Life on the Road: Technology Adoption, Capital Reallocation, and Environmental Standards in the Commercial Truck Market

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Abstract

This paper considers the lifecycle and movement of capital in the heavy-duty trucking context. Over the lifecycle, the vehicles may move across different firm types and geographies, so vehicle standards that affect the availability and attributes of new and used vehicles will have heterogeneous effects across these buyers and regions. To understand the lifecycle of trucks, we use federal inspection data, which indicates historical truck ownership and provides a proxy for changes in ownership, and the Vehicle Inventory and Use Survey, which provides a snapshot of the different ownership patterns across firm types and regions. We document that heavy-duty trucks begin life in large, general-freight firms and migrate to small, specialized firms as they age. New vehicle regulations have long-lived effects on sales, mileage, and scrapping.

1 Introduction

A literature has documented a life cycle pattern of capital: small and credit-constrained firms are more likely to invest in used capital, while larger and less constrained firms invest in new capital.[1] Heavy-duty trucks are an especially important type of physical capital where vintages matter. Historically, older vintages of heavy-duty trucks emit more pollution than newer vintages. In the near future, the effectiveness of trucking decarbonization depends on the rate at which diesel trucks are retired. Addressing these policy challenges therefore requires collecting long-run data on ownership and operation of used trucks, in order to understand the determinants of the life cycle of heavy-duty trucks.

This paper studies how the ownership and operation of heavy-duty trucks evolves over the course of a truck's life. Using survey and regulatory data covering more than twenty years, we document new life cycle patterns: New vehicles are more likely to be purchased by larger firms, firms operating in California and other large states, and general freight firms. Meanwhile, older vehicles are more likely to be purchased and operated by smaller firms and specialized freight firms.

By looking at policy variation around two recent vehicle regulations, we document suggestive evidence of the long-lived effects of regulations. Specifically, firms can respond to new regulations that reduce perceived vehicle quality by "pre-buying" vehicles before the regulation takes effect or using pre-regulation vehicles differently – driving them more and scrapping them more slowly. We see both pre-buying effects and more intensive use/delayed scrappage around the time that recent heavy-duty engine standards came into effect.

Finally, we develop a parsimonious model of purchase, sale, and scrapping, and outline next steps to estimate the model and conduct counterfactuals to study policies that affect upfront purchase price, maximum vehicle age allowed within a region, and a cash-for-clunkers style policy that purchases older vehicles.

This paper contributes to several areas of the literature. First, as discussed above, it extends research on life cycle patterns of long-lived capital, as studied in Eisfeldt & Rampini (2007), Eisfeldt & Shi (2018), Ersahin (2020), and Ma et al. (2022). The unique mobility of capital in the trucking context and the fragmentation of the trucking industry differentiate our setting from others in the literature. Further, the availability of vehicle-level identifiers allows us to see how specific pieces of capital are utilized in addition to how they are traded.

Second, we extend a small literature on the effect of policies that affect heavy-duty truck purchases and use. Most closely related is Rittenhouse & Zaragoza-Watkins (2018) who document a pre-buy effect around the 2007 heavy-duty engine standards, but a number

[1] Eisfeldt & Rampini (2007), Eisfeldt & Shi (2018), Ersahin (2020), Ma et al. (2022)

of papers have also considered the effects of fuel economy standards for heavy-duty trucks (Bushnell & Hughes 2024, Adenbaum et al. 2019, Weber 2024). Leard et al. (2016) study vehicle usage decisions in response to fuel costs. None of these papers addresses the full truck life cycle, particularly scrappage and used vehicle markets, nor do they consider vehicle age-related policies, like a maximum vehicle age or a cash-for-clunkers program (although Li et al. (2013) study the U.S. cash-for-clunkers policy for passenger cars).

2 Background

Heavy-duty trucks are a critical part of the freight transportation system in the United States. In 2022, 72% of all freight, or more than 11.46 billion tons of freight, was transported via trucks, and the sector employs more than 3 million people as drivers (Cannon 2023, ATA 2023). The industry is highly fragmented – 95.8% of fleets operate 10 or fewer vehicles, while 99.7% operate 100 or fewer – but the largest fleets operate thousands of trucks (ATA 2023).

The highest weight capacity trucks – classes 7 and 8, with weight capacities in excess of 26,001 pounds – are used by a variety of industries to transport goods, either as for-hire vehicles or by firms transporting their own products. This paper focuses on class 7 and 8 combination tractors, i.e., tractors to which trailers can be attached. These vehicles have an average MSRP of \$120,000[2] and can remain in commercial use for more than 20 years (see stylized facts, below). While they are a small fraction of vehicles on the road, they are a major contributor to on-road greenhouse gas and NOx emissions (Tong et al. 2021). Hence, understanding the uses and movement of these vehicles over their lifecycle is economically important.

In recent years, a number of environmental policies have affected the truck market. These include criteria pollutant standards for heavy-duty vehicle engines that went into effect in 2002, 2007, and 2010; the first-ever fuel efficiency and greenhouse gas emissions standards for heavy trucks beginning in 2014; and the Advanced Clean Trucks and Advanced Clean Fleets rules from California. The engine standards, implemented by EPA, restrict allowable particulate and NOx emissions, which manufacturers could comply with via additional pollution control technology. These standards, particularly the 2007 engine standards, were accompanied by concern about both higher costs and reduced engine performance. The fuel economy standards set fuel economy targets at the manufacturer level for different categories of heavy trucks. Original equipment manufacturers (OEMs) could comply with these standards via a range of technological improvements, including low rolling resistance tires and improved aerodynamics.

[2]Statistic for all class 7 and 8 vehicles, 2011-2019, in 2021 dollars (Weber 2024).

Finally, state-level policies generate spatial variation in regulatory stringency. As in the passenger vehicle setting, the state of California has been at the vanguard of heavy truck policy. The Advanced Clean Trucks (ACT) rule requires OEMs to sell zero emissions vehicle (ZEV) trucks as an increasing percentage of their California vehicle sales, beginning in 2024. The later Advanced Clean Fleets regulation ramps up the ACT ZEV requirement to 100% in 2036 and requires certain fleets to phase in ZEVs and, importantly, phase out the use of older diesel trucks in California. The implications for truck owners outside of California is uncertain: Will the quality of trucks outside California deteroriate due to greater availability of used trucks? Or will average quality increase in the long run as higher-quality new trucks move outside of California through the used truck market? Answering these questions requires leveraging detailed data sources on the uses and operations of the used truck market.

3 Data

We combine two main data sources for this project: the U.S. Census Vehicle and Inventory and Use Survey (2021), and U.S. Federal Motor Carrier Safety Administration inspections reports. The former allows us to observe detailed information about how used trucks are operated, including how they are driven, who operates them, and what after-market technologies have been added. The latter allows us to observed a history of ownership for the same vehicle, allowing us to see transitions in the truck market. By merging the two together using vehicle identification numbers, we can develop a cohesive picture of the used truck market.

U.S. Census Vehicle Inventory and Use Survey We use the 2021 Vehicle Inventory and Use Survey (VIUS), a survey of 150,000 Class 1 through 8 trucks conducted between February and October of 2022. The survey asks about vehicle attributes, driving patterns, economic activities served by the vehicles, etc. Unless otherwise specified, we focus on observations identified as Class 7 and 8 tractor trailers (13,145 observations, representing approximately 2.1 million vehicles on the road[3]).

U.S. FMCSA Inspections We use inspection data from the Federal Motor Carrier Safety Administration (FMCSA) vehicle inspections. Each of these public inspections records the Vehicle Identification Number (VIN) number of the inspected vehicle along with the De-

[3]All statistics are calculated using reported tabulation weights, which are also estimates of the number of vehicles represented by each survey respondent.

partment of Transportation (DOT) number of the firm employing the vehicle. By decoding the VIN, we can observe detailed information about the vehicle and its characteristics. We use repeat inspections of the same vehicle over time to construct a panel dataset that tracks changes in vehicle ownership. For additional information about firm operational classification and cargo carried, we merge inspections with FMCSA carrier registrations.

This dataset averages 900,000 inspections per year from 2000 to 2021, totalling 20.2 million observations. Over these twenty-two years, we observe 6.6 million unique vehicles (VINs) and 1.0 million unique firms (DOT numbers).

	Mean	**Std Dev**	**Min**	**Max**
Inspections per Year	918,385	179,755	522,944	1,140,775
Inspections per Vehicle	3.03	2.83	1	38
Inspections per Firm	19.1	402.6	1	208,339
Unique Firms per Vehicle	1.58	1.1	1	22
Unique Vehicles per Firm	10.41	207.9	1	100,556

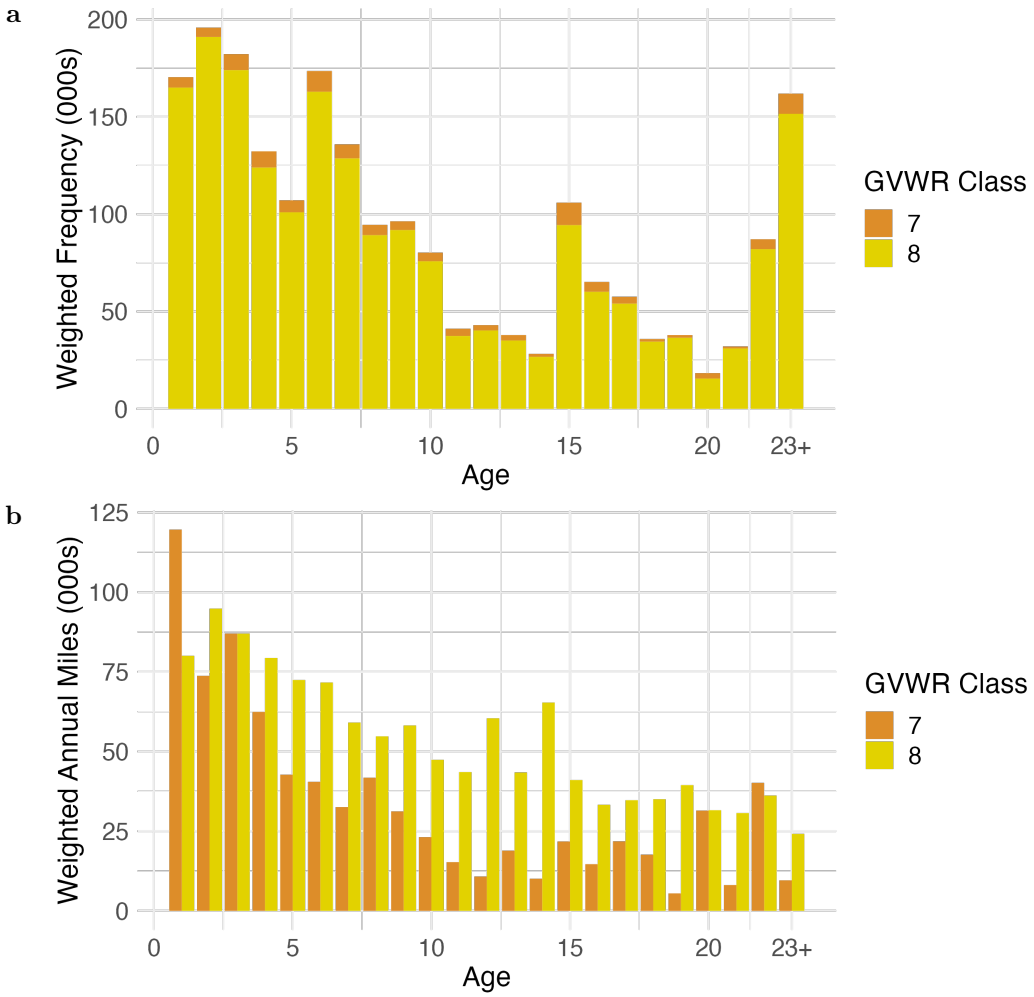
Table 1: Summary Statistics (FMCSA Inspections)

4 Stylized Facts

In this section, we document three sets of stylized facts: heavy-duty trucks are long-lived and long-utilized assets, truck are used differently over the course of their life, and these lifecycle effects cause new vehicle regulations to have long-lived effects. We document each of these facts using a mix of our data sources, showing that these patterns are robust to sampling selection and methodology.

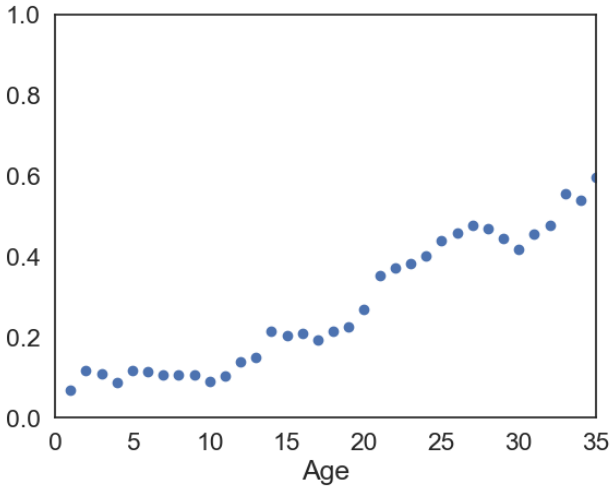
4.1 Heavy duty trucks are long-lived and long-utilized assets

Age Distribution The VIUS data includes vehicle model year, ranging from pre-1999 to 2021-2022 (the first and last category include multiple model years). We calculate age by subtracting the model year from 2022, the year of the survey. As Figure 1 Panel A indicates, the majority (65%) of trucks in the data are 10 years old or newer, but many older vehicles remain on the road, including nearly 8% of vehicles from model year 1999 or earlier. Notably, older vehicles continue to be driven quite a bit, as well. Figure 1 Panel B shows average reported miles driven in 2021 by vehicle age. While vehicle miles traveled (VMT) declines over the lifespan, Class 8 vehicles ages 11+ are driven an average of 37,000 miles per year (vs. 74,000 miles for vehicles ages 1-10).



Note: Figure 1a plots the weighted frequency of vehicles of each age in 2022, by gross vehicle weight rating (GVWR). Figure 1b plots the average annual mileage of vehicles of each age in 2022, by GVWR. Source: Census Vehicle Inventory and Use Survey

Figure 1: Age and mileage-by-age distribution of vehicles in VIUS.



Note: Figure 2 plots the estimated annual scrap rate, averaged over all model years between 2000 and 2021. Source: FMCSA Inspections

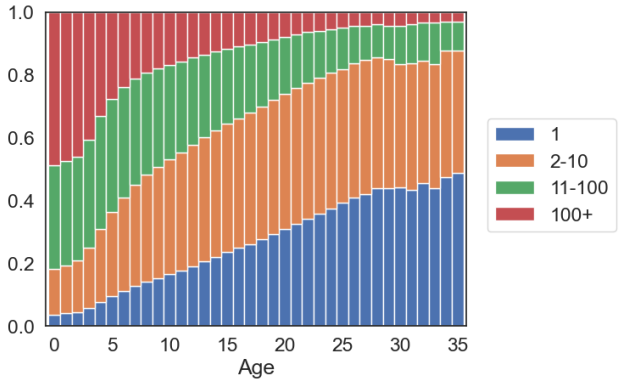
Figure 2: Scrap rate as a function of age

Scrap Rate We use our inspections data to construct the age profile of the scrap rate: As a vehicle ages, how does the probability that the vehicle is scrapped change?[4] Since we do not explicitly observe scrapping, we estimate the scrap rate from the probability that a vehicle inspected in one year is not inspected in the next. This may occur because the vehicle was scrapped, or this may be due to the vehicle failing to be inspected. The probability of scrapping given age a can be therefore expressed as a function of the annual inspection probability, $\hat{P}$, and the probability of a vehicle not being inspected at age $a+1$ conditional on being inspected at age a, $1 - P(a+1 \mid a)$.[5] For parsimony, we assume that $\hat{P}$ does not depend on age, and vehicles are never scrapped in their first year of operation, so we can estimate $\hat{P}$ using $P^n(1 \mid 0)$. We estimate an average annual probability of being inspected of 53.7 percent.

In Figure 2, we plot the estimated overall scrap rate as a function of vehicle age. Scrap rates are low for the first 10-15 years of a vehicle's life, at around 10 percent. Between years 15 and 20, scrap rates are elevated at around 20 percent, and above 20 years the scrap rate rises to around 40 percent. Overall, these rates are low and consistent with vehicles having long lives.

[4] We define scrapping as the vehicle no longer being used as a commercial vehicle subject to federal inspections. This may include literal destruction or disassembly, export to other markets, or use in a niche application.

[5]
$$\begin{aligned} 1 - P^{insp}(a+1 \mid a) &= P^{scrap}(a) + (1 - P^{scrap}(a)) \times (1 - \hat{P}) \\ \implies P^{scrap}(a) &= 1 - P^{insp}(a+1 \mid a)/\hat{P} \end{aligned} \tag{1}$$



Note: Figure 3 plots the share of vehicles of each model year owned by firms in each size category, averaged over 2000-2022. Firm sizes are measured by the number of VINs associated with the firm DOT number in the same year. Source: FMCSA Inspections

Figure 3: Share of Vehicles Owned by Different Firm Sizes, by age

4.2 Trucks are used differently at different points in their life cycle

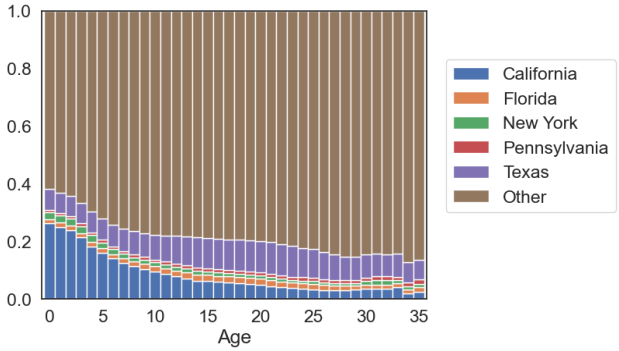
In this section, we demonstrate three patterns about vehicle life cycles: (1) New vehicles are purchased by larger firms, while older vehicles are predominantly owned by small firms, (2) Newer vehicles are more likely to be operated in the top five states in the U.S., and especially California, (3) Newer vehicles are more likely to be registered in the top five states in the U.S., and (4) New vehicles are more likely to be operated by general freight business, while used vehicles are more likely to be operated by specialized businesses. Together, these consistent life cycle patterns suggest an interaction between vehicle characteristics (especially age) and firm characteristics.

Firm Size In this section, we show that existing results on the relationship between firm size and capital age hold in our setting. We construct a rough measure of firm size by observing how many other vehicles of the same firm (DOT number) are inspected in the same year.[6] In Figure 3, we plot the share of vehicles of each age that are owned by firms with one vehicle, with two to ten, with eleven to one hundred, and with over one hundred vehicles. New vehicles and vehicles below five years are overwhelmingly owned by large firms. Between ages five and 10, the share of used vehicles owned by firms below ten vehicles increases. Above age fifteen, the majority of vehicles are owned by small firms.

Geography We measure the main operating area for each firm using the state in which the firm's vehicles are most commonly inspected.[7] In Figure 4, we plot the share of vehicles of each age that are owned by firms operating in each of the top five states (California, Texas,

[6]Since inspection is probabilistic, this is an underestimate of the true firm size.

[7]Since many of the firms in our sample are interstate carriers, operating location is a more direct measure of business activity than registration location.



Note: Figure 4 plots the share of vehicles of each model year owned by firms which primarily operate in each of the top five states. Modal operating state is assigned to each firm based on the most frequent state in which that firm's vehicles are inspected. Source: FMCSA Inspections

Figure 4: Share of Vehicles Owned by Owner Modal Operating State, by age

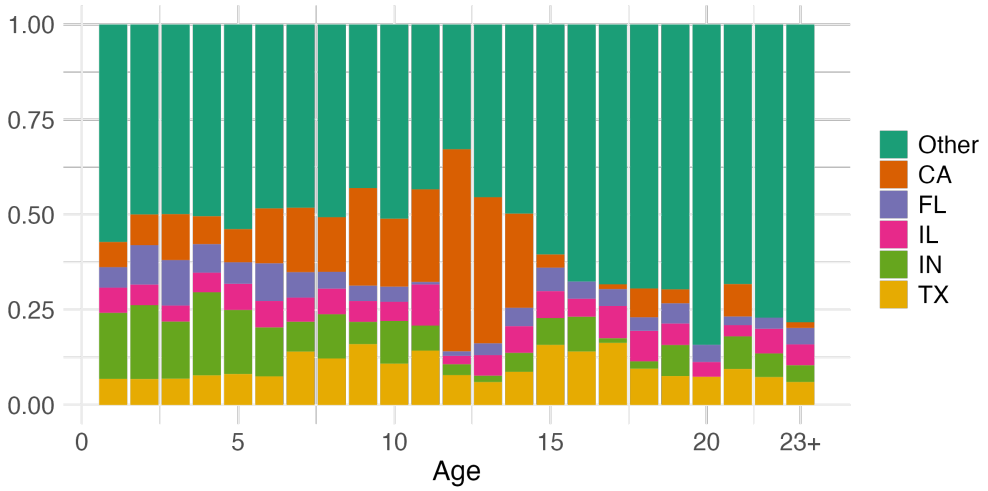
New York, Florida, and Pennsylvania), and aggregate all other states into "Other." More than twenty percent of new vehicles are purchased by firms mainly operating in California. In contrast, only ten percent of ten-year-old vehicles are owned by California-operating firms. Texas exhibits the opposite pattern: Texas-operating firms own a larger share of ten- or twenty-year-old trucks than they do of new trucks.

Geography of Ownership The location where a vehicle is registered may or may not reflect where a vehicle is used if the vehicle is engaged in interstate transport. Thus, we separately examine the state in which vehicles are registered in Figure 5. Newer vehicles are particularly likely to be registered in Indiana, while vehicles between five and 15 years are most likely to be registered in California. Among the VIUS vehicles, the older vehicles are less likely to be registered in the top five states (California, Florida, Illinois, Indiana, and Texas), spreading out around the country.

We can also examine whether a vehicle of any age was acquired new or used. In Figure 6, we compare the share of vehicles acquired new that are registered in each state to the share of vehicles acquired used that are registered in each state. Vehicles registered in Indiana and Florida represent a much larger share of new vehicles compared to used vehicles, while the opposite is true for vehicles registered in Texas (and, to a lesser extent, Illinois). California registrations are approximately the same share of vehicles acquired new and used.

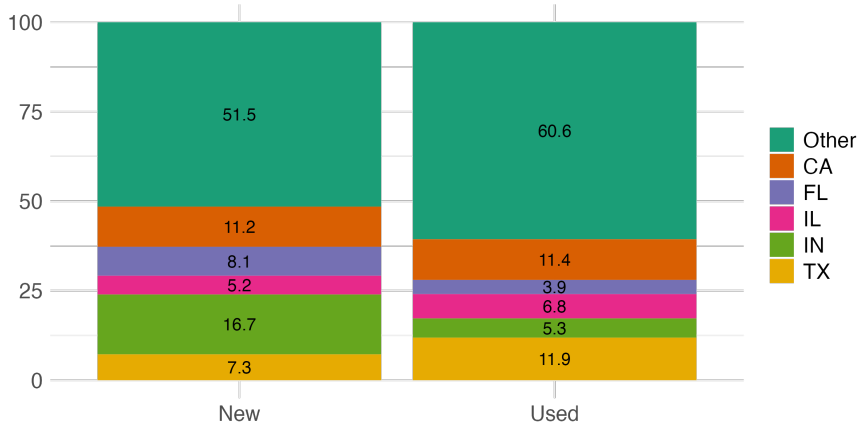
Industry We separate two dimensions of firm industry: operation class and commodity carried. Operation class refers to whether the vehicle is operating for-hire or transporting private property, while commodity refers to the actual products transported.

Firms declare their operation class in the motor carrier registrations. In Panel A of Figure 7, we plot the share of vehicles of each age that are owned by firms operating for-hire and



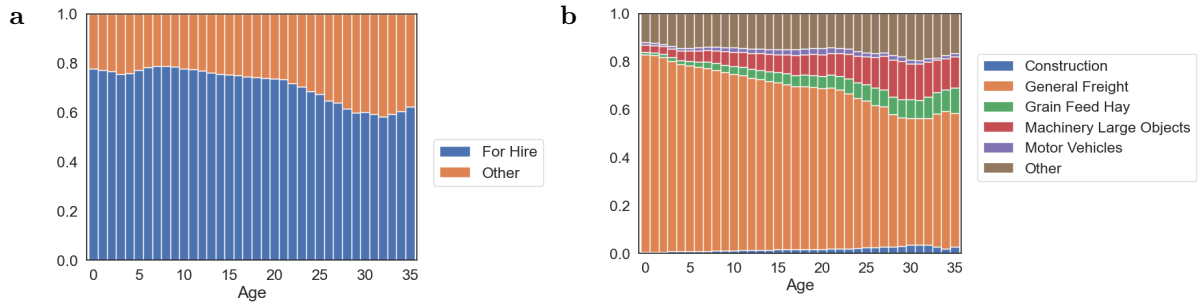
Note: Figure 5 plots the weighted share of model year registered to each state. Source: Census Vehicle Inventory and Use Survey

Figure 5: Share of Vehicles Owned by Registration State, by age



Note: Figure 6 plots the weighted share of new and used vehicles registered to each state. In the survey, truck owners are explicitly asked whether they acquired their vehicle new or used. Source: Census Vehicle Inventory and Use Survey

Figure 6: Share of Vehicles Acquired New or Used by Registration State



Note: Figure 7 plots the share of vehicles of each model year owned by firm type. Panel A separates firms based on their operation class: For-Hire versus Other (including Private Property). Panel B separates firms based on their primary commodity class, where commodity class is assigned based on reported commodities carried in FMCSA registrations. Source: FMCSA Inspections, FMCSA Registrations

Figure 7: Share of Vehicles Owned by Owner Commodity, by age

all other firms. For-hire firms operate the majority of vehicles, and their share is especially pronounced for new vehicles.

In the motor carrier registrations, firms declare the set of commodities that they carry.[8] In Panel B of Figure 7, we plot the share of vehicles of each age that are owned by firms operating in each of the top commodity categories. Most vehicles are operated by general freight firms, which purchase over 80 percent of new vehicles. As vehicles age, the share that are operated by non-general freight firms, including grain/feed/hay, machinery/large objects, and motor vehicles, increases.

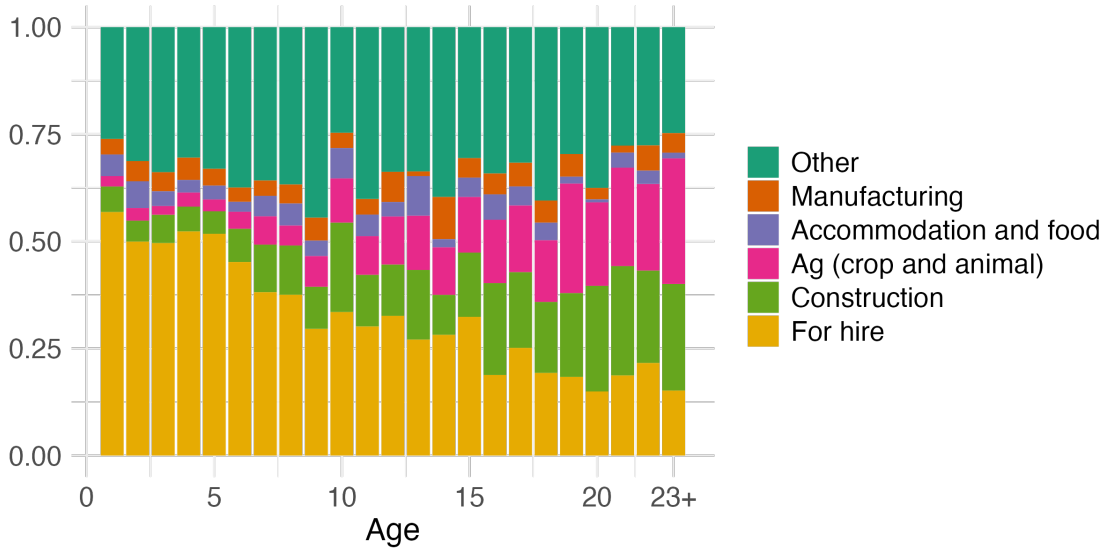
Similarly, the VIUS asks vehicle owners about "Kind of business activity the vehicle was most often used for in 2021." Tractor-trailers are connected to 25 unique industries, of which the top five defined categories[9] are for-hire transportation, agriculture (crop and animal production), construction, manufacturing, and accommodation and food. Figure 8 shows the share of each vehicle age in the 2021 VIUS by reported business activity. The share of vehicles used for for-hire transportation is large across the age spectrum, but for-hire vehicles represent a disproportionate share of new vehicles and drop off over time. Among older vehicles observed in VIUS, firms in the construction and agriculture industry own an outsize share of the vehicles.

4.3 New vehicle regulations have long-lived effects

The long lives and life cycles of vehicles have implications for the effects of new vehicle regulations, either on ex-ante purchase decisions or ex-post operation decisions. Using policy variation around two regulatory changes, this section documents three potential mechanisms for new vehicle regulations to have long-lived effects: (1) firms may "pre-buy" vehicles before

[8]Firms may report carrying multiple commodities. In this case, we assign them the most common commodity among the ones that they report.

[9]Excluding "Other transportation and warehousing"



Note: Figure 8 plots the weighted share of vehicles in each model year by self-reported business activity. Source: Census Vehicle Inventory and Use Survey

Figure 8: Share of Vehicles Owned by Business Activity, by Age

regulations take effect, (2) firms may use older vintages more intensely, and (3) firms may be slower to scrap older vintages. The evidence also suggests that policy impacts interact with other industry state variables, including demand for freight and the stock of existing vehicles.

New Vehicles by Year (Inspections) Figure 9 measures the number of new vehicles in our sample using the set of unique VINs ever inspected by the FMCSA program. We observe a significant break in sales between model years 2007 and 2008, suggestive of firms buying grandfathered vehicles in advance of new regulations.[10]

Discussions with industry participants suggest that the difference between model year 2007 and model year 2008 sales was exacerbated by changes in macroeconomic conditions and industry profitability. Understanding the effect of new vehicle regulations therefore requires estimating how these other dynamic variables affect vehicle operating profits and therefore purchase decisions.

Model Year and Mileage Table 2 shows both lifetime VMT and annualized lifetime VMT by vehicle model year. As expected, mean VMT/year declines over time, although there appears to be a spike in lifetime VMT and VMT/year for model year 2010 vehicles, indicating excess use of these vehicles. Additionally, vehicle count, which is generally declin-

[10]Between calendar year 2010 and 2018, an average of 153,000 class 7 and 8 tractor trailers were sold in the United States. Thus, these numbers are consistent with known vehicle sales. Source: IHS Markit data.



Note: Figure 9 plots the number of unique VINs ever inspected for vehicles of each model year. The vertical dashed line separates the 2007 and 2008 model years. Source: FMCSA Inspections

Figure 9: New Vehicles by Model Year

ing (albeit noisily), is particularly high for model year 2007, suggestive of a pre-buy effect similar to what Rittenhouse & Zaragoza-Watkins (2018) observe.

Scrap Rate by Model Year In addition to miles driven, firms can also adjust by changing how quickly they scrap used vehicles. We adapt the methodology used to compute scrap rates in Section 4.1 to compute model-year-specific annual scrap rates. In Figure 10, we plot these estimated scrap rates for model years 2007/2008 (Panel A) and 2010/2011 (Panel B).

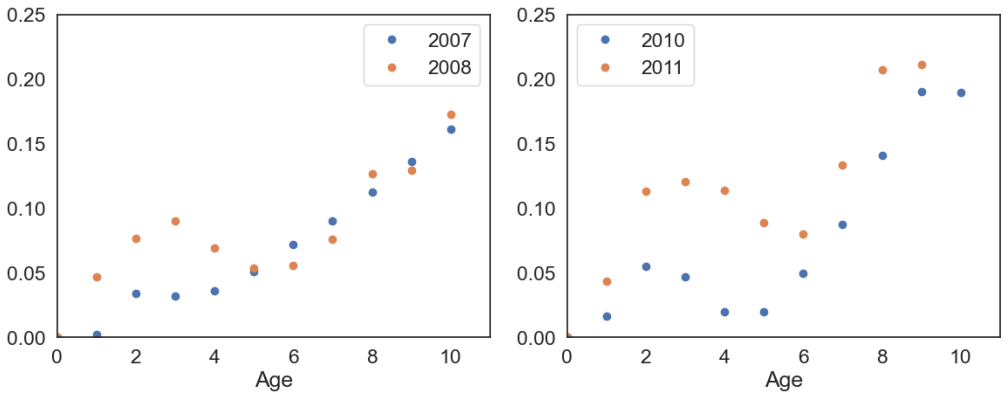
In both cases, scrap rates for the pre-regulation year are lower than those for the post-regulation year, averaging 1.8 (5.4) percentage points per year over the first nine years of vehicle for 2007/2008 (2010/2011). The differences in scrap rates are most pronounced in earlier years.

Further, scrap rates at the model year level are not monotonically increasing: both model years 2010 and 2011 see falls in scrap rates around year five. This timing coincides with a boom in trucking freight markets, suggesting that scrapping behaviour is also responsive to time-varying profitability.

Model Year	Age	Mean Lifetime VMT (000s)	Mean VMT/year (000s)	Count
2021-2022	1	135	135	170407
2020	2	252	126	195868
2019	3	316	105	182239
2018	4	401	100	132290
2017	5	481	96	107129
2016	6	506	84	173577
2015	7	506	72	135892
2014	8	592	74	94529
2013	9	625	69	96337
2012	10	630	63	80268
2011	11	570	52	41168
2010	12	692	58	42987
2009	13	666	51	37892
2008	14	743	53	28243
2007	15	802	53	105929
2006	16	828	52	65195
2005	17	825	49	57606
2004	18	818	45	35870
2003	19	963	51	37873
2002	20	864	43	18330
2001	21	963	46	32043
2000	22	1022	46	51401
1999	22	1067	48	35713
Pre-1999	23	850	37	161952

Notes: Table 2 calculates the average of reported lifetime miles, the average of reported lifetime miles driven per year, and the (weighted) count of vehicles by vehicle model year and age.

Table 2: Lifetime and annual VMT and number of vehicles by model year (VIUS)



Note: Figure 10 plots estimated annual scrap rates at each age for specific model years. Panel A compares model years 2007 and 2008, and Panel B compares model years 2010 and 2011. Source: FMCSA Inspections

Figure 10: Annual Scrap Rate: 2010 vs. 2011

5 Empirical Model

This section describes a simple model of truck purchase, sale, and scrapping behaviour, and discusses our intended next steps to estimate model parameters and conduct policy counterfactuals.

5.1 Model

There are two types of firms: incumbent firms and potential buyers. There are $N(s_t)$ potential buyers, and $N(i)$ incumbent drivers. Each firm can only own one truck.

The flow profits from operating a truck in any given period t is $\Pi(a, i, s_t)$ where a is age and i is industry, and s_t is a state variable.

In every period, incumbent firms can be used, sold, or scrapped, with payoffs

$$\begin{cases} \Pi(a, i, s_t) + \epsilon_a & \text{Used} \\ P(a, s_t) + \epsilon_t & \text{Sold} \\ P^s(a, s_t) + \epsilon_s & \text{Scrapped} \end{cases} \tag{2}$$

The firm has a value function of owning a truck of age a of

$$V(a, i, s_t) = \max \begin{cases} \Pi(a, i, s_t) + \epsilon_a + \beta E[V(a+1, i, s' \mid a, s_t)] & Operate \\ P(a, s_t) + \beta V(\emptyset) & Sell \\ P^s(a, s_t) + \beta V(\emptyset) & Scrap \end{cases} \tag{3}$$

In every period, potential buyers can purchase new vehicles at $P^n(s_t)$ or used vehicles at $P(a, s_t)$. Let P be the vector of prices, $P = (P^n, \{P(a)\})$. The value function of a firm without a vehicle is

$$V(\emptyset, i, s_t) = \max \begin{cases} \Pi(0, i, s_t) - P^n + \epsilon_o + \beta E_{s'}[V(1, i, s')] & New \\ \max_a\{\Pi(a, s_t) - P(a) + \epsilon_a + \beta E_{s'}[V(a', i, s')]\} & Used \\ \epsilon_\emptyset + \beta E_{s'}[V(\emptyset, i, s')] & OO \end{cases} \tag{4}$$

where s' is the next period state variable.

Given firm beliefs about the evolution of the state variables and the distribution of the cost shocks, ϵ, these equations yield a probability of buying a used vehicle of age a, $Pr^{buy}(a, P, s_t)$, and a probability of selling a used vehicle of age a, $Pr^{sell}(a, P, s_t)$.

Total vehicle demand is

$$D(a, P, s_t) = N(s_t) \times Pr^{buy}(a, P, s_t)$$

Let $f(i, a)$ be the share of trucks in industry i which are of age a. Total vehicle supply is

$$S(a, P, s_t) = \sum_i N(i) \times f(i, a) \times Pr^{sell}(a, P, s_t)$$

New and used vehicle prices clear the market.

$$N(s_t) \times Pr^{buy}(a, P^n, P^u, s_t) = \sum_i N(i) \times f(i, a) \times Pr^{sell}(a, i, P, s_t) \quad \forall a$$

5.2 Empirical Strategy

Estimation The key empirical object for us to estimate is the shape of the profit function, $\Pi(a, i, s_t)$, and the distribution of the scrap values $P^s(a)$. We will estimate this function by matching two types of moments: driving moments and transaction moments. Given a guess of the model parameters, we will compute predicted moments, and we will iterate over candidate parameters to match predicted to empirical moments.

$$\theta^* = \arg\min_\theta (\frac{1}{T} \sum_t g(\theta))^T \hat{W} (\frac{1}{T} \sum_t g(\theta))^T$$

where the observations t are firm-year tuples.[11] Differences in probability of buying and selling vehicle types across industry are informative about how Π responds to industry. Differences in prices over time are informative about how Π responds to age.

As a proof of concept, we estimate a simple version of our empirical strategy which (1) omits the role of dynamic state variables, and (2) reduces firm and vehicle heterogeneity down to two dimensions. Firms may either be general freight or specialized (machinery), and vehicles are only differentiated by their age. We match two types of moments: the estimated scrap probability by type, and the probability of purchasing a vehicle of each age. For normalization, we set the scrap value to be constant at zero for both types of firms. We estimate the shape of the profit function $\Pi(a, i)$, which we take as linear with an indicator

[11] We will compute value functions under the following assumptions on firms' beliefs: myopia ($\beta = 0$) and rational expectations. We will compute equilibria under the following assumptions: steady-state equilibria, moment-based Markov Equilibria (Ifrach & Weintraub 2016, Jeon 2022), and oblivious equilibrium (Weintraub et al. 2008).

for a new vehicle,

$$\Pi(a, i) = \beta_0^i \times 1_{a=0} + \beta^i + \beta_{age}^i \times a \tag{5}$$

where a is vehicle age and i is industry (general or specialized).

Table 3 contains preliminary estimates from this estimation procedure. General freight firms have higher profits on average, but their profits decay faster in vehicle age than specialized firms. Intuitively, the identification comes from the pattern in Figure 7; the lifecycle pattern of new vehicles starting at general freight firms and migrating to specialized firms is rationalized by the model through the age gradient of profits. We find that both general and specialized firms highly value new vehicles.

Coefficient	Estimate
New Vehicle (General)	2.71
New Vehicle (Specialized)	2.88
Constant (General)	0.281
Age (General)	-0.044
Constant (Specialized)	-0.149
Age (Specialized)	-0.032

Table 3: Preliminary Estimation Results

Quantification Given model estimates, we will discuss their magnitudes in real terms, focusing on how changes in vehicle characteristics (a) impact the profitability Π and probability of buying, selling, or scrapping vehicles (Pr) for the average firm. For example, we will quantify how an additional year affects these probabilities.

Counterfactual We will consider three types of policy counterfactuals. For each counterfactual simulation, we will compute the following statistics: prices (by vehicle age and type), active vehicles (by age and type), miles driven (by vehicle age and type) and firm profits (by industry).

Increase in Price of New Vehicles: One counterfactual scenario involves evaluating the impact of an increase in the price of new vehicles. This scenario will help us understand how firms might alter their purchasing behavior in response to higher costs, potentially leading to a preference for older or more fuel-efficient vehicles.

Maximum Vehicle Age: Another scenario considers the implementation of a maximum vehicle age, both on a national scale and within specific markets. This policy would mandate

the retirement of vehicles that exceed a certain age, affecting fleet composition and potentially accelerating the adoption of newer, more efficient models.

Cash-for-Clunkers Program: The third scenario examines the effects of a cash-for-clunkers program, which increases the price at which older vehicles can be sold. This policy, analyzed both nationally and within specific markets, aims to incentivize firms to retire older, less efficient vehicles in favor of newer ones, thereby impacting the overall fleet efficiency and emissions.

6 Conclusion

Using new data on the ownership and operation of used vehicles, this paper documents new patterns about the lifecycle of heavy-duty trucks. While trucks are long-lived assets, the firms that own and operate them change as trucks age, implying that there are complex interactions between firm and vehicle characteristics in operating profitability. Increased use and delayed scrapping of grandfathered vehicles can dampen the long-run effect of new environmental regulations.

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