Young Firms, Dirty Capital: Decarbonization and Capital Upgrading*

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Abstract

Does climate policy induce capital upgrading — and equally so across all firms? We use the universe of heavy goods vehicles registered to Swedish firms, matched to annual financial accounts, covering more than 100,000 truck acquisition events over 2007–2020. Our setting exploits Sweden's progressive biofuel blending scheme, which raised diesel costs. Young firms acquire older and lower Euro-standard trucks than established firms – consistent with young firms having insufficient internal funds to meet the larger down payments required for newer, cleaner capital. Studying entry, exit, and fleet-level margins, we show that this gap widens as diesel costs rise, with young firms substituting toward used trucks and leasing to partially offset the financing hurdle. At the fleet level, young firms with high diesel exposure maintain older and lower Euro-standard fleets as blending intensifies, with blending widening the pre-existing fleet age gap between young and established firms by roughly 8 percent. Our results highlight that the distributional consequences of climate policy depend critically on the financing environment faced by firms, and that instruments targeting the financing margin are needed complements to cost-raising policy.

Keywords: Carbon pricing, Climate policy, Investment, Environmental taxes
JEL codes: Q53, Q54, G31

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1 Introduction

Decarbonizing the economy requires replacing old, energy-intensive capital with cleaner alternatives at scale. Policymakers typically rely on instruments that raise the operating cost of dirty capital — carbon taxes, fuel mandates, emission standards – to accelerate this transition. A large literature documents that such policies can stimulate green innovation and reduce emissions (e.g., Acemoglu et al., 2016, Aghion et al., 2016, Calel and Dechezleprêtre, 2016, Martinsson et al., 2024). Yet a central question remains unanswered: does raising the operating cost of dirty capital actually induce firms to upgrade — and equally so across all firms? If newer, cleaner capital requires larger upfront investment, firms with limited internal funds may face a financing hurdle that prevents them from acting on the incentive to upgrade, even as the operating cost of their existing capital rises (e.g., Rampini, 2019, Lanteri and Rampini, 2025, Ma et al., 2022). Understanding this dimension is important both for assessing who bears the costs of decarbonization and for designing complementary policy instruments that ensure its benefits are broadly shared.

We study capital upgrading decisions in the market for heavy goods vehicles in Sweden over 2007–2020, a period in which the share of biofuel in Swedish diesel increased from 3 to 27 percent, raising the effective operating cost of diesel trucks.[1] Our data cover the universe of heavy goods vehicles registered to Swedish firms – 112,657 truck acquisition events and 82,824 exit events – matched to annual financial accounts. We document how the policy-induced increase in diesel costs shapes truck acquisition decisions, fleet composition, and capital reallocation through the secondary market, and whether these responses differ systematically across firms.

Our empirical strategy exploits three sources of variation: the progressive increase in the blend share over the sample period, which creates a time-series policy shock; pre-determined differences across firms in diesel exposure, which generate cross-sectional heterogeneity in the incentive to upgrade; and differences in firm age, which generate cross-sectional heterogeneity in the ability to fund upgrades.

[1] Biofuel blending increased diesel fuel prices over this time period, see Martinsson et al. (2026).

The empirical analysis is organized around three margins. At the *entry margin*, we study which trucks firms acquire when they add to their fleets. At the *exit margin*, we study where trucks go when firms upgrade and whether the biofuel blending accelerates the exit of dirty trucks from the domestic market. At the (net) *fleet level*, we study whether the combined effect of entry and exit decisions moves fleet composition in the aggregate.

We document four main findings. First, young firms acquire older trucks than established firms at transaction, and this gap widens significantly as the blend share rises. The effect is larger in the trucking industry where diesel exposure is highest, is robust across four alternative proxies for a firm's ability to fund capital acquisitions, and is partially offset by leasing – consistent with leasing reducing the effective down payment requirement and enabling access to newer capital that young firms could not afford to purchase outright. Second, when established firms upgrade their fleets, they release used trucks into the secondary market that flow disproportionately to younger firms, partially offsetting the financing hurdle through secondary market access.

Third, biofuel blending accelerates the permanent retirement of dirty trucks from the domestic market through scrapping – reducing the stock of cheap used capital available to young firms over time – while the export channel is not significantly affected. Fourth, at the fleet level, young firms with high diesel exposure maintain older and lower Euro-standard fleets as the biofuel share increases. Furthermore, biofuel blending widened the fleet age gap between young and established high-exposure firms by 0.364 years – roughly 8 percent of the pre-existing cross-sectional gap – over the time period. We also find that these effects load exclusively on the policy-induced blend component – not on the residual fossil fuel price – establishing that we identify a response to climate policy rather than a generic fuel cost effect.

The theoretical underpinning of our analysis draws on three building blocks. Rampini (2019) shows that financing durable assets requires a down payment – the share of the asset price that cannot be pledged as collateral – and that firms with limited internal funds therefore invest in cheaper, older capital. Eisfeldt and Rampini (2009) show that leasing relaxes this constraint because the lessor retains ownership and can repossess more easily

than a secured lender. Lanteri and Rampini (2025) extend this framework to show that if both clean and dirty technologies coexist in equilibrium, clean capital must command a higher price – embedding the present value of future energy savings – implying that the down payment requirement is largest precisely for the capital that is cheapest to operate. Together, these papers predict that young firms with limited internal funds optimally hold dirtier and older capital, not because they lack the incentive to upgrade but because they face a larger financing hurdle to doing so.

Our paper contributes to four strands of literature. First, we contribute to the literature on capital upgrading and decarbonization. Prior work documents that carbon pricing can stimulate green innovation (e.g., Acemoglu et al., 2016, Aghion et al., 2016, Calel and Dechezleprêtre, 2016, Brown et al., 2022) and capital investment in high-emitting firms (Brown et al., 2026). We complement this evidence by showing that the capital upgrading response to climate policy is highly heterogeneous across firms: the firms with the strongest incentive to upgrade are also the least able to do so when they face larger down payment requirements relative to their internal funds. This heterogeneity is absent from the existing empirical literature, which focuses primarily on aggregate or average investment responses.

Second, we contribute to the literature on secondary markets for durable assets, which documents the important allocative role of secondary markets across aircraft (Gavazza, 2011), bulk shipping (Kalouptsidi, 2014), automobiles (e.g., Stolyarov, 2002, Gavazza et al., 2014, Busse et al., 2013), and industrial equipment (Ma et al., 2022). We provide unusually granular evidence on the secondary market for heavy goods vehicles across the full universe of Swedish firms, and show how climate policy reshapes secondary market reallocation. Our findings contrast with Duchin et al. (2025), who document that firms divest pollutive plants to less regulated buyers with no reduction in aggregate pollution – consistent with greenwashing through the asset market. In our setting, biofuel blending accelerates the permanent retirement of dirty trucks through scrapping rather than their reallocation to less regulated users, suggesting genuine decarbonization at the asset level. The dirty trucks that do remain in domestic circulation, however, flow disproportionately to younger and more constrained firms, raising a distributional concern that is distinct from but complementary

to the greenwashing concern in Duchin et al. (2025).

Third, we contribute to the literature on used capital markets and firm dynamics. Ma et al. (2022) document that young firms disproportionately acquire older vintage capital, and that local supply of used capital shapes entry, investment, and growth. We extend their analysis by showing that the firm age gradient in capital vintage responds to climate policy: biofuel blending steepens the gradient by raising the cost of dirty capital while the financing hurdle prevents young firms from fully responding. We also directly document the seller side of the reallocation process, showing where trucks go when they leave firms' fleets and how climate policy shapes the exit margin through scrapping and export.

Fourth, we relate to the literature on the distributional effects of environmental policy. A growing body of work documents that carbon pricing and fuel taxes have heterogeneous effects across households (e.g., Känzig, 2025) and firms (e.g., Colmer et al., 2025). We show that the financing channel is a first-order source of heterogeneity in firms' capital upgrading responses to climate policy, and provide the first empirical evidence of the mechanism in a real policy setting. Cost-raising instruments create genuine incentives to upgrade and accelerate the retirement of dirty capital – but their distributional consequences depend critically on the financing environment faced by firms. Ensuring that the costs and benefits of decarbonization are broadly shared requires complementary instruments that target the financing margin directly.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting, data, and testable predictions. Section 3 presents descriptive evidence on the Swedish market for heavy goods vehicles. Section 4 studies the entry margin. Section 5 studies the exit margin. Section 6 examines the net fleet effect. Section 7 concludes.

2 Setting, Data, and Testable Predictions

2.1 Institutional Setting

2.1.1 Biofuel blending in Sweden

Sweden has pursued an active climate policy agenda in the transport sector throughout our sample period, with a particular focus on reducing the carbon intensity of road diesel. The central policy instrument we exploit is the progressive increase in the share of biofuels blended into Swedish diesel fuel, which raises the effective operating cost of diesel-powered vehicles. Figure 1 displays the biofuel blend share alongside the after-tax real diesel fuel price over 2007–2020. The blend share rises monotonically from 3 percent in 2007 to 27 percent by 2018, where it stabilizes through 2020. Throughout the sample period, the blend share is determined at the national level and is orthogonal to the investment decisions of any individual firm in our sample.

Biofuels are more expensive than fossil diesel at wholesale production cost during this time period implying that progressive blending raised the resource cost of producing diesel fuel (see Martinsson et al., 2026). We show in section 6 that the effect on fleet upgrading loads entirely on the blend share component of diesel prices and not on the residual fossil fuel price component, confirming that we are identifying a policy effect rather than a generic fuel cost response.

2.1.2 Euro emission standards

The energy efficiency of heavy goods vehicles is governed by EU-wide Euro emission standards, which set mandatory limits on exhaust pollutants for newly constructed trucks. During our sample period, trucks carry Euro standards ranging from 0 to VI, with higher standards corresponding to cleaner and more fuel-efficient engines. Euro V became mandatory for new truck registrations from 2009 and Euro VI from 2014. As the blend share rises and diesel costs increase, the operating cost differential between low and high Euro-standard trucks widens: a Euro III truck operating in 2018 faces a substantially higher

annual fuel bill than a Euro VI truck of equivalent utilization, because the fuel efficiency advantage of the newer engine translates into a larger absolute saving per liter as the price of diesel rises. This creates a time-varying and heterogeneous incentive to upgrade fleet vintage that is strongest for firms with the highest diesel exposure and most pronounced in the later years of our sample.

2.2 Data

Our dataset combines two primary sources. The first is the Swedish vehicle registry, maintained by the Swedish Transport Agency (*Transportstyrelsen*), which records the full universe of heavy goods vehicles registered to Swedish firms over 2007–2020. For each truck-year observation we observe the truck's Euro standard, vintage year, engine power, annual kilometers driven (from mandatory odometer reporting), weight class, and whether the truck is held under a leasing arrangement or owned outright. We observe ownership changes when a truck moves from one firm to another, and the destination of trucks that exit the sample, including whether they are scrapped, exported, or transferred to a new owner within Sweden. The second source is Serrano, from which we obtain annual financial accounts — balance sheets and income statements — for all limited liability companies in Sweden, matched to the vehicle registry by organizational number. See the appendix (section A) for an exhaustive description of the data and sample construction.

2.2.1 Sample construction

We restrict the sample to limited liability companies (*aktiebolag*) operating heavy goods vehicles (HGV) (defined as trucks weighing more than 3.5 tonnes) during the sample period, excluding sole proprietorships for which financial accounts are not systematically available. We exclude firms in the electricity sector (NACE 35), water supply and waste management (NACE 36–38), wholesale and retail trade and repair of motor vehicles and motorcycles (NACE section 45), and rental and leasing activities (NACE section 77). Firms in NACE industry 35–38 are predominantly public sector owned and face fundamentally different investment incentives. Firms in NACE industries 45 and 77 own trucks for commercial

resale or operational leasing purposes rather than for operational use, and their acquisition decisions are therefore driven by inventory and rental market considerations rather than by the fuel cost economics that motivate our analysis. The resulting dataset covers the full universe of private limited liability companies that operated at least one heavy goods vehicle in Sweden during 2007–2020 for their own operational purposes.[2]

We work with two complementary samples. The *truck-transaction-year sample* contains one observation for each truck that enters a firm's fleet in a given year, capturing the characteristics of the truck at acquisition and the financial characteristics of the acquiring firm. This sample contains 112,657 observations and is the basis for the entry margin analysis in section 4. We complement this with an exit event sample, which contains one observation for each truck leaving a firm's fleet, recording the destination of the truck — whether it is purchased by another limited liability company in our sample, sold to another legal entity, scrapped, or exported. This sample contains 82,824 observations and underpins the asset reallocation and exit analysis in section 5. The *fleet-level sample* is a firm-year panel containing one observation per firm per year, capturing the average characteristics of a firm's entire fleet. This sample contains 201,761 firm-year observations and forms the basis for the net fleet effect analysis in section 6.

2.2.2 Key variables

Table 1 presents summary statistics for both samples. In the truck-transaction-year sample, the average truck age at acquisition is 4.92 years with substantial dispersion — the interquartile range spans 0 to 8 years, reflecting the mix of new and used truck acquisitions in the sample. Firm age, defined as the number of years since incorporation, is our primary proxy for a firm's ability to fund capital acquisitions from internal resources. It averages 19.84 years in the sample with a median of 16 years. As we discuss below, younger firms face larger down payment requirements relative to their internal funds, making firm age a natural measure of the financing hurdle that shapes capital acquisition decisions. Nineteen percent of truck-transaction observations involve leased trucks.

[2]The results in the paper do not materially change if trucks from the excluded industries are included.

The Euro standard measure we use throughout is the ratio of a truck's Euro standard to the maximum Euro standard available in a given year, which ranges from 0 to 1 and adjusts for the progressive tightening of the regulatory frontier over time. The unadjusted mean Euro standard of 4.36 corresponds to approximately Euro IV–V. Among the additional proxies for a firm's ability to fund acquisitions from internal resources, cash flow to total assets averages 0.15 with an interquartile range of 0.10 to 0.22, and log total assets averages 9.88. Credit scores, available for a subset of 69,671 observations, average 98.67 on a scale of 100 minus the probability of default.

For the exit margin analysis, among all exiting trucks 1 percent are scrapped and 1 percent are exported in a given year. Conditional on being a Low Euro truck — defined as having an adjusted Euro standard below 0.4 — the scrapping rate rises to 3 percent while the export rate remains at 1 percent, consistent with Low Euro trucks facing lower domestic residual values as the blend share raises their operating costs.

In the fleet-level sample, average fleet age is 12.66 years and average fleet Euro standard is 0.51. Intensity — the sum of engine power times annual kilometers driven across all trucks in a firm's fleet, scaled by output — averages 5.84 with substantial dispersion, reflecting meaningful heterogeneity in firms' diesel cost exposure. The young firm indicator, which equals one for firms below the median firm age in a given year, classifies 48 percent of firm-year observations as young.

2.2.3 Sector composition

Table 2 presents summary statistics by sector. The trucking sector (NACE 4941) dominates the sample, accounting for 52 percent of truck-years and 56 percent of transactions. Trucking firms operate the youngest and cleanest fleets — average truck age at acquisition of 3.19 years versus 4.92 years for the full sample, and an average Euro standard of 0.85 versus 0.78 — reflecting both their greater intensity of use and their correspondingly stronger incentive to maintain fuel-efficient fleets. The higher intensity of use is also visible directly in the data: trucking firms drive their trucks far more than firms in other sectors, with average annual vehicle kilometers traveled of 51,864 compared to 36,142 for agriculture, 26,370 for

manufacturing, and 29,055 for construction. This high utilization amplifies the fuel cost savings from upgrading to higher Euro-standard trucks, making the economic case for fleet renewal especially strong in the trucking sector. Construction firms account for 14 percent of transactions and operate the oldest trucks at acquisition (8.28 years on average), while manufacturing and services firms occupy intermediate positions.

2.3 Testable predictions

Our empirical analysis builds on three theoretical contributions. Rampini (2019) establishes that purchasing durable assets requires a down payment – the portion of the asset price that cannot be pledged as collateral – and that firms with limited internal resources therefore gravitate toward cheaper, older equipment. Eisfeldt and Rampini (2009) show that leasing lowers this barrier: because the lessor retains ownership and can repossess more easily than a secured lender, leasing extends financing capacity to firms that could not otherwise afford newer assets. Lanteri and Rampini (2025) complete the framework by demonstrating that in equilibrium where both clean and dirty capital are used, clean capital must command a higher price than dirty capital – reflecting the present value of future energy savings – so that the down payment is largest precisely for the assets with the lowest operating costs. The joint implication is that firms with limited internal resources are not simply unwilling to upgrade – they face a financing hurdle that makes the cleanest and newest capital the hardest to access.

Our setting introduces a time-varying policy shock — the progressive increase in the biofuel blend share — that raises the operating cost of dirty, older capital. As diesel costs rise, the total cost of ownership advantage of newer, cleaner trucks grows. Established firms with accumulated internal funds respond by upgrading their fleets. Younger firms face the same incentive to upgrade but a larger financing hurdle: newer, cleaner trucks are more expensive and require larger down payments that young firms cannot easily fund from internal resources. The biofuel blend share therefore widens the energy efficiency gap between young and established firms. This logic generates three testable predictions.

- **Prediction 1 (Entry margin).** At the point of acquisition, young firms acquire older trucks than established firms, and this gap widens as the biofuel blend share rises. Facing larger down payment requirements, young firms substitute toward used-but-newer trucks when they upgrade — accessing energy efficiency gains through the secondary market rather than through new purchases — and toward leasing arrangements that reduce the effective down payment entirely. We test this prediction in section 4.

- **Prediction 2 (Seller side).** As established firms upgrade their fleets, they release used trucks into the secondary market that flow disproportionately to younger firms, partially offsetting the financing hurdle through used-market access. Simultaneously, biofuel blending accelerates the exit of dirty trucks from the domestic market — through scrapping as their residual value falls, and through export as domestic demand for dirty capital diminishes — reducing the stock of cheap used capital available to young firms over time. We test this prediction in section 5.

- **Prediction 3 (Net fleet effect).** The combined effect of the entry and exit margins cumulates into fleet-level outcomes: young firms with high diesel intensity maintain older, lower Euro-standard fleets as the biofuel blending intensifies, while established firms with equivalent diesel intensity upgrade most aggressively. The triple interaction of firm age, diesel exposure, and the blend share captures this differential net fleet response, reflecting the joint operation of the entry and exit channels documented in Predictions 1 and 2. We test this prediction in section 6.

3 The Market for Heavy Goods Vehicles: Descriptive Evidence

We begin with a descriptive characterization of the Swedish market for heavy goods vehicles, documenting patterns in truck acquisitions, fleet composition, and capital reallocation that motivate the regression analysis in sections 4–6.

3.1 Truck transactions and capital reallocation

Table 3 reveals several informative patterns in how trucks flow through the Swedish market. Comparing trucks entering firms' fleets across different acquisition modes, leased trucks are considerably newer than owned trucks at acquisition — average age of 2.41 years versus 5.53 years — and carry higher Euro standards (0.88 versus 0.75). This pattern is consistent with the theoretical prediction of Eisfeldt and Rampini (2009): leasing relaxes the down payment barrier to accessing newer, cleaner capital. New trucks enter fleets at age zero, as expected, with the highest Euro standards (0.99), while used owned trucks average 8.30 years of age and a Euro standard of 0.63 at acquisition.

The exit side of the market is equally informative. Among trucks leaving firms' fleets, those sold to other limited liability companies in our sample are substantially younger and cleaner than those exported or scrapped — average age of 7.90 years and Euro standard of 0.63 for domestic LLC sales, compared to 13.71 years and 0.42 for trucks sold to other domestic legal entities, 11.38 years and 0.49 for exported trucks, and 21.33 years and 0.24 for scrapped trucks. This ranking reveals a clear quality gradient in the disposition of used trucks: the highest quality used capital is absorbed within the domestic LLC market, intermediate quality trucks are exported or sold to other legal entities, and the oldest and dirtiest trucks are scrapped. Scrapped trucks also travel very little in the final year before exit — average annual VKT of just 8,585 compared to 64,291 for trucks sold domestically to other LLCs — consistent with scrapping being triggered by the end of a truck's operational life rather than by a voluntary upgrading decision.

The cumulative VKT data shed further light on the selection into each exit channel. One might expect scrapped trucks to have accumulated the most kilometers, having exhausted their operational life. Instead, exported trucks have the highest cumulative kilometers of any exit category at 536,311 on average, suggesting that trucks directed to export markets are not the most worn-out vehicles but rather those that retain residual value in markets with lower fuel costs or less stringent emission standards. Scrapped trucks, by contrast, have accumulated 368,388 cumulative kilometers on average – lower than exported trucks —

consistent with scrapping removing trucks from the market before they have fully exhausted their operational life, likely because rising diesel costs have made them uneconomical to operate domestically.

3.2 Firm age and capital vintage at acquisition

Figures 2 and 3 document the central stylized fact of the paper: the age and Euro standard of trucks acquired by a firm vary systematically and monotonically with firm age. Figure 2 plots average truck age at acquisition against firm age for firms between zero and thirty years old, with 95 percent confidence intervals. The pattern is pronounced: newly incorporated firms acquire trucks that are on average 8.5 years old, while firms that are thirty years old acquire trucks that are approximately 4 years old. The relationship is steep and approximately linear across the firm age distribution, with each additional year of firm age associated with a meaningful reduction in the age of the truck acquired.

Figure 3 shows the mirror image for Euro standards. Newly incorporated firms acquire trucks with an average adjusted Euro standard of approximately 0.60, while thirty-year-old firms acquire trucks with an average Euro standard of approximately 0.85. The positive relationship between firm age and acquired Euro standard is similarly monotonic and statistically precise throughout the distribution. Together, Figures 2 and 3 establish that firm age is a powerful predictor of capital vintage at acquisition, with young firms consistently acquiring older and dirtier trucks than their more established counterparts. This pattern closely mirrors the finding of Ma et al. (2022) for US equipment financing — that young firms disproportionately acquire older vintage capital — and extends it to the European heavy goods vehicle market with a direct measure of emission intensity.

Importantly, these patterns hold across the full firm age distribution rather than being driven by a handful of very young or very old firms. The confidence intervals are tight throughout, indicating that the relationships are precisely estimated and not driven by outliers. The slight non-monotonicity visible around firm ages five to ten in both figures likely reflects compositional changes in the sample — the mix of industries and fleet sizes changes as firms age — but the overall trend is clear and robust.

3.3 New, clean and used, dirty

Figure 4 completes the descriptive picture by decomposing the firm age gradient into its two natural components: the share of acquisitions that are new and clean (panel a) and the share that are used and dirty (panel b). Panel (a) shows that the share of new and clean truck acquisitions rises monotonically with firm age, from approximately 10 percent for newly incorporated firms to approximately 40 percent for thirty-year-old firms. Panel (b) shows the symmetric pattern: the share of used and dirty acquisitions falls monotonically with firm age, from approximately 60 percent for newly incorporated firms to approximately 20 percent for the oldest firms in the sample.

These two panels together characterize the mechanism at the heart of the paper. Young firms are concentrated at the bottom of the capital quality distribution — acquiring predominantly used, dirty trucks — while established firms are concentrated at the top, acquiring predominantly new, clean trucks. The key question the regression analysis addresses is whether this distributional gap widens as the biofuel blend share rises, and whether the widening is driven by the down payment barrier that makes newer, cleaner trucks less accessible to firms with limited internal funds. The descriptive patterns in Figures 2–4 establish that the gap is large and systematic in the cross-section; the regressions identify how it responds to the policy-induced cost shock over time.

4 The Entry Margin: Which Firms Buy Which Trucks?

4.1 Empirical specification

We estimate the following baseline specification on the truck-transaction-year sample:

$$\begin{aligned} \textit{Truck age}_{v,t} = \beta_0 + \beta_1 \textit{Firm age}_{i,t} + \beta_2 \textit{Lease}_{v,t} + \beta_3 \textit{Firm age}_{i,t} \times \textit{Lease}_{v,t} + \\ \beta_4 \textit{Firm age}_{i,t} \times \textit{Blend}_t + \beta_5 \textit{Lease}_{v,t} \times \textit{Blend}_t + \\ \beta_6 \textit{Firm age}_{i,t} \times \textit{Lease}_{v,t} \times \textit{Blend}_t + \eta_{r,t} + \eta_j + \varepsilon_{v,t} \end{aligned} \tag{1}$$

where Truck age$_{v,t}$ is the age of truck v at the time it enters firm i's fleet in year t, measured as calendar year minus vintage year. Firm age$_{i,t}$ is the number of years since firm i's incorporation. Lease$_{v,t}$ is an indicator equal to one if the transaction involves a leased truck. Blend$_t$ is the biofuel blend share in year t. $\eta_{r,t}$ denotes region-by-year fixed effects, absorbing all time-varying regional demand shocks, and η_j denotes four-digit industry fixed effects, absorbing persistent cross-sectional differences across industries. Standard errors are clustered at the firm level throughout.

The coefficient of primary interest is β_4 on the interaction Firm age$_{i,t}$ $\times$ Blend$_t$. Under Prediction 1, $\beta_4 < 0$: as the blend share rises, young firms fall further behind established firms in the age of trucks they acquire. The coefficient $\beta_1 < 0$ captures the baseline cross-sectional relationship between firm age and acquired truck age documented in Figure 2. The triple interaction coefficient β_6 on Firm age$_{i,t}$ $\times$ Lease$_{v,t}$ $\times$ Blend$_t$ tests whether leasing attenuates the policy-induced widening of the gap, with the prediction $\beta_6 > 0$: the blend-share-induced disadvantage of young firms is smaller for transactions involving leased trucks.

4.2 Baseline results

Table 4 reports estimates of Equation 1. Column (1) presents the baseline specification on the owned-truck subsample, excluding leased transactions. The coefficient on firm age is -0.058, highly significant, and indicates that each additional year of firm age is associated with acquiring a truck that is 0.058 years younger. The magnitude is economically meaningful: a firm that is twenty years older than another acquires a truck that is on average 1.16 years newer, which corresponds to a meaningful improvement in Euro standard given the approximately five-year regulatory cycle between Euro standard introductions.

Column (2) adds the leasing indicator to the full sample including leased transactions. The coefficient on Lease is -2.634, confirming that leased trucks are substantially newer at acquisition than owned trucks, consistent with the descriptive evidence in Table 3 and with leasing enabling access to newer capital.

Column (3) adds the interaction between firm age and the leasing indicator. The positive coefficient on Firm age $\times$ Lease of 0.016 indicates that the age advantage of leasing — that

is, the tendency for leased trucks to be newer than owned trucks at acquisition — is larger for young firms than for established ones. For a firm aged five years, leasing is associated with acquiring a truck that is $2.634 - (0.016 \times 5) = 2.55$ years newer than an equivalent owned truck; for a firm aged thirty years, this advantage narrows to $2.634 - (0.016 \times 30) = 2.15$ years. This pattern is consistent with established firms being able to access newer owned trucks through outright purchase, making leasing a less critical channel for them, while young firms benefit most from leasing as a route to newer capital.

Column (4) introduces the blend share interaction on the owned-truck subsample. The coefficient on Firm age $\times$ Blend is -0.129 and highly significant. This is the central finding of the entry margin analysis: as the biofuel blend share rises, the gap in acquired truck age between young and established firms widens significantly. To assess the economic magnitude, consider the increase in the blend share from 0.05 in 2009 to 0.25 in 2017 — an increase of 0.20. The coefficient of -0.129 implies that over this period, the truck age gap between a firm at the 25th percentile of firm age (6 years) and a firm at the 75th percentile (28 years) widened by an additional $0.129 \times 0.20 \times (28 - 6) = 0.57$ years. This widening is on top of the baseline cross-sectional gap and represents a meaningful deterioration in the relative capital quality of young firms as climate policy intensified.

Column (5) adds the full triple interaction to the complete sample. The triple interaction coefficient on Firm age $\times$ Lease $\times$ Blend is 0.127 and significant at the 1 percent level. This confirms that leasing partially offsets the policy-induced widening of the age gap: young firms that access trucks through leasing arrangements are better insulated from the biofuel blending effect on their acquisition quality. The Lease $\times$ Blend coefficient of -3.037 indicates that leased trucks themselves become relatively newer as the blend share rises, consistent with the leasing market responding to the increasing operating cost of dirty capital by directing cleaner trucks toward lease contracts. Note that the Firm age $\times$ Lease interaction becomes insignificant in column (5) once the triple interaction is included, suggesting that the baseline leasing advantage for young firms operates primarily through the policy channel rather than unconditionally.[3]

[3]We show in section 6 that this effect loads on the policy-induced blend share component of diesel prices

4.3 Heterogeneity across industries and alternative internal finance proxies

4.3.1 Trucking versus non-trucking firms

Table 5 reports separate estimates for the trucking sector (NACE 4941, columns 1–4) and all other industries (columns 5–8). The baseline firm age coefficient is larger in magnitude for non-trucking firms (-0.071 versus -0.047), reflecting greater cross-sectional heterogeneity in truck acquisition patterns outside the specialist trucking industry. However, the policy interaction coefficient Firm age $\times$ Blend is substantially larger and more precisely estimated for trucking firms (-0.159 to -0.160, significant at the 1 percent level) than for non-trucking firms (-0.096 to -0.102, significant only at the 10 percent level). This heterogeneity is consistent with the mechanism: trucking firms are far more exposed to diesel costs than firms for which trucks are a peripheral asset, so biofuel blending creates a stronger differential incentive to upgrade among trucking firms, and the down payment barrier bites more sharply for young trucking firms that face both a larger incentive and a larger hurdle. The triple interaction Firm age $\times$ Lease $\times$ Blend is similar across the two sub-samples.

4.3.2 Alternative proxies for internal funds

Table 6 reports estimates replacing firm age with three alternative proxies for a firm's ability to fund capital acquisitions from internal resources: cash flow to total assets, (the natural logarithm of) total assets, and credit score. In all three cases the standalone proxy coefficient is negative and highly significant, confirming that firms with lower cash flows, smaller asset bases, and lower credit scores acquire older trucks at transaction. Overall, the direction is uniform and the significance is unambiguous across all specifications.[4]

The leasing interactions are positive and significant for all three proxies: firms with lower cash flows, smaller asset bases, and lower credit scores benefit more from leasing in terms of

rather than on the residual fossil fuel price, confirming that we are identifying a response to climate policy rather than to the broader fuel cost environment.

[4]The magnitudes differ across proxies — a one standard deviation decrease in cash flow to assets (0.11) is associated with a $2.641 \times 0.11 = 0.29$ year increase in acquired truck age, a one standard deviation decrease in log total assets (2.10) with a $1.173 \times 2.10 = 2.46$ year increase, and a one standard deviation decrease in credit score (3.20) with a $0.150 \times 3.20 = 0.48$ year increase.

accessing newer trucks. A one standard deviation decrease in cash flow to assets increases the leasing advantage by $2.573 \times 0.11 = 0.28$ years, consistent with cash-poor firms relying more heavily on leasing to access newer capital than firms with ample internal funds. The same pattern holds for log total assets and credit score, confirming that the leasing channel identified in Table 4 reflects a genuine financing mechanism rather than a selection effect.

The consistency of results across firm age, cash flow, asset size, and credit score — four proxies that capture different dimensions of a firm's ability to fund acquisitions — provides strong evidence that the baseline finding is not an artifact of any particular measure. Young firms, cash-poor firms, small firms, and low-rated firms all acquire systematically older trucks, and all benefit disproportionately from leasing as a route to newer capital.

5 The Exit Margin: Where Do Trucks Go When Firms Upgrade?

The entry margin results in section 4 document that young firms acquire older and lower Euro-standard trucks than established firms, and that this gap widens as the biofuel blend share rises. In this section we turn to the seller side of the market and ask two complementary questions. First, does biofuel blending accelerate the exit of dirty trucks from the domestic Swedish market through scrapping and export? Second, when established firms upgrade their fleets and release used trucks into the secondary market, do young firms benefit disproportionately from access to this supply of cleaner used capital?

5.1 Scrapping and export of dirty trucks

We estimate the following specification on the exit event sample, which contains one observation for each truck leaving a firm's fleet:

$$Y_{v,t} = \beta_0 + \beta_1 \textit{Low Euro truck}_v + \beta_2 \textit{Low Euro truck}_v \times \text{Blend}_t + \eta_{r,t} + \eta_j + \varepsilon_{v,t} \qquad (2)$$

where $Y_{v,t}$ is either an indicator equal to one if truck v is scrapped upon exiting a firm's fleet in year t, or an indicator equal to one if truck v is exported. Low Euro truck$_v$ is an indicator equal to one if the truck has an adjusted Euro standard below 0.4, corresponding approximately to Euro III and below. Blend$_t$ is the biofuel blend share in year t. $\eta_{r,t}$ denotes region-by-year fixed effects and η_j denotes four-digit industry fixed effects. Standard errors are clustered at the firm level.

The coefficient of primary interest is β_2 on the interaction Low Euro truck$_v$ $\times$ Blend$_t$. Under Prediction 2, $\beta_2 > 0$ for both scrapping and export outcomes: as the blend share rises, low Euro-standard trucks become relatively more likely to exit the domestic market.

Table 7 reports estimates of Equation 2. Columns (1) and (2) report results for the scrapping outcome and columns (3) and (4) for the export outcome. Column (1) reports the unconditional scrapping differential. The coefficient on Low Euro truck is 0.021 and highly significant, confirming that dirty trucks are more likely to be scrapped than clean trucks on average across the sample period.

Column (2) adds the blend share interaction. The coefficient on Low Euro truck $\times$ Blend is 0.279 and statistically significant.[5] The large and highly significant interaction coefficient establishes that biofuel blending substantially accelerates the scrapping of dirty trucks: each percentage point increase in the blend share raises the scrapping probability of a dirty truck relative to a clean truck by 0.279 percentage points. Over the full range of the blend share in our sample — from 0.03 in 2007 to 0.27 in 2018, an increase of 0.24 — this implies a cumulative increase in the relative scrapping probability of dirty trucks of $0.279 \times 0.24 = 0.067$ percentage points, representing a meaningful acceleration in the permanent retirement of dirty capital from the Swedish fleet.

Columns (3) and (4) report the corresponding results for the export outcome. Column (3) shows that the unconditional export differential between dirty and clean trucks is essentially

[5]The standalone Low Euro truck coefficient becomes -0.012 in column (2). This reflects the out-of-sample nature of the zero blend share baseline: at a blend share of zero — outside the range of our data, which spans 0.03 to 0.27 — dirty trucks would be predicted to be less likely to be scrapped than clean trucks. At the sample mean blend share the net effect of being a dirty truck on scrapping probability is positive, consistent with the unconditional result in column (1). We verify this by estimating the specification without the interaction, which yields a positive and significant coefficient on Low Euro truck.

zero — the coefficient on Low Euro truck is 0.001 and statistically indistinguishable from zero. Column (4) adds the blend share interaction. The coefficient on Low Euro truck × Blend is 0.031, positive but not statistically significant at conventional levels. The direction is consistent with biofuel blending creating a domestic-international price wedge that makes dirty trucks relatively more attractive in export markets as their domestic residual value falls, but the effect is too imprecisely estimated to draw strong conclusions.

Taken together, the results in Table 7 indicate that biofuel blending accelerates the permanent retirement of dirty capital from the Swedish fleet primarily through the scrapping channel rather than through export. Dirty trucks are not simply redirected to foreign markets as biofuel blending intensifies — they are retired. This finding has an important implication for the general equilibrium story: as the mandate intensifies, the stock of cheap dirty used trucks available to young firms in the domestic secondary market shrinks, compounding the entry margin disadvantage documented in section 4.

5.2 Secondary market access for young firms

The second question in this section asks whether young firms benefit disproportionately from the supply of used (relatively) clean trucks released by established firms as they upgrade. We construct a sector-level supply shock measuring the rate at which mature firms release clean trucks into the secondary market:

$$\text{Sector supply shock}_{s,t} = \frac{\sum_{i \in \text{mature},s} \mathbf{1}[\text{Euro}_v \geq 0.75, \text{exit}_{v,t}]}{\text{Total fleet}_{s,t}} \tag{3}$$

where the numerator counts trucks with adjusted Euro standard above 0.75 that exit established firms (above the median firm age in a given year) in sector s in year t, and the denominator is the total number of trucks in sector s in year t, based on the six sector groupings in Table 2. We lag the supply shock by one year to reduce simultaneity concerns, since last year's upgrading decisions by established firms determine the current year's available supply of used clean trucks in the secondary market.

The estimating equation is:

$$\begin{aligned} \textit{Euro standard}_{v,t} = \phi_0 + \phi_1\, \textit{Young}_{i,t} + \phi_2\, \textit{Young}_{i,t} \times \textit{Sector supply shock}_{s,t-1} + \\ \eta_{r,t} + \eta_j + \eta_{s,t} + \varepsilon_{v,t} \end{aligned} \tag{4}$$

where Euro standard$_{v,t}$ is the adjusted Euro standard of truck v acquired in year t. Young$_{i,t}$ is an indicator equal to one if the acquiring firm i is below the median firm age in year t. Sector supply shock$_{s,t-1}$ is the lagged supply shock for sector s, matched to acquiring firms by their sector classification. $\eta_{r,t}$ denotes region-by-year fixed effects, η_j denotes four-digit NACE industry fixed effects, and $\eta_{s,t}$ denotes sector-by-year fixed effects, which absorb sector-level time trends and the standalone variation in the supply shock. In column (2) below η_j is replaced with firm fixed effects α_i, which absorb all time invariant firm characteristics and identify the supply shock effect from within-firm variation over time. Standard errors are clustered at the firm level. The coefficient of interest is ϕ_2: under Prediction 2, $\phi_2 > 0$, indicating that young firms disproportionately improve the Euro standard of their acquisitions in years when the within-sector supply of clean used trucks is larger.

Table 8 reports estimates of Equation 4. Column (1) includes industry fixed effects. The coefficient on Young is -0.085 and highly statistically significant, confirming the baseline cross-sectional finding from section 4: young firms acquire lower Euro-standard trucks than established firms on average. The coefficient on Young $\times$ Sector supply shock is 0.663, and significant at the 1 percent level. This indicates that young firms disproportionately improve the Euro standard of their truck acquisitions in years when mature firms in their industry release more clean trucks into the secondary market. The secondary market is therefore functioning as a partial relief valve for young firms: when established firms upgrade and release high-quality used trucks, young firms are better positioned than their established counterparts to absorb this supply.

Column (2) replaces industry fixed effects with firm fixed effects, tightening the identification by exploiting only within-firm variation over time. The Young coefficient

falls sharply to −0.018 and now significant only at the 10 percent level, since firm fixed effects absorb the time-invariant component of the young firm disadvantage. The supply shock interaction grows substantially to 1.286 and is highly statistically significant. The increase in the coefficient under firm fixed effects reflects attenuation bias in column (1) from unobserved firm-level heterogeneity — cross-sectional differences across firms within an industry that are correlated with both the supply shock and acquisition quality. Firm fixed effects remove this noise and sharpen the identification. The sample drops from 90,704 to 81,887 observations when firm fixed effects are included, since firms with only one acquisition event cannot contribute to within-firm identification. The fact that the coefficient grows despite this restriction — which disproportionately drops the smallest and youngest firms for whom the mechanism should be most relevant — suggests that the column (1) estimate is a lower bound on the true effect.

Together, the results in Tables 7 and 8 paint a coherent picture of the exit margin. Biofuel blending accelerates the retirement of dirty trucks from the domestic fleet through scrapping, reducing the stock of cheap used capital available to young firms over time. Simultaneously, the upgrading decisions of established firms generate a flow of clean used trucks into the secondary market from which young firms benefit disproportionately, partially offsetting their acquisition disadvantage. The net effect of these two forces on fleet composition is the subject of section 6.

6 The Net Effect: Does Fleet Composition Actually Change?

Sections 4 and 5 document the entry and exit margins separately: young firms acquire older and lower Euro-standard trucks at transaction, and biofuel blending accelerates the scrapping of dirty trucks from the domestic fleet. In this section we ask whether these two forces are large enough in aggregate to move the needle on fleet composition. We examine how the average age and average Euro standard of a firm's entire fleet respond to the blend mandate, and whether this response differs between young and established firms with high diesel exposure.

6.1 Empirical specification

We estimate the following specification on the fleet-level sample:

$$\begin{aligned}\bar{Y}_{i,t} = \beta_0 + \beta_1 \mathit{Intensity}_{i,t-s} + \beta_2 \mathit{Intensity}_{i,t-s} \times \text{Blend}_t + \beta_3 \mathit{Young}_{i,t} + \\ \beta_4 \mathit{Young}_{i,t} \times \mathit{Blend}_t + \beta_5 \mathit{Intensity}_{i,t-s} \times \mathit{Young}_{i,t} + \\ \beta_6 \mathit{Intensity}_{i,t-s} \times \mathit{Young}_{i,t} \times \mathit{Blend}_t + \gamma X_{i,t-1} + \alpha_i + \eta_{r,t} + \eta_{s,t} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where $\bar{Y}_{i,t}$ is either the average truck age (*Average age fleet*) or the average Euro standard (*Average Euro standard fleet*) of firm i's fleet in year t. α_i denotes fleet fixed effects, absorbing all time-invariant firm characteristics. $\eta_{r,t}$ denotes region-by-year fixed effects and $\eta_{s,t}$ denotes sector-by-year fixed effects. $\text{Intensity}_{i,t-s}$ is the trucking intensity of firm i measured at lag s, capturing diesel cost exposure. $\text{Young}_{i,t}$ is an indicator equal to one if firm i is below the median firm age in year t. Blend_t is the biofuel blend share in year t. $X_{i,t-1}$ is a vector of lagged firm-level controls including the natural logarithm of output, the natural logarithm of total assets, total debt ratio, cash flow to assets, and a fleet expansion indicator. Standard errors are clustered at the firm level.

The coefficient of primary interest is β_6 on the triple interaction $\text{Intensity}_{i,t-s} \times \text{Young}_{i,t} \times \text{Blend}_t$. Under Prediction 3, $\beta_6 > 0$ for fleet age and $\beta_6 < 0$ for fleet Euro standard: young firms with high diesel exposure fall further behind established firms of equivalent exposure as the blend share rises, maintaining older and dirtier fleets. The coefficient β_2 on $\text{Intensity}_{i,t-s} \times \text{Blend}_t$ captures the response of high-exposure established firms to biofuel blending and is expected to be negative for fleet age and positive for fleet Euro standard — established firms with high diesel exposure upgrade most aggressively as the blend share rises.

We explore the sensitivity of the results to the lag length s used to measure intensity, estimating the specification at $s = 0, 1, 2, 3$. Using a lagged intensity measure reduces the concern that current intensity is endogenous to current fleet composition decisions. Our preferred specification uses $s = 1$.

6.2 Baseline results: Fleet age

Table 9 reports estimates of Equation 5 with average fleet age as the dependent variable. Column (1) includes only fleet fixed effects and region-by-year fixed effects, with intensity measured at $s = 1$. The coefficient on Intensity_{t-1} is -0.040 and highly significant, indicating that firms with higher diesel exposure maintain younger fleets on average — consistent with the stronger incentive to invest in fuel-efficient capital.

Column (2) adds the interaction $\text{Intensity}_{t-1} \times \text{Blend}$. The coefficient is -0.267 and statistically significant, while the standalone intensity coefficient falls to -0.004 and becomes insignificant. This indicates that the fleet age effect of intensity operates primarily through the blend share channel: high-exposure firms maintain younger fleets as biofuel blending intensifies, but there is no unconditional relationship between intensity and fleet age once the policy variation is accounted for.

Columns (3) and (4) add the Young indicator, the Young $\times$ Blend interaction, and the triple interaction $\text{Intensity}_{t-1} \times \text{Young} \times \text{Blend}$, without and with sector-by-year fixed effects respectively. The triple interaction coefficient is 0.199 in column (3) and 0.155 in column (4), both highly significant. This is the central result of the fleet analysis: young firms with high diesel exposure maintain systematically older fleets as the blend share rises, relative to established firms with equivalent diesel exposure.[6]

Column (5) adds the full set of lagged firm-level controls. The triple interaction remains highly significant at 0.195, confirming that the result is not driven by correlated variation in firm size, leverage, cash flow, or fleet expansion decisions. The controls themselves carry intuitive signs — larger firms, more profitable firms, and firms that expanded their fleets in the prior year maintain younger fleets, consistent with these characteristics facilitating access to newer capital. Importantly, the triple interaction $\text{Intensity}_{t-s} \times \text{Young} \times \text{Blend}$ remains highly significant throughout, confirming that the differential response to biofuel blending

[6]The Young $\times$ Blend coefficient is negative and significant in columns (3) and (4), but this lower-order term is identified at zero diesel intensity — outside the support of the data — and should not be interpreted in isolation. The economically meaningful result is the triple interaction, which captures the differential fleet age response for young firms with positive diesel exposure. The Young $\times$ Blend coefficient becomes insignificant once the firm-level controls are included in columns (5) through (8).

among young high-exposure firms is robust to controlling for these firm characteristics.

Columns (6) through (8) assess the sensitivity of the triple interaction to the lag length used to measure intensity, at $s = 0$, $s = 2$, and $s = 3$ respectively, using the full control specification. The main results are robust across all four lag specifications, confirming that the finding does not depend on the precise timing of the intensity measurement.

6.3 Identification: Blend share versus diesel fuel price

A key identification concern is that the triple interaction captures a response to the general level of diesel fuel prices rather than to the policy-induced blend share component specifically. Table 10 addresses this directly by replacing the blend share with the diesel fuel price and then including both simultaneously.

Columns (1) and (2) use the diesel fuel price as the policy variable in place of the blend share. In column (1), the triple interaction Intensity$_{t-1}$ × Young × Diesel fuel price is 0.467 and significant at the 5 percent level. However, in column (2), when the blend share interactions are added alongside the diesel fuel price interactions, the diesel fuel price triple interaction falls sharply to 0.149 and becomes statistically indistinguishable from zero, while the blend share triple interaction is 0.192 and remains highly significant. This horse race establishes that the effect loads on the policy-induced blend share component of diesel prices and not on the residual fossil fuel price variation — the finding documented in section 4 for the transaction sample extends cleanly to the fleet level.

6.4 Fleet Euro standard results

Columns (3) through (6) of Table 10 report estimates with average fleet Euro standard as the dependent variable, providing a direct measure of fleet emission intensity alongside the fleet age results. Columns (3) and (4) use the blend share as the policy variable at $s = 1$ and $s = 3$ respectively. The triple interaction Intensity$_{t-s}$ × Young × Blend is −0.0067 at $s = 1$ and −0.0055 at $s = 3$, both highly significant with the expected negative sign: young firms with high diesel exposure maintain lower Euro-standard fleets as the blend share rises.

Columns (5) and (6) report the horse race between the diesel fuel price and the blend

share for the Euro standard outcome. Column (5) uses the diesel fuel price only. The triple interaction is -0.0142, significant at the 10 percent level. Column (6) adds the blend share interactions. The diesel fuel price triple interaction becomes -0.0032 and is no longer significant, while the blend share triple interaction is -0.0066 and remains highly significant. The identification result is symmetric across both outcome variables: the policy effect on fleet composition loads entirely on the blend share and not on the underlying fossil fuel price.

6.5 Economic magnitude

To assess the economic significance of the fleet-level results, consider the increase in the blend share from 0.05 in 2009 to 0.25 in 2017 — an increase of 0.20. Using the preferred specification in column (5) of Table 9, the triple interaction coefficient of 0.195 implies that over this period, the fleet age gap between a young firm at the 75th percentile of diesel intensity (9.53) and a young firm at the 25th percentile (0.20) widened by $0.195 \times 0.20 \times (9.53 - 0.20) = 0.364$ years relative to the corresponding gap for established firms.

Put differently, biofuel blending caused the fleet of a young high-exposure firm to age by an additional 0.364 years relative to an otherwise identical established firm over the 2009–2017 period, on top of the baseline fleet age gap between the two groups. To contextualize this magnitude, Figure 2 documents that newly incorporated firms acquire trucks that are on average approximately 4.5 years older than those acquired by thirty-year-old firms in the cross-section. The policy-induced widening of 0.364 years therefore represents roughly 8 percent of this pre-existing cross-sectional gap, accumulating over eight years of progressive policy tightening. The corresponding result for Euro standard from column (3) of Table 10 implies a widening of $0.0067 \times 0.20 \times (9.53 - 0.20) = 0.013$ in the adjusted Euro standard gap, representing a meaningful deterioration in the relative emission intensity of young high-exposure firms' fleets as climate policy intensified.

7 Conclusion

This paper studies how climate policy shapes capital upgrading across firms that differ in their ability to fund investments from internal resources. Using the universe of heavy goods vehicles registered to Swedish firms over 2007–2020, we exploit the progressive increase in Sweden's biofuel blend share as an exogenous, policy-induced increase in the operating cost of diesel trucks. As the blend share rises, the incentive to upgrade to newer, cleaner trucks grows — but so does the down payment required to acquire them. Firms with limited internal funds face a larger financing hurdle to escaping the higher operating costs imposed by the policy.

We document this distributional effect across three margins. At the entry margin, young firms acquire older trucks than established firms, and this gap widens significantly as the blend share rises, is concentrated in the trucking industry where diesel exposure is highest, and is partially offset by leasing. At the exit margin, biofuel blending accelerates the permanent retirement of dirty trucks through scrapping, while established firms' upgrading decisions release clean used trucks into the secondary market from which young firms benefit disproportionately.

At the (net) fleet level, young firms with high diesel exposure maintain older and lower Euro-standard fleets as the biofuel blending intensifies, with the blend share widening the fleet age gap between young and established high-exposure firms by 0.364 years. A horse race between the blend share and the diesel fuel price confirms that the effect loads exclusively on the policy-induced blend component, establishing that we identify a response to climate policy rather than a generic fuel cost effect.

More broadly, the findings suggest that the distributional consequences of climate policy depend critically on the interaction between the policy instrument and the financing environment faced by firms. Settings where clean capital requires larger upfront investment — shipping, agriculture, manufacturing — are likely to exhibit similar patterns, and the relative effectiveness of cost-raising versus down-payment-reducing instruments in those contexts remains an important question for future research.

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Figure 1: Bio fuel blending share and diesel fuel prices

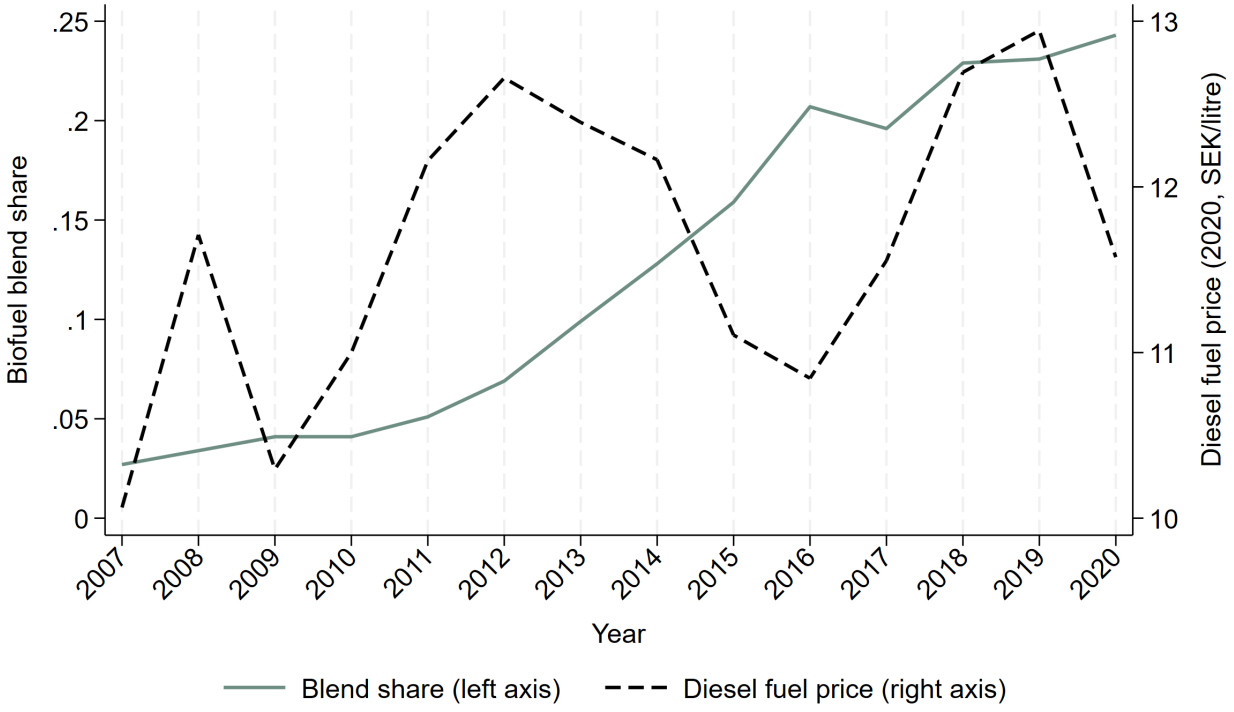


Figure 1 displays the biofuel blending share (solid line, left axis) and the after-tax diesel price excluding VAT, in 2020 SEK per liter (dashed line, right axis).

Figure 2: Truck age and firm age

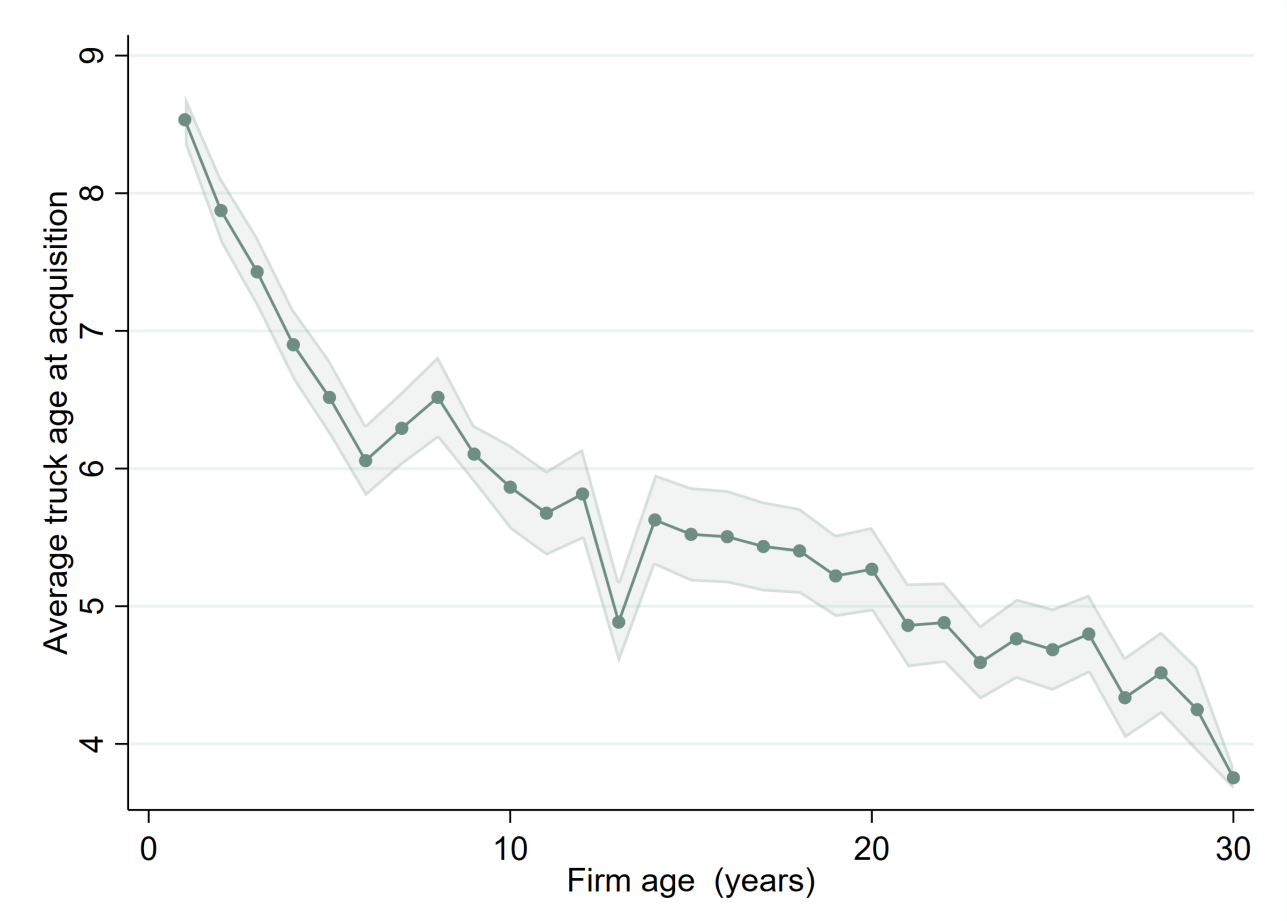


Figure 2 displays the average truck age at acquisition across firm age groups (0 to 30 years), with 95% confidence intervals.

Figure 3: Average Euro standard

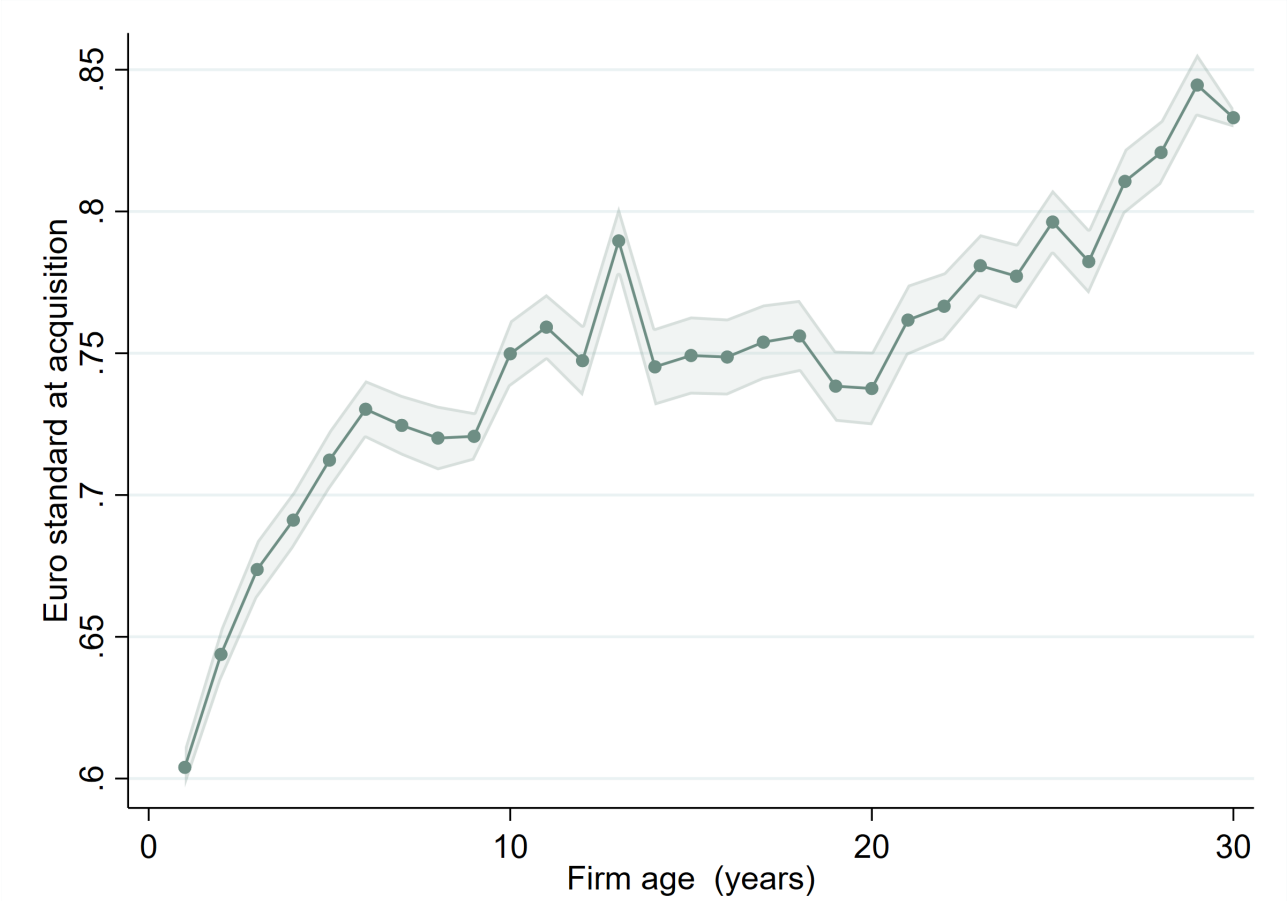
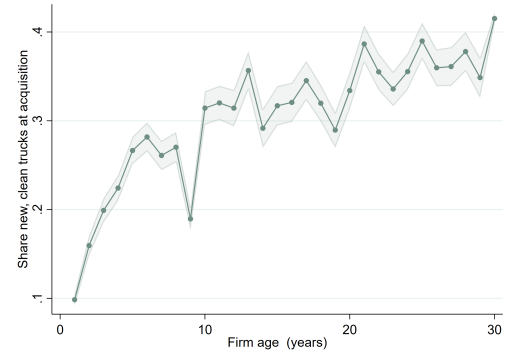


Figure 3 displays the average Euro standard at acquisition across firm age groups (0 to 30 years), with 95% confidence intervals.

Figure 4: Share new, clean and used, dirty

(a) Share new and clean



(b) Share used and dirty

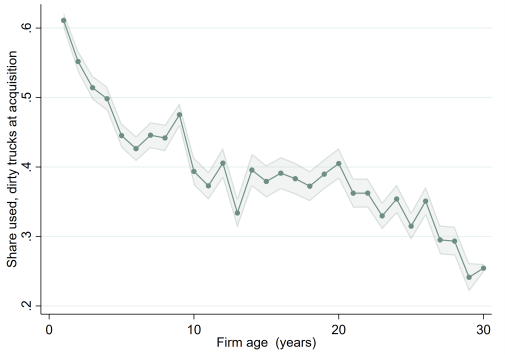


Figure 4 displays the share of new and clean trucks acquired (panel (a)) and the share of used and dirty trucks acquired (panel (b)) across firm age groups (0 to 30 years), with 95% confidence intervals.

Table 1: Summary statistics of key variables

	Obs	Mean	25th	Median	75th	St Dev
			Panel: Truck-transaction-year sample			
Truck age	112,657	4.92	0.00	2.00	8.00	6.66
Firm age	112,657	19.84	6.00	16.00	28.00	18.09
Share leased	112,657	0.19	0.00	0.00	0.00	0.40
Euro standard (unadj)	112,657	4.36	3.00	5.00	6.00	1.62
Euro standard	112,657	0.78	0.60	0.83	1.00	0.27
Cash flow	112,349	0.15	0.10	0.16	0.22	0.11
log (total assets)	112,349	9.88	8.54	9.58	10.73	2.10
Credit score	69,671	98.67	98.74	99.51	99.86	3.20
Sector supply shock	112,657	0.02	0.00	0.00	0.00	0.01
Scrapped	82,824	0.01	0.00	0.00	0.00	0.01
Exported	82,824	0.01	0.00	0.00	0.00	0.01
Low Euro truck	82,824	0.17	0.00	0.00	0.00	0.01
Scrapped (if Low Euro truck)	13,860	0.03	0.00	0.00	0.00	0.16
Exported (if Low Euro truck)	13,860	0.01	0.00	0.00	0.00	0.09
			Panel: Fleet level sample			
Average age fleet	201,761	12.66	5.00	10.00	18.00	9.83
Average Euro standard fleet	201,761	0.51	0.30	0.53	0.76	0.31
Intensity	201,761	5.84	0.20	1.80	9.53	7.91
Young	201,761	0.48	0.00	0.00	1.00	0.50
Blend	201,761	0.13	0.05	0.13	0.21	0.08
Diesel fuel price	201,761	11.78	11.11	11.71	12.39	0.78
ln(output)	201,761	8.89	7.79	8.79	9.86	1.74
ln(total assets)	201,716	8.67	7.68	8.57	9.54	1.57
Total debt	201,716	0.59	0.39	0.60	0.78	0.28
Cash flow	201,716	0.14	0.07	0.15	0.22	0.14
Fleet expansion	201,761	0.15	0.00	0.00	0.00	0.36

Table 1 reports summary statistics across the two main samples used in the paper. Panel A presents statistics for the truck-transaction-year sample. Truck age is calculated as calendar year minus vintage year. Firm age is calendar year minus year of incorporation. Share leased is the share of truck transactions involving a leased truck. Euro standards are mandatory EU-wide regulations of emissions and pollutants allowed in newly constructed trucks. Trucks during our sample period have Euro standards ranging from 0 to VI, where higher values correspond to cleaner trucks. Euro standard (unadj) is the unadjusted Euro standard, ranging from 0 to 6. Euro standard is the ratio of a truck's Euro standard to the maximum Euro standard in a given year, ranging from 0 to 1. Cash flow is cash flow divided by total assets. Credit score is 100 minus the probability of default based on UC's risk forecast variable. Sector supply shock is the ratio of the number of clean trucks (Euro standard ≥ 0.75) sold by mature firms (above the median firm age in a given year) to all trucks in a sector in a given year. Scrapped is an indicator variable equal to one if a truck leaving a firm is scrapped. Exported is an indicator variable equal to one if a truck leaving a firm is exported. Low Euro truck is an indicator variable equal to one if a truck has an adjusted Euro standard below 0.4. Scrapped (if Low Euro truck) is an indicator variable equal to one if a Low Euro truck leaving a firm is scrapped. Exported (if Low Euro truck) is an indicator variable equal to one if a Low Euro truck leaving a firm is exported. Panel B presents statistics for the fleet-level sample. Average fleet age is the average truck age of a firm's fleet. Average fleet Euro standard is the average Euro standard of the trucks in a firm's fleet. Intensity is the ratio of the sum, across all trucks in a firm's fleet, of the product of engine power and vehicle kilometers traveled for each truck, divided by PPI-deflated sales. Young is an indicator variable equal to one if a firm is below the median firm age in a given year. Blend is the annual biofuel blending share. Diesel fuel price is the after-tax price per liter of diesel in 2020 prices, excluding VAT. Output is PPI-deflated sales. Total assets is the book value of all assets. Total debt is total debt divided by total assets. Fleet expansion is an indicator variable equal to one if the firm experienced a net expansion of its fleet.

Table 2: Summary statistics by sector

	# truck-years	Fraction sample	# Transactions	Fraction sample	New trucks	Fraction all	Leased trucks	Fraction Leased	Truck age	Average VKT	Euro standard	Firm age	# Scrapped	Fraction sample	# Exported	Fraction sample
Sample	933,910	1.00	112,657	1.00	40,378	0.36	21,944	0.02	4.92	42,944	0.78	19.84	11,476	1.00	8,521	1.00
Agriculture	24,279	0.03	2,424	0.02	415	0.17	201	0.01	9.41	36,142	0.61	16.17	382	0.03	120	0.01
Manufacturing	80,794	0.09	6,815	0.06	2,428	0.36	1,302	0.02	6.46	26,370	0.72	33.91	1,604	0.14	793	0.09
Construction	131,791	0.14	16,712	0.15	3,413	0.20	2,209	0.02	8.28	29,055	0.64	15.82	1,642	0.14	774	0.09
Trade	75,827	0.08	7,037	0.06	2,215	0.31	1,788	0.02	6.53	27,767	0.71	26.47	2,928	0.26	1,257	0.15
Trucking	487,038	0.52	63,203	0.56	27,393	0.43	12,362	0.03	3.19	51,864	0.85	19.68	2,855	0.25	4,235	0.50
Services	134,181	0.14	16,466	0.15	4,514	0.27	4,082	0.03	6.19	37,128	0.73	16.42	2,065	0.18	1,342	0.16

Table 2 presents summary statistics across six broad sector groupings broadly consistent with Statistics Sweden's (SCB) industry classifications. Agriculture corresponds to SCB section A; Manufacturing covers mining and manufacturing (sections B and C); Construction corresponds to section F; Trade covers wholesale and retail (section G); Trucking is broken out from section H (Transportation and storage) and is defined as four-digit NACE 4941; Services covers the non-trucking part of section H and the remaining sections I–U. Sections D (electricity) and E (water supply and waste management) are excluded as they are predominantly public sector owned. Sections 45 (wholesale and retail trade and repair of motor vehicles and motorcycles) and 77 (rental and leasing activities) are also excluded as firms in these sectors own trucks for commercial resale or leasing purposes rather than for operational use.

Table 3: Characteristics of trucks entering and leaving firms

							Leave reason:			
	All truck years	**Trucks entering firms in sample (no lease)**	**Trucks entering firms in sample (lease)**	**Trucks entering firms in sample (new, no lease)**	**Trucks entering firms in sample (used, no lease)**	**Trucks leaving firms in sample**	**Sold to domestic LLC**	**Sold to other domestic legal entity**	**Exported**	**Scrapped**
# observations	933,910	90,833	21,957	30,302	60,659	143,281	99,497	23,757	8,521	11,476
Cumulative VKT	306,461	152,156	129,663	30,842	269,441	411,309	405,706	418,828	536,311	368,388
VKT	49,982	41,452	49,177	30,796	46,786	52,825	64,291	36,967	22,545	8,585
Zero VKT	0.12	0.00	0.00	0.00	0.01	0.07	0.03	0.10	0.02	0.42
Truck age	9.87	5.53	2.41	0.00	8.30	10.15	7.90	13.71	11.38	21.33
Euro standard	0.60	0.75	0.88	0.99	0.63	0.55	0.63	0.42	0.49	0.24

Table 3 presents characteristics of trucks transacted in our sample. Cumulative VKT captures the total vehicle kilometers traveled for trucks with a vintage year of 2007 or later. VKT is the average annual vehicle kilometers traveled. Zero VKT is an indicator variable equal to one if the truck traveled zero kilometers in a given year. Truck age is calendar year minus vintage year. Euro standard is the ratio of a truck's Euro standard to the maximum Euro standard in a given year, ranging from 0 to 1.

Table 4: Baseline truck-transaction-year results

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Truck age at transaction				
Firm age	-0.058***	-0.055***	-0.058***	-0.041***	-0.041***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Lease		-2.634***	-2.928***		-2.526***
		(0.080)	(0.112)		(0.213)
Firm age × Lease			0.016***		-0.001
			(0.006)		(0.012)
Firm age × Blend				-0.129***	-0.128***
				(0.038)	(0.038)
Lease × Blend					-3.037**
					(1.260)
Firm age × Lease × Blend					0.127***
					(0.062)
Region × year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	90,704	112,657	112,657	90,704	112,657
Adjusted R^2	0.214	0.228	0.228	0.215	0.283

Table 4 reports OLS estimates of Equation 1. *Truck* $age_{v,t}$ is the dependent variable. *Firm* $age_{i,t}$ measures years since incorporation for firm i in year t. *Lease* is an indicator variable equal to one if the truck transaction involves a leased truck. $Blend_t$ is the biofuel blending share in year t. The sample comprises one observation for each truck that enters a firm's fleet in a given year (*truck-transaction-year sample*) during 2007–2020. Columns (1) and (4) include transactions excluding leased trucks. All regressions include region-by-year and four-digit industry fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: Baseline truck-transaction-year results: Trucking industry vs. other industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Truck age at transaction							
	Trucking sector				**Outside trucking sector**			
Firm age	-0.047***	-0.047***	-0.026***	-0.025***	-0.071***	-0.070***	-0.057***	-0.057***
	(0.003)	(0.004)	(0.007)	(0.008)	(0.006)	(0.006)	(0.010)	(0.011)
Lease		-1.908***		-1.378***		-4.757***		-4.489***
		(0.127)		(0.217)		(0.174)		(0.307)
Firm age × Lease		0.016***		0.002		0.030***		0.015
		(0.005)		(0.011)		(0.008)		(0.012)
Firm age × Blend			-0.159***	-0.160***			-0.102*	-0.096*
			(0.038)	(0.042)			(0.056)	(0.057)
Lease × Blend				-3.957***				-2.042
				(1.306)				(2.023)
Firm age × Lease × Blend				0.112*				0.109
				(0.058)				(0.074)
Region × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,840	63,202	50,840	63,202	39,863	49,454	39,863	49,454
Adjusted R^2	0.048	0.063	0.049	0.064	0.163	0.210	0.164	0.326

Table 5 reports OLS estimates of Equation 1. *Truck* $age_{v,t}$ is the dependent variable. *Firm* $age_{i,t}$ measures years since incorporation for firm i in year t. *Lease* is an indicator variable equal to one if the truck transaction involves a leased truck. $Blend_t$ is the biofuel blending share in year t. The sample comprises one observation for each truck that enters a firm's fleet in a given year (*truck-transaction-year sample*) during 2007–2020. Columns (1)–(4) include trucks from the trucking sector only (NACE 4941) and columns (5)–(8) include trucks from all other industries in the sample. Columns (1), (3), (5), and (7) include transactions excluding leased trucks. All regressions include region-by-year and four-digit industry fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6: Truck-transaction-year results: Other measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Truck age at transaction					
	Cash flow to assets		**ln(total assets)**		**Credit score**	
Measure	-2.641***	-3.123***	-1.173***	-1.135***	-0.150***	-0.151***
	(0.369)	(0.368)	(0.042)	(0.041)	(0.016)	(0.016)
Lease		-2.961***		-6.426***		-9.659***
		(0.101)		(0.512)		(2.089)
Measure × Lease		2.573***		0.400***		0.074***
		(0.471)		(0.056)		(0.021)
Region × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,518	112,348	90,518	112,348	57,528	69,637
Adjusted R^2	0.200	0.213	0.256	0.268	0.189	0.199

Table 6 reports OLS estimates of Equation 1. *Truck age*$_{v,t}$ is the dependent variable. The variable *Measure*$_{i,t}$ takes one of three forms: in columns (1)–(2) it is *Cash flow*$_{i,t}$, defined as cash flow divided by total assets for firm i in year t; in columns (3)–(4) it is *ln(total assets*$_{i,t}$*)*, the log of total assets for firm i in year t; and in columns (5)–(6) it is *Credit score*$_{i,t}$, defined as 100 minus the probability of default for firm i in year t. *Lease* is an indicator variable equal to one if the truck transaction involves a leased truck. The sample comprises one observation for each truck that enters a firm's fleet in a given year (*truck-transaction-year sample*) during 2007–2020. Columns (1), (3), and (5) include transactions excluding leased trucks. All regressions include region-by-year and four-digit industry fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7: Truck leaving firm: Scrapped and exported

	(1)	(2)	(3)	(4)
	Scrapped		**Exported**	
Low Euro truck	0.021***	-0.012***	0.001	-0.003**
	(0.002)	(0.002)	(0.001)	(0.001)
Low Euro truck × Blend		0.279***		0.031
		(0.033)		(0.019)
Region × year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	82,609	82,609	82,609	82,609
Adjusted R^2	0.115	0.122	0.110	0.110

Table 7 reports OLS estimates of Equation 2. *Scrapped* is the dependent variable in columns (1)–(2) and *Exported* in columns (3)–(4). *Scrapped* is an indicator variable equal to one if a truck leaving a firm is scrapped; *Exported* is an indicator variable equal to one if a truck leaving a firm is exported. *Low Euro truck* is an indicator variable equal to one if a truck has an adjusted Euro standard below 0.4. $Blend_t$ is the biofuel blending share in year t. The sample contains one observation for each truck leaving a firm's fleet, regardless of destination — whether acquired by another limited liability company in our sample, sold to another legal entity, scrapped, or exported — during 2007–2020. All regressions include region-by-year and four-digit industry fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8: Industry supply shock clean, used trucks

	(1)	(2)
	Dependent variable: Euro standard	
Young	-0.085***	-0.018*
	(0.007)	(0.009)
Young ×	0.663***	1.286***
Sector supply shock$_{t-1}$	(0.244)	(0.250)
Region × year FE	Yes	Yes
Industry FE	Yes	No
Sector × year FE	Yes	Yes
Firm fixed FE	No	Yes
Observations	90,704	81,887
Adjusted R^2	0.294	0.503

Table 8 reports OLS estimates of Equation 4. *Euro standard*$_{v,t}$ is the dependent variable. *Young* is an indicator variable equal to one if a firm is below the median firm age in a given year. *Sector supply shock*$_{s,t-1}$ is the ratio of the number of clean trucks (Euro standard ≥ 0.75) sold by mature firms (above the median firm age in a given year) to all trucks in broad sector s in year t, lagged one year. Broad sector refers to the six sector groupings in Table 2. The sample comprises one observation for each owned truck that enters a firm's fleet in a given year (*truck-transaction-year sample*) during 2007–2020, excluding leased trucks. All regressions include region-by-year and sector-by-year fixed effects; column (1) additionally includes four-digit industry fixed effects and column (2) firm fixed effects. Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 9: Baseline fleet level regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Average truck age of fleet							
	s = 1	s = 1	s = 1	s = 1	s = 1	s = 0	s = 2	s = 3
Intensity_{t-s}	-0.040***	-0.004	-0.017**	-0.029***	-0.037***	-0.048***	-0.021***	-0.016
	(0.003)	(0.005)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)
Intensity_{t-s} × Blend		-0.267***	-0.322***	-0.234***	-0.283***	-0.336***	-0.211***	-0.127**
		(0.027)	(0.044)	(0.050)	(0.047)	(0.047)	(0.050)	(0.054)
Young			0.131	0.088	-0.118	-0.126	-0.076	-0.033
			(0.125)	(0.125)	(0.120)	(0.122)	(0.125)	(0.135)
Young × Blend			-3.959***	-3.470***	-1.021	-1.178*	-1.348*	-1.079
			(0.696)	(0.704)	(0.675)	(0.687)	(0.695)	(0.725)
Intensity_{t-s} × Young			0.005	0.010	0.003	0.002	0.002	0.000
			(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)
Intensity_{t-s} × Young x Blend			0.199***	0.155***	0.195***	0.225***	0.188***	0.133**
			(0.053)	(0.054)	(0.051)	(0.053)	(0.054)	(0.058)
$\ln(\text{Output}_{t-1})$					-0.546***	-0.487***	-0.525***	-0.521***
					(0.039)	(0.041)	(0.043)	(0.046)
$\ln(\text{Total assets}_{t-1})$					-1.360***	-1.388***	-1.387***	-1.389***
					(0.046)	(0.047)	(0.049)	(0.052)
Total debt_{t-1}					-0.747***	-0.817***	-0.749***	-0.817***
					(0.106)	(0.108)	(0.111)	(0.118)
Cash flow_{t-1}					-0.293***	-0.310***	-0.146***	-0.143***
					(0.100)	(0.023)	(0.106)	(0.115)
$\text{Fleet expansion}_{t-1}$					-0.150***	-0.172***	-0.256***	-0.224***
					(0.023)	(0.023)	(0.024)	(0.025)
Fleet FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × year FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	204,155	204,155	204,155	204,155	204,110	201,761	173,491	147,783
Adjusted R^2	0.900	0.900	0.900	0.900	0.906	0.906	0.915	0.906

Table 9 reports OLS estimates of Equation 5. *Average fleet age*$_{i,t}$ is the dependent variable, computed as the average *Truck age* across all heavy goods vehicles operated by firm i in year t. *Intensity*$_{i,t-s}$ is the ratio of the sum, across all trucks in a firm's fleet, of the product of engine power and vehicle kilometers traveled for each truck, divided by PPI-deflated sales. *Intensity* is measured with a one-year lag ($s = 1$) in columns (1)–(5), contemporaneously ($s = 0$) in column (6), with a two-year lag ($s = 2$) in column (7), and with a three-year lag ($s = 3$) in column (8). *Young* is an indicator variable equal to one if a firm is below the median firm age in a given year. *Blend*$_t$ is the annual biofuel blending share in year t. The sample comprises one observation per firm per year (*fleet-level sample*) during 2007–2020. All regressions include fleet and region-by-year fixed effects; columns (3)–(8) additionally include sector-by-year fixed effects. Columns (5)–(8) include the following lagged firm-level controls: *ln(Output*$_{i,t-1}$*)* (log of PPI-deflated sales); *ln(Total assets*$_{i,t-1}$*)* (log of the book value of total assets); *Total debt*$_{i,t-1}$ (total debt divided by total assets); *Cash flow*$_{i,t-1}$ (cash flow divided by total assets); and *Fleet expansion*$_{i,t-1}$ (an indicator variable equal to one if the firm experienced a net expansion of its fleet). Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 10: Fleet level regressions: Fuel prices vs climate policy

	(1)	(2)	(3)	(4)	(5)	(6)
	Average age fleet		Average Euro standard fleet			
	s = 1	s = 1	s = 1	s = 3	s = 1	s = 1
$\text{Intensity}_{t\text{-}s}$	-0.004	-0.014	0.0006***	0.0005	-0.0017*	-0.0014
	(0.026)	(0.026)	(0.0003)	(0.0003)	(0.0009)	(0.0009)
$\text{Intensity}_{t\text{-}s}$ × Diesel fuel price	-0.636***	-0.198			0.0323***	0.0175**
	(0.214)	(0.202)			(0.0074)	(0.0070)
Young	0.162	0.142	0.0001	-0.0026	-0.0162	-0.0155
	(0.319)	(0.317)	(0.0040)	(0.0045)	(0.0101)	(0.0109)
Young × Diesel fuel price	-3.719	-2.251			0.1892**	0.1354
	(2.572)	(2.387)			(0.0889)	(0.0836)
$\text{Intensity}_{t\text{-}s}$ × Young	-0.021	-0.014	0.0002	0.0003	0.0008	0.0005
	(0.027)	(0.027)	(0.0003)	(0.0004)	(0.0010)	(0.0010)
$\text{Intensity}_{t\text{-}s}$ × Young × Diesel fuel price	0.467**	0.149			-0.0142*	-0.0032
	(0.226)	(0.214)			(0.0081)	(0.0078)
$\text{Intensity}_{t\text{-}s}$ × Blend		-0.280***	0.0098***	0.0033*		0.0095***
		(0.047)	(0.0015)	(0.0017)		(0.0015)
Young × Blend		-0.982	0.0394**	0.0439*		0.0371*
		(0.202)	(0.0225)	(0.0244)		(0.0224)
$\text{Intensity}_{t\text{-}s}$ × Young × Blend		0.192***	-0.0067***	-0.0055***		-0.0066***
		(0.051)	(0.0017)	(0.0020)		(0.0017)
Fleet FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector × year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204,110	204,110	204,110	147,783	204,110	204,110
Adjusted R^2	0.906	0.906	0.882	0.901	0.882	0.882

Table 10 reports OLS estimates of Equation 5. *Average fleet age*$_{i,t}$ is the dependent variable in columns (1)–(2), computed as the average *Truck age* across all heavy goods vehicles operated by firm i in year t. *Average fleet Euro standard*$_{i,t}$ is the dependent variable in columns (3)–(6), computed as the average *Euro standard* across all heavy goods vehicles operated by firm i in year t. *Intensity*$_{i,t\text{-}s}$ is the ratio of the sum, across all trucks in a firm's fleet, of the product of engine power and vehicle kilometers traveled for each truck, divided by PPI-deflated sales. *Intensity* is measured with a one-year lag ($s = 1$) in columns (1)–(3) and (5)–(6) and with a three-year lag ($s = 3$) in column (4). *Young* is an indicator variable equal to one if a firm is below the median firm age in a given year. *Blend*$_t$ is the annual biofuel blending share in year t. *Diesel fuel price*$_t$ is the after-tax price per liter of diesel in 2020 prices, excluding VAT, in year t. The sample comprises one observation per firm per year (*fleet-level sample*) during 2007–2020. All regressions include fleet, region-by-year, and sector-by-year fixed effects and the following lagged firm-level controls: *ln(Output*$_{i,t\text{-}1}$*)* (log of PPI-deflated sales); *ln(Total assets*$_{i,t\text{-}1}$*)* (log of the book value of total assets); *Total debt*$_{i,t\text{-}1}$ (total debt divided by total assets); *Cash flow*$_{i,t\text{-}1}$ (cash flow divided by total assets); and *Fleet expansion*$_{i,t\text{-}1}$ (an indicator variable equal to one if the firm experienced a net expansion of its fleet). Standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

A Appendix

A.1 Datasets

Heavy-duty truck registration data: We obtain registration data for heavy-duty trucks (weight >3,500 kg) from 2007 to 2020 provided by the Swedish Transport Agency (Transportstyrelsen) and the Road Traffic Registry (Vägtrafikregistret). In this data, each truck is assigned a consistent anonymous identifier (Vehicle Indentification Number), allowing us to track it over time[7]. The data includes ownership information indicating whether each truck is registered to a firm or an individual. The ownership data is as of December 31st in a given year. Firms and individuals are identified through consistent anonymous organization and personal identifiers, respectively. The firm identifier allows us to link this data to firm-level financial variables. For each truck, this dataset includes characteristics such as fuel type, year of production, status (active, unregistered, or temporarily unused), reason for deregistration, curb weight, gross weight, towing capability, distance driven in a given year, and manufacturer. The distance driven in a given year is collected from the annual vehicle inspections. According to Regulation (EC) No 595/2009 European Commission (2009) of the European Parliament and of the Council, EU emission standards establish binding emission limits for motor vehicles as a condition for type approval, which vehicles must satisfy before they can be registered or put into service in the EU. We then classify the EU emission standard based on the vehicle's production year, in accordance with the implementation dates of each standard.[8] In the sample, we retain diesel-powered trucks with Euro emission standards ranging from Euro 0 (trucks produced prior to the implementation of Euro I) to Euro VI.

Administrative data on firms' truck fleets: We use firm-level vehicle data from the FRIDA database maintained by Statistics Sweden (SCB). According to SCB, FRIDA is based on administrative records from the Swedish Tax Agency (Skatteverket), including standardized accounting extracts (SRU data). This dataset includes additional truck-level information from 2007 to 2020, such as engine power and leasing status. Since this dataset does not contain vehicle identifiers, we match it to the vehicle registration data using firm identifiers, vehicle age, total truck weight, distance driven, and year. However, the distance traveled recorded in the vehicle registration data and the administrative data is inconsistent in some cases. We first retain exact matches, for the residual observations, we then perform a fuzzy matching procedure. Specifically, within the same firm-year-age-weight group, we allow potential matches when the absolute difference in distance driven between the two datasets is below the median distance difference among possible matches.[9]

[7]Due to permission and privacy reasons, all real information related to micro-objects are removed. All data is anonymized and provided through Statistics Sweden (SCB).

[8]We use the same method as described in Martinsson et al. (2026). According to EU standards, for example (Directive 2005/55/EC European Commission (2005), Directive 1999/96/EC European Commission (1999) and Regulation (EC) No 595/2009 European Commission (2009)), Euro emission class V was enforced on heavy trucks registered after October 1, 2009, while Euro VI was applied to heavy trucks registered after December 31, 2013. We place trucks that were produced from 2010 to 2013 in the category Euro V. Besides, we create a separate category entitled Euro 0 for trucks produced prior to 1994, predating the Euro I registration. We utilize the same approach for other emission classes that vary with vehicle type.

[9]The median threshold for possible matches is approximately 128 km, and these fuzzy-matched observations comprise around 8% of the observations in the data.

Firm-level financial data: We obtain firm-level financial data from the Bisnode Serrano database. The database includes comprehensive balance sheet and income statement data, bankruptcy records, legal form of the entity, founded year of the entity, and NACE Rev. 2 industry classifications for the period 1998–2020. The Swedish Companies Registration Office (SCRO) (Swedish: Bolagsverket) assigns each Swedish limited liability firm a unique and permanent identifier, known as the organization number, which enables us to link with the vehicle data. Since firms can switch their NACE Rev. 2 codes during the sample period, we construct a harmonized industry code for each firm using the four-digit NACE code from its most recent observation. All accounting variables, including sales, total assets, tangible fixed assets, and cash flow, are measured at the calendar-year level and deflated using the Consumer Price Index (CPI) and the Swedish Producer Price Index (PPI), with 2020 as the base year.

A.2 Sample construction

We construct our sample by merging all datasets using firm- and year-level identifiers. The sample includes all diesel-powered heavy-duty vehicles owned by Swedish limited liability companies (Aktiebolag) between 2007 and 2020.

Since our analysis focuses on truck transaction dynamics, we further define truck entry and exit at the firm level. A truck is defined as an entry in year t if it is first observed in a given firm in that year. As the sample begins in 2007, we classify a truck as an entry in 2007 only if it was produced in that year. We apply analogous logic to define truck exit. A truck is classified as an exit in year t if year t is the final year in which it is observed under the ownership of that firm.

The Swedish Transport Analysis Agency (Trafikanalys) and Statistics Sweden (SCB) group reasons for deregistering into four categories: (i) *Actually scrapped*, (ii) *Administrative deregistration*, referring to the automatic removal of a vehicle from the register by the authority after it has remained continuously off-road (*avställd*) for three years, (iii) *Exported from Sweden*, and (iv) *Unknown* (a residual category generated by SCB). We inspect the data and find that the first category - administrative deregistrations, increases sharply in certain years, suggesting an possible inconsistent reporting pattern. To address this issue, we introduce a fifth category: *Supplementary administrative deregistration*. This category is constructed according to the official definition: if a truck has remained continuously off-road for three consecutive years (from $(t-3)$ to $(t-1)$), it is classified in year t as *should be administratively deregistered*.

To track where trucks go after exiting our sample, we classify truck exits into two categories. The first is full exit, defined as deregistration. The second is transaction exit, where the truck is sold and remains active in the market. For transaction exits, we identify the new owner's legal form using the Bisnode Serrano database and distinguish three groups: (i) sold to a Swedish limited liability company; (ii) sold to a non-Swedish limited liability entity (e.g., cooperatives or public entities); and (iii) sold to an entity without a registered legal form, including individuals.