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 life cycle and movement of capital in the heavy-duty trucking context. Over the life cycle, the vehicles may move across different firms, industries, 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 life cycle 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 have social consequences. 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. Vehicle scrappage varies over the lifecycle, increasing with age, and differs by industry and geography.

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. We see both pre-buying effects and more intensive use 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 up-front 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 are two papers that consider the importance of

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

scrappage – Sallee (2023), which discusses the tradeoffs associated with different policies to induce retirement, and Lohawala et al. (2025), which estimates empirical scrappage rate and quantifies the importance of scrappage estimates in measuring the effects of policy. Importantly, neither paper estimates empirically how scrappage decisions respond to policies and the corresponding distributional consequences. Also relevant to our paper is Rittenhouse & Zaragoza-Watkins (2018) who document a pre-buy effect around the 2007 heavy-duty engine standards, but a number 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.

Some related work has studied these questions in the context of passenger vehicles. For instance Li et al. (2013) study the U.S. cash-for-clunkers policy for passenger cars, Jacobsen (2013) examines how fuel economy standards affect the used vehicle market, Jacobsen & van Benthem (2015) consider the effects of fuel prices and fuel efficiency policy on vehicle scrappage, and Gillingham et al. (2022) model passenger vehicle transitions among heterogeneous consumers in Denmark. The purchase and scrappage decisions in the truck market, unlike the light-duty vehicle market, are primarily made by firms with different considerations than households choosing to buy or sell their personal vehicle; the usage patterns of heavy-duty trucks also look quite from passenger cars. Thus, understanding how similar policies might affect these different vehicle markets is an important contribution.

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

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

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.

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, providing information on transitions in the truck market. By merging the two together using Vehicle Identification Numbers (VINs), 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) of the inspected vehicle along with the Department 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).

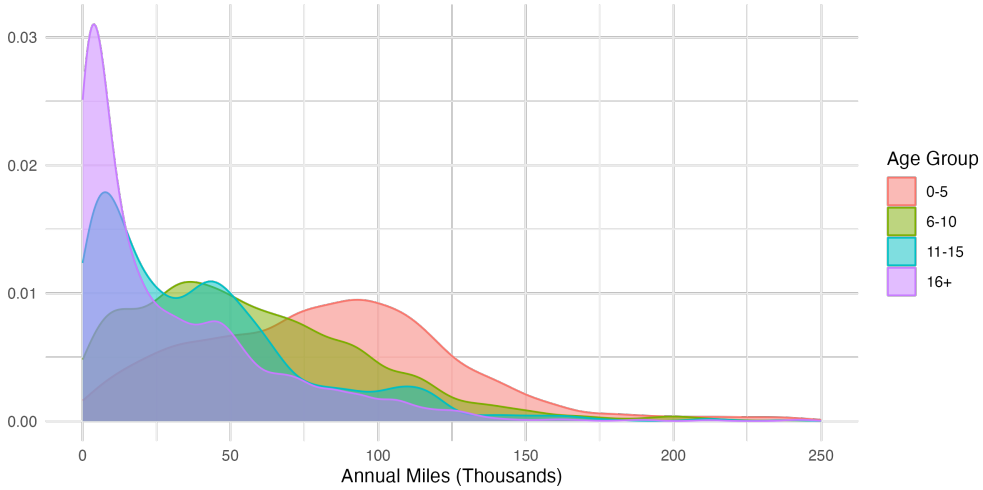
	Mean	**Std Dev**	**Min**	**Max**
Inspections per Year	918,385	179,755	522,944	1,140,775
Inspections per Vehicle	3.03	2.83	1	38
Inspections per Firm	19.1	402.6	1	208,339
Unique Firms per Vehicle	1.58	1.1	1	22
Unique Vehicles per Firm	10.41	207.9	1	100,556

Table 1: Summary Statistics (FMCSA Inspections)

4 Scrap Rate Estimation

Our data provide us with observations of inspections, where each inspection tells us (1) the vehicle is actively driven on highways, (2) vehicle characteristics, and (3) firm/fleet

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



Note: Figure 1 plots the probability density functions of reported miles driven in the last year among trucks of different age groups. Source: Census Vehicle Inventory and Use Survey

Figure 1: Distribution of miles driven by age groups.

characteristics. The probability of inspection in a given year may depend on vehicle and firm characteristics as well.

We are interested in observing the scrappage of vehicles. Traditionally, scrap rate has been inferred based on changes in vehicle registrations (Jacobsen & van Benthem 2015, Lohawala et al. 2025). Under this approach, a vehicle would not be regarded as scrapped if it is still registered but rarely used (or rarely used on the highway, where inspections occur). While these vehicles are part of the fleet, they may have little bearing on the emissions from trucks given their infrequent usage. As figure 1 shows, the share of vehicles used for limited miles is increasing in age; more than 40% of vehicles ages 16+ reported driving less than 10,000 miles in the previous year, compared to approximately 3% of vehicles ages 0-5.

We instead estimate scrappage based on inspections, which are only generated when vehicles are actively operated. However, inspections are probabilistic, and the probability of inspection may vary by state and vehicle characteristics (Liang 2024). We will therefore need to estimate scrap probabilities with a model, as we develop in the following section. While our approach has its own tradeoffs, since there may be error in our model-based estimates, we believe that it gets closer to the economically relevant measures.[4]

4.1 Methodology

Our empirical challenge is to estimate the evolution of a population, given random samples of that population. This mirrors a class of classic problems in wildlife ecology, which attempt

[4]Both measures of scrappage also miss vehicles that leave the country. The US is a major exporter of used heavy-duty vehicles (United Nations Environment Programme 2024).

to measure animal behavior using repeat counts or measurements (McClintock et al. 2020). Our setting, where we want to model operation (life) and scrapping (death) given inspections (captures) is similar to the Cormack-Jolly-Seber survival model. Inspired by these methods, we write down our problem as a hidden Markov model and estimate the scrap parameters using hmmTMB (Michelot 2023). In our setting, we have a binary hidden state process S_t which is 1 if a truck is active and 0 if a truck is scrapped. We assume that

$$p(S_{t+1} = 1 \mid S_t = 1) = f(a, i, x \mid \theta_S) \tag{1}$$
$$p(S_{t+1} = 1 \mid S_t = 0) = 0 \tag{2}$$

where a are vehicle characteristics, i are firm characteristics, and x are industry state variables, and θ_S are parameters. Once a vehicle is scrapped, it cannot return to being active.

We observe a binary process Z_t which is 1 if a truck is inspected in year t and 0 otherwise. We assume that

$$p(Z_t = 1 \mid S_t = 1) = g(a, i, x \mid \theta_Z) \tag{3}$$
$$p(Z_t = 1 \mid S_t = 0) = 0 \tag{4}$$

where θ_Z are parameters, and a truck cannot be inspected if it is scrapped.

To construct an estimation dataset, we draw a random sample of N VINs from all of our vehicle inspections. For each VIN, we construct a series of (Z_t, a_t, i_t, x_t) observations for $t \in [0, T]$. With this panel dataset, we optimize for the values of $\theta = (\theta_S, \theta_Z)$ which maximizes the likelihood of the observed data.

4.2 Parametrization of f and g

We define our covariates as follows:

- a is vehicle age, $a \in [0, \infty)$, defined as calendar year minus model year.
- i is industry (general or specialized) or geography (California or non-California).
- x is calendar year

We let the scrap probability be

$$f(a, i, x \mid \theta_S) = b_{ix}(a) \tag{5}$$
$$g(a, i, x \mid \theta_S) = c_{ix}(a) \tag{6}$$

where b and c are non-linear functions of industry i and calendar year x, which may include a constant.

5 Stylized Facts

In this section, we document four sets of stylized facts: heavy-duty trucks are long-lived and long-utilized assets; truck are used differently over the course of their life; the used vehicle market is important, and trucks are traded across industry and geography; and these life cycle 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.

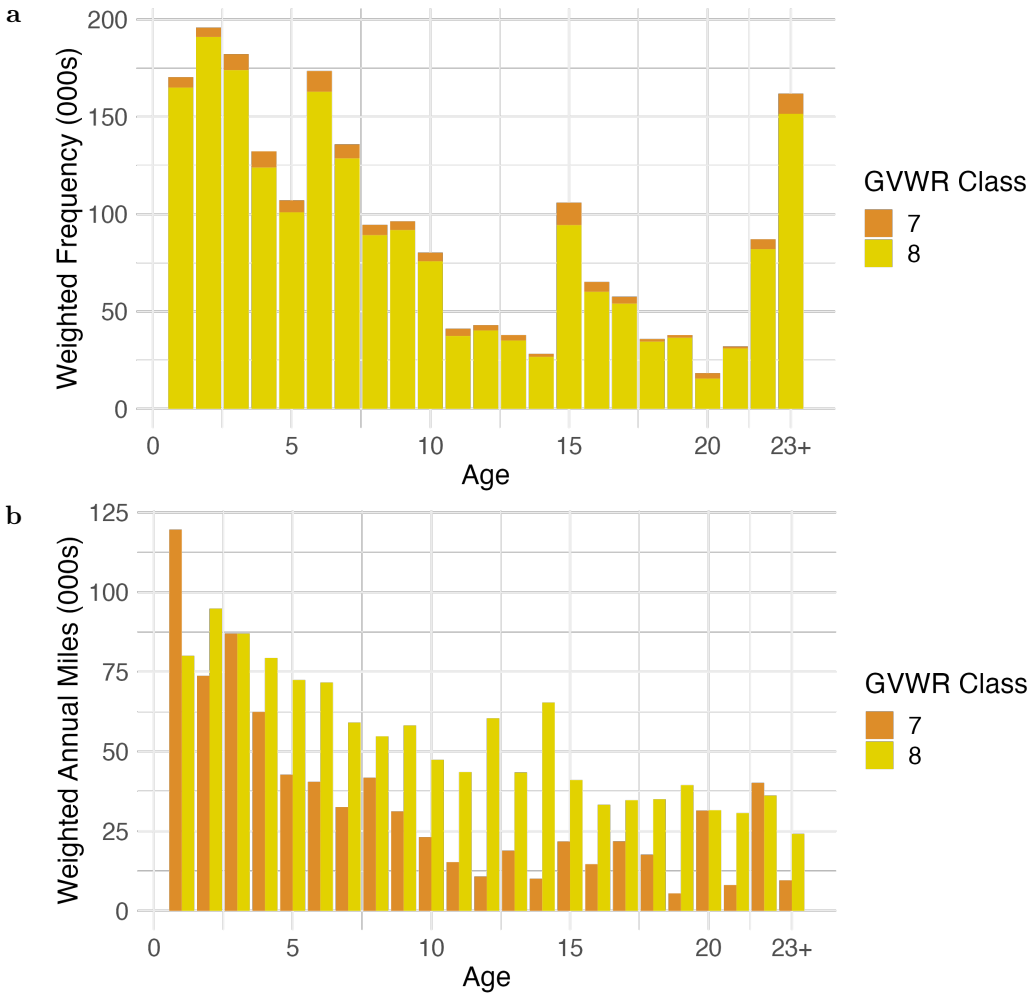
5.1 Heavy duty trucks are long-lived and long-utilized assets

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 2 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 2 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).

Scrap Rate As discussed in section 4.1, we estimate scrap rate based on inspections. Table 2 reports the estimated coefficients, but we also generate implied scrap rate over the life cycle for ease of interpretation.

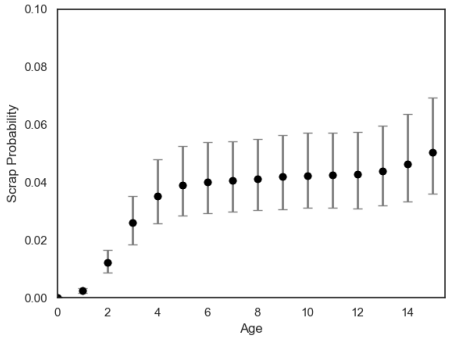
Figure 3 shows the scrap pattern over the vehicle lifespan from the baseline model. As expected, scrap rates are low but increasing during the first five years of a vehicle's life, starting at 0 and increasing to approximately 5%. After remaining level between ages 4 and 12, scrap rates increase more rapidly in the later years of a vehicle's life, from approximately 6% to 8%. Overall, these scrap rates are low and consistent with vehicles having long lives.[5]

[5]We can compare our estimated scrappage rates to estimates based on registration data. Lohawala et al. (2025) estimate 5-year scrappage rates for vehicles of each age. We can calculate implied 5-year scrappage rates for a vehicle of some age a using our yearly scrappage estimates. We estimate a 5-year scrappage rate for 5-year-old trucks (in the general freight industry in California) of 18.7% vs. Lohawala et al.'s 10%. For 10-year-old trucks, our implied 5-year scrappage rate is 20% vs. Lohawala et al.'s 17.8%. To the extent that general freight vehicles are scrapped at higher rates early in their lifespan in California than the average



Note: Figure 2a plots the weighted frequency of vehicles of each age in 2022, by gross vehicle weight rating (GVWR). Figure 2b plots the average annual mileage of vehicles of each age in 2022, by GVWR. Source: Census Vehicle Inventory and Use Survey

Figure 2: Age and mileage-by-age distribution of vehicles in VIUS.



Note: This figure plots the estimated scrap probability as a function of age, for a truck operating for a general freight firm in California in 2000-2005. This scrap probability is estimated using a HMM where $f(a,i,x) = g(a,i,x) = \theta_0 + \sum_{n=1}^{6} \theta_n a^n + FE_i + FE_x$. Year is coded as 5-year intervals between 2000 and 2020. 95% confidence intervals are computed using draws from the estimated distribution of model parameters. Source: FMCSA Inspections

Figure 3: Scrap probability estimate by age

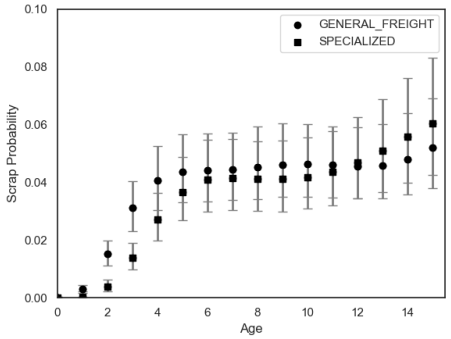
Figure 4 shows the scrap pattern over the lifespan from a model allowing the age pattern to differ across industries, with separate scrappage estimates for general freight vs. more specialized industries. Particularly in the early years of a vehicle's life, vehicles used by general freight firms are scrapped at a higher rate. While these individual differences are small, the effects on the fleet can be large. Based on these estimates, at age 5, only 87% of general freight trucks are still on the road vs. 92% of specialized vehicles. At age 10, 69% of general freight trucks are still on the road vs. 75% of specialized vehicles.

5.2 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 businesses, 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

medium- and heavy-duty vehicles included in Lohawala et al. (2025), our high scrappage estimates may be reasonable.



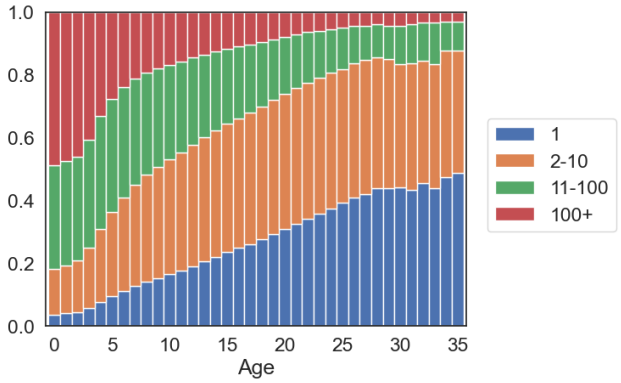
Note: Figure 4 plots the estimated scrap probability as a function of age and commodity, for a truck operating in California in 2000-2005. This scrap probability is estimated using a HMM where $f(a, i, x) = \theta_0 + \sum_{n=1}^{6} \theta_{i,n} a^n + FE_i + FE_x$. Year is coded as 5-year intervals between 2000 and 2020. 95% confidence intervals are computed using draws from the estimated distribution of model parameters. Source: FMCSA Inspections

Figure 4: Trucks change ownership and use over time

Parameter	(1)
Age	
Age	841.241 (60.632)
Age^2	-799.688 (104.884)
Age^3	511.172 (79.396)
Age^4	-426.58 (88.001)
Age^5	126.192 (41.98)
Age^6	-104.798 (34.756)
Industry	
Specialized	-0.186 (0.019)
Non-California	-0.233 (0.017)
Time	
2000-2004	-1.672 (0.182)
2005-2009	-0.654 (0.083)
2010-2014	-0.536 (0.08)
2015-2019	0.007 (0.082)
Intercept	-2.414 (0.107)

Note: This table presents parameter estimates from the estimation of Figure 3. Source: FMCSA Inspections

Table 2: Parameter estimates



Note: Figure 5 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 5: Share of Vehicles Owned by Different Firm Sizes, by age

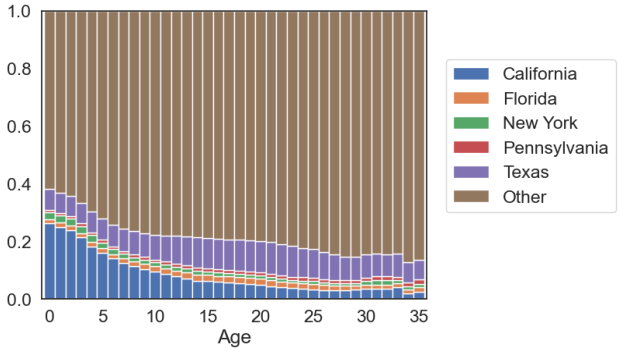
observing how many other vehicles of the same firm (DOT number) are inspected in the same year.[6] In Figure 5, we plot the share of vehicles of each age that are owned by firms with one vehicle, with two to 10, with 11 to 100, and with over 100 vehicles. New vehicles and vehicles below five years are overwhelmingly owned by large firms. Between ages five and 10, the share of used vehicles owned by firms below 10 vehicles increases. Above age 15, 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 6, we plot the share of vehicles of each age that are owned by firms operating in each of the top five states (California, Texas, New York, Florida, and Pennsylvania), and aggregate all other states into "Other." More than 20 percent of new vehicles are purchased by firms mainly operating in California. In contrast, only 10 percent of 10-year-old vehicles are owned by California-operating firms. Texas exhibits the opposite pattern: Texas-operating firms own a larger share of 10- or 20-year-old trucks than they do of new trucks.

In appendix A, we also consider the distribution of vehicles by state of registration rather than state of operation. To the extent that firms have multiple locations and can choose among potential registration states, the choice of where to register a vehicle may reflect a strategic choice based on tax treatment and registration costs rather than operating patterns. Even so, we see some movement across state of registration as trucks age.

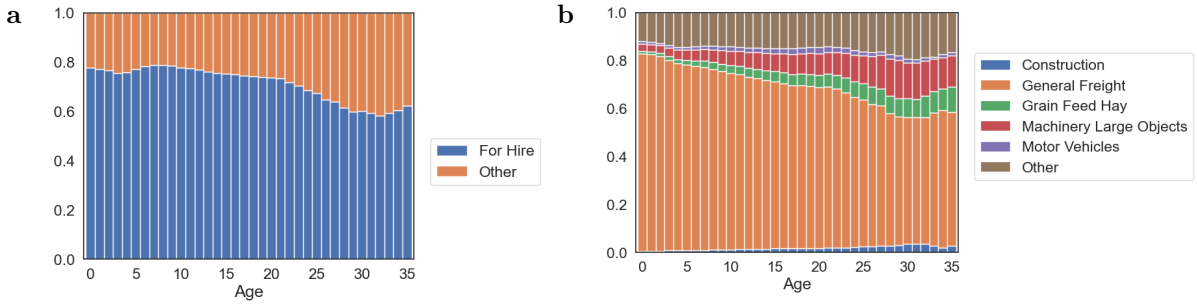
[6]Since inspection is probabilistic, this is an underestimate of the true firm size.

[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 6 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 6: Share of Vehicles Owned by Owner Modal Operating State, by age



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

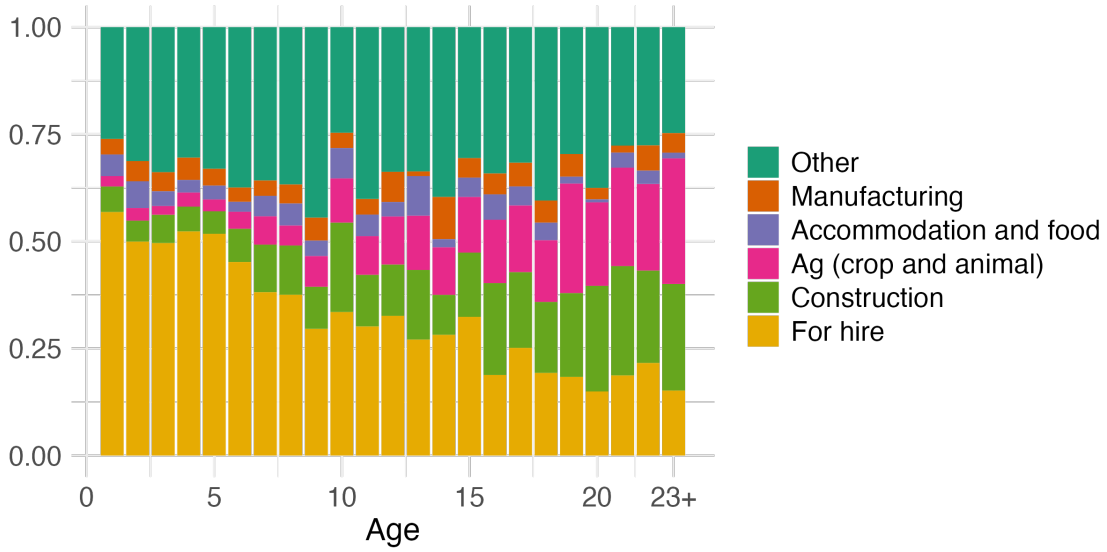
Industry We separate two dimensions of firm industry: operation class and commodity carried. Operation class refers to whether the vehicle is operating for-hire or transporting private property, while commodity refers to the actual products transported.

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 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

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



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

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.

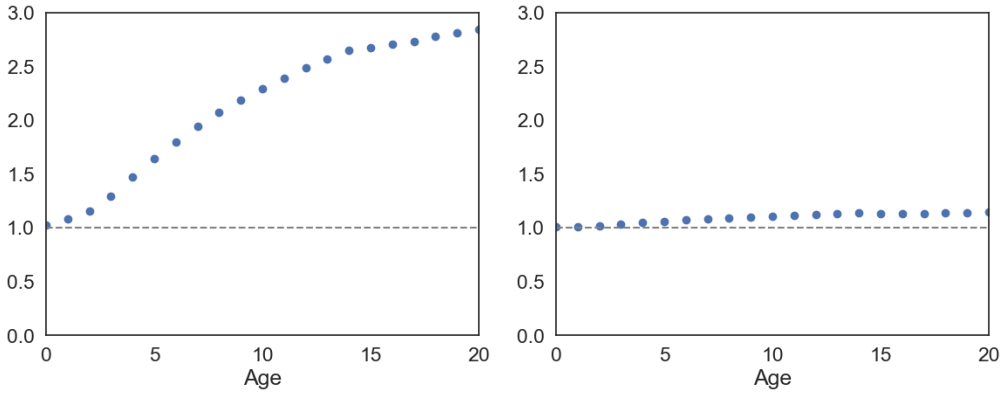
5.3 Trade in Vehicles

The changes in commodity and geography across the life cycle can arise from either differential retirement of vehicles across industries or trade in used vehicles between industries. This section documents that trade in used vehicles is significant, and especially important for understanding the changing geographic composition of vehicles as they age.

Panel A of Figure 9 plots the average cumulative owners (current and previous) associated with a truck inspected at each age, based on all previous inspections of that truck.[10] On

[9]Excluding "Other transportation and warehousing"

[10]The statistics in both panels of Figure 9 are conservative. Due to random inspection, there may be intermediate owners which we do not observe. In addition, we do not observe commodity information for some firms; we drop these observations rather than imputing commodity.



Note: Panel A plots the total number of current and previous owners (DOT Number) associated with a truck (VIN) inspected at a given age. Panel B plots the total number of current and previous commodities carried associated with a truck inspected at a given age. Source: FMCSA Inspections

Figure 9: Trucks change ownership and use over time

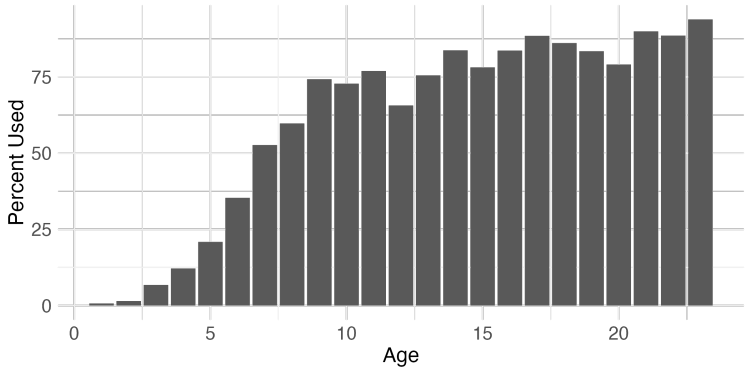
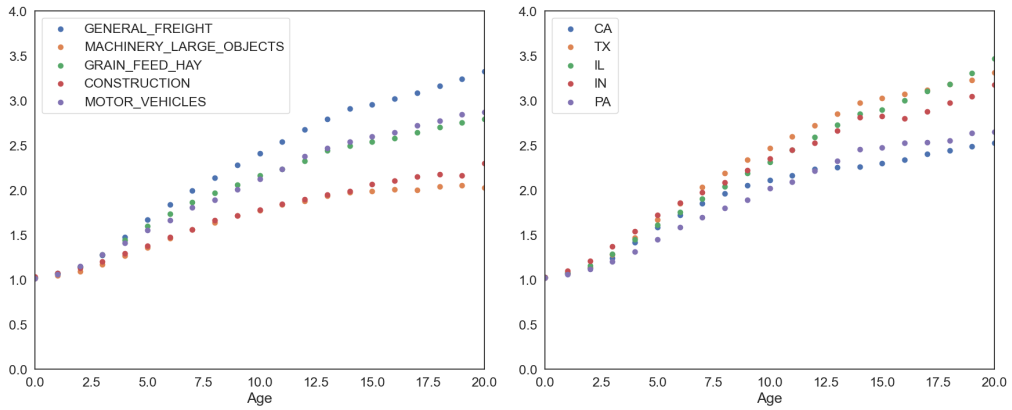


Figure 10: Share of vehicles of each age that were acquired used (i.e., on owner 2+). Source: Census Vehicle Inventory and Use Survey

average, a truck is resold once in its first ten years of life and twice in its first twenty years of life. Panel B of Figure 9 plots the average cumulative number of owner commodities associated with a truck inspected at each age. On average, over the first twenty years of life, about 15 percent of trucks are owned by a firm of a different primary commodity class from their original owner.

We find a similar pattern in the Census VIUS. Figure 10 plots the share of vehicles of each age which were purchased used (as opposed to new). This value grows monotonically in vehicles' first year of life. For vehicles of age 10 and over, about 75 percent of trucks were purchased used, i.e., they are on their second owner or more.



Note: Panel A plots the total number of current and previous owners (DOT Number) associated with a truck (VIN) inspected at a given age, by the commodity of the current owner. Panel B plots the same statistic, by the modal inspection state of the current owner. Source: FMCSA Inspections

Figure 11: Number of Previous Owners

The next figure dives into the heterogeneity in trade across sub-sectors of the trucking industry. Panel A of Figure 11 plots the average cumulative owners for trucks at each age, conditional on the commodity of the current owner. Trucks owned by general freight firms are significantly more likely to have had previous owners compared to firms carrying construction or machinery.[11] Panel B of Figure 11 plots the symmetric statistic by modal operating state of the current owner. States are similar in the first ten years of life. In the second decade of life, California-operating firms own vehicles with fewer previous owners than other states, especially Texas and Illinois.

Ownership transitions may also be associated with changes in operating state and commodity. In the same dataset, we find that 22.15 percent of ownership transitions are associated with a change of state, and 9.84 percent of ownership transitions are associated with a change of commodity. In the next section, we dive deeper into the distribution of inter-state trade in trucks.

5.3.1 California Exodus

California is a place of special interest to our study: the state plays an outsized role in the overall trucking market and it is also a setting of active state-level policymaking. In this section, we focus specifically on the truck trade patterns to and from California.

[11]This dynamic could reflect vehicle specialization across industries, or heterogeneity across industries in preferences over vehicle age.

Statistic	Percentage
Share of all trucks which are CA trucks	18.43%
Share of CA trucks which ever leave CA	50.79%
Share of non-CA trucks which were ever CA trucks	10.09%

Note: Statistics represent shares of highway inspections. State represents the modal inspection state of the firm (DOT Number) associated with a truck (VIN). Source: FMCSA Inspections

Table 3: Transitions into and out of California

Table 3 presents statistics about the life cycle transitions of California trucks.[12] A plurality of all trucks are owned by California-operating firms, and of these California trucks, over half eventually leave the state later in their life. By implication, a significant portion of non-California trucks were once California trucks earlier in their lives.

Consequently, any state-level policies which affect new vehicles in California are likely to have spillover effects on other jurisdictions, especially if policies have long-lived effects. In the next section, we turn to the long-run effects of truck regulations.

5.4 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 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 12 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.[13]

Discussions with industry participants suggest that the difference between model year 2007 and model year 2008 sales was exacerbated by changes in macroeconomic conditions

[12] As before, we define operating state based on the modal inspection state of the firm that owns each truck.

[13] 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 12 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 12: New Vehicles by Model Year

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

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 4 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 4: Lifetime and annual VMT and number of vehicles by model year (VIUS)

6 Empirical Model

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

6.1 Model

There are several different industries, i, which buy heavy-duty trucks.[14] Within each industry, there are two types of firms: incumbent firms and potential buyers. There are N_{ti}^p

[14] i might index industries or industry-geography pairs.

potential buyers, and N_{ti}^{inc} incumbent owners in each period t. Each firm can only own one truck.

In every period, firms' states are given by $a \in \{\varnothing, 1, \ldots, \overline{a}-1\}$. Potential buyers who do not own a vehicle have state $\varnothing$. $\overline{a}$ is the maximum age a vehicle can reach, at which point it is automatically scrapped. Truck owners with state a can use, sell without replacement, or sell with replacement their existing vehicle. Potential buyers can purchase a new or used truck. Sales and purchases happen at the beginning of the period, after which owners can use their vehicles and receive flow profits $\Pi(a, i)$ where a is vehicle age. A firm that sells their truck of age a receives the market-clearing price P_a for a vehicle of that age; a firm that buys a truck of age $\tilde{a}$ likewise pays the market-clearing price $P_{\tilde{a}}$. The full vector of prices by age is given by $\mathbf{P}$.

When the vehicle reaches maximum age $\overline{a}$, the vehicle is scrapped with probability 1. After scrappage, vehicle owners receive a payoff $EV(\overline{a})$. In addition, every vehicle of age a used by a firm of industry i has a probability $\alpha_{i,a}(P_a)$ of being scrapped. That is, probability of scrappage depends on the industry of the owner, the vehicle age, and the price of vehicles of that age.

$V(i, a, \mathbf{P})$ is the value function for a firm in industry i in state a when prices are given by the vector $\mathbf{P}$. The Bellman equation for a firm with a truck of age a is given by:

$$\begin{aligned} V(i,a,\mathbf{P}) &= \max[v(i,a,\varnothing) + \varepsilon(\varnothing), \max_{\tilde{a}\in\{0,\overline{a}-1\}} v(i,a,\tilde{a}) + \varepsilon(\tilde{a})] \\ v(i,a,\varnothing) &= \pi(\varnothing, i) + P_a + \beta EV(i,\varnothing,\mathbf{P}') \\ v(i,a,\tilde{a}) &= \pi(\tilde{a}, i) + P_a - P_{\tilde{a}} + \beta\alpha_{i,a}(P_a)EV(\overline{a}) + \beta(1-\alpha_{i,a}(P_a))EV(i,a',\mathbf{P}') \end{aligned}$$

And similarly, the Bellman equation for a firm that does not own a vehicle is

$$\begin{aligned} V(i,\varnothing,\mathbf{P}) &= \max[v(\varnothing,\varnothing) + \varepsilon(\varnothing), \max_{\tilde{a}\in\{0,\overline{a}-1} v(\varnothing,\tilde{a}) + \varepsilon(\tilde{a})] \\ v(\varnothing,\tilde{a}) &= \pi(\tilde{a}, i) - P_{\tilde{a}} + \beta\alpha_{i,a}(P_a)EV(\overline{a}) + \beta(1-\alpha_{i,a}(P_a))EV(i,a',\mathbf{P}') \\ v(\varnothing,\varnothing) &= \pi(\varnothing, i) + \beta EV(\varnothing,i,\mathbf{P}') \end{aligned}$$

6.2 Empirical Strategy

Estimation The key empirical object for us to estimate is the shape of the profit function, $\Pi(a, i)$ and the expected scrap value $EV(\bar{a})$. We will estimate this function by matching two types of moments: market clearing conditions and industry-specific ownership shares of vehicles of age a. Given a guess of the model parameters, we proceed with value function iteration from which we compute predicted moments, and we will iterate over candidate

parameters to match predicted to empirical moments.

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

where the observations m are firm-year tuples. 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.

In our initial estimation, we take $\alpha_{i,a}$ as given from the data. However, for our counterfactual simulations, we endogenize $\alpha_{i,a}$. Thus, we estimate $\alpha_{i,a} = f(P_a, i, a)$ using our scrap estimates.

Appendix B contains estimates from a simplified version of our empirical strategy, omitting dynamic state variables and based on a preliminary version of scrappage estimates.

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.

7 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.

8 Figure and Tables

	CA	Other
CA	34%	66%
Other	13%	87%

Note: This table presents the probability that a vehicle is purchased by a CA (non-CA) firm when a vehicle has an ownership transition, conditional on the previous owner being a CA (non-CA) firm. Source: FMCSA Inspections and Registrations

Table 5: State Transition Matrix for Ownership Transitions

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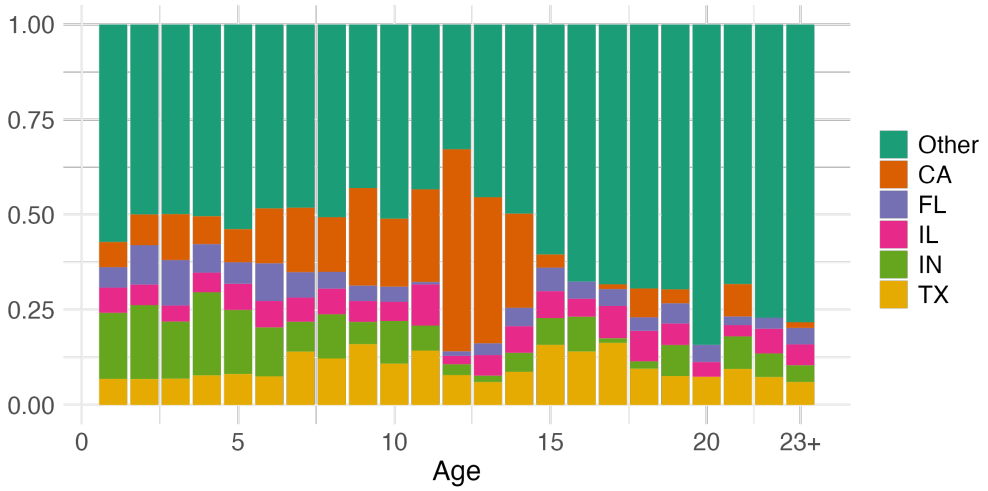
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A Additional Descriptives

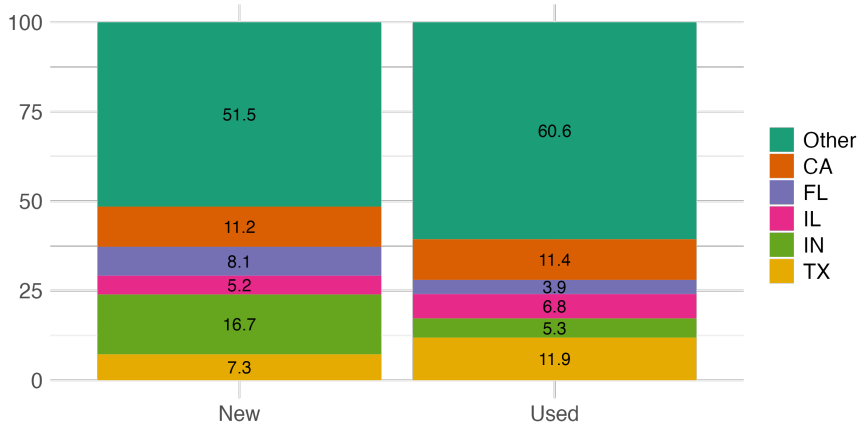
Geography of Ownership The location where a vehicle is registered may or may not reflect where a vehicle is used if the vehicle is engaged in interstate transport. Thus, we separately examine the state in which vehicles are registered in Figure A.1. Newer vehicles are particularly likely to be registered 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 A.2, 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.



Note: Figure A.1 plots the weighted share of model year registered to each state. Source: Census Vehicle Inventory and Use Survey

Figure A.1: Share of Vehicles Owned by Registration State, by age



Note: Figure A.2 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 A.2: Share of Vehicles Acquired New or Used by Registration State

B Model Proof of Concept

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.[15] 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 for a new vehicle,

$$\Pi(a, i) = \beta_0^i \times 1_{a=0} + \beta^i + \beta_{age}^i \times a \tag{7}$$

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

Table A.1 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 A.1: Preliminary Estimation Results

[15] Note that these estimates are also based on an earlier version of the scrappage estimates that led to higher scrap rates across the board.