same depreciation class, z_t does not vary between locomotives and freight cars. However, there is firm-level variation in the effective tax rate through the state tax component.

Additional Control Variables

Local GDP Exposure. I construct a firm-specific measure of exposure to local demand shocks using:

$$\Delta \log Y_{i,t} = \sum_s \left(\frac{\text{Track Miles}_{i,s,t}}{\text{Total Track Miles}_{i,t}} \right) \cdot \Delta \log \text{GDP}_{s,t}, \tag{A.7}$$

where $\Delta \log \text{GDP}_{s,t}$ is the log change in gross state product from the Bureau of Economic Analysis. This measure captures how aggregate demand shocks in a railroad's service territory might affect maintenance decisions.

Local Wage Index. I construct a firm-specific maintenance wage index using Bureau of Labor Statistics data on wages by state in the Installation, Maintenance, and Repair Occupation (SOC Code 49-0000):

$$W_{i,t} = \sum_s \left(\frac{\text{Track Miles}_{i,s,t}}{\text{Total Track Miles}_{i,t}} \right) \cdot \frac{w_{s,t}}{w_{s,1999}}, \tag{A.8}$$

where $w_{s,t}$ is the average wage in state s at time t, normalized to 1999 = 1. This provides an alternative measure of maintenance labor costs that is not firm-specific and can serve as an instrument for firm-level wage variation.

Maintenance Share of User Cost. Following the definition in Section 3, I calculate:

$$s_{m,i,j,t} = \frac{(1 - \tau_{i,t}) \cdot p^M_{i,j,t} \cdot m_{i,j,t}}{(1 - \tau_{i,t} z_t) \cdot p^I_{j,t} \cdot (r^k + \delta_j) + (1 - \tau_{i,t}) \cdot p^M_{i,j,t} \cdot m_{i,j,t}}. \tag{A.9}$$

The depreciation rate δ_j is assumed constant across firms but varies by asset type:

- Locomotives: $\delta = 0.04$ (4% annual depreciation)
- Freight cars: $\delta = 0.03$ (3% annual depreciation)

These rates are industry standards for freight railroads and are consistent with the depreciation rates railroads report to the STB for composite depreciation calculations. The discount rate is $r^k = 0.0713$ as noted above.

Summary Statistics

Tables B.1 and B.2 present summary statistics for the R-1 sample, separately for locomotives and freight cars.

Table B.1: Summary Statistics: R-1 Data (Locomotives)

Variable	Mean	10th Pctl	Median	90th Pctl	N
Year	2011.19	2001.10	2011.00	2021.00	172
$m_{i,j,t}$ (Total)	0.17	0.07	0.14	0.30	172
$m_{i,j,t}$ (Internal)	0.11	0.04	0.09	0.19	172
$m_{i,j,t}$ (External)	0.06	0.00	0.05	0.11	172
$m_{i,j,t}$ (Physical)	0.03	0.02	0.02	0.04	172
$\log M_{i,j,t}$	11.99	10.35	12.37	13.41	172
$\log I_{i,j,t}$	11.34	9.19	11.94	13.31	172
Investment Rate	0.15	0.02	0.10	0.28	172
$P_{i,j,t}$	1.11	1.00	1.10	1.25	172
Capital Age	1.48	1.24	1.51	1.69	172
Local GDP Exposure	1.99	-0.21	2.13	4.09	172
$z_{i,j,t}$	0.56	0.36	0.50	0.83	172
Labor Cost Share (lag)	0.41	0.29	0.37	0.57	172
Local Wage Index	1.33	1.08	1.32	1.64	172
Effective Tax Rate	1.04	1.00	1.04	1.09	172
Maintenance Share (s_m)	0.59	0.45	0.59	0.74	172

Notes: Sample covers 7 firms over 25 years (1999-2023), with some missing observations. Maintenance and investment rates are scaled as shares of beginning-of-period book capital.

Table B.2: Summary Statistics: R-1 Data (Freight Cars)

Variable	Mean	10th Pctl	Median	90th Pctl	N
Year	2011.19	2001.10	2011.00	2021.00	172
$m_{i,j,t}$ (Total)	0.22	0.08	0.16	0.45	172
$m_{i,j,t}$ (Internal)	0.15	0.05	0.10	0.34	172
$m_{i,j,t}$ (External)	0.07	0.02	0.05	0.12	172
$m_{i,j,t}$ (Physical)	0.03	0.02	0.03	0.06	172
$\log M_{i,j,t}$	11.70	10.35	11.92	13.03	172
$\log I_{i,j,t}$	9.33	6.02	10.56	12.21	172
Investment Rate	0.08	0.00	0.05	0.19	172
$P_{i,j,t}$	0.90	0.77	0.88	1.04	172
Capital Age	1.59	1.18	1.62	1.93	172
Local GDP Exposure	1.99	-0.21	2.13	4.09	172
$z_{i,j,t}$	0.52	0.36	0.53	0.67	172
Labor Cost Share (lag)	0.39	0.26	0.39	0.51	172
Local Wage Index	1.33	1.08	1.32	1.64	172
Effective Tax Rate	1.04	1.00	1.04	1.09	172
Maintenance Share (s_m)	0.60	0.41	0.60	0.78	172

Notes: Sample covers 7 firms over 25 years (1999-2023), with some missing observations. Maintenance and investment rates are scaled as shares of beginning-of-period book capital.

B.2 SOI Data Construction

Data Sources and Sample Construction

The Statistics of Income (SOI) is published annually by the Internal Revenue Service and aggregates corporate tax return data into industry-level samples. The SOI uses a stratified sampling procedure that oversamples large corporations and then applies weights to make the sample representative of the full corporate population. Corporations report maintenance expenditures (labeled "repairs and maintenance") and book capital as line items on their tax forms (Form 1120), which the SOI aggregates across firms within industries.

I use the SOI Corporate Sample files from 1999-2019. The data are publicly available at the industry level but not at the firm level. Each observation is an industry-year cell, with all dollar amounts representing weighted aggregates across firms in that industry. The SOI reports data at varying levels of aggregation, roughly corresponding to 2-3 digit NAICS codes. However, the number of SOI industries fluctuates over time as the IRS adjusts its classification scheme. In 2014, for example, the SOI changed from a "major" to a "minor" industry scheme.

To maintain consistency across years, I map SOI industries to Bureau of Economic Analysis (BEA) industry definitions, which are more stable over time. Specifically, I use the 49-industry classification from the BEA's Fixed Asset Tables. This mapping is not one-to-one—some SOI industries must be aggregated—but it ensures definitional consistency across my sample period. I exclude several categories the financial industry and passthrough entitities from the analysis, focusing only on corporate filings. The resulting sample consists of 49 industries observed annually from 1999-2019, yielding up to 1,029 industry-year observations. Some industry-year cells have missing data, resulting in a final sample of approximately 1,116 observations.

I use the BEA industry definition rather than the raw SOI definition for three reasons. First, I combine SOI data with BEA data in some specifications (e.g., using BEA depreciation rates, capital composition weights, and price deflators). Using a consistent industry definition facilitates this merging. Second, the BEA definition is more aggregated than the SOI definition. This aggregation arguably better captures general equilibrium effects: when national tax policy changes, firms can reallocate capital within broadly defined industries, and the BEA aggregation level implicitly nets out this within-industry reallocation. Third, the BEA classification is stable over time, whereas the SOI classification changes periodically, creating artificial breaks in the panel.

Taxable vs. Untaxable Firms. For some analyses, I separate the sample into taxable and untaxable firms. I define **taxable firms** as those with positive net income in a given year, and **untaxable firms** as those without positive net income. The SOI reports both categories separately.

This classification is imperfect. Some firms in the "taxable" category may not actually face positive tax liability because they have accumulated net operating losses (NOLs) from prior years that they can carry forward to offset current income. Conversely, some "untaxable" firms may face some tax liability through alternative minimum tax provisions or other mechanisms. Despite these limitations, the taxable/untaxable split provides a useful approximation: taxable firms face stronger incentives to respond to tax policy changes than untaxable firms.

Variable Construction

Maintenance Rate. The maintenance rate is defined as the ratio of the maintenance and repairs line item to lagged book capital:

$$m_{i,t} = \frac{\text{Repairs and Maintenance}_{i,t}}{\text{Book Capital}_{i,t-1}}, \tag{A.10}$$

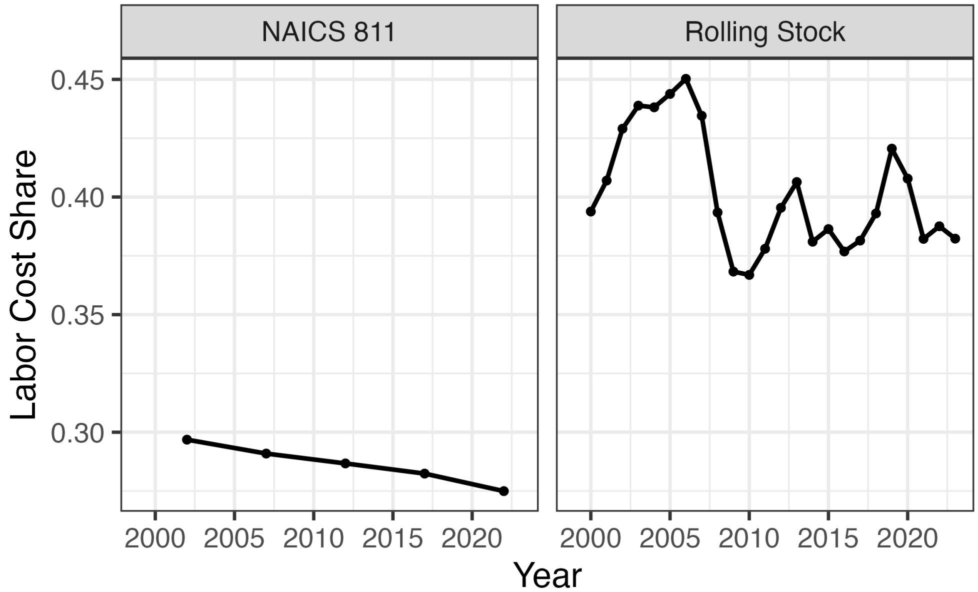
where i indexes industries and t indexes years.

The SOI maintenance measure is noisier than the R-1 measure for two important reasons:

First, labor costs are likely understated. On corporate tax forms, labor expenditures are reported as a separate line item (wages and salaries). As a result, the repairs and maintenance line primarily reflects spending on materials and external maintenance services purchased from vendors. Internal maintenance performed by the firm's own employees—which can be substantial—is not fully captured. Additionally, some materials costs may be classified under cost of goods sold rather than the maintenance line item, further understating true maintenance expenditures.

In the R-1 railroad panel, internal labor accounts for about 40 percent of total maintenance expenditures on both freight cars and locomotives (Figure 5). There is not a corresponding aggregate labor cost share, but Appendix Figure B.2 plots the ratio of labor costs to total receipts for the maintenance and repair sector using the Economic Census from 2002-2022. The labor share is consistently 30%. Thus, materials and parts are usually around 60-70% of maintenance expenditures. Given the rough agreement between the railroad data and the equipment repair sector, we could reasonably boost the typical SOI maintenance rate to between 7% and 8%, or about 2/3 as large as the usual investment rate.

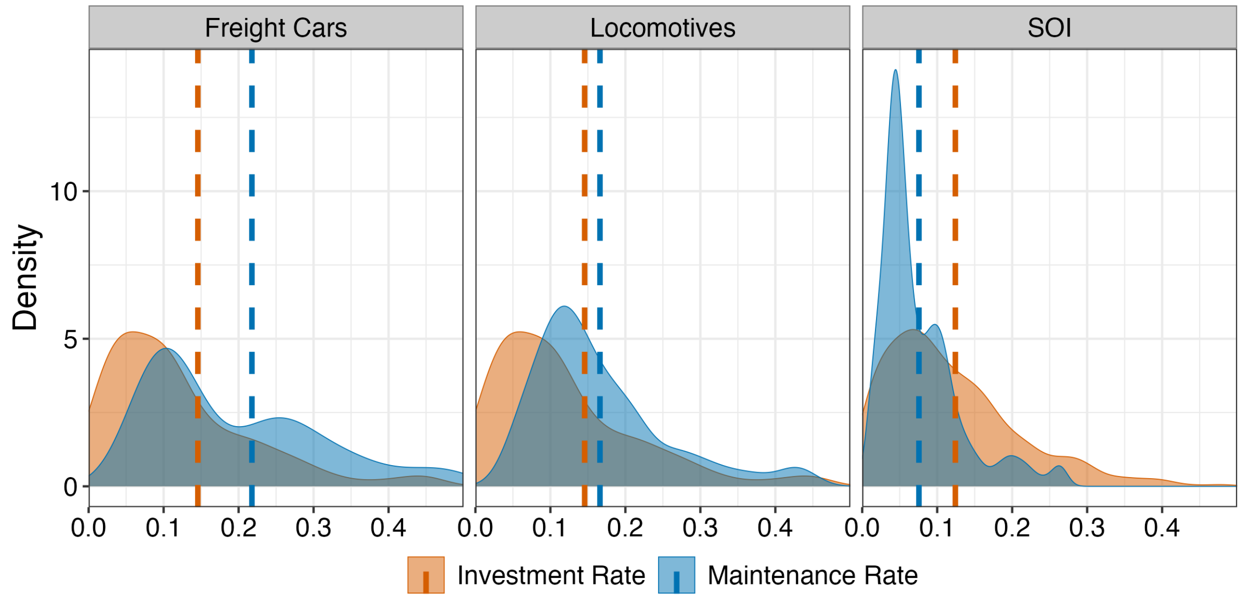
Figure B.2: Aggregate Internal Labor Cost Share



Notes: The share is computed by dividing labor costs by total internal maintenance costs. The left panel plots the ratio of labor costs to total receipts for NAICS code 811, which is the maintenance and repair sector, from 2002-2022. Each data point comes from the Economic Census. The right panel is the average for all rolling stock in the R-1 data.

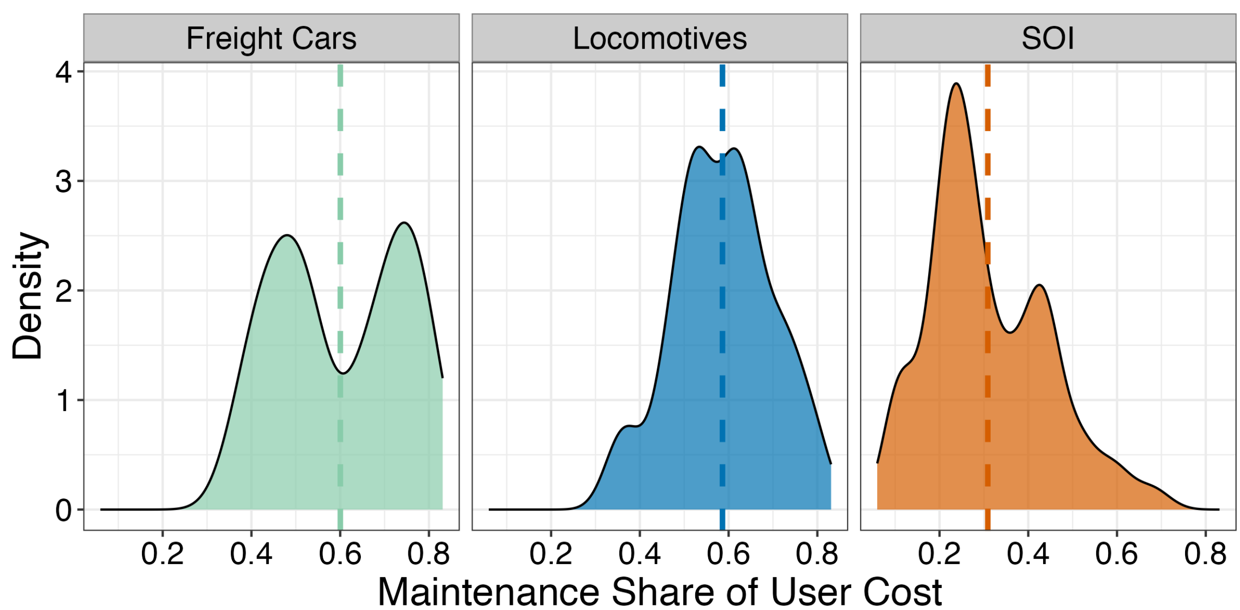
The Equipment Maintenance and Repair sector (NAICS 811) suggests that labor accounts for 30-45% of total maintenance costs. If this labor share applies broadly, then reported SOI maintenance may understate true maintenance by a factor of roughly 1.4. In robustness checks, I construct an "adjusted" maintenance rate by dividing reported maintenance by 0.65 to approximate total maintenance inclusive of labor. The elasticity results are invariant to this measure, but the *level* results in the main text are necessarily conservative because they are a lower bound.

Figure B.3: Density plots for maintenance and gross investment rates (adjusted)



Note: Each density plot is constructed with beginning of period book capital in the denominator. The dashed lines are mean maintenance and investment rates. From left to right, the mean maintenance rates are 7.9%, 21.8%, and 16.6%. The corresponding investment rates are 13.8%, 7.9%, and 14.6%. The SOI maintenance rate is adjusted for missing labor and materials costs.

Figure B.4: Density plots for the maintenance share of user cost (adjusted)



Note: Each density plot is constructed with beginning of period book capital in the denominator. The dashed lines are mean maintenance shares. Across the SOI, freight cars, and locomotives, the mean maintenance shares are 30%, 60%, and 58.6%. The maintenance rate is adjusted for labor costs.

Second, the capital stock denominator uses tax depreciation. The SOI constructs book capital using firms' reported accumulated depreciation, which follows tax depreciation schedules rather than economic depreciation. Tax depreciation can be accelerated (especially during bonus depreciation periods), causing book capital to understate true economic capital. This introduces measurement error in the denominator, which may attenuate estimated elasticities. Despite these measurement issues, SOI maintenance rates are comparable to those observed in aggregate Canadian *survey* data, which is constructed by Statistics Canada.

Investment Rate. The net investment rate is:

$$\frac{I_{i,t}}{K_{i,t}} = \frac{\text{Gross Investment}_{i,t} - \text{Tax Depreciation}_{i,t}}{\text{Book Capital}_{i,t-1}}. \tag{A.11}$$

Capital Age. I proxy for capital age using the ratio of gross to net book capital:

$$\text{Capital Age}_{i,t} = \frac{\text{Gross Book Capital}_{i,t}}{\text{Net Book Capital}_{i,t}}. \tag{A.12}$$

Higher values indicate older capital (more accumulated depreciation relative to gross value). This measure is imperfect because it reflects tax depreciation schedules rather than true physical age, but it provides a useful control for capital vintage effects.

I winsorize maintenance rates, investment rates, and capital age at the 2nd and 98th percentiles to reduce the influence of outliers and measurement error.

Policy Wedge Construction

The key source of identification in the SOI data is variation in the policy wedge:

$$\text{Wedge}_{i,t} = \frac{1 - \tau_t}{1 - \tau_t z_{i,t}}, \tag{A.13}$$

where τ_t is the statutory federal corporate tax rate (35% before 2018, 21% thereafter) and $z_{i,t}$ is the net present value of depreciation allowances for industry i at time t.

I construct $z_{i,t}$ in three steps:

Step 1: Asset-Level Present Value of Depreciation. For every asset type j with MACRS class life T, I compute the baseline present value of depreciation allowances as:

$$z_{i,j} = \sum_{t=0}^{T} \left(\frac{1}{1 + r_i^k} \right)^t d_t, \tag{A.14}$$

where d_t is the depreciation rate in year t under the applicable MACRS schedule (e.g., 200% declining balance for 5-year property, 150% declining balance for 15-year property, straight-line for structures), and r_i^k is the industry-specific discount rate.

I obtain industry-specific discount rates from Gormsen and Huber (2022), who estimate firm-level costs of capital using equity returns and leverage. I map their firm-level estimates to BEA industries and take a time-series average within each industry.

Step 2: Adjusting for Bonus Depreciation. Time-series variation in $z_{i,j,t}$ comes from changes in bonus depreciation policy. Let θ_t denote the bonus depreciation rate (the percentage of asset cost that can be immediately expensed). Then:

$$z_{i,j,t} = \theta_t + (1 - \theta_t) z_{i,j}, \tag{A.15}$$

where θ_t only applies to eligible assets (primarily equipment). Structures are generally ineligible for bonus depreciation. My sample ends before the TCJA bonus provisions began phasing out.

Step 3: Aggregating to Industry-Level Wedges. To construct the industry-specific $z_{i,t}$, I aggregate across the 36 detailed asset categories in the BEA's Fixed Asset Tables using capital-weighted shares:

$$z_{i,t} = \sum_{j=1}^{36} \alpha_{i,j} \cdot z_{i,j,t}, \tag{A.16}$$

where $\alpha_{i,j}$ is the share of asset type j in industry i's total capital stock. I map the 36 BEA assets to their corresponding MACRS depreciation classes using the concordance from House and Shapiro (2008).

Capital Weights and Exogeneity. A key consideration is which years to use for constructing the capital weights $\alpha_{i,j}$. Using contemporaneous weights would introduce endogeneity: if tax policy affects investment, it also affects capital composition, which would feed back into the construction of $z_{i,t}$.

To maintain exogeneity while preserving relevance, I use two different weighting periods:

- **1998-2001 weights** for all years 1999-2017: These years had no variation in tax policy (no bonus depreciation, stable MACRS schedules), so capital weights are pre-determined relative to subsequent policy changes.
- **2014-2017 weights** for years 2018-2019: These years also had stable policy (50% bonus ramping down to zero), making them pre-determined relative to the TCJA changes in 2018.

This approach balances two objectives: maintaining exogeneity (using pre-policy weights) while ensuring relevance (using weights not too far in the past from the policy change). The 2017 TCJA represented a major structural break (corporate rate cut from 35% to 21% plus 100% bonus), so using 2014-2017 weights better captures the capital composition relevant to that reform.

Industries with more equipment-intensive capital structures (higher shares of short-lived assets eligible for bonus depreciation) experience larger changes in $z_{i,t}$ when bonus depreciation rates change. Figure 4 in the main text shows substantial cross-industry variation in the wedge over time, with equipment-intensive industries like manufacturing experiencing larger policy-driven changes than structures-intensive industries like utilities or real estate.

Maintenance Share of User Cost

Following the definition in Section 3, I calculate the maintenance share of user cost as:

$$s_{m,i,t} = \frac{(1-\tau_t^c) \cdot p_t^M \cdot m_{i,t}}{(1-\tau_t^c z_{i,t}) \cdot p_t^I \cdot (r_i^k + \delta_i) + (1-\tau_t^c) \cdot p_t^M \cdot m_{i,t}}, \tag{A.17}$$

where:

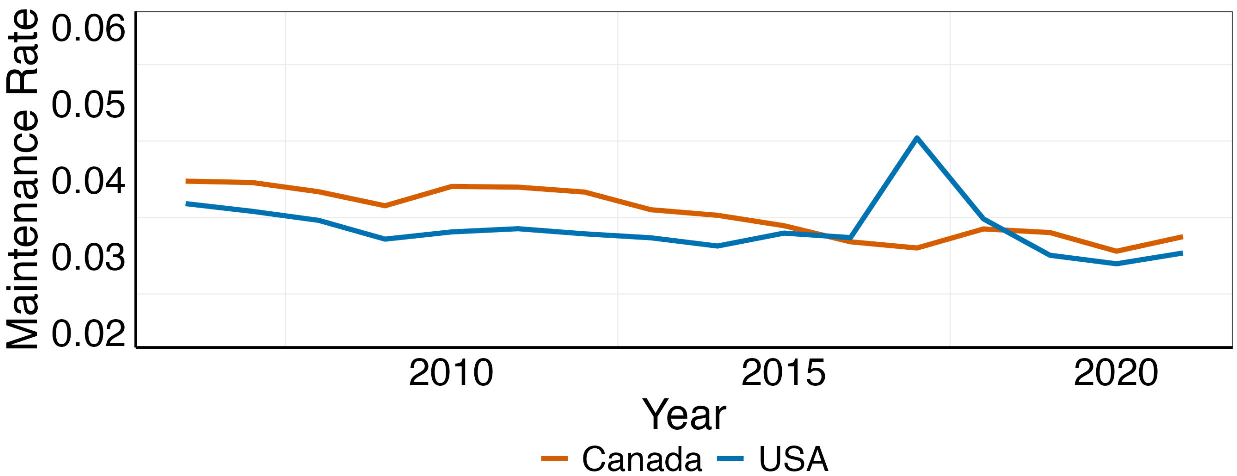
- r_i^k is the industry-average discount rate from Gormsen and Huber (2022)
- δ_i is a capital-weighted industry-average depreciation rate constructed from the BEA Fixed Asset Tables. For each industry, I compute $\delta_i = \sum_j \alpha_{i,j}\delta_j$, where δ_j is the BEA's estimate of economic depreciation for asset type j.
- p_t^I is the implicit price deflator for fixed investment from the BEA National Income and Product Accounts (NIPA Table 1.1.4)
- p_t^M is the Producer Price Index for equipment maintenance and repair services (BLS series PCU8111). For years before 2007 when this series is unavailable, I use the PPI for automotive repair and maintenance as a proxy.

Table B.3 also reports an "adjusted" maintenance share that accounts for the labor understatement issue discussed above. This is calculated by dividing reported maintenance by 0.65 before computing the share, under the assumption that labor accounts for approximately 35% of total maintenance costs.

Comparison to Canadian Data

To validate the SOI maintenance rates, I compare them to aggregate maintenance data from Canada. The Canadian data compiled by Statistics Canada are from survey data on maintenance expenditures combined with an estimated aggregate economic capital stock. Figure B.5 plots the aggregate maintenance rate (total maintenance divided by total book capital) for both the U.S. SOI sample and Canadian data.

Figure B.5: American vs. Canadian Maintenance Rates



Note: This figure plots the maintenance rate (net of govenrnment capital and maintenance) from Statistics Canada against the SOI maintenance rate.

The two series track each other closely, with mean maintenance rates of 4.8% (U.S.) and 5.1% (Canada). Both exhibit similar cyclical patterns, rising during recessions (when investment falls but maintenance continues) and declining during booms. This similarity suggests that despite measurement issues, the SOI provides a reasonable proxy for economy-wide maintenance behavior.

Summary Statistics

Table B.3 presents summary statistics for the SOI sample, separately for all firms, taxable firms, and untaxable firms.

Table B.3: Summary Statistics: SOI Data

Variable	Mean	10th Pctl	Median	90th Pctl	N
All Firms					
Year	2009.95	2001.00	2010.00	2019.00	1116
$m_{i,t}$	0.05	0.02	0.04	0.09	1116
Investment Rate	0.06	-0.14	0.06	0.23	1116
Wedge	0.83	0.76	0.82	0.92	1116
Maintenance Share (s_m)	0.22	0.09	0.19	0.38	1116
s_m (Adjusted)	0.30	0.13	0.27	0.48	1116
Capital Age	2.21	1.66	2.15	2.80	1116
Taxable Firms					
Year	2009.04	2000.00	2009.00	2019.00	1114
$m_{i,t}$	0.05	0.02	0.04	0.10	1114
Investment Rate	0.11	-0.47	0.05	0.61	1114
Wedge	0.83	0.76	0.82	0.92	1114
Maintenance Share (s_m)	0.23	0.09	0.21	0.42	1114
s_m (Adjusted)	0.31	0.13	0.29	0.53	1114
Capital Age	2.25	1.69	2.19	2.93	1114
Untaxable Firms					
Year	2009.05	2000.00	2009.00	2019.00	1113
$m_{i,t}$	0.05	0.01	0.04	0.09	1113
Investment Rate	0.13	-0.40	0.02	0.83	1113
Wedge	0.83	0.76	0.82	0.92	1113
Maintenance Share (s_m)	0.23	0.07	0.20	0.43	1113
s_m (Adjusted)	0.30	0.11	0.28	0.54	1113
Capital Age	2.12	1.52	2.06	2.75	1113

Notes: Sample covers 49 industries over 21 years (1999-2019). Maintenance and investment rates are winsorized at 2nd and 98th percentiles. "Adjusted" maintenance share divides reported maintenance by 0.65 to approximate total maintenance inclusive of labor costs. Wedge is $\frac{1-\tau_t}{1-\tau_t z_{i,t}}$.

C Empirical Robustness and Identification Details

This appendix provides detailed validation of identification strategies, robustness checks, and supplementary analyses for the maintenance demand estimates in Section 5.

C.1 R-1 Estimates

Extended Motivation for Shift-Share Design

The shift-share instrument in equation (13) is designed to approximate an idealized experiment in which maintenance input costs are shifted by forces outside individual firms' control. To motivate this approach more fully, consider a hypothetical experiment in which a central planner randomly assigns shifts to national or state-level labor markets. For instance, imagine national wage negotiations or state-level policies that randomly alter prevailing wage indices for maintenance occupations. In such a setting, these cost changes would be as good as randomly assigned from the perspective of individual firms, ensuring that resulting changes in maintenance input prices are not driven by firm-level or region-specific unobserved conditions.

The instrument approximates this ideal by using state-level input cost indices as "shifts" and employing firm- and capital-type-specific cost shares as "shares." This design choice deserves elaboration on two dimensions: the exogeneity of shifts and the pre-determination of shares.

Why State-Level Wages Are Plausibly Exogenous. The wage indices $W_{s,t}$ come from BLS data on Installation, Maintenance, and Repair occupations (SOC 49-0000) at the state level. These wages reflect broad economic conditions in each state: labor market tightness, cost of living adjustments, state-level unionization rates, and prevailing wage regulations. Importantly, railroad maintenance facilities are geographically dispersed across their service territories based on network structure and historical infrastructure investments made decades ago.

For example, Union Pacific has major maintenance facilities in Omaha (historical headquarters), North Platte (geographic midpoint of the system), and various division points determined by operational considerations like crew change requirements and locomotive fueling needs. These locations were not chosen to minimize current labor costs—indeed, many were established in the 19th century. The geographic footprint is therefore predetermined relative to current wage movements, making the weighted average of state wages plausibly orthogonal to firm-specific maintenance decisions.

Connection to Borusyak, Hull, and Jaravel (2024) The instrument follows what Borusyak, Hull, and Jaravel (2024) term the "many exogenous shifts" approach rather than the "exogenous shares" approach. The distinction is important for understanding the identification assumption. In the exogenous shares approach, identification relies on the shares being exogenous—for example, a firm's initial capital composition or geographic footprint being uncorrelated with future growth opportunities. The shifts can be endogenous because they are differentially weighted by exogenous shares.

In the many exogenous shifts approach, identification relies on having numerous shifts that are individually exogenous to the outcome of interest. The shares can be endogenous because the law of large numbers ensures that endogeneity in shares averages out across many independent shifts. My design follows this approach. The shifts are numerous and individually plausible exogenous to firm-asset-level maintenance decisions. State labor markets are large relative to any individual railroad's employment in that state, so reverse causality is implausible. The shares—geographic footprints and internal cost structures—are persistent but not necessarily exogenous in the strict sense. However, with many plausibly exogenous shifts, the design delivers valid identification.

First Stage Results

Table C.1 presents first-stage results for the baseline instrument and alternative specifications. The first stage is strong across all specifications, with F-statistics ranging from 10.5 to 11.5. The coefficient on the instrument is positive and statistically significant in all cases, indicating that increases in the instrument raise the relative price of maintenance as expected. The baseline specification (column 1) yields a coefficient of 0.165. Adding controls (column 2) leaves the first stage essentially unchanged, suggesting the instrument is not confounded by local demand conditions, capital age, or firm-specific trends. Either varying the lag structure of labor shares or using a national wage index rather than state-level indices weighted by geography yields a slightly smaller but still strong first stage.

Table C.1: First-Stage Regressions for Varying Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
$Z_{i,j,t}$	0.165^{**}	0.173^{**}	0.002^{**}	0.002^{**}	0.156^{***}	0.164^{**}
	(0.049)	(0.051)	(0.000)	(0.000)	(0.041)	(0.045)
Capital Age		−0.012		−0.026		−0.020
		(0.032)		(0.028)		(0.031)
GDP Exposure		-0.004^{*}		−0.002		−0.003
		(0.002)		(0.003)		(0.002)
Num.Obs.	340	340	314	314	326	326
Effective F-stat	11.54	11.52	14.32	13.27	10.16	9.74
Firm Trends	N	Y	N	Y	N	Y
Instrument Type	Baseline	Baseline	Shares Lagged 3 Years	Shares Lagged 3 Years	National Wage Index	National Wage Index

* p < 0.1, ** p < 0.05, *** p < 0.01

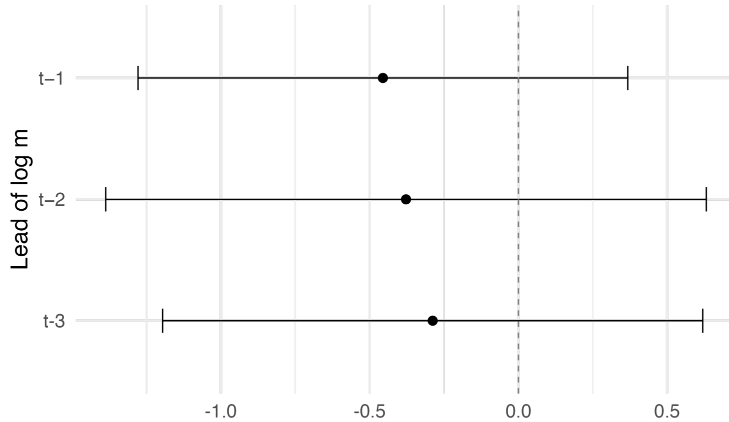
Notes: This table estimates the first stage of regressions for the main freight rail specification in (12). The first two columns use the baseline instrument described in the main text, with second adding firm-specific trends and controls for local demand shocks and capital age. The second columns are the same instrument, but with the labor share lagged three years instead of two. The final two columns use a national wage index, which is the employment cost index for workers in maintenance and repair (FRED item CIU2020000430000I). Standard errors are clustered by firm. The effective F-stat is from Montiel-Olea and Pflueger (2013).

Validation Tests

The instrument must satisfy two conditions for valid identification. First, it should not predict past maintenance rates (no anticipation). Second, the shares component should be orthogonal to pre-period determinants of maintenance (balance).

Pre-Trends. Figure C.1 tests whether lagged maintenance rates predict the instrument. If firms anticipate future wage shocks and adjust maintenance in advance, lagged maintenance should predict $Z_{i,j,t}$. I regress $Z_{i,j,t}$ on lags of log $m_{i,j,t}$, controlling for firm-asset and time fixed effects.

Figure C.1: Lead tests of the log maintenance rate on $Z_{i,j,t}$

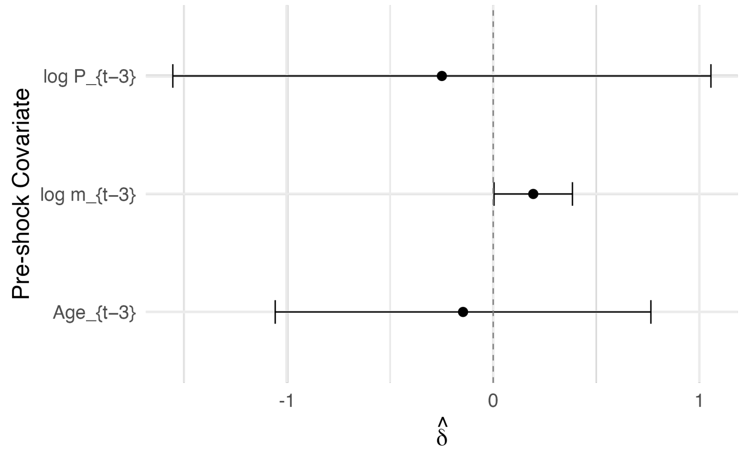


Note: This figure plots coefficients from regressing a pre-shock maintenance rate on the instrument $Z_{i,j,t}$ after controlling for firm-year trends, year fixed effects, and firm-asset fixed effects. Standard errors are clustered by industry.

None of the lagged maintenance coefficients are statistically significant or economically meaningful. This indicates firms do not anticipate future wage shocks, supporting the exclusion restriction.

Balance. Figure C.2 tests whether the labor share—the potentially endogenous component of the instrument—is correlated with pre-period observables. I regress the labor share on lagged maintenance rates, lagged relative prices, and lagged capital age. None of the coefficients are statistically significant. This confirms that the labor share—though potentially endogenous in principle—is not systematically correlated with observable determinants of maintenance, supporting the pre-determination assumption.

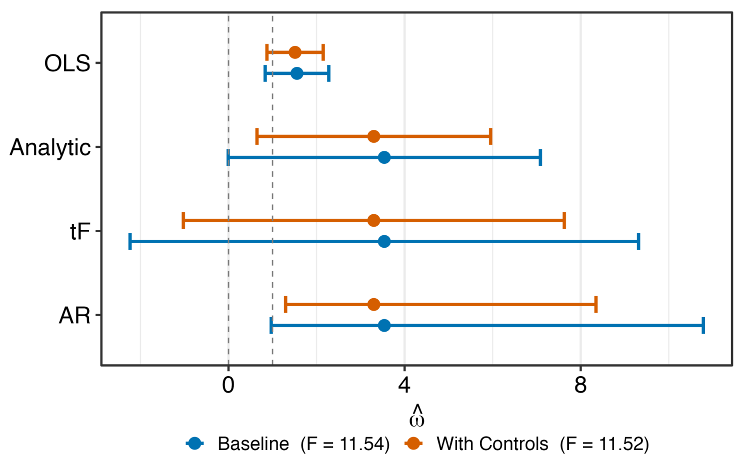
Figure C.2: Balance tests on pre-shock outcomes



Note: This figure plots coefficients from regressing the variable on the y-axis against the instrument $Z_{i,j,t}$ after controlling for firm-asset and year fixed effects and firm trends. Standard errors are clustered by firm.

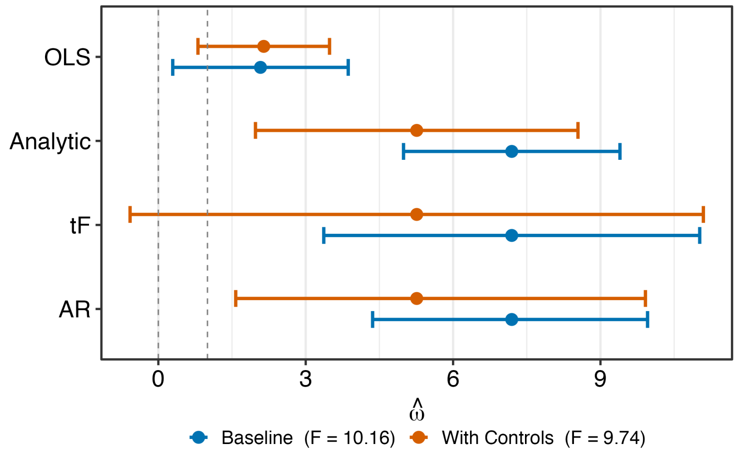
Robustness Checks

Figure C.3: Maintenance demand elasticity with 95% confidence interval (Physical Capital)



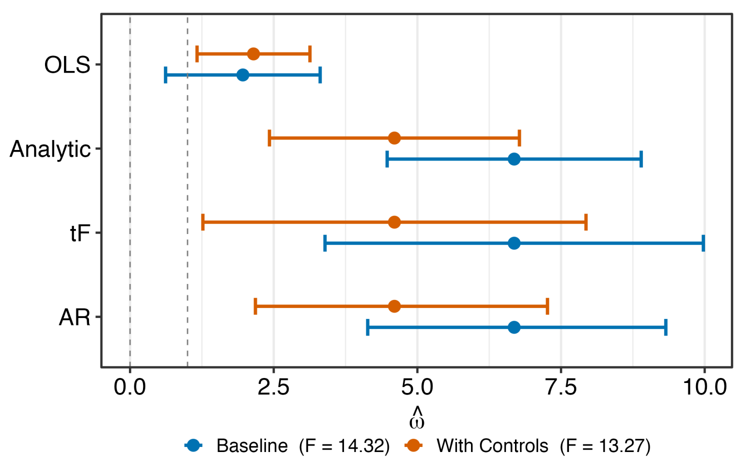
Note: This figure plots the point estimates and result for estimating (12), except I replace the maintenance rate with a physical measure of the capital stock. The blue lines contain no controls, while the orange lines control for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13). Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

Figure C.4: Maintenance demand elasticity with 95% confidence interval (National Instrument)



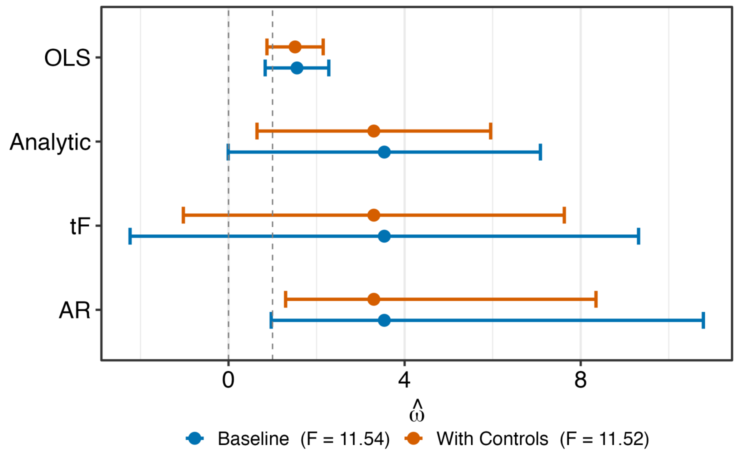
Note: This figure plots the point estimates and result for estimating (12). The blue lines contain no controls, while the orange lines control for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13), except that I use a national measure of the wage index so there is no weighting by state.. Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

Figure C.5: Maintenance demand elasticity with 95% confidence interval (Thrice-Lagged Instrument)



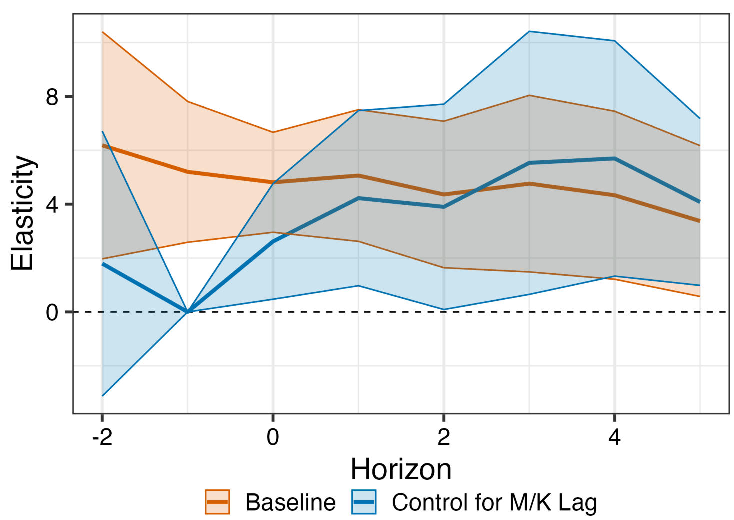
Note: This figure plots the point estimates and result for estimating (12). The blue lines contain no controls, while the orange lines control for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13), except that I use three lags of the shares rather than two. Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

Figure C.6: Maintenance demand elasticity with 95% confidence interval (Controls for Lagged Maintenance)



Note: This figure plots the point estimates and result for estimating (12). The blue lines control for lagged maintenance, while the orange lines add controls for local GDP exposure, firm-year trends, and the age of the capital stock. All standard errors are clustered by firm. The top estimate is for OLS only, while the bottom three all correspond to the instrument specified in (13), except that I use three lags of the shares rather than two. Analytic confidence intervals are from traditional Wald estimates, while the tF and AR confidence intervals result from inverting the tF (Lee et al. 2022) and Anderson and Rubin (1949) tests, respectively. The F-statistic reported in the legend is the effective F-statistic from Montiel-Olea and Pflueger (2013).

Figure C.7: Local Projection of Relative Price Shocks on the Maintenance Rate (R-1)



Note: This figure plots the IV coefficients ω_h from the local projection

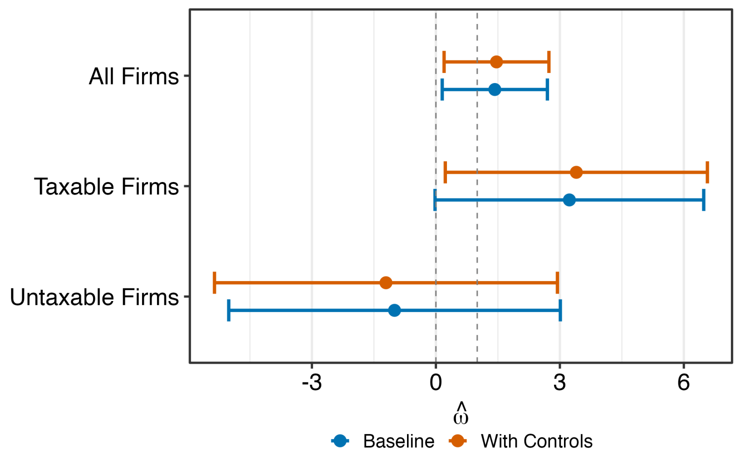
$$\log m_{i,j,t+h} = \alpha_{ij} + \lambda_t - \omega_h \log P_{i,j,t} + \text{Controls} + u_{i,j,t+h}.$$

The line in blue controls for the lagged maintenance rate, while the line in orange does not.

C.2 SOI Robustness Checks

SOI Sampling Changes. In 2013, the IRS changed the number of industries sampled in the SOI. Some industries became too small to report maintenance separately, potentially introducing measurement error. Figure C.8 shows results are unchanged when ending the sample in 2013 rather than 2019.

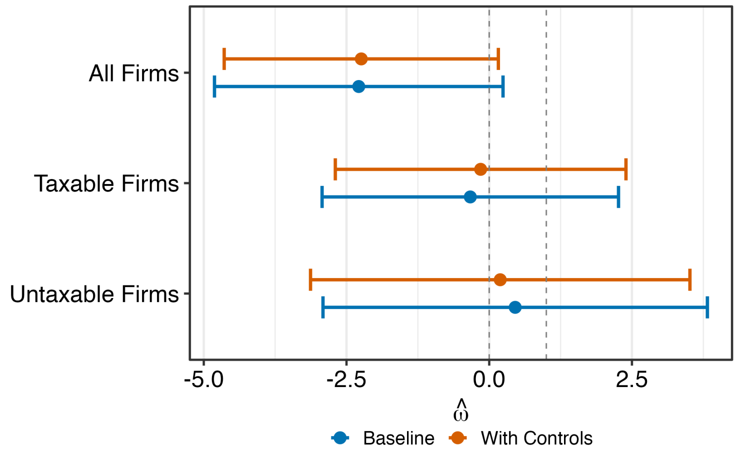
Figure C.8: Maintenance demand elasticity with 95% confidence interval



Note: This figure plots the point estimates and result for estimating (14), except it limits the data to pre-2014. All estimates have two-way fixed effects together with linear and quadratic trends in two-digit NAICS codes. Orange lines control for the age of the capital stock. All standard errors are clustered by industry. The top estimate is for the All Firm sample, while the bottom two groups of estimates split the SOI into a taxable and an untaxable sample.

Investment Weights (Placebo Test). Figure C.10 re-estimates equation (14) using investment-weighted $z_{i,t}$ rather than capital-weighted. The elasticity collapses to near zero and is statistically insignificant across all specifications. This confirms that maintenance responds to the user cost of the installed capital base, not recent investment flows.

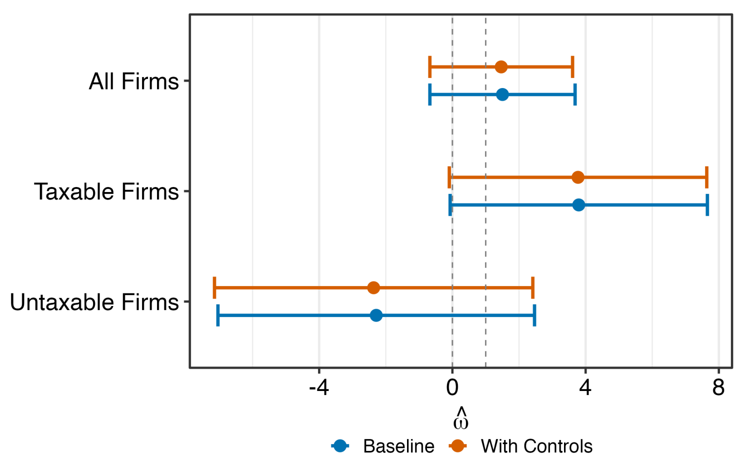
Figure C.9: Maintenance demand elasticity with 95% confidence interval



Note: This figure plots the point estimates and result for estimating (14), uses investment weights. All estimates have two-way fixed effects together with linear and quadratic trends in two-digit NAICS codes. Orange lines control for the age of the capital stock. All standard errors are clustered by industry. The top estimate is for the All Firm sample, while the bottom two groups of estimates split the SOI into a taxable and an untaxable sample.

BEA Capital Stocks. The baseline SOI analysis uses capital stocks constructed from tax depreciation reported in corporate returns. This may introduce measurement error if tax and economic depreciation diverge. Figure C.10 uses BEA capital stocks instead, which are constructed using economic depreciation rates and investment flows. Results are similar though less precise.

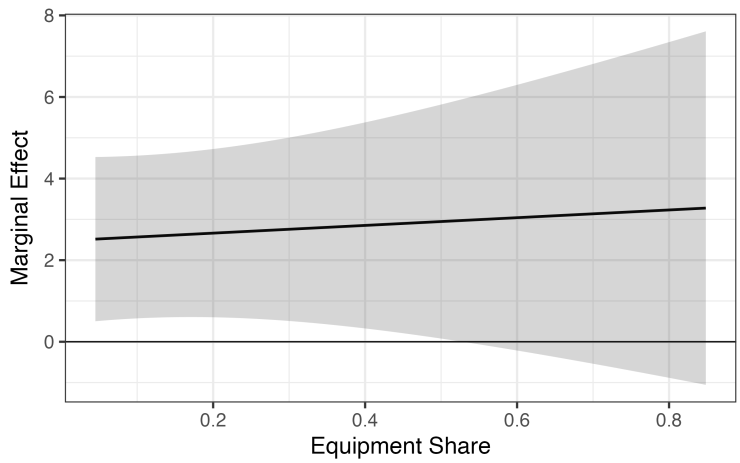
Figure C.10: Maintenance demand elasticity with 95% confidence interval



Note: This figure plots the point estimates and result for estimating (14), except it uses the BEA capital stock in the denominator. All estimates have two-way fixed effects together with linear and quadratic trends in two-digit NAICS codes. Orange lines control for the age of the capital stock. All standard errors are clustered by industry. The top estimate is for the All Firm sample, while the bottom two groups of estimates split the SOI into a taxable and an untaxable sample.

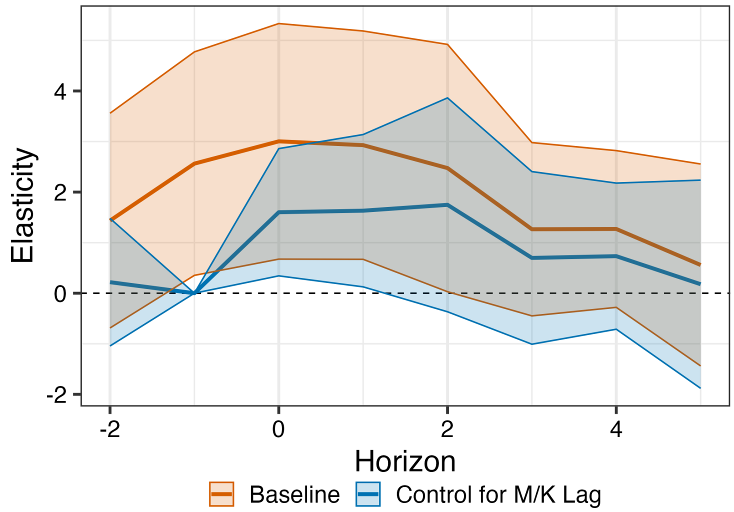
No Selection by Equipment Intensity. Koby and Wolf (2020) raise concerns that bonus depreciation identification may be confounded by selection: equipment-intensive industries may have inherently different elasticities than structures-intensive industries. If true, differential exposure to bonus would be correlated with pre-existing elasticity heterogeneity, biasing estimates. To test this, I add an interaction between the equipment-capital ratio and the wedge term to equation (14). If the elasticity varies by equipment intensity, the interaction should be significant. Figure C.11 shows the interaction is small and statistically insignificant, indicating the elasticity is homogeneous across industries. This rules out selection effects.

Figure C.11: Marginal Effect of Wedge on Maintenance Rate by Equipment Share



Note: Marginal (absolute-value) maintenance-wedge elasticity by equipment-capital ratio. The black line plots $\left|\partial \log m / \partial \log(\{wedge\})\right|$ against each industry's average equipment-capital ratio. Shaded bands are 95% confidence intervals.

Figure C.12: Local Projection of Relative Price Shocks on the Maintenance Rate (SOI)



Note: This figure plots the coefficients ω_h from the regression

$$\log m_{i,t+h} = \alpha_i + \lambda_t - \omega_h \log\left(\frac{1-\tau_t^c}{1-\tau_t^c z_{i,t}}\right) + \text{Controls} + \varepsilon_{i,t+h}.$$

The path in blue controls for the lagged maintenance rate. Both specifications control for industry trends and correspond to the SOI sample with all types of firms.

C.3 Meta-Analysis Details

This appendix describes the meta-analytic procedure used to combine maintenance demand estimates from the R-1 and SOI datasets into a single demand schedule for policy counterfactuals.

Estimating the Level Parameter γ. The demand function $m = \gamma(P)^{-\omega}$ requires both an elasticity ω and a level parameter γ. Cross-sectional estimation yields $\hat{\omega}$ but not $\hat{\gamma}$ directly. I recover $\hat{\gamma}$ by inverting the demand function at sample means:

$$\hat{\gamma} = \bar{m}\bar{P}^{-\hat{\omega}}, \tag{A.18}$$

where $\bar{m}$ and $\bar{P}$ are sample means of the maintenance rate and relative price, respectively.

Standard errors for $\hat{\gamma}$ are obtained using the delta method for SOI samples and a wild cluster bootstrap for the R-1 sample to account for weak instrument concerns. The covariance between $\hat{\omega}$ and $\hat{\gamma}$ is calculated via the delta method. In particular, for every regression i, I obtain the covariance from:

$$\text{Cov}(\hat{\gamma}_i, \hat{\omega}_i) \approx \frac{\partial \gamma_i}{\partial \omega_i}\text{Var}(\hat{\omega}_i) = [-\bar{m}_i \bar{P}_i^{-\omega_i} \ln \bar{P}_i]\text{Var}(\hat{\omega}_i) = -\gamma_i \ln(\bar{P}_i)\text{Var}(\hat{\omega}_i). \tag{A.19}$$

For the R-1 data, I use Anderson-Rubin confidence intervals for $\text{Var}(\hat{\omega}_i)$ to account for weak instrument concerns. Due to several approximation steps, the variance-covariance matrix is occasionally not positive-definite, so I perturb the covariance entries using the nearest-positive-definite method until the matrix becomes positive-definite.

Meta-Analytic Pooling. I estimate two separate random-effects models via restricted maximum likelihood (REML).

Level parameter (γ): I pool only SOI estimates of γ because the goal is to construct an aggregate maintenance demand function. Using firm-level railroad estimates would overstate the level of aggregate maintenance. REML estimates both the pooled parameter γ and the heterogeneity variance τ^2 by maximizing the restricted likelihood.

Elasticity (ω): I pool both R-1 and SOI estimates of ω, allowing for unstructured between-study covariance across datasets. This approach automatically gives more weight to tighter estimates (primarily from R-1) while preserving information from both identification strategies. The REML specification is analogous to the level parameter case but includes estimates from both datasets. I exclude physical capital specifications (using horsepower or ton capacity) because they use different denominators than the SOI book capital and are not directly comparable.

From the SOI, I exclude specifications with untaxable firms because they face no tax incentive by construction and exhibit elasticities statistically indistinguishable from zero, serving as a placebo test rather than an informative estimate of the demand parameter.

Covariance Matrix Construction. The full parameter vector for the demand function is $\theta = (\gamma, \omega)$. For inference on policy counterfactuals, I need the 2×2 covariance matrix $\Sigma = \text{Var}(\theta)$. The diagonal elements come directly from the REML estimates: $\text{Var}(\gamma)$ from the level parameter pooling and $\text{Var}(\omega)$ from the elasticity pooling. The off-diagonal element $\text{Cov}(\gamma, \omega)$ is obtained by taking a precision-weighted average of the empirical covariances from SOI samples:

$$\widehat{\text{Cov}}(\gamma, \omega) = \frac{\sum_{i \in \text{SOI}} w_i \widehat{\text{Cov}}(\hat{\gamma}_i, \hat{\omega}_i)}{\sum_{i \in \text{SOI}} w_i}, \tag{A.20}$$

where $w_i = 1/(\sigma_i^2 + \tau^2)$ are the precision weights from REML.

In some iterations, this empirical covariance exceeds the positive-definite bound $\sqrt{\text{Var}(\gamma)\text{Var}(\omega)}$ because estimates come from different samples with different units of observation. When this occurs, I truncate the correlation to $\rho = 0.99$ of the bound to ensure a valid covariance matrix:

$$\widehat{\text{Cov}}(\gamma, \omega) = 0.99 \times \sqrt{\text{Var}(\gamma)\text{Var}(\omega)}. \tag{A.21}$$

This ensures the covariance matrix is positive-definite for subsequent inference while preserving the strong positive correlation between γ and ω implied by the delta method.

Comparison to Individual Datasets. Figure 9 in the main text plots the pooled demand curve alongside the individual R-1 and SOI curves. The pooled curve lies between the two but closer to the SOI in terms of the level parameter γ (to capture aggregate maintenance intensity) and closer to the R-1 in terms of the elasticity ω (to benefit from precision). The 95% confidence band around the pooled curve reflects both within-study sampling error and between-study heterogeneity, appropriately reflecting model uncertainty about which identification strategy better captures the policy-relevant elasticity.

The pooled curve is more elastic than the SOI curve because the meta-analysis places substantial weight on the larger R-1 elasticity estimates. However, it passes through a lower level of maintenance at any given relative price compared to the R-1 curve, because the level parameter γ comes exclusively from SOI estimates. This combination reflects the goal of constructing an aggregate demand schedule (favoring SOI for the level) that incorporates the precision of firm-level identification (favoring R-1 for the slope).

D Derivations for the Main Model

D.1 Tax Elasticity of User Cost

Benchmark Case

Under the benchmark,

$$\Psi = \frac{r^k + \delta}{1 - \tau}.$$

Consequently, the tax elasticity is

$$\begin{aligned} \varepsilon_\Psi &= \frac{\partial \Psi}{\partial \tau} \frac{\tau}{\Psi} \\ &= \frac{r^k + \delta}{(1-\tau)^2} \times \frac{1-\tau}{r^k + \delta} \times \tau \\ &= \frac{\tau}{1-\tau}. \end{aligned} \tag{A.22}$$

NGMM Tax Elasticity

Under the NGMM with $p^M = p^I$, the user cost of capital is

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

Let $\tilde{\Psi} \equiv r^k + \delta(m) + (1-\tau)m$. The elasticity is therefore

$$\begin{aligned} \varepsilon_\Psi &= \frac{(1-\tau)\Big[\delta'(m)m'(\tau) + (1-\tau)m'(\tau) - m\Big] + \tilde{\Psi}}{(1-\tau)^2} \times \frac{1-\tau}{\tilde{\Psi}} \times \tau \\ &= \frac{\tau}{1-\tau}\left(1 - \frac{m}{\Psi} + \frac{\delta'(m)m'(\tau) + (1-\tau)m'(\tau)}{\Psi}\right) \end{aligned} \tag{A.23}$$

By the envelope theorem, we could discard the terms $\delta'(m)m'(\tau) + (1-\tau)m'(\tau)$ because when m is chosen optimally they cancel out since $\delta'(m) = -(1-\tau)$. However, it will behoove us to instead rewrite them in elasticity form. Let

$$\varepsilon_m = \frac{\partial m}{\partial(1-\tau)}\frac{1-\tau}{m},$$

so

$$m'(\tau) = -\frac{m}{1-\tau}\varepsilon_m,$$

where ε_m is the maintenance demand elasticity. Next, define

$$\varepsilon_\delta = \frac{\partial\delta}{\partial m}\frac{m}{\delta} \Rightarrow \delta'(m)m'(\tau) = \frac{\delta(m)}{m}\varepsilon_\delta \times \left(-\frac{m}{1-\tau}\right) = \frac{\delta(m)}{1-\tau}\varepsilon_\delta\varepsilon_m,$$

where ε_δ is the elasticity of depreciation with respect to maintenance. Putting those pieces together yields

$$\delta'(m)m'(\tau) + (1-\tau)m'(\tau) = -\varepsilon_m\left[\frac{\delta(m)\varepsilon_\delta}{1-\tau} + m\right]$$

Thus,

$$\varepsilon_\Psi = \frac{\tau}{1-\tau}\left(1 - \frac{m}{\Psi} - \frac{\varepsilon_m}{\Psi}\left[\frac{\delta(m)\varepsilon_\delta}{1-\tau} + m\right]\right). \tag{A.24}$$

D.2 The Tax Elasticity of Investment

In steady state, investment is given by $I = \delta(m)K$. Defined explicitly in terms of tax rates,

$$I(\tau) = \delta(m(\tau)) \cdot K(\tau, m(\tau), \delta(m(\tau))) \tag{A.25}$$

To first order,

$$\varepsilon_I \approx \tau\left[\frac{\delta'(m(\tau))}{\delta(m(\tau))}m'(\tau)+\frac{1}{K}\left(\frac{\partial K}{\partial \tau}+\frac{\partial K}{\partial m(\tau)}m'(\tau)+\frac{\partial K}{\partial \delta(m(\tau))}\delta'(m(\tau))m'(\tau)\right)\right] \tag{A.26}$$
$$= \varepsilon_\delta + \varepsilon_K.$$

With the Cobb-Douglas user cost specification and a depreciation technology

$$\delta(m) = \delta_0 - \frac{\gamma^{1/\omega}}{1-1/\omega}m^{1-1/\omega}$$

and replacing m with the corresponding optimality condition, steady state investment becomes

$$X = \left(\delta_0 - \frac{\gamma}{1-1/\omega}(1-\tau)^{1-\omega}\right)\left(\frac{r^k+\delta_0+\frac{\gamma}{1-\omega}(1-\tau)^{1-\omega}}{\alpha(1-\tau)}\right)^{\frac{-1}{1-\alpha}}, \tag{A.27}$$

I derive each in component in steps. Given τ small,

$$\delta(m) \approx \delta_0 + \frac{\gamma\omega}{1-\omega}\left(1-(1-\omega)\tau\right).$$

Since

$$\frac{\partial \delta(m)}{\partial \tau} = -\gamma\omega,$$

the tax semi-elasticity is

$$\varepsilon_\delta \approx \frac{-\gamma\omega}{\delta_0 + \frac{\gamma\omega}{1-\omega}}, \tag{A.28}$$

where I assume that $\tau \approx 0$. Since the pre-reform tax rate is 4%, this is a sensible approximation. Now consider the tax semi-elasticity of capital. In the first step,

$$\frac{\partial K}{\partial \tau}\frac{1}{K} = \frac{-1}{1-\alpha}\left(\frac{\alpha(1-\tau)}{r^k+\delta_0+\frac{\gamma}{1-\omega}(1-\tau)^{1-\omega}}\right)\left(\frac{\alpha\left(\gamma(1-\tau)^{1-\omega}+r^k+\delta_0+\frac{\gamma}{1-\omega}(1-\tau)^{1-\omega}\right)}{(\alpha(1-\tau))^2}\right)$$
$$= \frac{-1}{1-\alpha}\frac{1}{1-\tau}\left(1-\frac{\gamma(1-\tau)^{1-\omega}}{r^k+\delta_0+\frac{\gamma}{1-\omega}(1-\tau)^{1-\omega}}\right)$$

To first order, the semi-elasticity becomes approximately

$$\varepsilon_K \approx \frac{-1}{1-\alpha}\left(1-\frac{\gamma}{r^k+\delta_0+\frac{\gamma}{1-\omega}}\right). \tag{A.29}$$

Consequently, the tax semi-elasticity of investment is approximately

$$
\begin{aligned}
\varepsilon_I &\approx \varepsilon_\delta + \varepsilon_K \\
&\approx \frac{-\gamma\omega}{\delta_0 + \frac{\gamma\omega}{1-\omega}} + \frac{-1}{1-\alpha}\left(1 - \frac{\gamma}{r^k + \delta_0 + \frac{\gamma}{1-\omega}}\right).
\end{aligned}
\tag{A.30}
$$

Applying the parameters used in the quantitative section implies that $\varepsilon_I \approx -5$.

D.3 Omitted Variable Bias in Investment Regressions

Standard approaches to recovering the tax elasticity of investment are flawed. A typical approach runs a cross-sectional regression like

$$
f\left(I_{i,t}, K_{i,t}\right) = \alpha_i + T_t + \hat{\beta}\log\left(\frac{r^k + \delta}{1 - \tau_{i,t}}\right) + \epsilon_{i,t}, \tag{A.31}
$$

where $f\left(I_{i,t}, K_{i,t}\right)$ is typically the investment rate $I_{i,t}/K_{i,t}$ or $\log I_{i,t}$, α_i is a firm fixed effect, and T_t is a time fixed effect. The estimated coefficient $\hat{\beta}$ yields the price elasticity of investment. For example, Kitchen and Knittel (2011), Zwick and Mahon (2017), and Garrett, Ohrn, and Suárez Serrato (2020) use such regressions to evaluate bonus depreciation, while Kennedy et al. (2023) and Chodorow-Reich et al. (2025) do the same for the the 2017 Tax Cuts and Jobs Act. The maintenance model suggests that (A.31) is misspecified. Instead, economists should estimate

$$
f\left(I_{i,t}, K_{i,t}\right) = \alpha_i + T_t + \beta\log\left(\frac{r^k + \delta(m_{i,t})}{1 - \tau_{i,t}} + m_{i,t}.\right) + \epsilon_{i,t}. \tag{A.32}
$$

Misspecification arises because the demand for investment depends on the demand for maintenance and hence standard regressions do not properly capture the true change in the incentive to build new capital. This introduces an omitted variable bias in standard regressions which biases downward estimated investment elasticities. The insight is analogous to the lesson of Goolsbee (1998a), which emphasizes that an underlying model of a perfectly competitive capital goods market leads to an underestimate of the investment demand elasticity if the supply of equipment is not perfectly competitive. In the same way 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.

Corollary 2 *With a constant elasticity of demand for maintenance $m_{i,t} = \gamma(1-\tau_{i,t})^{-\omega}$, the true price elasticity of investment is*

$$
\beta \approx \frac{\hat{\beta}}{1 - \frac{\gamma}{r^k + \delta_0 + \frac{\gamma}{1-\omega}}}. \tag{A.33}
$$

Proof. Consider the regressions

$$f\left(I_{i,t},K_{i,t}\right)=\alpha_i+T_t+\hat{\beta}\log\left(\frac{r^k+\delta}{1-\tau_{i,t}}\right)+\epsilon_{i,t}, \tag{A.34}$$

and

$$f\left(I_{i,t},K_{i,t}\right)=\alpha_i+T_t+\beta\log\left(\frac{r^k+\delta(m_{i,t})}{1-\tau_{i,t}}+m_{i,t}\right)+\epsilon_{i,t}. \tag{A.35}$$

Under the assumption that $\tau_{i,t}$ is small, the omitted term is

$$\begin{aligned}
\text{Omitted Term} &= \log\left(\frac{r^k+\delta_0+\frac{\gamma}{1-\omega}(1-\tau_{i,t})^{1-\omega}}{1-\tau_{i,t}}\right)-\log\left(\frac{r^k+\delta}{1-\tau_{i,t}}\right)\\
&\approx \log\left(\frac{r^k+\delta_0+\frac{\gamma}{1-\omega}(1-(1-\omega)\tau_{i,t})}{r^k+\delta}\right)\\
&= \log\left(\frac{r^k+\delta_0+\frac{\gamma}{1-\omega}}{r^k+\delta}\left(1-\frac{\gamma\tau_{i,t}}{r^k+\delta_0+\frac{\gamma}{1-\omega}}\right)\right)\\
&\approx \frac{\gamma\tau_{i,t}}{r^k+\delta_0+\frac{\gamma}{1-\omega}},
\end{aligned}$$

where I omit the constants since they will not affect the covariance. Using that, the omitted variable bias is given by:

$$\begin{aligned}
\text{Bias} &= \beta\cdot\frac{\text{Cov}\left(\log\left(r^k+\delta\right)-\log\left(1-\tau_{i,t}\right),\frac{\gamma\tau_{i,t}}{r^k+\delta_0+\frac{\gamma}{1-\omega}}\right)}{\text{Var}\left(\log\left(\frac{r^k+\delta}{1-\tau_{i,t}}\right)\right)}\\
&\approx \beta\cdot\frac{\text{Cov}\left(\tau_{i,t},\frac{\gamma\tau_{i,t}}{r^k+\delta_0+\frac{\gamma}{1-\omega}}\right)}{\text{Var}\left(\tau_{i,t}\right)}\\
&= \beta\cdot\frac{\gamma}{r^k+\delta_0+\frac{\gamma}{1-\omega}}
\end{aligned} \tag{A.36}$$

Since we can write

$$\hat{\beta}=\beta\left(1+\text{Bias}\right),$$

a general expression for the true elasticity parameter is

$$\beta\approx\frac{\hat{\beta}}{1-\frac{\gamma}{r^k+\delta_0+\frac{\gamma}{1-\omega}}}. \tag{A.37}$$

Therefore, we cannot use the standard tools of public finance to assess the effects of tax reforms unless we also know the maintenance demand function. Under this paper's parameterization, a maintenance-corrected coefficient boosts the estimated elasticity by a factor of about 1.5. Note, moreover, that this formula corresponds to many estimated elasticities. For example, many papers regress investment or the investment rate on the tax term alone, which itself comes from an approximation of the log user cost above. Therefore, the consensus range of investment rate elasticities from Hassett and Hubbard (2002) of 0.5-1 is perhaps more like 0.75-1.5. □

D.4 Adjustment Costs

In the general case, consider a firm choosing sequences of maintenance, investment, labor, and capital to maximize profits:

$$\begin{aligned} \max_{I_t, M_t, L_t, K_{t+1}} \sum_{t=0}^{\infty} \left(\frac{1}{1+r^k}\right)^t \Bigg\{ & (1-\tau_t^c)\left(F\left(K_t, L_t\right) - w_t L_t - \frac{\phi}{2}\left(\frac{I_t}{K_t} - \delta(m_t)\right)^2 K_t - p_t^M M_t\right) \\ & - \left(1 - c_t - z_t\tau_t\right) p_t^I I_t \Bigg\} \quad \text{s.t.} \quad K_{t+1} = (1-\delta) K_t + I_t. \end{aligned} \tag{A.38}$$

Letting q_t denote the multiplier on the law of motion for capital, the first-order conditions on maintenance and investment are

$$-q_t\delta'(m_t) = (1-\tau_t^c)\left(p_t^M - \phi\delta'(m_t)\left(\frac{I_t}{K_t} - \delta(m_t)\right)\right) \tag{A.39}$$

$$(1-\tau_t^c)\phi\left(\frac{I_t}{K_t} - \delta(m_t)\right) = q_t - \left(1 - c_t - z_t\tau_t^c\right) p_t^I. \tag{A.40}$$

Using the investment FOC, the maintenance FOC can be rewritten as

$$-\delta'(m_t) = \frac{1-\tau_t^c}{1-c_t-z_t\tau_t^c}\frac{p_t^M}{p_t^I}. \tag{A.41}$$

Rearranging the investment FOC, we have

$$\frac{I_t}{K_t} = \frac{1}{(1-\tau_t)\phi}\left(q_t - (1-c_t-z_t\tau_t^c)p_t^I\right) + \delta(m_t) \tag{A.42}$$

For simplicity, define

$$\kappa \equiv (1-c_t-z_t\tau_t^c)p_t^I \qquad i_t \equiv I_t/K_t$$

and drop time subscripts so

$$i = \frac{q-\kappa}{(1-\tau^c)\phi} + \delta(m).$$

In steady state, it is clear that

$$-\delta'(m) = \frac{1-\tau^c}{q} p^M.$$

Consequently,

$$\frac{\partial i}{\partial q} = \frac{1}{1-\tau^c}\frac{1}{\phi} + \frac{\partial \delta(m)}{\partial q}$$

Re-expressing as elasticities,

$$|\varepsilon_I| \equiv \left|\frac{\partial \ln i}{\partial \ln q}\right| = \left|\frac{\partial i}{\partial \kappa}\right| \frac{q}{i}, \tag{A.43}$$

$$|\varepsilon_\delta| \equiv \left|\frac{\partial \ln \delta}{\partial \ln q}\right| = \left|\frac{\partial \delta}{\partial q}\right| \frac{q}{\delta(m)}. \tag{A.44}$$

Since i and δ both rise when q rises, the partial derivatives are positive. The short-run elasticity is therefore, after substituting $\delta = i$ in steady state,

$$|\varepsilon_I| = \frac{\kappa}{i(1-\tau^c)\,\phi} + |\varepsilon_\delta|\,. \tag{3}$$

Local to a zero marginal tax rate (*i.e.*, $\kappa = q \approx 1$) and given estimates for the short-run elasticities $\hat{\varepsilon}_I$ and $\hat{\varepsilon}_\delta$, we can solve for the adjustment cost parameter as

$$\phi^{NGMM} = \frac{1}{\delta(m)} \frac{1}{|\hat{\varepsilon}_I| - |\hat{\varepsilon}_\delta|}.$$

When maintenance demand is inelastic, this collapses to

$$\phi = \frac{1}{\delta(m)} \frac{1}{|\hat{\varepsilon}_I|}.$$

Since $\hat{\varepsilon}_I$ is smaller in the NGMM than the NGM even with inelastic demand demand for maintenance, adjustment costs will be larger in the NGMM. Finally, if demand is elastically zero for maintenance, then we recover the NGM adjustment cost expression

$$\phi = \frac{1}{\delta} \frac{1}{|\hat{\varepsilon}_I|}.$$

D.5 Stability Under Cobb-Douglas Production

Profit Function

Consider a firm with Cobb-Douglas production

$$F(K_t, L_t) = K_t^{\alpha_K} L_t^{\alpha_L}.$$

The firm pays a wage bill $w_t L_t$. We can use the first-order condition to write the expression $F(K_t, L_t) - w_t L_t$ entirely in terms of labor by manipulating the static optimization problem for labor demand. Since

$$w_t = \alpha_L K_t^{\alpha_K} L_t^{\alpha_L - 1},$$

we can rewrite income net of the wage bill as

$$\begin{aligned} K_t^{\alpha_K} L_t^{\alpha_L} - w_t L_t &= (1 - \alpha_L) K_t^{\alpha_K} L_t^{\alpha_L} \\ &= (1 - \alpha_L) K_t^{\alpha_K} \left(\frac{\alpha_L K_t^{\alpha_K}}{w_t} \right)^{\frac{\alpha_L}{1-\alpha_L}} \\ &= Z_t K_t^{\alpha}, \end{aligned}$$

where

$$\alpha \equiv \frac{\alpha_K}{1 - \alpha_L} \quad \text{and} \quad Z_t \equiv (1 - \alpha_L) \left(\frac{\alpha_L}{w_t} \right)^{\frac{\alpha_L}{1-\alpha_L}}.$$

Linearized System

As in Chodorow-Reich et al. (2025), I make the assumption that the tax policy parameters are already at their steady state values. That means maintenance is already at its steady state value when considering convergence toward the post-TCJA steady state and hence depreciation is also fixed.[24] Let variables with hats denote log-deviations and note that the deviation for λ_t is additive, *i.e.*, $\hat{\lambda}_t = \lambda_t - \bar{\lambda}$. In steady state,

$$h(\bar{\lambda}) = 0 \tag{A.45}$$

$$h'(\bar{\lambda}) = \frac{1}{\phi(1 - \tau)}. \tag{A.46}$$

24. Introducing adjustment costs on maintenance would change the results quantitatively, but not qualitatively.

The linearized system therefore reduces to

$$\hat{\lambda}_t(1+r^k) = (1-\tau)F''(\bar{K})\bar{K}\hat{K}_{t+1} + \hat{\lambda}_{t+1}\left(1-\delta(m)+\delta'(\bar{m})\bar{m}\right) \tag{A.47}$$

$$\hat{K}_{t+1} = \frac{\hat{\lambda}_t}{\phi(1-\tau)} + \hat{K}_t \tag{A.48}$$

From Equations (A.47) and (A.48), the system can be represented as:

$$\begin{bmatrix} \hat{\lambda}_{t+1} \\ \hat{K}_{t+1} \end{bmatrix} = \boldsymbol{A} \begin{bmatrix} \hat{\lambda}_t \\ \hat{K}_t \end{bmatrix}$$

where

$$\boldsymbol{A} = \begin{bmatrix} \dfrac{1+r^k-\frac{1}{\phi}F''(\bar{K})\bar{K}}{1-\delta(\bar{m})+\delta'(\bar{m})\bar{m}} & \dfrac{-(1-\tau)F''(\bar{K})\bar{K}}{1-\delta(\bar{m})+\delta'(\bar{m})\bar{m}} \\ \dfrac{1}{\phi(1-\tau)} & 1 \end{bmatrix}$$

This matrix has eigenvalues

$$\mu = \frac{C_1 \pm \sqrt{C_1^2 - 4(1+r^k)C_2}}{2C_2}$$

where

$$C_1 = 2 + r^k - \delta(\bar{m}) + \delta'(\bar{m})\bar{m} - \frac{1}{\phi}F''(\bar{K})\bar{K}$$
$$C_2 = 1 - \delta(\bar{m}) + \delta'(\bar{m})\bar{m}$$

and associated eigenvector

$$\mathbf{v} = \begin{bmatrix} 1 \\ \dfrac{-1}{\phi(1-\tau)(1-\mu)} \end{bmatrix}.$$

Short-Run to Long-Run Investment Ratio χ_{SR}

This subsection shows that there is a constant ratio between investment deviations in the short run and the long run. The proof is similar to Chodorow-Reich et al. (2025), but instead is in discrete time. Because maintenance instantaneously adjusts, it suffices to show that the ratio of capital deviations is constant. First, note that

$$
\begin{aligned}
\frac{K_{t+1}-K_t}{K_0} &= \frac{\bar{K}}{K_0}\frac{K_{t+1}-K_t}{\bar{K}} \\
&= \frac{\bar{K}}{K_0}\frac{(K_{t+1}-\bar{K})-(K_t-\bar{K})}{\bar{K}} \\
&= \frac{\bar{K}}{K_0}\left(\hat{K}_{t+1}-\hat{K}_t\right) \\
&= \frac{\bar{K}}{K_0}\left(\mu_1^{t+1}\hat{K}_0-\mu_1^t\hat{K}_0\right) \\
&= (\mu_1-1)\,\mu^t\frac{\bar{K}}{K_0}\hat{K}_0 \\
&= (1-\mu_1)\,\mu_1^t\tilde{k},
\end{aligned}
$$

where

$$
\tilde{k} = \frac{\bar{K}-K_0}{K_0}
$$

is the long-run change in capital given the initial position K_0. We can then derive the average change in investment from period zero to T relative to period zero as

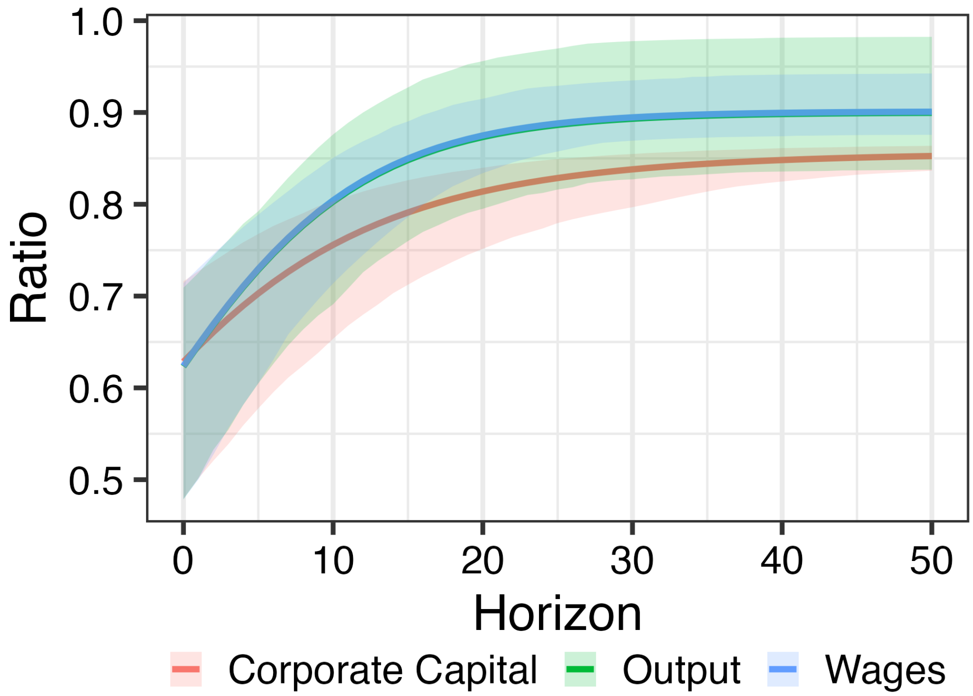
$$
\begin{aligned}
\frac{1}{T+1}\sum_{t=0}^{T}\frac{I_t-I_0}{I_0} &= \frac{1}{T+1}\sum_{t=0}^{T}\frac{K_{t+1}-(1-\delta(m))K_t-\delta(m)K_0}{\delta(m)K_0} \\
&= \frac{1}{\delta(m)\,(T+1)}\sum_{t=0}^{T}\left(\delta(m)\frac{K_t-K_0}{K_0}+\frac{K_{t+1}-K_t}{K_0}\right) \\
&= \frac{1}{\delta(m)\,(T+1)}\sum_{t=0}^{T}\left(\delta(m)\frac{K_t-K_0}{K_0}+(1-\mu_1)\mu_1^t\tilde{k}\right) \\
&\approx \frac{1}{\delta(m)\,(T+1)}\sum_{t=0}^{T}\left(\delta(m)\left(\tilde{k}+\frac{K_t-\bar{K}}{K_0}\right)+(1-\mu_1)\mu_1^t\tilde{k}\right) \\
&\approx \frac{1}{\delta(m)\,(T+1)}\sum_{t=0}^{T}\left(\delta(m)\left(\tilde{k}-\mu_1^t\tilde{k}\right)+(1-\mu_1)\mu_1^t\tilde{k}\right) \\
&= \tilde{k}\left(1+\frac{(1-\mu_1-\delta(m))(1-\mu^{T+1})}{\delta(m)(1-\mu_1)(T+1)}\right)
\end{aligned}
$$

Therefore the ratio of short-run to long-run investment is a constant:

$$
\begin{aligned}
\chi_{SR} = \frac{\text{Average Deviation}}{\text{Long-Run Deviation}} &= \tilde{k}\left(1+\frac{(1-\mu_1-\delta(m))(1-\mu^{T+1})}{\delta(m)(1-\mu_1)(T+1)}\right)/\tilde{k} \\
&= 1+\frac{(1-\mu_1-\delta(m))(1-\mu^{T+1})}{\delta(m)(1-\mu_1)(T+1)}.
\end{aligned}
\tag{A.49}
$$

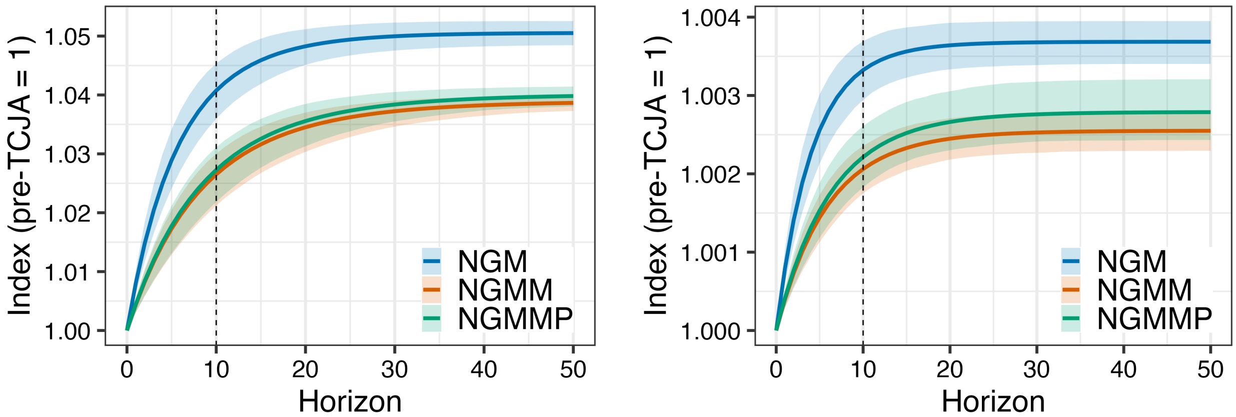
E Quantification

Figure E.1: NGMMP-NGM Ratio of Aggregates



Notes: The NGM corporate capital, output, and wages are exactly as in the main text. The NGMMP is an extension of the baseline NGMM which specifies that the price of maintenance rises with wages. I assume that wages are half the cost of maintenance.

Figure E.2: The Effect of TCJA on Corporate Capital and Aggregate Output with Crowding Out

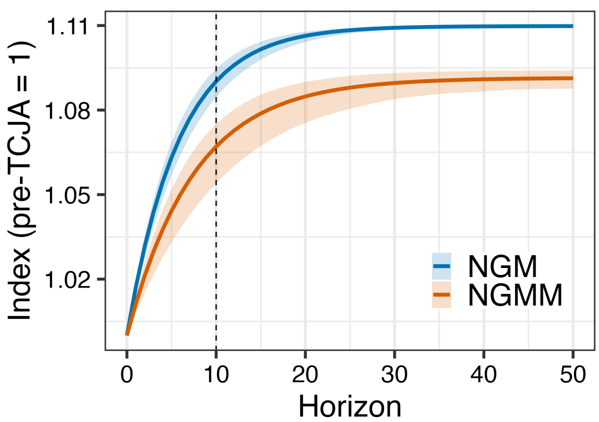


(a) Paths of Corporate Capital

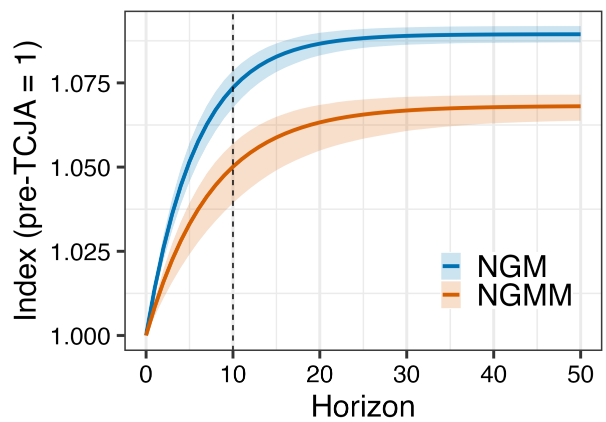
(b) Paths of Output

Notes: Panel (a) shows the response of capital to the TCJA in the NGMM (orange line) and the NGM (blue line), and the NGMMP (green line), and Panel (b) plots the corresponding IRFs for aggregate output. To account for crowding out, we translate the 2027 debt-output ratio into an increase in discount rates using the static score of each model. The increase in debt-output corresponds to an increase in discount rates drawn from Neveu and Schafer (2024). A one percentage point increase in the debt-GDP ratio corresponds to a 2.2 percentage point increase in the discount rate (SE = 1.0). All lines are bootstrapped with a 95% confidence interval accounting for uncertainty in maintenance demand and crowding out.

Figure E.3: The Effect of TCJA on Corporate Capital in Partial Equilibrium



(a) Baseline



(b) Crowding Out

Notes: Panel (a) shows the response of corporate capital to the TCJA in the NGMM (orange line) and the NGM (blue line), and Panel (b) plots the corresponding IRFs with crowding out. To account for crowding out, we translate the 2027 debt-output ratio into an increase in discount rates using the static score of each model. The increase in debt-output corresponds to an increase in discount rates drawn from Neveu and Schafer (2024). A one percentage point increase in the debt-GDP ratio corresponds to a 2.2 percentage point increase in the discount rate (SE = 1.0). All lines are bootstrapped with a 95% confidence interval accounting for uncertainty in maintenance demand and crowding out.

F Model Extensions

F.1 Capital Reallocation

This subsection extends the base model to heterogeneous firms which only differ in their tax status. That leads to reallocation through variation in the marginal product of capital. A fraction $\lambda \in (0,1)$ of firms is taxable (Type T) and the remaining $1-\lambda$ are untaxed (Type U). Variation in taxability comes from realization of an i.i.d. fixed cost F, which is assumed to be sufficiently large that it exceeds profits. Untaxed firms also pay a higher cost of investment $p^I + b$, which is meant to account (in a reduced-form way) for the fact that untaxable firms often face some kind of financial constraint that hinders their ability to access new investment (Lian and Ma 2020). This formulation allows us to model the fact that investment is typically more expensive for unprofitable firms without explicitly modeling the borrowing constraint.

Each period, a firm observes its tax type $\theta \in \{T, U\}$:

- Type T (taxable) firms face corporate tax τ^c.

- Type U (untaxed) firms pay no corporate tax because they have a fixed cost F. They also have a higher cost of investment $p^I + b$.

After observing its type, a firm chooses:

1. Maintenance expenditure M, with $m = \frac{M}{K}$ being the maintenance intensity.
2. Investment I (at new capital price p^I).
3. Net used–capital sales s, where $s > 0$ indicates selling a fraction of the capital and $s < 0$ indicates buying used capital. Firms pay a convex adjustment cost $G(s)$ for participating in the used capital market, which can be thought of as accounting for information frictions in a reduced–form way. For example, a firm selling a used car must furnish information about the vehicle, which is costly to do. The equilibrium used–capital price is denoted by q.

Putting together maintenance expenditures $m = M/K$, investment I, and capital sales s, the law of motion for capital (independently of tax status) is

$$K' = \Big[1 - \delta(m)\Big](1 - s)K + I. \tag{A.50}$$

Because firms vary in their tax status, they also vary in their cash flows. Profitable firms have cash flows

$$\pi^T = (1 - \tau^c)\Big[F(K) - p^m M + q\, s\, K - G(s)\Big] - \big(1 - c - \tau^c z\big)p^I I,$$

where z incorporates the possibility that the firm may be untaxable in the future and hence will not always be able to take advantage of a tax depreciation allowance. Note that capital sales are taxed at rate τ^c, reflecting current policy practice. Given those cash flows, we get the following recursive formulation for a firm choosing K', s, M:

$$\begin{aligned} V^T(K) = \max_{m,s,K'} \Bigg\{ &(1 - \tau^c)\Big[F(K) - p^m\, mK + q\, s\, K - G(s)\Big] \\ &- \big(1 - c - \tau^c z\big)p^I\Big(K' - [1 - \delta(m)](1 - s)K\Big) + \frac{V^*(K')}{1 + r^k} \Bigg\}, \end{aligned} \tag{A.51}$$

where

$$V^*(K') = \lambda\, V^T(K') + (1 - \lambda)\, V^U(K')$$

is the expected continuation value. Taxable firms therefore have the following FOCs:

$$\textbf{Investment:} \quad \frac{V^{*'}(K')}{1 + r^k} = \big(1 - c - \tau^c z\big)p^I, \tag{A.52}$$

$$\textbf{Maintenance:} \quad -\delta'(m) = \frac{1 - \tau^c}{1 - c - \tau^c z} \frac{p^m}{p^I\,(1 - s)}, \tag{A.53}$$

$$\textbf{Sales:} \quad (1 - \tau^c)\Big[q - G'(s)\Big] = \big(1 - c - \tau^c z\big)p^I\,[1 - \delta(m)]. \tag{A.54}$$

On the other hand, untaxed type U firms do not face any tax, so their cash flows are

$$\pi^U = F(K) - p^m M + q\,s\,K - G(s) - (1-\tau^c\tilde{z})(p^I + b)I - F.$$

Given those cash flows, we get the following recursive formulation for a firm choosing K', s, M:

$$\begin{aligned} V^U(K) = \max_{m,s,K'} \Bigg\{ & F(K) - p^m\, mK + q\,s\,K - G(s) \\ & - (1-\tau^c\tilde{z})(p^I+b)\Big(K' - [1-\delta(m)](1-s)K\Big) + \frac{V^*(K')}{1+r^k}\Bigg\}. \end{aligned} \tag{A.55}$$

The type U FOCs are:

$$\textbf{Investment:} \quad \frac{V^{*'}(K')}{1+r^k} = (1-\tau^c\tilde{z})(p^I+b), \tag{A.56}$$

$$\textbf{Maintenance:} \quad -\delta'(m) = \frac{p^m}{(1-\tau^c\tilde{z})(p^I+b)(1-s)}, \tag{A.57}$$

$$\textbf{Sales:} \quad q - G'(s) = (1-\tau^c\tilde{z})(p^I+b)\,[1-\delta(m)]. \tag{A.58}$$

The envelope condition enables us to define the user cost of capital in this economy. For taxed firms,

$$V^{T\prime}(K) = (1-\tau^c)\Big[F'(K) - p^m\, m^T + q\,s^T\Big] + \big(1 - c - \tau^c z\big)p^I\,(1-\delta(m^T)),$$

while for untaxed firms we have

$$V^{U\prime}(K) = F'(K) - p^m\, m^U + q\,s^U + (1-\tau^c\tilde{z})(p^I+b)\,(1-\delta(m^U)).$$

The combined envelope condition is

$$V^{*'}(K) = \lambda\, V^{T\prime}(K) + (1-\lambda)\, V^{U\prime}(K).$$

Equilibrium

An equilibrium in this economy is a collection of policies $\{V^T,\, V^U\}$, prices $\{q, p^I, p^M\}$ (the latter two exogenous) and allocations $\{\, m^T,\, s^T,\, K'^T,\, m^U,\, s^U,\, K'^U\}$ such that:

1. For all K, the Bellman equations for $V^T(K)$ and $V^U(K)$ are satisfied with the corresponding optimal policies.

2. The chosen policy functions satisfy the FOCs for investment, maintenance, and used–capital sales (with type–specific controls m^θ and s^θ) and the envelope conditions hold.

3. The law of motion for capital,

$$K' = \Big[1 - \delta(m^\theta)\Big](1 - s)K + I,$$

is satisfied for each firm.

4. The used–capital market clears at the equilibrium price q; that is, the total net sales of used capital by all firms (taxable and untaxed) sum to zero:

$$\int s^T(K)\, d\mu(K) + \int s^U(K)\, d\nu(K) = 0,$$

where $\mu(K)$ and $\nu(K)$ are the distributions of capital among taxable and untaxed firms.

5. The expected continuation value is given by

$$V^*(K') = \lambda\, V^T(K') + (1 - \lambda)V^U(K'),$$

and firms form rational expectations consistent with the aggregate outcomes.

Trading Conditions

Trading of used capital will only arise under certain conditions. In particular, an active trading market is characterized by:

- Taxable firms choosing $s^T > 0$ (selling used capital) because their subsidized cost $\frac{1-c-\tau^c z}{1-\tau^c}\, p^I(1-\delta(m^T))$ is lower than that faced by untaxed firms.
- Untaxed firms choosing $s^U < 0$ (buying used capital) because the equilibrium used capital price q (adjusted by the marginal cost $G'(s^U)$) falls below the cost of acquiring new capital $p^I(1 - \delta(m^U))$.
- An equilibrium price q that satisfies

$$q = \frac{1 - c - \tau^c z}{1 - \tau^c}\, p^I(1 - \delta(m^T)) + G'(s^T) = (1 - \tau^c \tilde{z})(p^I + b)(1 - \delta(m^U)) + G'(s^U),$$

along with the market clearing condition

$$\lambda\, s^T + (1 - \lambda)\, s^U = 0.$$

Essentially, we require that the gap between the pre–tax price and after–tax price of new capital is sufficiently large that it is worth it for firms to sell used capital and for untaxed firms to buy it, i.e.,

$$\frac{(1-c-\tau^c z)p^I\left[1-\delta(m^T)\right]}{1-\tau^c} < q < (1-\tau^c\tilde{z})(p^I+b)[1-\delta(m^U)].$$

I focus on this equilibrium because we observe active used capital trading in practice.

Aggregate User Cost of Capital

It is straightforward to observe that the aggregate user cost of capital in this economy is a weighted average of user costs for the taxable and untaxable firms:

$$\boxed{\Psi_{\text{agg}} = \frac{\lambda\, K^T}{K}\,\Psi^T + \frac{(1-\lambda)\, K^U}{K}\,\Psi^U, \quad \text{with } K = \lambda\, K^T + (1-\lambda)\, K^U.}$$

Indeed, one can observe that the proportional change in user cost will be strictly smaller to first order in this economy than in the representative firm economy in the main model because the share of untaxable firms will not react very much. Moreover, capital sales will prop up the maintenance rate (since the maintenance optimality condition implies a higher maintenance rate for untaxable firms), so maintenance and depreciation change less in this economy in the aggregate.

F.2 Extension to Multiple Maintenance Inputs

In this section, I extend the model to consider multiple inputs to maintenance production as well as a choice between using internal or external maintenance services. Production is carried out entirely using capital:

$$Y_t = F(K_t).$$

Capital evolves according to

$$K_{t+1} = \Big[1-\delta(m_{I,t}, m_{E,t})\Big]K_t + I_t,$$

where $m_{I,t}$ is internal maintenance intensity and $m_{E,t}$ is external maintenance intensity. I assume that internal maintenance is the sum of labor and materials purchases

$$M_{I,t} = g(L_{m,t}, I_{m,t}).$$

The firm purchases internal maintenance labor at price w_t materials at price p_t^X. External maintenance $m_{E,t} = M_{E,t}/K_t$ is purchased at price p_t^m and faces some convex cost of adjustment $C(M_{E,t}, M_{E,t-1})$, with $C(M_E, M_E) = 0$ in steady state. This is to reflect the fact that external maintenance contracts are typically quite sticky. Since internal maintenance also includes labor, then internal maintenance is also sticky, but presumably less so than external maintenance because internal resources can be reallocated more quickly. I could capture that by having an outside option for labor or introducing a separate adjustment cost for internal maintenance, but it would be unnecessarily complicated. Note that with multiple maintenance types, the price of maintenance is a weighted average of each.

Taking K_0 as given, the firm chooses the sequence $\{K_{t+1},\ L_{m,t},\ I_{m,t},\ M_{E,t}\}_{t\geq 0}$ to maximize

$$\mathcal{L} = \sum_{t=0}^{\infty} \left(\frac{1}{1+r^k}\right)^t \Bigg\{(1-\tau_t^c)\Big[F(K_t) - w_t\, L_{m,t} - p_t^I\, I_{m,t} - M_{E,t} - C\big(M_{E,t}, M_{E,t-1}\big)\Big] \\ -\ (1-\tau_t^c z_t)p_t^I\Big[K_{t+1} - \Big(1-\delta\Big(m_{I,t}, m_{E,t}\Big)\Big)K_t\Big]\Bigg\},$$

subject to $m_{i,t} = \frac{g(L_{m,t}, I_{m,t})}{K_t}$. The first-order conditions are not substantially different from the baseline model. Starting with the capital Euler equation, we have The capital Euler equation is:

$$(1-\tau_t^c z_t)p_t^I = \frac{1}{1+r^k}\Bigg\{(1-\tau_{t+1}^c)\, F_K(K_{t+1}) + (1-\tau_{t+1}^c z_{t+1})\, p_{t+1}^I\Big[1-\delta\big(m_{I,t+1}, m_{E,t+1}\big) \\ + p_{t+1}^{M,I} m_{I,t+1} + p_{t+1}^{M,E} m_{E,t+1}\Big]\Bigg\}, \tag{A.59}$$

which in steady state simplifies to

$$F_K = p^I(1-\tau^c z)\left(\frac{r^k + \delta(m_I, m_E)}{1-\tau^c}\right) + p^{M,I} m_I + p^{M,E} m_E, \tag{A.60}$$

where $p^{M,I}$ is the price of internal maintenance. If internal maintenance is a CES aggregator of labor and materials, then $p^{M,I}$ would just be the usual CES price index of p^I and w.

There are three maintenance choices. Beginning with the choice of internal labor $L_{m,t}$, the firm's optimal choice is satisfied when

$$-\delta_1(t)\, g_L(t) = \frac{(1-\tau_t^c)w_t}{(1-\tau_t^c z_t)p_t^I}. \tag{A.61}$$

Similarly, optimal materials is given by

$$-\delta_1(t)\, g_M(t) = \frac{(1-\tau_t^c)p_t^X}{(1-\tau_t^c z_t)p_t^I}, \tag{A.62}$$

which implies the marginal rate of substitution between materials and labor is

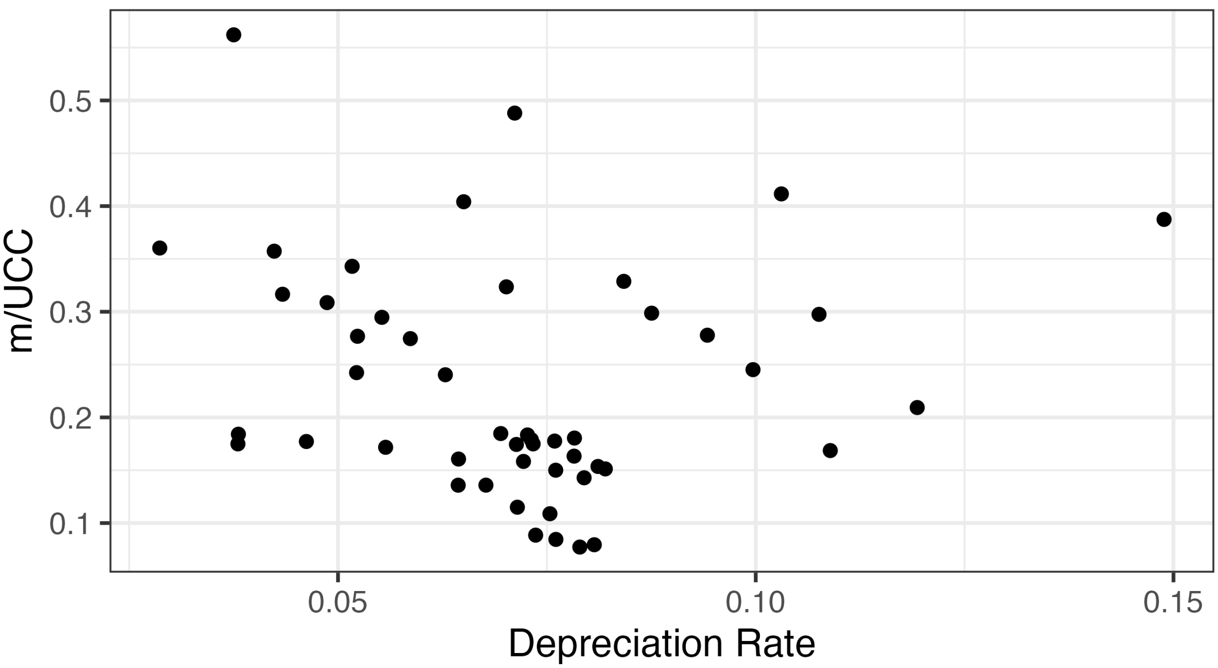
$$\frac{g_L(t)}{g_M(t)} = \frac{w_t}{p_t^I}. \tag{A.63}$$

On the other hand, external maintenance choice is given by

$$-\delta_2(t) = \frac{(1-\tau_t^c)\Big[1 + C_1(t)\Big] + \frac{1}{1+r^k}(1-\tau_{t+1}^c)\, C_2(t+1)}{(1-\tau_t^c z_t)p_t^I}. \tag{A.64}$$

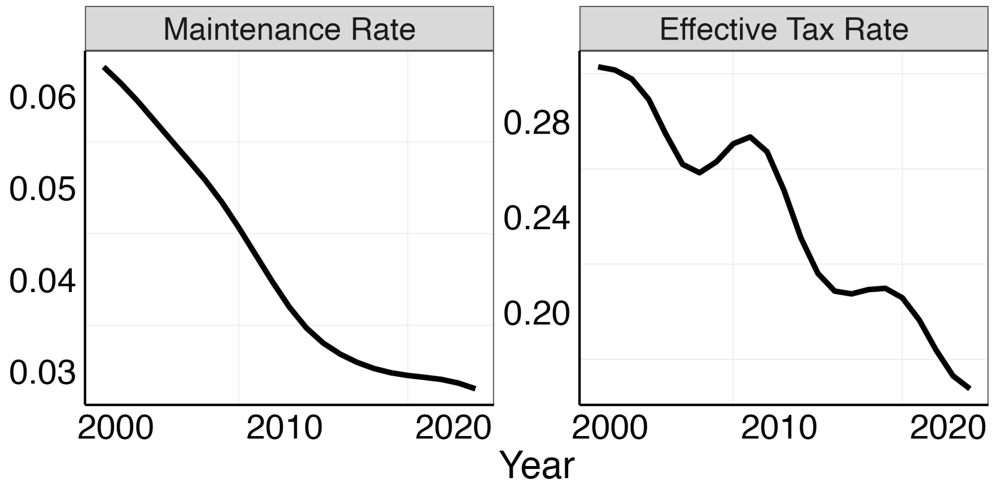
G Additional Figures and Tables

Figure G.1: The industry maintenance share of user cost is decreasing in the depreciation rate



Note: Each point is the time series average of maintenance shares and depreciation rates within an industry.

Figure G.2: Trends in Maintenance and Corporate Tax Rates



Notes: The maintenance rate is constructed as gross output in NAICS 811 excluding home repair as a share of current cost private equipment capital. The effective tax rate is the ratio of domestic corporate taxes paid to pre-tax profits from BEA Tables 6.16D and 6.17D. The cyclical component of each series has been removed with a Hodrick-Prescott filter.