Climate Policy and Firm Efficiency: Lessons From the Trucking Industry*

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Abstract

Can climate policy affect firm-level efficiency and industry structure? Due to a biofuel blending requirement, Swedish diesel prices increased significantly over the period 2007–2020 compared to other countries. We examine how this policy-induced cost increase affected the CO_2 emissions and operating efficiency of the Swedish trucking industry. Using panel data on individual trucks and their corporate owners, our results suggests that large trucking companies responded to higher fuel prices by significantly improving their truck utilization relative to their smaller competitors. We estimate a CO_2 emission to tax inclusive fuel cost elasticity higher than -1 for trucks belonging to large fleets, but close to zero for other trucks. Transportation firms with large fleets, relative to other firms, increase revenue and market share as carbon pricing increases while at the same time lowering their emissions, increasing their output per kilometer driven and improving margins. We provide evidence consistent with these productivity increases being due to improvements in logistics related to investment in hub-and-spoke distribution networks, induced by higher fuel prices. As a result, the Swedish trucking industry was able to reduce its CO_2 emissions by 6% over the period 2007–2020, despite growing by more than 20% in size. Adding the effect from replacing diesel with renewable biofuel implies that the policy reduced fossil CO_2 emissions with as much as 30%.

Keywords: Carbon pricing, Climate policy, Trucking, Transportation, Market structure, Mobile emissions, Green growth

JEL codes: H23, L11, L90, Q54, Q58

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1 Introduction

In recent years, it has become increasingly clear that significant policy measures are needed to reduce greenhouse gas emissions in order to contain global climate change (Masson-Delmotte et al., 2018). Putting a price on carbon emissions is one of the main policy tools to make emitters internalize the externality they cause (e.g., Nordhaus, 1993, Rockström et al., 2017). While carbon pricing should induce firms to lower emissions to restore profitability, e.g., by increasing fuel efficiency (Hassler et al., 2021) or switching to greener technologies (Acemoglu et al., 2016), it also has an immediate, negative effect on competitiveness and overall output. At worst, policies could become counterproductive, if it makes high-emitting firms so constrained that they are unable to make the necessary investment needed to switch to lower-emitting technologies and business models (see Hartzmark and Shue, 2023, in the context of SRI). While studies on energy saving technical change (e.g., Newell and Jaffe, 1999, Hassler et al., 2021) show that the positive effects of increased innovation should overtake the short-term costs of decreased competitiveness over the longer run the literature is silent on the short run responses and adjustment that is spurred by a policy-induced relative price increase on fossil fuels.

In this paper, we aim to shed light on the competitive effects of carbon pricing by focusing on the heavy trucking industry, one of the highest-emitting sectors in the economy. In 2021, road vehicles accounted for 12 % of global carbon emissions, a third of which came from heavy trucks and buses (IEA, 2023). In addition, carbon emissions from heavy trucks have grown by 55% since 2000, compared to a 38% growth for road transports overall.[1] Despite the recent growth in EVs, electric heavy trucks are (as of 2024) still at a very early stage of commercialization, implying that diesel will likely continue to be the dominant in the trucking industry for many years to come.[2]

To examine the effect of climate policy on commercial trucking, we utilize novel data on the Swedish trucking sector. The Swedish transportation sector offers several unique features

[1] See IEA (2023). Going forward, IEA (2017) suggests that global freight volumes will increase by 139% from 2015 to 2050, leading to a growth in CO_2 emissions of at least 55%.

[2] Electrificationcoalition.org (2023) describes the challenges involved in electrifying heavy trucks (https://electrificationcoalition.org/wp-content/uploads/2023/06/Piloting-Freight-Web.pdf).

making it an ideal case to study. First, in addition to being an early adopter of carbon taxation (Martinsson et al., 2024), Sweden mandated high fractions of biofuels to be blended in to diesel, reaching above 25% starting in 2017, resulting in the highest diesel price in the EU (Commission, 2020).[3] Second, the existence of rich vehicle level data of corporate owned heavy duty vehicles facilitates novel micro-level analysis of how pricing affects transportation emissions and efficiency. The truck level data identifies every individual truck through its unique identification number, and contains both time-invariant vehicle characteristics (e.g., weight) and annual vehicle inspection details (including the distance traveled). Each truck can be connected to its corporate owner, enabling us to analyze both vehicle- and firm-level responses to the policy-induced fuel cost increase.

Using this data, we construct a panel ranging between 30,000 to 40,000 heavy trucks (maximum weight greater 3.5 ton) per year owned by Swedish trucking firms during 2007–2020. Using this data we test how tax inclusive diesel prices (our measure of carbon pricing) affect truck level driving patterns and emissions, as well as, how the trucking firms respond at a fleet level and ultimately how this translates in to economic and carbon emission efficiency.

We first document the evolution of the Swedish trucking sector 2007–2020. Over this period, the sector experienced an increase in total freight weight of 43%, a fuel-cost increase of close to 10%, and an aggregate revenue growth of 20%. Despite the increase in total freight volumes, yearly vehicle kilometers traveled (VKT) were down, resulting in a 6% decrease in aggregate CO_2 emissions over the same period.

We then show that these aggregate changes mask systematic and sizeable within-sector differences across different segments of the trucking industry. Firms with smaller fleets (under 10 trucks) lost 11 percentage points of market share to trucking companies with larger fleets (50 or more trucks). Larger firms managed to grow revenues by over 100%, a rate considerably higher than the growth in number of trucks (+60%) and vehicle-kilometers

[3] In contrast, the European Union (2009) only legislates 6% of transport to be biofuels. In a recent change of policy, however, the current Swedish government decided to reduce the mandated blending if biofuel down to 6% starting from January 1, 2024, and possibly removing it completely in 2027. See https://trans.info/sweden-cuts-biofuel-requirements-in-petrol-and-diesel-to-reduce-fuel-costs-367834.

traveled (+36%). Together, these changes translated into sector-wide increases in sales per VKT (+19%), and lower fuel cost to sales (-19%), CO_2 emissions intensities (-22%) and VKT per truck (-19%), indicating a significant increase in overall trucking-sector productivity.

To establish the extent to which these changes can be attributed to carbon pricing policies, we first estimate the tax inclusive fuel cost to VKT elasticity at the truck level. Including both truck and firm-by-year fixed effects and other controls (to control for demand changes and other confounding factors), we estimate that a one percent increase in fuel price leads to a between 0.3 to 0.6 percent decrease in VKT per truck.[4] Using truck level CO_2 emissions as an alternative outcome variable, we estimate elasticities of a similar magnitude.

Consistent with previous findings on output and productivity, we document important and significant heterogeneity in truck-level elasticities across firms with different on fleet sizse. Trucks belonging to firms with fleets with fewer than 50 trucks display a non-robust, often insignificant within VKT to fuel cost effect. In contrast, trucks that belong to larger fleets have an elasticity that is almost twice as high as that for the sector as a whole; a one percent increase in fuel cost translates in to between 0.6% to 1.4% lower VKT (depending on specification) and even larger emissions reductions. This suggests that an important channel through which firms with larger fleets have gained market share is through adapting how they use their trucks in response to higher fuel costs in a way that smaller firms have not been able to do.

Equipped with this insight we aggregate the truck-level input changes to the firm level, in order to study how higher fuel costs impact the economic and emissions efficiency of individual trucking firms. First, we find that firms with larger truck fleets outperform their smaller truck fleet competitors in terms of VKT and CO_2 emissions at the fleet level as well. The long run, firm-level fuel cost to VKT elasticity is -1.4 for firms with large fleets, which is about 80% higher than the sector wide elasticity. We also show that the VKT to fuel cost elasticity is driven by policy-induced increases in fuel prices (i.e. carbon taxation and bio-fuel blending) rather than changes in the market price of diesel oil.

[4]Our elasticity estimates end up similar in magnitude to official estimates of around -0,4 provided by Swedish transportation agencies *Trafikverket* and *Trafikanalys* (NIER, 2024).

Firms with large truck fleets also generate more economic activity and less CO_2 emissions from their trucking inputs. The long run elasticity of fuel cost to sales per VKT is 1 compared to 0.4 (for firms with smaller fleets). Over time, large fleet firms do so while also improving EBIT margins which smaller and middle sized fleet trucking firms do not. In other words, in response to a one percent increase in tax inclusive fuel cost, larger fleet firms increase sales per VKT by 1 percent (or by 140% more than smaller fleet firms) while decreasing their emissions and improving long run profitability.

We hypothesise that the way large-fleet firms achieve these efficiency gains is through improving their logistics systems, through a combination of IT (Baker and Hubbard, 2003) and improvements to hub-and-spoke distribution structures, which allows trucks to run shorter distances with a fuller load, thus decreasing VKT without lowering amount of freight. Investing in such logistics improvements exhibit economies of scale, both because many of the costs (such as IT systems) are fixed and because the potential efficiency benefits are larger for firms with larger transportation networks.

We find support for this hypothesis from running three tests. First, we find that negative the *VKT* to fuel cost elasticity is not homogeneous across a firm's fleet; as fuel costs increase, firms increase distance driven for their lighter trucks and decrease it for their heaviest trucks, consistent with a switch to a hub-and-spoke distribution model (rather than point-to-point distribution). Second, firms in the "less than truckload" (LTL) segment (as opposed to the "truckload" segment; see Zingales (1998)), where the gains from logistics improvements are greater, display the by far largest response to fuel cost increases. In fact, among large firms, the entire effect from higher fuel prices on driving distance, productivity and EBIT margins is driven by trucking companies specialized in LTL. We also show that the intensity of logistics workers per active truck increased steadily over our sample period, particularly among large LTL firms, accompanied by and increased ownership of truck terminals, consistent with significant investments in hub-and-spoke distribution networks.

We believe our paper contributes to several strands of research. First, it relates to a growing academic literature on how carbon pricing affects corporate emissions, which so far primarily has studied manufacturing (e.g., Martinsson et al., 2024, Colmer et al., 2024). As

emphasized by Rapson and Muehlegger (2023), the trade-offs between reducing emissions and ensuring economic efficiency are particularly acute in the transportation sector. We contribute to the literature by showing that carbon pricing and related regulation, such as biofuel blending requirements, can be effective in both reducing emissions and increase the productive efficiency in transportation, consistent with Hassler et al. (2021) and Porter and Linde (1995).

Second, we add to the literature studying how fuel costs affect transportation emissions. While there is some evidence at the aggregate level (Andersson, 2019), existing micro-level evidence looks at households' CO_2 emissions respond to changing fuel prices (e.g., Knittel and Sandler, 2011), while little is known about how firms' transportation emissions respond. The European Union's (EU) flagship climate regulation, the EU Emissions Trading System (EU ETS), which has been widely studied in the context of industrial (stationary) installation emissions (e.g., Colmer et al., 2024) does not regulate mobile emissions. Instead, the EU has relied on the individual member states when it comes to lowering emissions outside of the EU ETS (so called effort sharing regulation, ESR). The most widely adopted measure to lower fossil CO_2 emissions from transport, in addition to carbon and energy taxes, has been to promote blending in renewable energy sources in the transport fuel.[5] Our paper provides novel evidence on how firms respond to such policies.

Finally, we contribute to the literature studying how regulation and technology affects the economic organization, corporate financing, and productivity of the trucking industry, where previous contributions include Allen and Liu (1995), Zingales (1998), Baker and Hubbard (2003), and Barrot (2016).

2 Institutional background

2.1 The Swedish trucking sector

This study focuses on the freight transport by road sector (NACE 4941). This excludes rail transport, taxi operations and pipelines from the broader land transportation sector.

[5]The Renewable Energy Directive (REDI) 2009/28/EC.

However, in order to evaluate Sweden's transport sector relative to other similarly developed countries we plot the average share of total value added coming from total land transportation over time in Figure B.3. Land transport (from which 4941 is a sub-industry) comprises about 2.5% of value added in Sweden (averaged over 2007–2018), which is lower fraction than in Japan and Italy but higher than in the United States.

Freight transportation in Sweden is heavily dominated by the domestically-owned heavy duty vehicles that we focus on. In 2020, 91% of all freight within Sweden was transported by Swedish-owned trucks while the remaining fraction is made up of railway freight transportation and foreign-owned trucks (Trafikanalys, 2022).[6] This fraction has been quite stable over time. We plot the development of the Swedish heavy duty vehicles sector, expressed as an index with 2009 as base year, in Figure 2.[7] The number of transports by heavy duty vehicles is up by 13% and the vehicle kilometers traveled (VKT) is up by 22%. Transportation work, which is the product of VKT and the freight weight (in tons) is up by 27%. Most importantly, the total weight of transported freight is up by 43%. As the number of transports have grown significantly, this implies that the average freight per transport has increased. Freight weight per unit of transport is up by 26% (solid black line in Figure 2). We also plot the transportation work across different commodity groups (Figure B.4). The ten groups plotted in Figure B.4 comprise about 90% of transportation work over the sample period. There are some compositional changes over time, but they are generally quite small.

2.2 Pricing of diesel fuel in Sweden

The objective of our study is to measure the effect of policy-induced fuel price increases on the Swedish trucking industry. Similar to Aghion et al. (2016), we use the tax-inclusive fuel price as our main independent variable, which in our case is the diesel price (since we focus

[6] Our data only include driving distances of vehicles registered by Swedish firms. According to EU regulation foreign trucking firms can operate in other member countries if the transports are international or if transports fall under the EU rules for cabotage (Government, 2022). The Swedish transportation agency provides aggregate statistics for transport work conducted by foreign firms under the cabotage rules. According to this data cabotage is up from about 2% of total transport work in 2007 to around 4% in 2020.

[7] The data is from the annual Swedish road goods transport report during 2009–2020 (*Lastbilsundersökningen* in Swedish). The report is published by Transport Analysis (a government agency).

on heavy-duty vehicles that almost exclusively run on diesel). The tax-inclusive price on diesel consists of three components: i) the price of fossil diesel, ii) fuel taxes (energy and carbon) and, iii) the price of blended-in bio fuels.

Figure 1 plots Sweden's tax-inclusive diesel price (black solid line) since 1990. The black dashed line is the sum of carbon and energy taxes per liter of diesel and the dotted, light gray line captures the fraction of biofuels blended in to diesel. The most significant development since 2005 was the introduction and rapidly increasing fraction of biofuels. At the start of the period, diesel contained about 5% of biofuels in the diesel, and this fraction increased gradually over time, reaching a peak of 35% in 2022. As the prices of the two blended-in sources of biofuels – Hydrotreated Vegetable Oil (HVO) and Fatty Acid Methyl Esters (FAME) – were considerably higher than fossil diesel, diesel prices in Sweden eventually ended up higher than in other European countries.

Since 2016, Sweden had a markedly higher biofuel share in diesel compared to other EU countries (Figure B.1), resulting in a tax-inclusive diesel price that became 18% higher than the EU average and a tax-exclusive price (but still accounting for price of biofuels) that became 25% higher (Commission, 2020). We plot the tax inclusive diesel price in a selection of EU countries in Figure B.2, which illustrates how Sweden's diesel price eventually became the highest in the EU.[8]

2.3 Swedish CO_2 emissions from trucking

In Figure 3, we plot aggregate CO_2 emissions from heavy duty vehicles in Sweden over our sample period using data from Statistics Sweden. The primary motive behind the biofuel blending policy was to lower the life-cycle greenhouse gas emissions from transportation, as biofuels generate biogenic rather than fossil CO_2 emissions (Swedish Energy Agency, 2022)). This effect is clearly visible in Figure 3: from 2005, the share of biogenic emissions increases and reaches about 1,500 kilotons in 2022, leading to a large decline in fossil greenhouse gas

[8]The cross-country comparison converts fuel prices into Euros, and is thus affected by exchange rate movements. In particular, the Swedish krona depreciated significantly relative to the Euro and GBP for much of this period, resulting in a less dramatic increase in the Swedish diesel fuel price when measured in Euros (Figure B.2) compared to SEK (Figure 1).

emissions from trucking. In the empirical analysis, we focus on total CO_2 emissions from individual vehicles and firm vehicle fleets, i.e. the sum of fossil and biogenic CO_2 emissions (solid black line). While the decrease is less dramatic compared fossil emissions, total CO_2 emissions are still down by about 17% in 2022 relative to to the peak year of 2007 (and despite the increase in trucking freight activity shown in Figure 2).

2.4 The empirical setting

Our objective is to study how policy-induced relative price increases of transportation fuel affect behavior and industrial organization in the short run. Specifically, we explore how changes in diesel prices, driven primarily through the blending in of (more expensive) biofuels, affect trucking firms. We discuss two important features of our research design here.

2.4.1 Relative prices

First, in order to establish that the biofuel blending policy indeed led to a relative factor price increase of fuel, we compare the evolution of the (blended) diesel price in Sweden to other relevant price indexes over our sample period in Figure 4a.

The cost of purchasing a representative basket of goods and services (i.e., CPI) increased by 16% (gray dotted line). In terms of transportation, the cost of consuming one unit of road freight transportation (expressed as the producer price index for freight transport by road, NACE 4941) was 29% more expensive in 2020 compared to in 2007 (dashed black line). While fuel cost is a part of the PPI index for land transport, the (blended) tax inclusive diesel price was up by 33% during the same period (solid black line). If we take into account the sharp drop in worldwide oil prices in 2020, and instead consider 2019 as a comparison year, PPI for transport was up 27% higher relative to 2007, with the diesel price being almost 50% higher. We also plot the market price for crude oil. Oil prices were highly volatile during the time period; up by over 50% in the first half of the sample, and then beginning around 2015, a sharp decline. As discussed in subsection 2.2, Sweden started increase the biofuel blending requirement in 2016, which led diesel prices to increase substantially from this point and onwards, an effect that is visible by comparing the blended diesel price (solid black line)

with the crude oil price line.

To further illustrate that the diesel price increase is driven by climate policy measures rather than market prices for oil, Figure 4b decomposes the tax inclusive diesel price into a fossil price component and a climate policy component. As we do not have access to the price of non-blended fossil diesel in Sweden, we use before-tax diesel prices in Germany (converted into SEK) as a proxy.[9] The climate policy component (the part of the price coming from carbon and energy taxation and the biofuel price) is obtained by subtracting the fossil market price component from the total blended price. The fossil diesel price is up by about 7% in 2020, or 33% in 2019 before the Pandemic-induced oil price drop. In comparison, the climate policy component is up by over 60% during the time period and is the key driver behind the rise in Swedish diesel fuel prices.

The takeaway from these comparisons is that diesel prices increased relatively more than other input costs for Swedish trucking companies during the sample period.

2.4.2 Asset homogeneity

Our empirical setting allows us to study organizational and behavioral changes stemming from policy-induced energy-saving technical change. As fuel prices rise more than other input prices, as we have shown was the case in our setting, economic actors should begin saving on the costly input (e.g., Newell and Jaffe, 1999). Our data allows us to observe the individual asset through which such behavioral and organizational changes are reflected in the trucking sector, namely the heavy duty vehicle (HDV).

Our focus on HDVs also helps us rule out several alternative mechanisms. First, we can effectively cancel the fuel-switching mechanism as essentially all heavy trucks run on diesel. In fact, over 96% of all truck-years in Sweden run on diesel (Table B.1). In the subgroup of heavy trucks weighing over 20 tons over 99% run on diesel.[10]

Second, there has not been a dramatic improvement in CO_2 emissions standards of heavy

[9] Germany had very little or no blending in of bio fuels and we therefore consider this to be a reasonable approximation of the market price for diesel. The correlation between the German non-tax diesel price and crude oil is 0.80. The correlation between the Swedish blended diesel price and crude oil is only 0.20.

[10] Interestingly, the often cited goal of electrifying road transportation can also be examined in Table B.1. Only 69 out of 1.9 million truck-years in our sample involve an electric truck.

trucks during our sample period. In Figure B.5a we plot the CO_2 emissions per km by vintage for three different weight classes of trucks. Emissions standards improved by about 5–6% in 2010 and during the whole time period there is an improvement of about 8–9%. This implies that had the stock of trucks always comprised the latest vintage, CO_2 emissions would be down by about 8–9% even without behavioral or organizational changes. In Figure B.5b we plot CO_2 emissions per driven kilometer across firms with small, medium and large truck fleets. The actual CO_2 emissions per KM is down by between 4–4.5%.

3 Fuel Cost Across Trucks, Firms and Over Time

3.1 Sample construction

We construct our sample by merging vehicle level information with firm level data for the period 2007–2020. The Swedish Transport Analysis Agency provided vehicle level data and the firm data is from *Bisnode Serrano*. See the appendix (subsection A.1) for a detailed description of the datasets used in this study. We focus entirely on heavy duty vehicles owned by firms operating in the Freight transport by road sector (NACE: 4941). We construct two samples: one truck and one firm panel respectively. Table 1 provides summary statistics for the key variables used in the empirical analysis.

3.1.1 Truck level sample

We impose two sample requirements in the truck panel. First, we exclude trucks that are less than one year old (i.e., when vintage and calendar year is the same), since over 80% of VKT's in a trucks first year of existence are estimated. HDVs are legally mandated to be inspected every year starting 12 months after its first use, and our data on VKT based on the odometer reading from these inspections. This requirement excludes about 8% of the truck-years. Second, we exclude the year a truck is de-registered as the VKT also tends to estimated for such years year, which excludes roughly another 1% of our truck-years. We obtain emissions for each truck by using data on each vehicle's characteristics (e.g., weight and EU emission classes) and vehicle level emission factors [grams of CO_2/km] from the the

Swedish Transport Administration's emission reporting model.[11] Our final truck level sample consist of almost 400,000 truck-years from between 31,000 to almost 39,000 individual trucks per year.

3.1.2 Firm level sample

We create a corresponding sample at the firm level, derived from the trucks examined in the truck-level sample, leveraging the dataset's information about the ownership of each truck by specific firms. Consequently, the firm-level sample encompasses all companies within the Road Freight Transport sector that possess at least one heavy-duty vehicle. Almost 85% of all firms in this sector own at least one heavy truck. If several firms with the same corporate owner in a given year, we combine them in to one consolidated unit. In addition to the truck-level information, the firm-level data (from the Serrano data base provided by Bisnode) include complete financial statement information as well as various firm demographics, such as firm age and workplaces. The final firm-level sample contains 84,300 firm-years. Finally, we connect the firms to registry data on individual employees from Statistics Sweden's LISA data base, which includes a wealth detailed information on demographics, education, wages, and job characteristics for these individuals.

3.2 The Swedish transportation sector 2007–2020

We begin by showing how the Swedish heavy duty vehicles sector has developed in terms of sales (PPI-adjusted) and number of trucks in Figure 5. In the analysis that follows, we consider both average changes across all firms, as well as within-industry differences between firms with different fleet sizes, as there are ex ante reasons to believe that trucks part of a larger fleet are able to respond differently to fuel cost changes. We therefore divide the sample in to three groups based on the number of heavy duty vehicles the firm owns. The first group consists of firms owning less than 10 trucks, the middle group of firms owning between 10 and 49 trucks, and the third group of firms with 50 or more trucks.[12]

[11] The emission factors are based upon Consortium (2022)

[12] Our size classification is inspired by studies classifying firm size based on number of employees per firm. In such studies firms are typically grouped in to increments of 1-4 workers, 5-9, 10-19, etc. We therefore

Using this categorization, we examine how the Swedish trucking sector has developed over our sample period. Total output (expressed as PPI adjusted sales) increased from 76 to 93 billion SEK, see Figure 5a. The transport sector thus has increased by about 21%. If we compare to the 27% increase in freight weight reported in Figure 2 between 2009–2020 the output increase from our sample is very similar; the increase in output since 2009 is about 29%. However, the evolution differs significantly across firm size groups. Firms with smaller truck fleets experienced output declines by 8% while larger firms (with 50 or more trucks) grew by 108%. As a result, the smallest firms decreased their market share of 11 percentage points while the largest firms gained market share by the same amount. The pattern is similar for the number of heavy trucks in Figure 5b, with one difference being that the middle group of firms (with 10–49 trucks) also have gained market share.

While this evidence indicates a consolidation of the Swedish trucking sector, it continues to be highly fragmented throughout the whole sample period. The average HHI for the freight transport by road sector for 2007-2020 is around 27. This value can be compared to industries such as Restaurants (NACE: 5610, HHI: 38) and Construction (4120, HHI: 699).[13]

Next, Table 2 shows the development of the Swedish freight transport over time based on our sample. Panel A presents information on how the trucking sector has developed over time and across the three fleet size groups.[14] The trucking sector grew by 21% in terms of producer price (PPI) deflated sales.[15] The number of trucks grew at roughly the same rate, while potential transportation work and VKT have increased by 7% and declined by 1%, respectively. This implies that the trucking firms managed to grow revenues despite a reduction in the total distance driven by their fleets. Total tax-inclusive fuel costs, i.e., the amount paid by firms for fuel consumed, is up by 9%; again less than the increase in sales. The number of firms decreased slightly by about a 100 over the period. Number of

began by creating six groups based on truck fleet size by firm: 1–4, 5–9, 10–19, 20–49, 50–99, and 100–. We subsequently consolidated this grouping in to three. The grouping is in line with Button (2022), who also considers fleets with more than about 50 vehicles as "large".

[13]To put these numbers in perspective, the U.S. Department of Justice considers industries with an HHI above 1000 as being moderately concentrated (https://www.justice.gov/atr/herfindahl-hirschman-index).

[14]We only present the first and last year of the sample alongside the difference between the two. In almost all instances, these changes are gradual, smooth processes over the years. We will note in the text when this is not the case.

[15]The PPI is provided by Statistics Sweden.

employees in the sector was up by 14% reaching close to 54,000 workers. Finally, and perhaps the most relevant finding for climate policy, aggregate CO_2 emissions (fossil plus biogenic) from trucking fell by 6%, despite the concurrent increase in output.

In panel B we report a set of key ratios across firms and fleet size groups. Sector-wide sales to VKT was up by 19%, while tax-inclusive fuel cost to sales was down by 19% and CO_2 emissions by even more (-22%). Margins (expressed as EBIT to sales) were almost identical in 2020 as in 2007. Again, the sector-wide ratios hide important differences across firms size groups. The middle group underperformed the sector as a whole, with sales per VKT only growing 7% (vs 19%) and CO_2 emissions to sales decreasing by 10% (vs -22%)). Consistent with Panel A, the trucking firms with the largest fleets outperformed the others: sales to VKT were up by 52%, fuel cost to sales were down by 34% and CO_2 to sales were down by 37%.

Overall, the shift of market share and transport activity from smaller to larger fleet trucking firms were associated with both higher economic efficiency (as indicated by the ration of sales to various truck input characteristics) and a considerable improvement in carbon emission efficiency. Importantly from a climate policy perspective, the sector was able to achieve a "decoupling" between sales and emissions; the trucking sector was able to grow by 21% while at the same time reducing aggregate CO_2 emissions by 6%. This decoupling was entirely driven by firms with larger truck fleets.

Finally, in panel C we report a set of financing characteristics across firms and time. There was a slight uptick in bankruptcies over time, entirely driven by smaller firms, while the fraction of firms with high credit scores increased over time.[16] In line with the improvement in credit score, total debt to assets decreased by about 4 percentage points across all groups and dividends to assets went up by 0.5 percentage points. We do note that the relatively large increase in the dividend to assets ratio in 2020 – the year of the COVID outbreak – represents a break from the year before. If we instead consider 2019, dividends to assets are relatively stable over time. The perhaps most noticeable difference across the fleet size

[16]Credit scores are obtained from UC, see subsubsection A.1.2 and Caggese et al. (2019) for more detailed information on the credit scores.

groups is that firms with larger fleets are considerably older. Average firm age in 2020 was almost 50 years compared to 29 years and 18 years respectively for the middle and small truck fleet groups.

In Table 3 we document truck fleet characteristics over time and across truck fleet groups. Median vehicle age (panel A) and weight (panel B) were both quite stable over time and across groups. However, large fleet firms display a truck weight distribution more tilted toward lighter trucks; the truck at the 10^{th} and 90^{th} percentile respectively weigh 16 and 29 tons compared to 18 and 33 tons for the sector as a whole. In panel C, we document the share of de-registered trucks or trucks where the registration has temporarily been canceled.[17] About 14% of all trucks were out of use in 2020. The fraction of leased vehicles increased over time (this data ends in 2017). Firms with larger fleets had a higher share of leased vehicles compared to the sector as a whole in 2017 (16% vs 12%). Finally, we compile number of trucks (panel D) and VKT (panel E) by weight classes. The trend is similar across all groups and in both panels; a decreasing importance of trucks weighing less than 27 tons and an increase in heavier trucks. As we will discuss later, this is one indication of a shift in the trucking business model.

4 Estimation of Truck Level Elasticities

4.1 Baseline truck level specification

We begin and evaluate the relationship between the tax inclusive fuel cost and the distance each truck has traveled. We follow Knittel and Sandler (2011) and Gillingham and Munk-Nielsen (2019) and estimate the following baseline regression

$$ln(VKT)_{v,t} = \alpha + \beta \cdot ln(FC)_{v,t} + \eta_v + \eta_i + \eta_{i,t} + \epsilon_{v,t}. \tag{1}$$

where VKT is the vehicle kilometers traveled for vehicle v in year t. FC is fuel cost per transport work expressed as Swedish Krona (SEK) per km–ton for vehicle v in year t. η_v

[17] Temporarily canceled (in Swedish *Avställd*) means that truck is temporarily unused and the firm does not need to pay registration fees and taxes on the vehicle.

captures vehicle-specific, time-invariant factors that could impact the relation between VKT and fuel costs. $\eta_{i,t}$ absorbs changes in VKT that are common to all vehicles owned by a given firm in a given year. In our analysis, we also estimate Equation 1 excluding some of these fixed effects in order to gauge the total effect of fuel price changes on VKT of trucking companies, as we discuss below.

4.2 Changes in fuel costs and VKT

Table 4 presents the baseline results from estimating Equation 1. We begin in column 1 without truck fixed effects and obtain a highly statistically significant VKT to tax inclusive fuel cost elasticity of about -1.1. This suggests that as fuel costs are increased by 1%, the average truck in the sample drives about 1% shorter distance in a given year. In column 2 we also include vehicle fixed effects, to control for time-invariant vehicle characteristics, which lowers the elasticity slightly to about -0.9. In column 3 we add firm fixed effects (which is possible as vehicles can change ownership over time, which further reduces the elasticity to about -0.6. Controlling for vehicle and firm fixed effects, this elasticity estimate is identified from the time-series fuel price changes as well as cross-sectional variation due to firms responding differently across trucks of different weight in a given year .

In order to account for the possibility that reductions in VKT being are driven by lower demand rather than being a response to higher fuel-prices, we then try to control for time-varying demand in different ways. In column 4 we include firm sales divided by number of trucks to control for firm-specific demand fluctuations. Including this firm-year control variable lowers the fuel cost elasticity only slightly. In column 5, we include year fixed effects to control for sector-wide fluctuations in demand, which lowers the elasticity to about -0.3. Year fixed-effects naturally absorbs the average fuel price change in a given year, and the elasticity is identified from differential VKT responses to fuel price increases for trucks with fuel efficiency. The negative elasticity indicates that as fuel costs increase, firms drive relatively less with heavier, more fuel consuming trucks. In column 6 we include firm-year fixed effects, i.e., controlling for firm specific factors that might impact the VKT to fuel cost elasticity at the truck level in a given year. The inclusion of firm-year effects drops the

single truck firms from the estimation, leading to a reduction in sample size. When including this admittedly tight fixed-effects structure, the elasticity becomes roughly -0.5. In the final column, we add an indicator variable taking on the value one if the truck is owned by a firm above the median in fuel cost to sales, to test whether the responses are different across firms based on how salient fuel costs are to the particular firm. The interaction between FC and high fuel cost to sales is statistically significant and economically meaningful: when a truck is owned by a firm with above median fuel cost to sales, the estimated VKT to fuel cost elasticity is -0.55, or 15% larger than for a truck owned by firm below the median.

The VKT to fuel cost elasticity estimates in Table 4, are to our knowledge the first such estimates in the academic literature. The Swedish traffic agencies (*Trafikverket* and *Trafikanalys*) use elasticities of -0.42 and -0.40 for freight traffic by road (NIER, 2024). In comparison, we estimate an elasticity of about -0.6 when we allow for time-series variation in fuel prices, while the elasticity estimate end up between -0.3 and -0.5 when we control for average fuel price variation.

4.3 Heterogeneity and emissions

4.3.1 Truck fleet size

We continue by estimating Equation 1 separately for trucks of different size groups in Table 5. Table 2 showed the relative out-performance by firms with larger truck fleets relative to those with smaller fleets. In this section we test the extent to which the different size groups respond differently to changes in fuel cost.

In the first three columns we re-estimate Equation 1 for trucks that are owned by firms with less than 10 HDVs. These trucks display a lower elasticity in column 1, without controlling for aggregate fuel price changes. When we control for firm demand, however, these trucks do not display any significant sensitivity to changes in fuel cost. A similar pattern holds for trucks owned by firms with between 10–49 HDVs. Both groups display imprecisely estimated VKT to fuel cost elasticities of around zero. For firms with 10 to 49 trucks, it is only the trucks owned by firms with high fuel cost to sales that show a significant

VKT to fuel cost elasticity. In contrast, columns 7–9 show that trucks owned by firms with 50 or more HDVs display a considerably higher (i.e. more negative) and more precisely estimated elasticity. The fuel cost elasticity with sales per truck as the demand control is more than 20% higher than that of small fleet firms. When we include firm-year fixed effects, the difference in elasticity increases further and is highly statistically significant.

The findings in Table 5 are important for two reasons. Firstly, there is a significantly different fuel price response for trucks owned by large fleet firms compared to trucks from smaller firms. Secondly, large fleet firms respond to higher fuel prices by driving relatively less with heavier trucks (even when controlling for firm-specific demand fluctuations with firm-year fixed effects).

4.3.2 Fuel economy improvement and CO_2 emissions

We document a sizable fuel economy improvement starting from 2010 vintages in Figure B.5. Emission standards became about 5–6% stricter in terms of allowed CO_2 per KM. We therefore consider to what extent there are different *VKT* to fuel cost elasticities for trucks with vintages up to 2009 (i.e., the vintages with worse fuel economy) compared to those with vintages from 2010 and onward. We present the results in Table 6. We create an indicator variable (*Vintage* $>$ *2009*) taking on the value one if the truck is of vintage 2010 or later and zero otherwise. We expect a lower elasticity among the more recent vintages as a given VKT is more expensive for trucks of vintages prior to the passing of the stricter emission standard. The elasticity of trucks of vintages up to 2009 is -0.56 compared to -0.39 for trucks of later vintages. These results indicate that trucking firms save more on the more energy demanding assets. Across all fleet size groups there is a lower elasticity for trucks of more recent vintage. Trucks of earlier vintages display between 20–40% higher elasticity than those of vintages with better fuel economy.

For the final truck level regressions we switch the dependent variable from *ln(VKT)* to CO_2 emissions (*ln(CO_2 emissions)*) and re-estimate Equation 1. The CO_2 emissions variable depend on the *VKT* of the truck but it also considers its weight and fuel efficiency. We report results from this specification in Table 7. Overall the results are similar compared to with

VKT as dependent variable but the *CO_2 emissions* to fuel cost elasticity is slightly larger. The estimated elasticity across all trucks, presented in column 1, is around -0.6. In line with the results with *VKT* as outcome variable, trucks owned by firms with smaller and medium sized fleets do not respond or respond less to changes in tax inclusive fuel costs. On the other hand, trucks owned by larger fleet firms display a much higher *CO_2 emissions* to fuel cost elasticity compared to the sample-wide estimates in columns 1–2.

5 Firm Level Responses and Adjustments

5.1 Baseline Specifications

We begin with a similar specification to the truck level approach above. However, importantly, as in Martinsson et al. (2024), we also consider a delayed response from fuel price increases in the firm level setting by allowing for adjustment over time by estimating a distributed lag model (allowing for up to three lags). This is important for at least two reasons. First, it is important to distinguish between short and longer run elasticities with respect to fuel price changes (Dahl and Sterner, 1991). Second, our interest in how different transportation firms (e.g., small vs large fleets) respond to fuel price changes makes it important to allow for different response processes across firm groups. Also, as our overarching aim is to study efficiency and productivity responses and how the organization of the transport sector changes over time, this further calls for a more flexible specification allowing for the adjustment process to vary over time (and not simply rely on contemporaneous, so called "intermediate" elasticity responses (Andersson, 2019)). We use the firm level sample which aggregates all truck information to the firm-year level and we also employ standard firm variables such as sales and profitability. We estimate the following specification:

$$ln(Y)_{i,t} = \alpha + \sum_{s=0}^{q} \beta_{\mathrm{s}} \cdot ln(FC)_{i,t-s} + \gamma \mathrm{X_{i,t}} + \eta_i + \eta_t + \epsilon_{i,t}. \tag{2}$$

where the variable Y is different firm level outcome variables such as the the *VKT* for firm

i in year t. FC is fuel cost per transport work expressed as Swedish Krona (SEK) per km–ton for firm i in year t-s. The lagged terms of FC allow for a delayed adjustment to price changes. When Y is measured as VKT and CO_2 we expect $\sum_{s=0}^{q} \beta_s < 0$ if transport companies drive less in in response to higher fuel costs. While we have the opposite expectation, $\sum_{s=0}^{q} \beta_s > 0$, when Y captures firm efficiency outcomes such as *sales per VKT*, and *EBIT to sales* if firms can adapt to higher fuel prices by becoming more efficient and productive.

$\boldsymbol{X}$ is a vector of firm level control variables comprising the firm level natural logarithm of total assets (*ln(total assets)*) and age (*ln(firm age)*) respectively, as well as the ratio of total debt to total assets (*Debt to assets*). η_i captures firm-specific time-invariant factors that could impact the relation between vehicle distance traveled and fuel costs. η_t absorbs changes in, e.g., VKT that are common to all firms in a given year.

5.2 Baseline firm level results

We report results from estimating Equation 2 with VKT (in columns 1–5) and CO_2 *emissions* (in columns 6–7) as dependent variables in Table 8. The firm level VKT to tax inclusive fuel cost elasticity is estimated at -1.2 in column 1. This is very similar to the -1.1 estimate we document for the truck level sample when we exclude truck fixed effects in column 1 in Table 4, indicating that firms optimize transportation across their vehicles. This elasticity is markedly lower, -0.7, when we include the vector of firm level variables in column 2. Here we control for standard firm level characteristics such as firm size (size effects other than truck fleet size), age and leverage (which captures access to finance). In columns 3–5 we add lags *t-1* to *t-3* and find considerable adjustment over time as well as an 11% higher total elasticity in column 5 compared to in column 2 (-0.79 compared to -0.71). The short run elasticity varies between -0.43 to -0.48 whereas the long run elasticity, $\sum_{s=1}^{q} \beta_s$, is between -0.73 to -0.79 (or 60–70% higher). We obtain a very similar pattern with CO_2 *emissions* as the outcome variable in columns 6–7. Overall, we find support for the empirical prediction that changes in fuel cost is associated with reduction in VKT and emissions at the firm level. Furthermore, our findings show the importance allowing for gradual responses over time when modeling the firm level response to changes in fuel cost.

In Table 9 we re-estimate the specification presented in columns 2 and 5 from Table 8 across the three fleet size groups. We report the contemporaneous, "intermediate", elasticities in odd numbered columns and the fully specified distributed lag specification with three lags in even numbered columns. The elasticities are relatively similar when we consider only contemporaneous fuel cost changes in odd numbered columns across the fleet size groups. However, as we implement the lag-based specification we unveil considerable differences across fleet size groups; in particular for the smallest fleets (column 2) and the largest (column 6). The short run elasticity for firms with fleets of less than 10 trucks is -0.37 and the long run elasticity is -0.76. This shows the importance of allowing for adjustment over time and also that the contemporaneous and long-run elasiticity is quite similar (-0.70 compared -0.76). For the largest transportation companies there is a short run elasticity of -0.77 (more than twice the size compared to the small firms) and the long run elasticity is -1.35. In other words, trucking companies with large fleets have about a twice as large short run (-0.77 vs -0.37) as well long (-1.35 vs -0.76) VKT to fuel cost elasticity.[18]

5.3 Disentangling price and policy elasticities

So far we have treated the tax inclusive fuel cost as our policy treatment variable. However, as we show in Figure 4b, the largest cost increases stem from policy-induced changes rather than market based increases in the oil price. Also, the setting we study concerns policy-induced increases in the relative prices and how that affects transportation companies. We therefore decompose FC in to *FC–Policy* and *FC–Price* and re-estimate Equation 2. *FC–Policy* and *FC–Price* are defined as in subsection 2.4 and displayed in Figure 4b. We report results for all firms in columns 1–2; small fleet firms in columns 3–4; firms with fleets between 10–49 trucks in columns 5–6; and large fleet trucking firms in columns 7–8 in Table 10. We report specifications with only contemporaneous fuel cost variable in odd numbered columns and in even numbered columns we report the full specification with all three lags. The estimated

[18] We re-estimate Equation 2 with only contemporaneous FC on a sample requiring at least four consecutive observations in order to make sure our results with the distributed lag model are not sensitive to the reduction in sample size (Table B.2). The results without lags in Table 8 and Table 9 are similar when considering a similar sample a used in the distributed lag estimation.

VKT to *FC–Policy* elasticity is much larger and always significant across all specifications and samples, which is not the case for *FC–Price*. When we consider the full sample in columns 1–2 we find that the reported estimation results in Table 8 are completely driven by the policy component of the tax inclusive fuel cost. The estimation result for *FC–Price* is far from significant and even marginally positive in both columns 1 and 2. However, in columns 3–6 when we consider the small and middle sized fleet groups the price elasticities are negative albeit not statitistically significant at conventional levels. *FC–Policy* though is always negative and significant (both the contemporaneous and long-run elasticities).

Interestingly, both the policy and the price components of the tax inclusive fuel price are negative and highly statistically significant. In the case of the contemporaneous elasticity, in column 7, the policy-induced elasticity is -0.83 compared to -0.28 for the market price elasticity. This pattern is similar in column 8 when we consider the fully specified model. Therefore, one reason why we observe a larger overall *VKT* to fuel cost elasticity in Table 8 and Table 9 is driven by the fact that larger firms also respond to price changes. However, the *VKT* to policy cost elasticity is also 50–70% higher compared to the small and middle sized trucking companies (in both specifications).[19]

5.4 Firm productivity and profitability

The limitation of the results so far is that we have not related changes to input quantities of trucking, such as *VKT*, to any economic outcomes. In this sub-section we relate changes in tax inclusive fuel cost to: i) *sales per VKT*, and ii) *EBIT to sales*.

5.4.1 Fuel cost and output per VKT

Our preferred productivity measure is to relate output (produce price adjusted sales) to VKT. This way we test to what extent increases in carbon pricing affect firm level efficiency. The results are compiled in Table 11 for all firms in columns 1–2; small fleet firms in columns

[19] We also re-estimate these results on a sample requiring at least four consecutive observations in order to make sure our results with the distributed lag model are not sensitive to the reduction in sample size (Table B.2). Again, the results without lags in Table 10 are similar when considering a similar sample a used in the distributed lag estimation.

3–4; firms with fleets between 10–49 trucks in columns 5–6; and large fleet trucking firms in columns 7–8. Larger firms display a considerably higher *Sales per VKT* to fuel cost elasticity than the other firms. For both small and middle sized firms the contemporaneous and the long run elasticity is around 0.4; a one percent increase in fuel costs is associated with 0.4% higher sales per VKT. However, for large firms the elasticity is between 0.65 to 0.99. In other words, a 1% increase in fuel prices is associated with a 0.6–1% productivity improvement for large fleet firms (or 60–150% larger effect than for small and middle sized trucking companies).

5.4.2 Fuel cost and returns to output

Next we consider to what extent increases in fuel costs affect profitability of trucking companies, measured as *EBIT to sales*. More specifically we are interested in the relative difference across fleet size groups and the adjustment over time. The results are compiled in Table 12 and again we present estimates for all firms in columns 1–2; small fleet firms in columns 3–4; firms with fleets between 10–49 trucks in columns 5–6; and large fleet trucking firms in columns 7–8.

Across the full sample and the small fleet size group there is a negative and marginally significant relationship between *EBIT to sales* and *ln(FC)* when we consider only the contemporaneous case (columns 1 and 3). However, this relationship turns non-significant when we consider the full specification. On the flip side, large fleet firms display a positive relationship between changes in fuel cost and the EBIT margin. However, here the contemporaneous estimate in column 7 (a non significant effect of 0.047) vastly under-estimates the adjustment process. In column 8, we obtain a highly statistically significant long run effect of 0.20. It is first on lag 3 though that the annual fuel cost effect is statistically significant. These findings suggest that the productivity gains documented above in Table 11 generate long run profit margin improvements which materialize with some lag.

Overall, the estimation results in Table 11 and Table 12 show that the *VKT* to fuel cost response lead to sector wide productivity and efficiency gains. However, these gains

are unevenly distributed. Large trucking companies display 60-150% larger productivity responses (Table 11) which translates to, over time, EBIT margin improvements. While the relatively lower productivity increases in small and middle sized trucking companies do not lead to higher EBIT margins. We next turn to explore the mechanisms underlying our results.

6 Mechanisms

So far, we have provided evidence that trucking companies – particularly the large ones – have become more productive in response to increasing fuel costs over our sample period. Trucks with the highest fuel costs reduce the number of kilometers traveled as fuel costs increase. This translates to a reduction in total vehicle kilometers driven for the firm as a whole, accompanied with an increase in output per kilometer driven. Throughout, we observed the largest effects among firms with a large number of trucks, who also increased their market share over this period. In aggregate, following a period of increasing fuel costs due to biofuel blending, the Swedish trucking industry has thus been able to increase its output while at the same time lowering its CO_2 emissions (even when including the non-fossil biofuel emissions).

In this section we investigate the possible mechanisms that could be driving this productivity increase. One obvious way to decrease fuel costs is to switch to more fuel efficient vehicles. The vast majority of heavy trucks in Sweden are still run on diesel, and electric heavy trucks have not been commercialized as of yet (e.g., Table B.1). During our sample period, there has been some improvements in fuel efficiency for heavy trucks, as seem in Figure B.5. While we do document that the within truck fuel cost to VKT elasticity for trucks of the more fuel efficient vintages is slightly lower compared to the vintages with worse fuel economy (Table 6), this cannot explain the full set of findings in this study.

The main mechanism we explore can be broadly defined as improvements in logistics with the aim to operate with fuller trucks (or minimize so called "empty running") and this way lower VKT. The most likely way to optimize routes would be to focus on a central location/terminal (or hub) which serves a fixed point from which delivery routes (or spokes)

are drawn from. The opposite to hub and spoke distribution would be so called point-to-point where a truck drives from origin to final destination. We carry out three tests below.

6.1 Change in truck utilization

In the first test we divide the share of total firm-year VKT coming from trucks of different weight classes from lighter to the heaviest. This test explores whether higher fuel prices lead to changes in truck fleet utilization within firms. We hypothesize that a similar VKT decrease across all weight groups suggests that optimization is mostly in point-to-point distribution. In contrast, VKT responses with stronger decreases for the heaviest trucks and relative increases for lighter trucks would be more consistent with a hub and spoke distribution model. More specifically, if the behavioral responses we document above are driven by hub and spoke trucking we would expect that firms drive less with their heavier (more fuel consuming) trucks and more with relatively lighter ones. The interpretation is that firms optimize by creating networks of terminals in order to lower under utilized truck capacity, especially by the heaviest trucks which are more diligently routed to central terminals in order to re-load to lighter trucks for the final distance from the terminal to the end customer.

In order to test whether firms do respond by changing how they drive with different types of heavy trucks we divide the VKT of each firm and year in to VKT by weight classes. All VKT is divided up in to distance driven by trucks weighing i) under 20 tons, ii) between 20–26 tons, iii) between 27–28 tons and, iv) more than 28 tons. Generally, the groups under 27 tons are lighter heavy trucks and those weighing at least 27 tons are heavier. We expect to observe a larger VKT to fuel cost elasticity for the heavier the trucks if firms optimize in line with hub and spoke trucking.

For each firm we create four variables capturing the share of annual VKT that comes from either heavy truck weight class and estimate a version of Equation 2. We present $\sum_{s=1}^{q} \beta_s$ in Table 13 for all firms (panel A) and by fleet size groups (in panels B–D). The complete regression results for each firm sort are compiled in Table B.3, Table B.4, Table B.5, and Table B.6.

We begin in panel A and consider the four different outcomes across all firms. We see a

clear pattern of firms driving relatively more with lighter heavy trucks as fuel costs increase. In fact, firms drive more with the lightest groups of trucks as costs go up. And in line with predictions, the elasticity between share of VKT and fuel costs is large and negative for the two groups comprising the heaviest heavy trucks. In panels B–D we re-estimate the same specification as used in panel A but across the groups of firms sorted by fleet size. The pattern of monotonically decreasing fuel cost to VKT by size group, from the lightest to the heaviest trucks, persists across all fleet size groups. However, it is noticeable how much larger the elasticities are for the largest firms in panel D. This is expected as firms with larger fleets have more trucks across the different truck types. Overall, we interpret the findings in Table 13 as support of the mechanism that trucking firms optimize around terminal structures or a hub and spoke distribution network.

6.2 Type of trucking company

The next test considers so called less than truck load (LTL) vs truck load (TL) trucking. The findings in subsection 6.1 suggest that our documented VKT to fuel cost elasticity is to a large extent driven trucking companies optimizing through hub and spoke distribution. This kind of trucking is associated with less than truck load (LTL) trucking which concerns the transportation of freight smaller than to fill entire heavy trucks.[20] In this test we compare firms more likely to be operating in LTL trucking relative to TL trucking. However, there are no clear definitions of LTL and TL trucking firms. As a proxy for LTL specialized trucking companies, we consider a firm more likely to engage in LTL (TL) activity if it has (does not have) trucks across all the four weight classes used in subsection 6.1. As this proxy is highly correlated with fleet size (Zingales, 1998), we are most interested in the within fleet size group differences; particularly, a trucking firm with a large fleet which is relatively homogeneous (in terms of weight class) is likely not engaged in LTL trucking and is probably specialized in TL activities.

We present evidence of estimating Equation 2 on the two trucking company groups in

[20]Shipments larger than 10,000 pounds are typically shipped via LTL and larger shipments by truckload carriers.

Table 14. We again only present the $\sum_{s=1}^{q} \beta_s$ to conserve space.[21] We begin in panel A with *VKT* as dependent variable. Across all firms, in the first two columns, firms in the LTL group display a larger elasticity than the TL group. However, the interpretation of LTL vs TL firms is not clear across the firms with smaller fleet sizes (columns 3–6). Interestingly we observe significant and reasonably similar elasticities in columns 1 through 6. Importantly, though, within the group of large trucking firms there is a stark difference across firms considered LTL relative to TL. The *VKT* to fuel cost elasticity is around 20% higher compared to in Table 9 when all large fleet firms are pooled together. The elasticity is close -1.7 and highly significant. In contrast, the elasticity of large firms considered TL is only half as large and not statistically significant. Overall, these findings are consistent with our hypothesis that firms optimize though hub and spoke trucking. In panels B and C we confirm that the results presented above appear to be driven by large firms engaging in LTL trucking. Large LTL trucking firms (column 7 in panel B) display a large positive, highly significant *sales per VKT* to fuel cost elasticity compared to a non-significant, negative elasticity for the non-LTL large firms. In panel C we show that the EBIT margin improvements for large fleet trucking companies is completely driven by LTL specialized firms.

Finally, we display how firms' share of heavy trucks (Figure B.6a) and VKT (Figure B.6b) have changed over time. We plot the percent change across the four weight classes for the whole trucking sector (gray bars) and the LTL trucking firms (black bars). The overall pattern for the trucking sector is a reduction in the share of trucks and VKT from lighter trucks to heavier trucks. The share of number of trucks and VKT from trucks weighing under 20 tons was 0.25 and 0.16 in 2007 and drops to under 0.18 and 0.1 in 2020 (a drop of 30% and 40% respectively). On the flip side the same shares for the heaviest trucks (>28 tons) goes up 93% and 75% respectively. However, the firms more likely to engage in LTL trucking start out with lower shares of the smallest and largest trucks in 2007 and shifts more toward the heaviest trucks (the percent increase in number of trucks and VKT is 214% and 189%).

[21] The complete regression results for each firm sort are compiled in Table B.7, Table B.8, and Table B.9.

6.3 Logistics employees and IT investments

Next, we focus on the employees of trucking firms to investigate potential differences in employment dynamics between firms based on fleet size, particularly in the context of optimizing transshipment. Based on our findings above we expect, in particular for large fleet firms with their ability to optimize operations across a greater number of trucks and terminals, to respond to rising fuel costs by increasing the employment of workers in logistics-related roles. We use a matched employer-employee dataset and extract the number of workers employed in logistics-oriented occupations.[22] Logistics employees manage, for example, transportation planning, fleet and driver management and load optimization.

In order to capture whether such workers have increased over time we plot the number of logistics employees per active heavy truck across the fleet size groups in Figure 6. The ratio of logistics workers per truck is increasing across all size groups consistent with increasing investments in logistics networks. At the start of the sample period smaller fleet firms display a ratio of 0.02 compared to 0.08 for large fleet firms. In other words, large fleet trucking companies have four times as many logistics workers relative to the number of trucks they operate. The logistics workers per truck ratio for small firms increases to 0.035 in 2020 compared to about 0.13 for large fleet firms.

Figure 6 shows that large fleet firms, as expected, had a much higher logistics employees to truck ratio to start with and therefore, were already better positioned to optimize in response to higher fuel prices. Furthermore, this ratio increased across all fleet size groups indicating that higher fuel prices spurred trucking sector wide logistics improvements.

7 Conclusion

From a European perspective, Sweden has a relatively high tax inclusive diesel price; a contributing factor to the high diesel price is that Sweden mandates a greater biofuel share in the diesel used compared to other EU countries. On top of this, diesel is also subject to carbon and energy taxation. We assemble a comprehensive data set of around 30,000 to

[22] SCB's LISA dataset provides a code for each employee's occupation (ISCO-08).

40,000 heavy trucks and track them during 2007–2020. Our results indicate a robust and economically significant inverse relationship between the tax inclusive fuel cost and various truck related outcomes. While truck level fuel cost to vehicle kilometers traveled (VKT) elasticity is between -0.3 and -0.6, there is considerable heterogeneity depending on whether the truck is owned by a firm with a small or large truck fleet. In particular, it is only trucks owned by large truck fleets that display a consistently robust response to fuel cost changes (with an elasticity higher than -1). The VKT to fuel cost response translates in to significant reductions in truck level CO_2.

The main focus of our paper is the truck fleet level estimates allowing for optimization across trucks within the same firm (building on the within, truck level estimation results). The firm level elasticities are larger than the documented within truck level responses indicating that important adjustments occur between trucks, within firms. We document both short and long run VKT to fuel cost elasticities (-0.43 and -0.79) for the trucking sector as a whole. The adjustments over time are different across the different fleet size groups; while small and middle sized fleets display adjustment in time t and t-1, the larger fleet firms optimize VKT over even deeper lags. Large fleet firms display a short run elasticity of -0.77 (i.e., similar in size as the long run elasticity for small fleet firms) and a long run elasticity of -1.35. The fuel cost effect is mainly driven by the policy component (i.e., taxation and bio blending mandates) as opposed to market fossil diesel prices. These documented fuel cost responses lead to productivity gains, output per VKT increases (0.43 for the trucking sector); the large fleet firms also outperform in terms of productivity (the elasticity is 0.99 for large fleets compared 0.41 for small fleets). We also show that these productivity gains lead to EBIT margins improvements for large fleet firms, but with a time lag. For smaller fleet firms EBIT margins with respect to fuel cost increases vary between being marginally significant and negative and being close to zero (and insignificant).

Finally, we show that the efficiency and productivity increases were due investments in logistics related to so called hub and spoke distribution networks. We base this conclusion on the following three tests. First, the show that the negative VKT to fuel cost elasticity is not homogeneous across a firm's fleet; as fuel costs increase, firms drive relatively more with

their lighter trucks and less with the heaviest. These results are consistent with hub and spoke distribution (compared to so called point-to-point distribution). Second, firms more likely to specialize in less than truckload (LTL) trucking display the by far largest response to fuel costs. In fact, among large firms, the entire effect from higher fuel prices on driving distance, productivity and EBIT margins is driven by LTL trucking companies. Finally, we show that the intensity of logistics workers to trucks increases steadily over the time period which again is consistent with investments in terminal-centered distribution networks.

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Figure 1: Tax inclusive price, sum of taxes and fraction of biofuels in diesel

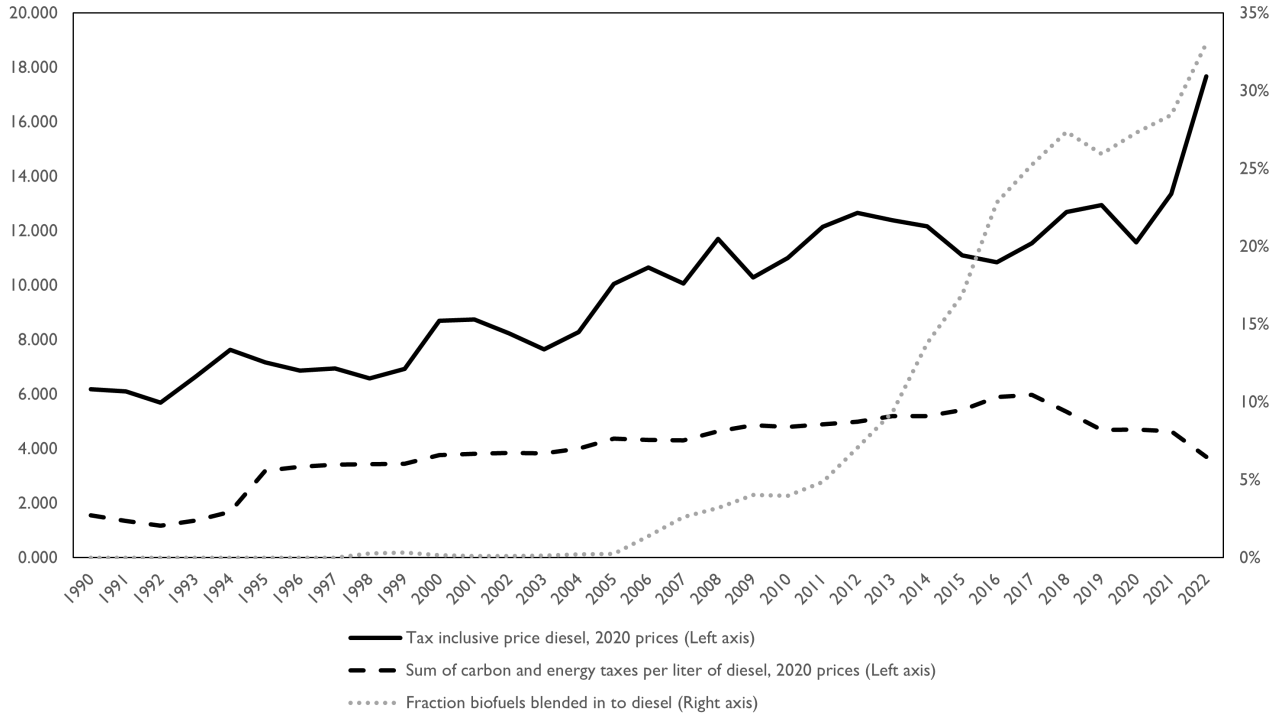


Figure 1 displays the tax inclusive diesel price (solid black line), the tax component (the sum of carbon and energy taxes) (dashed black line) and the fraction of blended in biofuels (dotted gray line) during 1990–2022.

Figure 2: Swedish Heavy Duty Vehicle Sector



Figure 2 displays number of transports by heavy duty vehicles (gray dotted line), driven distance by heavy duty vehicles (gray dashed line), total freight weight (black dashed line), transportation work (gray dashed-dotted line) and freight weight per unit of transport (black solid line) during 2009–2020. The values are re-calculated to an index with 2009 as base year.

Figure 3: CO_2 emissions from Heavy Duty Vehicles (in ktons)

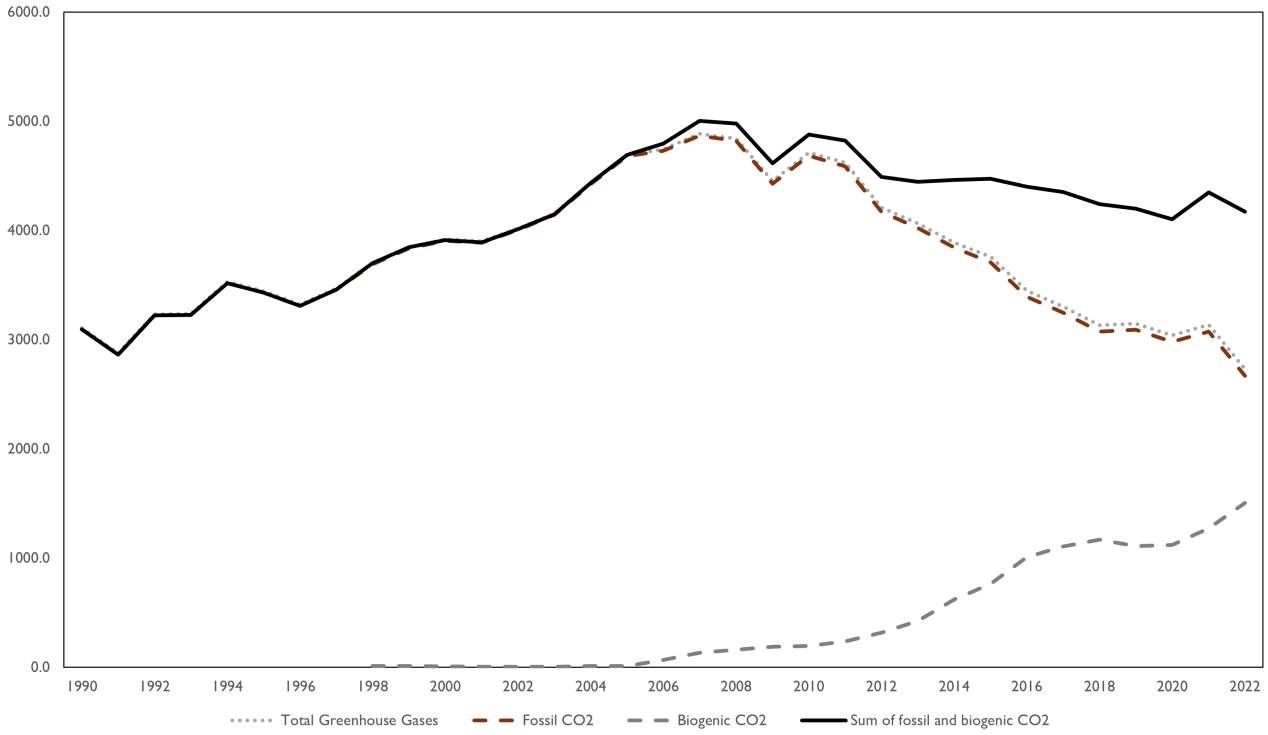
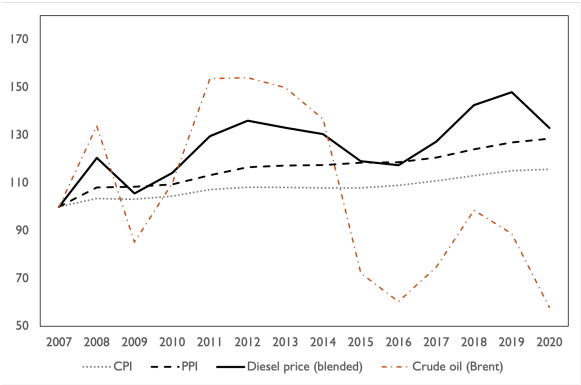


Figure 3 displays total greenhouse gas emissions (gray dotted line), fossil CO_2 emissions (brown dashed line), biogenic CO_2 emissions (dark gray dashed line) and the sum of fossil and biogenic CO_2 emissions (solid black line) from Swedish heavy duty vehicles in ktons, during 1990-2022 in ktons.

Figure 4: Diesel prices relative to other prices

(a) Diesel prices relative to other prices



(b) Decomposing diesel prices

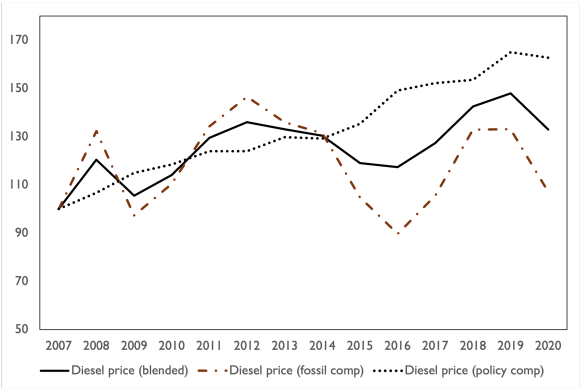
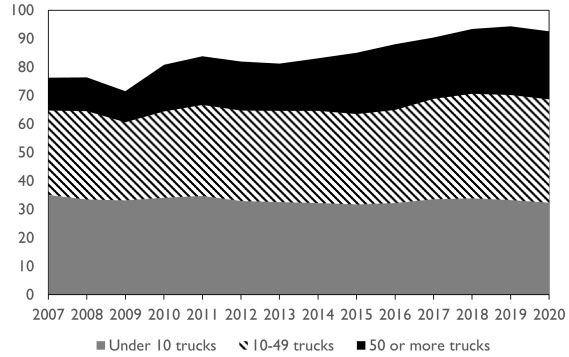


Figure 4 displays the tax inclusive diesel price relative other prices in (a) and decomposed in to a fossil and climate policy component in (b).

Figure 5: Sales and number of heavy duty vehicles by year

(a) Aggregate trucking sales (BSEK)



(b) Aggregate number of trucks

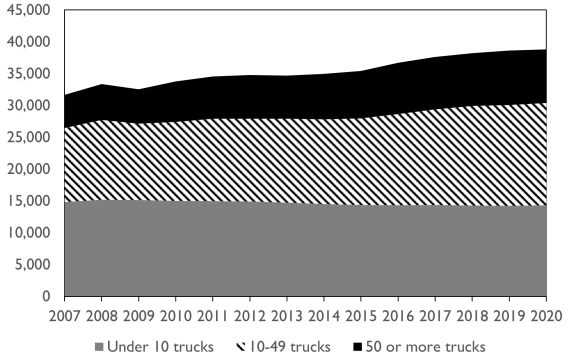


Figure 5 displays sales (billion SEK, PPI-adjusted) for firms with less than 10 trucks (bottom, in gray); firm with 10-49 trucks (middle, striped); firms with 50 or more trucks (top, in black) in (a) and number of heavy trucks for firms with less than 10 trucks (bottom, in gray); firm with 10-49 trucks (middle, striped); firms with 50 or more trucks (top, in black) in (b).

Figure 6: Number of logistics worker per truck

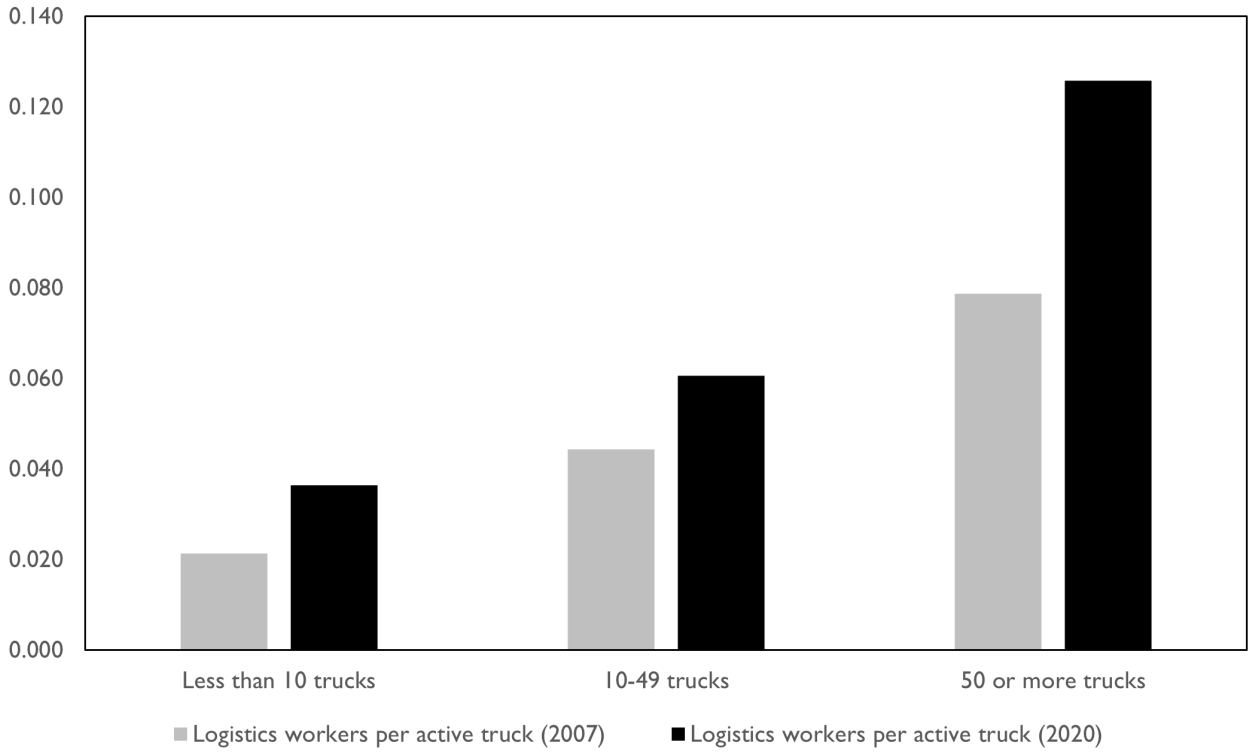


Figure 6 displays number of logistics workers per heavy trucks in 2007 (gray bars) and 2020 (black bars) for firms with less than 10 trucks; firms with 10–49 trucks; firms with 50 or more trucks. A worker is classified as a logistics worker if the main occupation is Stock Clerks (ISCO-08: 4321); Production clerk (ISCO-08: 4322); or Transport clerk (ISCO-08: 4323).

Table 1: Summary Statistics

	OBS	Mean	P10	Median	P90	St. Dev
			Panel A: Truck level sample			
VKT (1,000 km)	399,632	78.180	17.812	64.861	157.302	54.752
FC (sek per million km-ton)	399,632	0.274	0.183	0.231	0.350	0.552
CO_2 emissions (ton)	399,632	55.108	10.751	46.023	112.586	40.010
			Panel B: Firm level sample			
VKT (1,000 km)	84,300	367.522	61.357	145.938	888.305	641.456
FC (sek per million km-ton)	84,300	0.245	0.184	0.224	0.302	0.262
CO_2 emissions (ton)	84,300	260.124	20.338	105.204	629.402	446.124
Sales to VKT	83,466	53.889	15.527	29.010	87.289	98.547
EBIT to Sales	83,193	0.044	-0.049	0.045	0.100	0.203
Total assets (msek)	83,460	8.294	0.911	3.814	19.348	12.892
Firm age	84,300	17.624	2.000	16.000	37.000	13.628
Debt to assets	83,455	0.634	0.242	0.649	0.931	0.311

Table 1 reports summary statistics of the key truck (panel A) and firm (panel B) level variables used in this study. The truck sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. The firm sample comprises firms with at least one heavy truck in the freight transport by road sector (NACE 4941) during 2007–2020. Prices are expressed in constant 2020 Swedish Krona (SEK). *VKT* is vehicle kilometers traveled. *FC* is tax inclusive fuel cost per unit km–ton potential transport work. *CO_2 emissions* is total (fossil plus biogen) carbon dioxide emissions. *Sales to VKT* is PPI adjusted sales in SEK divided by *VKT*. *EBIT to sales* is earnings before interest and taxes divided by sales. *Total assets (msek))* is the book value of total assets in million SEK. *Firm age* is the number of years since incorporation. *Debt to assets* is total debt divided by the book value of total assets.

Table 2: The Swedish trucking sector over time and by groups

	Number of trucks owned by firm:											
	All firms			<10			10–49			≥50		
	2007	2020	Diff	2007	2020	Diff	2007	2020	Diff	2007	2020	Diff
Panel A: Counts and sums by truck, sales and CO_2 emissions												
Sales (bsek)	76	93	21%	35	32	-8%	30	36	22%	12	24	108%
Market share	-	-	-	46%	35%	-11%	39%	39%	0%	15%	26%	11%
Nr of Trucks	31,650	38,791	23%	14,812	14,329	-3%	11,638	16,047	38%	5,200	8,415	62%
Potential TW (bil. km-ton)	35,100	37,400	7%	16,600	13,400	-19%	12,800	16,000	25%	5,660	8,060	42%
Fuel cost (bsek)	7.25	7.92	9%	3.46	2.80	-19%	2.63	3.36	28%	1.16	1.76	51%
Nr of firms	6,200	6,101	-2%	5,498	5,155	-6%	648	863	33%	54	83	54%
Nr of employees	47,131	53,772	14%	22,391	18,183	-19%	17,280	21,572	25%	7,460	14,017	88%
Total CO_2 emissions	1,808	1,705	-6%	853	595	-30%	661	728	10%	294	382	30%
VKT (mil. km)	2,510	2,490	-1%	1,160	849	-27%	934	107	15%	422	576	36%
Panel B: Ratios by truck, sales and CO_2 emissions												
Sales (msek) per truck	2.4	2.4	-1%	2.4	2.3	-5%	2.6	2.3	-11%	2.2	2.8	28%
Sales (msek) to VKT	30.44	37.19	19%	30.26	38.16	26%	31.80	33.93	7%	27.25	41.49	52%
Fuel cost to sales	0.1055	0.0855	-19%	0.1094	0.0863	-21%	0.0981	0.0925	-6%	0.1119	0.0737	-34%
CO_2 emissions to sales	0.0237	0.0184	-22%	0.0243	0.0184	-24%	0.0223	0.0201	-10%	0.0255	0.0160	-37%
CO_2 emission per truck	0.0571	0.0440	-23%	0.0576	0.0415	-28%	0.0568	0.0454	-20%	0.0565	0.0454	-20%
VKT per truck	79,305	64,190	-19%	78,315	59,250	-24%	80,254	66,679	-17%	81,154	68,449	-16%
EBIT-to-Sales	0.0549	0.0549	0%	0.0659	0.0678	3%	0.0493	0.0522	6%	0.0353	0.0417	18%
Panel C: Firm financing characteristics												
Bankruptcy	0.0029	0.0034	0.0005	0.0031	0.0039	0.0008	0.0015	0.0012	-0.0004	0.0000	0.0000	0.0000
Average credit score	3.854	3.989	0.135	3.897	4.034	0.138	3.649	3.803	0.154	3.604	3.889	0.285
Debt to assets	0.623	0.583	-0.040	0.602	0.553	-0.049	0.648	0.610	-0.038	0.648	0.604	-0.044
Dividend to assets	0.018	0.023	0.005	0.018	0.019	0.002	0.019	0.019	0.000	0.019	0.037	0.018
Average firm age	16.7	20.4	3.638	15.6	18.4	2.887	24.8	29.3	4.463	40.5	48.1	7.571

Table 2 reports summary statistics of the key truck (panel A) and firm (panel B) level variables used in this study. The truck sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. The firm sample comprises firms with at least one heavy truck in the freight transport by road sector (NACE 4941) during 2007–2020. Prices are expressed in constant 2020 Swedish Krona (SEK). Values in columns 1-3 are for all heavy trucks and firms, for trucks and firms with under 10 trucks in their trucks fleet (columns 4–6), for trucks and firms with 10–49 trucks in their trucks fleet (columns 7–9), and for trucks and firms with 50 or more trucks in their trucks fleet (columns 10–12). For each segment we report the value in the first and final year of the sample period and the difference between the two. Panel A and B report truck and efficiency characteristics across firms. *Market share* is the share of *Sales (bsek)* for each group of firms. *Potential TW* is the potential transport work expressed as the product between payload (total minus curb weight) and VKT. See Table 1 for other variable descriptions. Panel C reports financing characteristics. *Bankrupcty* is the share of bankruptcy out of all firms in the group. *Averge credit score* is the average credit rating (from *Upplysningscentralen, UC*, on a scale from 1 (worst) to 5 (best)) during 2007–2017. *Dividend to assets* is the total cash dividend divided by the book value of total assets. *Average firm age* is the average number of years since incorporation.

Table 3: Vehicle fleet characteristics by groups

	Number of trucks owned by firm:											
	All firms			<10			10–49			≥50		
	2007	2020	Diff	2007	2020	Diff	2007	2020	Diff	2007	2020	Diff
Panel A: Age of vehicles												
P10	16	15	-1	17	18	1	14	15	1	12	14	2
Median	5	5	0	5	5	0	5	5	0	5	5	0
P90	0	1	1	0	1	1	0	1	1	0	1	1
Panel B: Weight of vehicles												
P10	16	18	2	16	19	3	16	18	2	15	16	1
Median	26	27	1	27	28	1	26	27	1	26	27	1
P90	29	33	4	30	35	5	29	32	4	27	29	2
Panel C: Fraction of vehicles not in use and leased												
Share de-registered	0.015	0.014	0.000	0.012	0.012	0.001	0.014	0.012	-0.002	0.025	0.021	-0.004
Sh. temporarily canceled	0.087	0.129	0.042	0.094	0.144	0.050	0.089	0.123	0.034	0.066	0.115	0.049
Total not in use	0.102	0.143	0.041	0.106	0.156	0.051	0.103	0.136	0.033	0.091	0.136	0.045
Share leased (ends 2017)	0.065	0.118	0.052	0.033	0.084	0.051	0.080	0.125	0.045	0.126	0.162	0.036
Panel D: Fraction of trucks by weight class												
<10 tons	0.028	0.016	-0.012	0.036	0.022	-0.015	0.023	0.013	-0.010	0.014	0.011	-0.004
10 – 19 tons	0.221	0.161	-0.061	0.158	0.108	-0.050	0.255	0.162	-0.093	0.323	0.246	-0.077
20 – 26 tons	0.301	0.129	-0.172	0.284	0.111	-0.172	0.316	0.134	-0.181	0.319	0.149	-0.170
27 – 28 tons	0.313	0.429	0.117	0.313	0.373	0.061	0.312	0.455	0.143	0.316	0.475	0.159
≥29 tons	0.137	0.265	0.128	0.209	0.386	0.177	0.094	0.235	0.141	0.028	0.119	0.091
Panel E: Fraction of vehicle kilometers traveled (VKT) by weight class												
<10 tons	0.009	0.005	-0.004	0.012	0.006	-0.006	0.008	0.004	-0.004	0.004	0.003	-0.001
10 – 19 tons	0.151	0.093	-0.058	0.099	0.059	-0.040	0.185	0.098	-0.087	0.215	0.134	-0.081
20 – 26 tons	0.296	0.097	-0.199	0.269	0.069	-0.201	0.313	0.104	-0.210	0.329	0.124	-0.205
27 – 28 tons	0.386	0.527	0.142	0.367	0.445	0.078	0.392	0.541	0.149	0.424	0.620	0.196
≥29 tons	0.159	0.278	0.120	0.253	0.421	0.168	0.101	0.253	0.152	0.028	0.119	0.091

Table 3 reports summary statistics of truck fleet characteristics. Values in columns 1-3 are for all heavy trucks and firms, for trucks and firms with under 10 trucks in their trucks fleet (columns 4–6), for trucks and firms with 10–49 trucks in their trucks fleet (columns 7–9), and for trucks and firms with 50 or more trucks in their trucks fleet (columns 10–12). For each segment we report the value in the first and final year of the sample period and the difference between the two. Panel A reports statistics on the vehicle age (year minus vintage). Panel B reports statistics on total weight (in tons) of vehicles. Panel C reports statistics on the share of de-registered, share of temporarily canceled, share total not in use, and share of trucks that are leased (variable ends in 2017) out of total number of heavy trucks. Panel D (E) reports statistics on number of trucks (VKT) distributed across five weight classes.

Table 4: Tax inclusive fuel cost and vehicle kilometers traveled

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(FC)_{v,t}$	-1.083***	-0.872***	-0.632***	-0.629***	-0.344**	-0.501***	-0.482***
	(0.026)	(0.027)	(0.026)	(0.026)	(0.164)	(0.183)	(0.182)
$\ln(\text{Sales per truck})_{i,t}$				0.247***	0.213***		
				(0.018)	(0.013)		
$\ln(FC)_{v,t}$ x *High fuel cost to sales*							-0.072***
							(0.019)
Vehicle fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes	Yes	No	No
Year fixed effects	No	No	No	No	Yes	No	No
Year x firm fixed effects	No	No	No	No	No	Yes	Yes
Observations	399,632	398,884	398,272	396,625	396,625	364,674	364,674
Adjusted R^2	0.136	0.617	0.645	0.655	0.680	0.696	0.696

Table 4 reports OLS estimates of Equation 1. $ln(VKT)_{v,t}$ is the dependent variable. VKT is the vehicle kilometer traveled by vehicle v in year t. FC is fuel cost per transport work (in KM–Ton) for vehicle v in year t. The sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. *High fuel cost to sales* is an indicator variable taking on the value one if the vehicle is owned by a firm (i) above the median in fuel cost to sales in year t. Regressions in columns 2–7 include vehicle fixed effects. Regressions in columns 3–5 include firm fixed effects, column 5 includes year fixed effects and regressions in columns 6–7 and include firm-year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: Tax inclusive fuel cost and vehicle kilometers traveled: Fleet size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Nr of trucks owned by firm:								
	<10	<10	<10	10–49	10–49	10–49	≥50	≥50	≥50
$\ln(FC)_{v,t}$	-0.490***	0.118	0.124	-0.541***	-0.383	-0.357	-0.606***	-1.501***	-1.470***
	(0.031)	(0.217)	(0.216)	(0.044)	(0.277)	(0.273)	(0.088)	(0.452)	(0.453)
$\ln(\text{Sales per truck})_{i,t}$	0.305***			0.215***			-0.063		
	(0.014)			(0.051)			(0.089)		
$\ln(FC)_{v,t}$			-0.025			-0.082***			-0.125***
x *High fuel cost to sales*			(0.040)			(0.029)			(0.047)
Vehicle fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Year x firm fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	157,949	125,728	125,728	149,246	149,182	149,182	79,250	79,248	79,248
Adjusted R^2	0.686	0.720	0.720	0.629	0.677	0.677	0.699	0.731	0.731

Table 5 reports OLS estimates of Equation 1. $ln(VKT)_{v,t}$ is the dependent variable. *VKT* is the vehicle kilometers traveled by vehicle v in year t. *FC* is fuel cost per transport work (in KM–Ton) for vehicle v in year t. The sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 1–3 include trucks owned by firms with a truck fleet of less than 10 trucks, columns 4–6 include trucks owned by firms with a truck fleet of 10 to 49 trucks, and columns 7–9 include trucks owned by firms with a truck fleet of 50 or more trucks. *High fuel cost to sales* is an indicator variable taking on the value one if the vehicle is owned by a firm (i) above the median in fuel cost to sales in year t. All regressions include vehicle fixed effects. Regressions in columns 1–2; 4–6; and 7–8 include firm fixed effects and regressions in columns 2–3; 5–6; and 8–9 include firm-year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6: Tax inclusive fuel cost and vehicle kilometers traveled: Trucks of 2010 vintage or later

	(1)	(2)	(3)	(4)
	Nr of trucks owned by firm:			
	All	**<10**	**10–49**	**≥50**
$\ln(FC)_{(v,t)}$	-0.557***	0.069	-0.422	-1.674***
	(0.182)	(0.217)	(0.280)	(0.449)
$\ln(FC)_{(v,t)}$	0.170**	0.246*	0.120	0.321**
x *(Vintage > 2009)*	(0.078)	(0.143)	(0.121)	(0.134)
Vehicle fixed effects	Yes	Yes	Yes	Yes
Year x firm fixed effects	Yes	Yes	Yes	Yes
Observations	365,993	126,402	149,563	79,312
Adjusted R^2	0.696	0.720	0.676	0.731

Table 6 reports OLS estimates of Equation 1. $ln(VKT)_{v,t}$ is the dependent variable. VKT is the vehicle kilometers traveled by vehicle v in year t. FC is fuel cost per transport work (in KM–Ton) for vehicle v in year t. The sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 1 and 4 include trucks owned by firms with a truck fleet of less than 10 trucks, columns 2 and 5 include trucks owned by firms with a truck fleet of 10 to 49 trucks, and columns 3 and 6 include trucks owned by firms with a truck fleet of 50 or more trucks. *(Vintage > 2009)* is an indicator variable taking on the value one if the vehicle's vintage is 2010 or later and zero otherwise. All regressions include vehicle and year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7: Tax inclusive fuel cost and CO_2 emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nr of trucks owned by firm:							
	All	All	<10	<10	10–49	10–49	≥50	≥50
$\ln(FC)_{v,t}$	-0.643***	-0.624***	0.047	0.052	-0.527*	-0.499*	-1.777***	-1.749***
	(0.203)	(0.202)	(0.223)	(0.223)	(0.296)	(0.292)	(0.508)	(0.510)
$\ln(FC)_{v,t}$		-0.072***		-0.027		-0.087***		-0.116**
x *High fuel cost to sales*		(0.019)		(0.040)		(0.029)		(0.047)
Vehicle fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	365,993	365,993	126,402	126,402	149,563	149,563	79,312	79,312
Adjusted R^2	0.723	0.725	0.743	0.743	0.704	0.704	0.769	0.769

Table 7 reports OLS estimates of Equation 1. *ln(CO_2 emissions)*$_{v,t}$ is the dependent variable. *CO_2 emissions* is the total CO_2 emissions by vehicle v in year t. *FC* is fuel cost per transport work (in KM–Ton) for vehicle v in year t. The sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) during 2007–2020. Column 3–4 include trucks owned by firms with a truck fleet of less than 10 trucks, columns 5–6 includes trucks owned by firms with a truck fleet of 10 to 49 trucks, and columns 7–8 includes trucks owned by firms with a truck fleet of 50 or more trucks. *High fuel cost to sales* is an indicator variable taking on the value one if the vehicle is owned by a firm (i) above the median in fuel cost to sales in year t. All regressions include vehicle and firm-year fixed effects. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8: Tax inclusive fuel cost and firm level adjustments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			ln(VKT)			ln(CO_2)	
$\ln(FC)_{i,t}$	-1.156***	-0.710***	-0.482***	-0.445***	-0.429***	-0.964***	-0.654***
	(0.056)	(0.051)	(0.067)	(0.076)	(0.089)	(0.051)	(0.091)
$\ln(FC)_{i,t-1}$			-0.251***	-0.233***	-0.286***		-0.292***
			(0.053)	(0.053)	(0.060)		(0.060)
$\ln(FC)_{i,t-2}$				-0.065	-0.079		-0.092
				(0.051)	(0.074)		(0.075)
$\ln(FC)_{i,t-3}$					0.004		-0.002
					(0.051)		(0.052)
$\ln(\text{total assets})_{i,t}$		0.586***	0.568***	0.553***	0.544***	0.575***	0.528***
		(0.011)	(0.012)	(0.014)	(0.015)	(0.011)	(0.015)
$\ln(\text{firm age})_{i,t}$		0.229***	0.168***	0.189***	0.201***	0.228***	0.196***
		(0.015)	(0.020)	(0.027)	(0.036)	(0.015)	(0.036)
$\text{Debt-to-assets}_{i,t}$		0.154***	0.148***	0.144***	0.133***	0.148***	0.125***
		(0.025)	(0.026)	(0.028)	(0.032)	(0.025)	(0.032)
$\sum\ln(FC)$			-0.733	-0.743	-0.790		-1.040
			(0.000)	(0.000)	(0.000)		(0.000)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	83,094	82,355	70,832	60,772	51,921	82,355	51,921
Adjusted R^2	0.765	0.810	0.828	0.834	0.842	0.812	0.842

Table 8 reports OLS estimates of Equation 2. $ln(VKT)_{i,t}$ is the dependent variable in columns 1–5, where *VKT* is the vehicle kilometers traveled by firm i in year t, and $ln(CO_2\ emissions)_{i,t}$ is the dependent variable in columns 6–7, where CO_2 *emissions* is the total CO_2 emissions by firm i in year t. *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. All regressions include firm and year fixed effects. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 9: Tax inclusive fuel cost and firm level adjustments: Fleet size

	(1)	(2)	(3)	(4)	(5)	(6)
	Nr of trucks owned by firm:					
	<10	**<10**	**10–49**	**10–49**	**≥50**	**≥50**
$\ln(FC)_{i,t}$	-0.701***	-0.366***	-0.595**	-0.890**	-0.704***	-0.765***
	(0.052)	(0.091)	(0.275)	(0.427)	(0.182)	(0.251)
$\ln(FC)_{i,t-1}$		-0.330***		-0.076		-0.136
		(0.063)		(0.065)		(0.178)
$\ln(FC)_{i,t-2}$		-0.046		0.157		-0.439**
		(0.065)		(0.104)		(0.184)
$\ln(FC)_{i,t-3}$		-0.019		-0.119		-0.012
		(0.045)		(0.076)		(0.137)
$\ln(\text{total assets})_{i,t}$	0.514***	0.478***	0.532***	0.501***	0.042	0.044
	(0.012)	(0.016)	(0.029)	(0.038)	(0.061)	(0.068)
$\ln(\text{firm age})_{i,t}$	0.250***	0.227***	0.221***	0.186***	-0.010	0.069
	(0.016)	(0.040)	(0.043)	(0.066)	(0.207)	(0.081)
$\text{Debt to assets}_{i,t}$	0.101***	0.078**	0.278***	0.220***	0.181	0.171*
	(0.026)	(0.032)	(0.067)	(0.064)	(0.123)	(0.099)
$\sum\ln(FC)$		-0.761		-0.928		-1.352
		(0.000)		(0.019)		(0.001)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,856	51,921	10,088	7,130	985	711
Adjusted R^2	0.720	0.842	0.885	0.902	0.905	0.924

Table 9 reports OLS estimates of Equation 2. $ln(VKT)_{i,t}$ is the dependent variable, where VKT is the vehicle kilometers traveled by firm i in year t. FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 1–2 include firms with a truck fleet of less than 10 trucks, columns 3–4 include firms with a truck fleet of 10 to 49 trucks, and columns 5–6 include firms with a truck fleet of 50 or more trucks. All regressions include firm and year fixed effects. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 10: Tax inclusive fuel cost and firm level adjustments: Disentangling price and policy effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	**All**	**<10**	**<10**	**10–49**	**10–49**	**≥50**	**≥50**
$\ln(\text{FC–Policy})_{i,t}$	-0.756***	-0.400***	-0.586***	-0.138	-0.448**	-0.735**	-0.831***	-0.875***
	(0.107)	(0.126)	(0.153)	(0.146)	(0.226)	(0.339)	(0.225)	(0.245)
$\ln(\text{FC–Policy})_{i,t-1}$		-0.326***		-0.429***		0.026		-0.286*
		(0.074)		(0.101)		(0.119)		(0.168)
$\ln(\text{FC–Policy})_{i,t-2}$		-0.208*		-0.290		0.152		0.254
		(0.115)		(0.181)		(0.161)		(0.161)
$\ln(\text{FC–Policy})_{i,t-3}$		-0.047		0.210		-0.129		-0.163
		(0.150)		(0.257)		(0.091)		(0.171)
$\ln(\text{FC–Price})_{i,t}$	0.043	-0.028	-0.114	-0.225	-0.175	-0.209	-0.282***	-0.385***
	(0.104)	(0.120)	(0.154)	(0.153)	(0.125)	(0.173)	(0.084)	(0.130)
$\ln(\text{FC–Price})_{i,t-1}$		0.033		0.093		-0.093		-0.030
		(0.075)		(0.108)		(0.110)		(0.108)
$\ln(\text{FC–Price})_{i,t-2}$		0.123		0.245		0.016		-0.305***
		(0.109)		(0.184)		(0.115)		(0.115)
$\ln(\text{FC–Price})_{i,t-3}$		-0.047		-0.227		0.006		0.053
		(0.150)		(0.258)		(0.072)		(0.074)
$\sum\ln(\text{FC–Policy})$		-0.981		-0.647		-0.686		-1.070
		(0.000)		(0.003)		(0.030)		(0.007)
$\sum\ln(\text{FC–Price})$		0.081		-0.114		-0.280		-0.667
		(0.159)		(0.601)		(0.256)		(0.002)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,340	51,917	70,841	43,778	10,088	7,130	985	711
Adjusted R^2	0.810	0.842	0.720	0.757	0.885	0.903	0.910	0.929

Table 10 reports OLS estimates of Equation 2. $ln(VKT)_{i,t}$ is the dependent variable, where VKT is the vehicle kilometers traveled by firm i in year t. *FC–Policy* is fuel cost per transport work (in KM–Ton) due to the policy component of the tax inclusive fuel cost for firm i in year t. *FC–Price* is fuel cost per transport work (in KM–Ton) due to the fossil diesel price component of the tax inclusive fuel cost for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 3–4 include firms with a truck fleet of less than 10 trucks, columns 5–6 include firms with a truck fleet of 10 to 49 trucks, and columns 7–8 include firms with a truck fleet of 50 or more trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(\text{FC–Policy})$ and $\sum\ln(\text{FC–Price})$ respectively present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 11: Tax inclusive fuel cost and firm level adjustments: Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	**All**	**<10**	**<10**	**10–49**	**10–49**	**≥50**	**≥50**
$\ln(FC)_{i,t}$	0.448***	0.347***	0.452***	0.300***	0.395**	0.715***	0.650***	0.577*
	(0.041)	(0.071)	(0.043)	(0.074)	(0.161)	(0.274)	(0.211)	(0.295)
$\ln(FC)_{i,t-1}$		0.163***		0.206***		-0.286**		0.124
		(0.051)		(0.053)		(0.108)		(0.225)
$\ln(FC)_{i,t-2}$		-0.036		-0.055		-0.138		0.317
		(0.042)		(0.042)		(0.084)		(0.202)
$\ln(FC)_{i,t-3}$		-0.048		-0.037		0.056		-0.027
		(0.039)		(0.039)		(0.070)		(0.177)
$\sum\ln(FC)$		0.426		0.414		0.347		0.991
		(0.000)		(0.000)		(0.098)		(0.061)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,349	51,919	70,850	43,780	10,088	7,130	985	711
Adjusted R^2	0.590	0.618	0.580	0.604	0.848	0.856	0.916	0.927

Table 11 reports OLS estimates of Equation 2. *ln(Sales to VKT)*$_{i,t}$ is the dependent variable, where *Sales per VKT* is PPI adjusted sales per VKT by firm i in year t. *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 3–4 include firms with a truck fleet of less than 10 trucks, columns 5–6 include firms with a truck fleet of 10 to 49 trucks, and columns 7–8 include firms with a truck fleet of 50 or more trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 12: Tax inclusive fuel cost and firm level adjustments: Profitability and margins

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	**All**	**<10**	**<10**	**10–49**	**10–49**	**≥50**	**≥50**
$\ln(FC)_{i,t}$	-0.023*	-0.013	-0.024*	-0.021	-0.003	0.055	0.047	0.063
	(0.013)	(0.018)	(0.014)	(0.019)	(0.040)	(0.079)	(0.029)	(0.044)
$\ln(FC)_{i,t-1}$		0.003		0.007		-0.237		0.045
		(0.015)		(0.016)		(0.160)		(0.042)
$\ln(FC)_{i,t-2}$		-0.022		-0.006		0.048		0.039
		(0.025)		(0.021)		(0.072)		(0.025)
$\ln(FC)_{i,t-3}$		0.019		0.008		0.040		0.054**
		(0.017)		(0.016)		(0.034)		(0.026)
$\sum\ln(FC)$		-0.014		-0.012		-0.094		0.201
		(0.583)		(0.656)		(0.278)		(0.005)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,101	51,919	70,617	43,698	10,075	7,127	981	710
Adjusted R^2	0.349	0.393	0.355	0.402	0.530	0.410	0.637	0.597

Table 12 reports OLS estimates of Equation 2. *EBIT to sales*$_{i,t}$ is the dependent variable, where *EBIT to Sales* is earnings before interest and taxes divided sales for firm i in year t. *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 3–4 include firms with a truck fleet of less than 10 trucks, columns 5–6 include firms with a truck fleet of 10 to 49 trucks, and columns 7–8 include firms with a truck fleet of 50 or more trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 13: Tax inclusive fuel cost and firm level adjustments: VKT by weight class

	(1)	(2)	(3)	(4)
	<20 ton	**20–26 ton**	**27–28 ton**	**>28 ton**
		Panel A: All firms		
∑ln(FC)	1.602	1.223	-0.746	-0.985
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,685	17,939	30,870	25,950
Adjusted R^2	0.866	0.692	0.657	0.757
	Panel B: Firms with less than 10 trucks			
∑ln(FC)	1.122	1.169	-0.581	-0.732
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,129	11,673	23,282	21,334
Adjusted R^2	0.816	0.671	0.626	0.654
	Panel C: Firms with 10–49 trucks			
∑ln(FC)	1.649	1.774	-1.593	-2.398
	(0.008)	(0.003)	(0.001)	(0.000)
Observations	1,156	5,330	6,607	4,026
Adjusted R^2	0.860	0.677	0.737	0.765
	Panel D: Firms with 50 or more trucks			
∑ln(FC)	5.052	2.008	-1.581	-2.535
	(0.141)	(0.092)	(0.057)	(0.399)
Observations	350	696	704	422
Adjusted R^2	0.821	0.767	0.870	0.632

Table 13 reports reports ∑ln(FC) and the corresponding F-test based on OLS estimates of Equation 2 where $ln(VKT_{c,i,t}/VKT_{i,t})$ is the dependent variable. $VKT_{c,i,t}$ is the vehicle kilometers traveled by vehicles across four weight class groups c for firm i in year t and $VKT_{i,t}$ is the vehicle kilometers traveled for firm i in year t. See Table B.3, Table B.4, Table B.5 and Table B.6 for detailed regression results for each panel. The four weight class groups are for trucks under 20 tons (c=1); trucks 20–26 tons (c=2); trucks 27–28 tons (c=3); trucks more than 28 tons (c=4). FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Panel A include all firms. Panels B to D include firms with a truck fleet with: less than 10 trucks; a truck fleet of 10 to 49 trucks; a truck fleet of 50 or more trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. The standard errors are clustered at the firm level.

Table 14: Tax inclusive fuel cost and firm level adjustments: Type of truck company

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		<10		10–49		≥50	
	All	Not all	All	Not all	All	Not all	All	Not all
	(LTL)	(TL)	(LTL)	(TL)	(LTL)	(TL)	(LTL)	(TL)
Panel A: VKT								
∑ln(FC)	-0.964	-0.742	-0.951	-0.711	-1.152	-0.608	-1.660	-0.821
	(0.000)	(0.000)	(0.000)	(0.000)	(0.057)	(0.051)	(0.000)	(0.245)
Observations	8,768	43,153	4,814	38,968	3,309	3,821	540	171
Adjusted R^2	0.885	0.816	0.751	0.755	0.900	0.904	0.931	0.901
Panel B: Sales per VKT								
∑ln(FC)	0.668	0.361	0.747	0.339	0.533	0.134	1.428	-0.148
	(0.000)	(0.000)	(0.000)	(0.000)	(0.076)	(0.527)	(0.029)	(0.827)
Observations	8,768	43,151	4,814	38,966	3,309	3,821	540	171
Adjusted R^2	0.717	0.601	0.673	0.595	0.872	0.831	0.922	0.951
Panel C: EBIT to sales								
∑ln(FC)	0.004	-0.017	0.026	-0.019	-0.150	-0.018	0.229	0.065
	(0.921)	(0.554)	(0.498)	(0.528)	(0.263)	(0.832)	(0.005)	(0.672)
Observations	8,753	43,079	4,805	38,893	3,306	3,821	539	171
Adjusted R^2	0.284	0.405	0.314	0.410	0.406	0.423	0.540	0.746

Table 14 reports reports ∑ln(FC) and the corresponding F-test based on OLS estimates of Equation 2 where $ln(VKT)_{i,t}$ is the dependent variable in panel A, where *VKT* is the vehicle kilometers traveled by firm i in year t, $ln(Sales\ per\ VKT)_{i,t}$ is the dependent variable in panel B, *Sales per VKT* is PPI adjusted sales per VKT by firm i in year t, and $EBIT\ to\ sales_{i,t}$ is the dependent variable in panel C, where *EBIT to Sales* is earnings before interest and taxes divided sales for firm i in year t. *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. See Table B.7, Table B.8 and Table B.9 for detailed regression results for each panel. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. Columns 1–2 include all firms. Columns 3–4 include firms with a truck fleet of less than 10 trucks, columns 5–6 include firms with a truck fleet of 10 to 49 trucks, and columns 7–8 include firms with a truck fleet of 50 or more trucks. Odd (even) numbered columns include firms with trucks in all four weight classes and are more likely to be less than truck load (LTL) companies (that do not have trucks in all weight classes and are more likely to be truck load (TL) companies). The four weight class groups are for trucks under 20 tons; trucks 20–26 tons; trucks 27–28 tons; trucks more than 28 tons. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. The standard errors are clustered at the firm level.

A Appendix

A.1 Description of datasets

We construct our sample data using data from multiple sources. The data is linked via a set of unique identifiers for firms, workplaces and vehicles. Due to permission and privacy reasons, all real information related to micro-objects are removed. The data is anonymized and provided through Statistics Sweden (SCB). Our study is based on trucks owned by Swedish limited liability companies (Swedish: Aktiebolag). To model vehicle level emissions, we obtain data on vehicle specific emission factors from the Swedish Transport Administration (Swedish: Trafikverket). These emission factors are then merged with vehicle level micro data on driven distances to obtain vehicle level emissions. Subsequently, this data is integrated with firm level financial data and data on fuel price and taxation. Below, we describe the data work in detail.

Firm-level financial data: We source firm level financial data from the Bisnode Serrano database. It includes comprehensive data of balance sheet and income statement, bankruptcy records, as well as NACE Rev.2 industrial classifications from 1998 to 2020. All accounting variables are converted into the respective calendar year. The Swedish Companies Registration Office (SCRO) (Swedish: Bolagsverket) assigns each Swedish limited liability firm a unique and permanent identifier entitled organization number. We link our datasets using the unique identifier.

Emission factors: We calculate vehicle specific emission factors using road transport emission data from the Swedish Transport Administration. This dataset is utilized for calculating Sweden's green house gas emissions reported to the Intergovernmental Panel on Climate Change (IPCC), which includes extensive information about the vehicle types, driven distances, driving patterns, fuel types, total CO_2 emissions, subsegments, European Emissions Classes, as well as weight groups for heavy trucks and buses at yearly level. This dataset contains around 830 different types of vehicles from 2019 to 2045. We generate an unique emission factor (EF) for each subsegment by scaling emissions (gram) based on the corresponding driven distance (km) which serves as a weighing.[23] For buses and heavy trucks with a gross weight more than 3.5 tons, the emission factor also depends on vehicles' weight. We have a total of five separate weight classes for heavy trucks: 3.5 to 10 tons; 10 to 20 tons, 20 to 27 tons, 27 to 29 tons and over 29 tons. The fuel factor, which represents the amount of CO_2 equivalent emitted per unit of fuel during delivery, is provided by the Swedish Energy Agency (Swedish: Energimyndigheten). We determine the fuel consumption per km by dividing emission factor by the fuel factor.[24] We calculate the emissions from fossil fuels and biofuels per km utilizing the proportion of fossil and non-fossil components in total CO_2 emissions. This dataset is provided by Trafikverket, ranging from 1990 to 2050.

Vehicle-level data: We obtain registration data for vehicles owned by corporations at vehicle, firm and year level during 2007 to 2020 from Transport Agency (Swedish: Transportstyrelsen) and Road traffic registry (Swedish: Vägtrafikregistret). Each vehicle owns a distinct identifier which enables us to track it across time. The dataset contains information on the status of vehicles, i.e., whether it is active, unregistered, or temporarily unused; fuel type; vintage; curb weight and gross

[23] The calculation of emission factors is described in Consortium (2022).

[24] The measurement of fuel consumption varies depending on the type of fuel utilized. For liquid fuels , which include gasoline, diesel, E85 and others, are represented as liters per km. For natural gas fuels like CNG and LNG, it is measured in kg per km. And for electrical or hybrid vehicles, it is in (or partially in) kWh per km.

weight; towing capability; driven distance and manufacturer. We calculate (potential) transport work by multiplying the difference between total weight and curb weight (i.e. payload capacity) with VKT. Due to the lack of emission standards in the dataset, we classify vehicles' emission classes based on their ages in accordance with the implementation date of each EU emission standard. The emission classes in our sample dataset range from Euro I to Euro VI, with a separate category for electric vehicles.[25] We also own the dummy identifier for leasing vehicles separated by vehicle types, which is applicable from 2007 to 2017. We utilize this variable to generate the number of yearly leased heavy trucks within firms.

Fuel prices and taxes: We collect historical data of excise tax rates including both environmental and CO_2 tax from the Swedish Tax Agency (Swedish: Skatteverket) since 1950s. We acquire annual average wholesale market price for regular fuels including gasoline, diesel and E85 from Drivkraft Sverige. The fuel price data is from 2007 to 2022. We get international fuel prices from the EU's Weekly Oil Bulletin.[26]

***Sample dataset*:** We integrate total emission factors, fossil and non-fossil emission factors, fuel consumption, fuel costs and taxes (all figures are scaled by km) with micro-level vehicles' registration dataset. The datasets are linked by vehicle types, fuel types, EU emission classes, and weight groups for heavy trucks. We estimate the payload capacity for trucks by subtracting the curb weight from the gross weight, then multiplying it by the distance driven. This data is then merged with accounting variables by linking firms' organization numbers across time.

Our sample dataset is from 2007 to 2020, with heavy trucks owned by corporations in road transportation sector (NACE four-digit 4941).

A.1.1 Implicit cost

In compliance with Act (2017:1201) on the reduction of greenhouse gas emissions from certain fossil fuels (Swedish: Lag (2017:1201) om reduktion av växthusgasutsläpp från vissa fossila drivmedel Ministry of Climate and Enterprise (RSE) (2017)), fuel providers are required to blend a specific percentage of renewable energy into diesel and gasoline in order to reduce emissions. There are two common types of biofuels, namely Hydrotreated vegetable oil (HVO) and Fatty acid methyl esters (FAME). There have been a substantial increase of combined biofuels' fraction in diesel, which is from approximately 5.6% in 2006 to 33.6% in 2022. The main factor contributing to the change is the increased quantity of HVO, since the FAME content remains at around 5% across time. Figure B.6 displays the shift of the renewable energy shares in diesel over years.

In accordance with the Swedish laws, specifically the Energy Tax Act Finansdepartementet (1994a) and the Value Added Tax Act Finansdepartementet (1994b)), a rate of 25% value added tax (VAT) is applied to fuels. The VAT is levied on every component of the fuel, which contains fuel price, energy tax and CO_2 tax. We adjust market fuel price by removing VAT for further analysis.

[25] We classify vehicles into emission classes depending on their age. 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 were enforced on heavy trucks registered after October 1, 2009, while Euro VI were applied to heavy trucks registered after December 31, 2013. We place trucks that are produced from 2010 to 2013 to 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 to other emission classes that vary with vehicle types.

[26] This data can be found here: https://energy.ec.europa.eu/data-and-analysis/weekly-oil-bulletin_en

A.1.2 Firm- and group-level dataset

We have administrative dataset from 1998 to 2020. We exclusively keep the legal form "49" which represents the Swedish limited liability companies (Swedish: Aktiebolag) for further analysis. Since firms can switch industrial sectors across time, we primarily take the latest 5-digit NACE Rev.2 industrial classification codes to make it static and consistent. We combine it with vehicle registration data by linking firm identifiers and years. We generate total fuel costs, fuel tax payments, total vehicles' emissions by aggregating the figures from each truck within the firm. In 2007, the industrial sector with the most heavy trucks is 4941 (Freight transport by road), accounting for 41% of the total. We restrict our sample to the road transport industry in our study. We utilize sales, number of employees, earnings before interest and taxes (EBIT), total assets, tangible fixed assets and cash flow to measure economic scale and size of the firms. All accounting values are deflated by Consumer Price Index (CPI) and Swedish Producer Price Index (PPI) with the base year of 2020.

We build a consolidated dataset for groups within road transportation sector by integrating vehicle, firm level dataset and corporate structure data from knc file in Bisnode serrano database. Each firm identity is linked to a unique parent company identity at yearly level. In the absence of a group identifier, we replace it with the firm's organization number and consider it as an independent entity. For a stand-alone firm, the consolidated figure will be its own value; while for firms matched with corporate structure data, we aggregate figures of all subsidiaries within the same group. We also have information on age of firms and bankruptcy records from the Bisnode Serrano database, and credit rating class from the UC database. Credit risk levels are ranked from highest to lowest in a risk class that spans from 1 to 5. We take the oldest age and highest risk level among all subsidiaries as the consolidated age and risk class for the group. If at least one entity declares bankruptcy in a given year, we mark the group experiences bankruptcy.

A.1.3 Workplace dataset

We have detailed information regarding workplaces. This dataset originates from Statistics Sweden (SCB) and spans from 1990 to 2020. Each workplace has a distinctive identifier that is linked with the organization number of the firm. This dataset comprises information on personnel compensation, workforce size, workplace location represented by municipality codes, and dynamic NACE Rev.2 five-digit industrial classification for each establishment. We further categorize workplaces into three classes: core transportation, auxiliary transportation and other diverse sectors.[27] We generate total personnel expenses and number of unique workplaces by years at both firm and group level. Since auxiliary transport and diverse workplaces are typically found outside of core transportation sectors, we integrate all subsidiaries within the group when consolidating workplace-related variables rather than including only firms belonging to the road transport sector.

[27] We use NACE Rev.2 sections to classify workplaces. Sections A-C, G, I, J, L, N and Q-Z are coded as "diversification". We put NACE Rev.2 two-digit "49" and NACE Rev.2 four-digit "5320" (other postal activities) into "core transportation" group. NACE Rev.2 two-digit "52", "62", "63", "69", "70", "71" are called "auxiliary transport", and other sectors are classified under "diversification."

A.1.4 Employer-Employee dataset

We obtain personal data from the Database for Health Insurance and Labour Market Studies provided by Statistics Sweden. This dataset comprises basic information including personal occupational status, income, educational level, etc., which is from 1990 to 2021. Each employee is assigned a personal number that is associated with the organization number of the firm. We integrate personal information with our sample dataset by linking firm identifiers. The Swedish Standard Classification of Occupations (SSYK) which is implements the ILO's ISCO-08 standard(ILO, 2012) categorizes personal occupational fields. We define logistics employees as those found in the following categories: We define logistics employees as those found in the following categories and minor groups in ISCO-08, in our case SSYK2012 and the corresponding code in SSYK1996:[28]

- **2141**: Industrial and Production Engineers (including logistics engineers)
- **332**: Sales and Purchasing Agents and Brokers (including freight brokers and transportation agents)
- **333**: Business Services Agents (including logistics and distribution managers)
- **432**: Material-Recording and Transport Clerks (including warehouse clerks, freight clerks, and shipping clerks)

In order for employees to be included, we demand that they are at least 16 years old and employed by firms. We obtain the monthly salary statistic for each occupation from Statistics Sweden, and we define that the required minimum salary should exceed 70% of the average salary of workers at skill level 2. For truckers, engineers, logistic employees, clerks, the threshold is approximately 20,000 SEK at 2022 year level. For managers and mba, the threshold is approximately 30,000 SEK.

[28]For further details on categories in SSYK2012 and corresponding categories, please refer to the following URL: https://www.scb.se/contentassets/0c0089cc085a45d49c1dc83923ad933a/webb_nyckel_ssyk96_ssyk2012_20160905.xlsx

A.2 Additional Tables and Figures

Figure B.1: Fraction of biofuels blended into diesel in EU countries

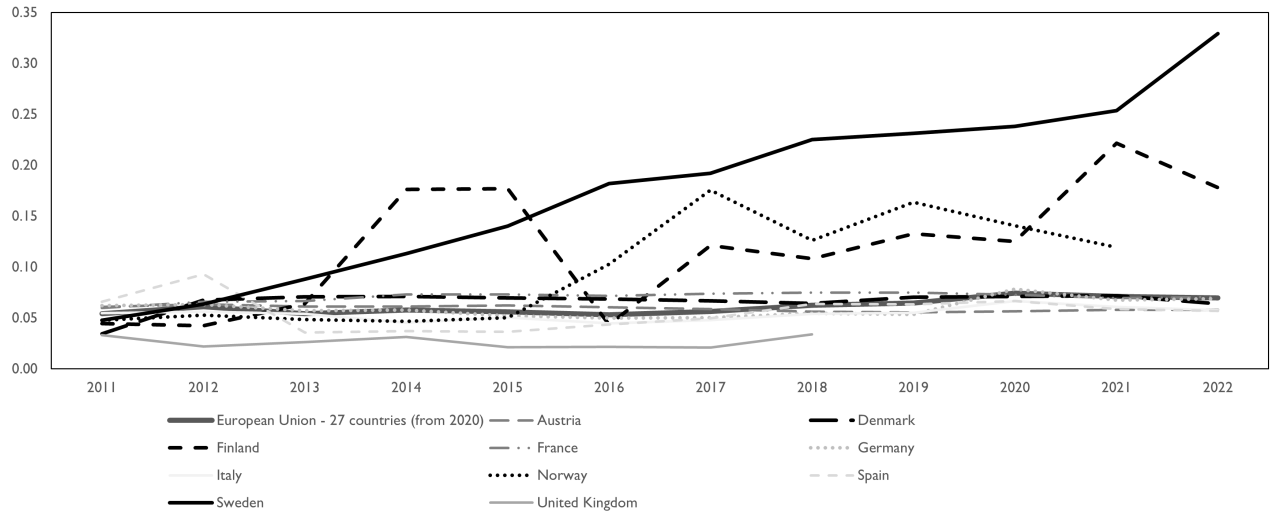


Figure B.1 displays the fraction of blended biofuels in diesel across a selection of EU countries. Source: Eurostat, Final energy consumption by type of fuel.

Figure B.2: Tax inclusive price of diesel in EU countries

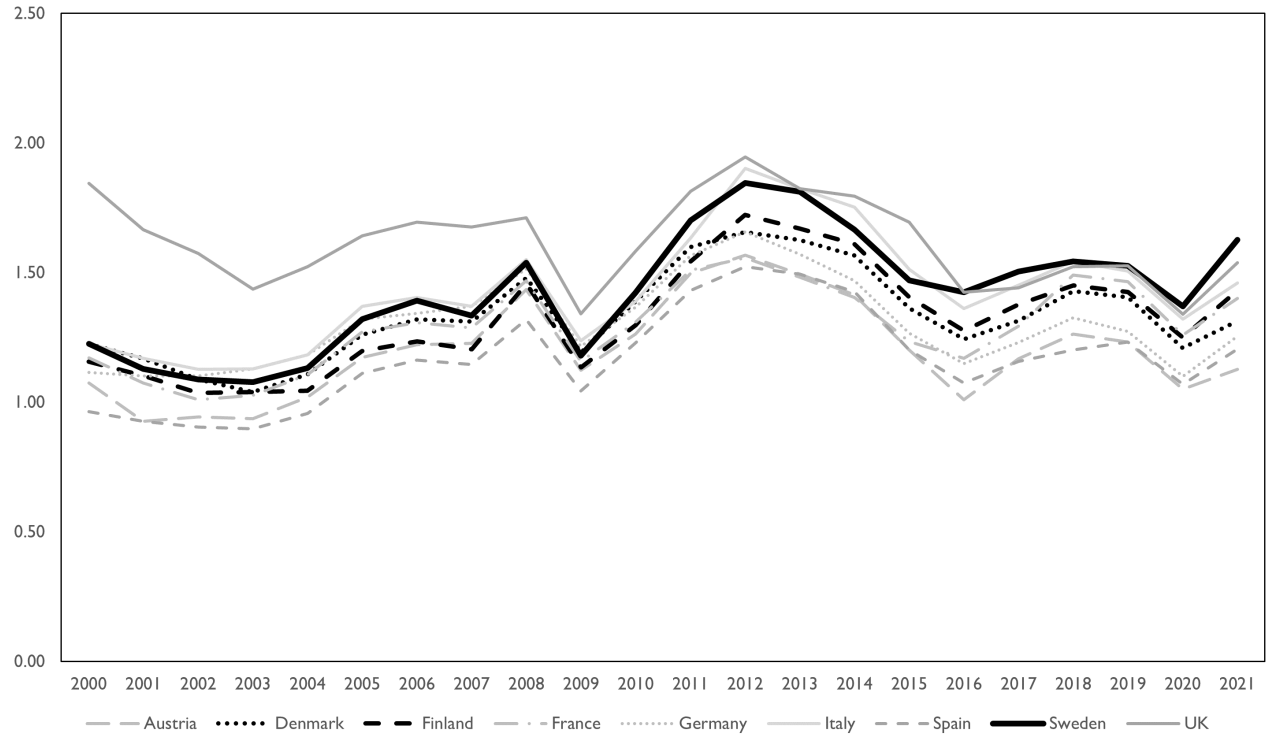


Figure B.2 displays the tax inclusive price per liter of diesel (expressed in EUR 2020) across a selection European countries. Source: Statista.

Figure B.3: Value added share of Land Transport (2007-2018)

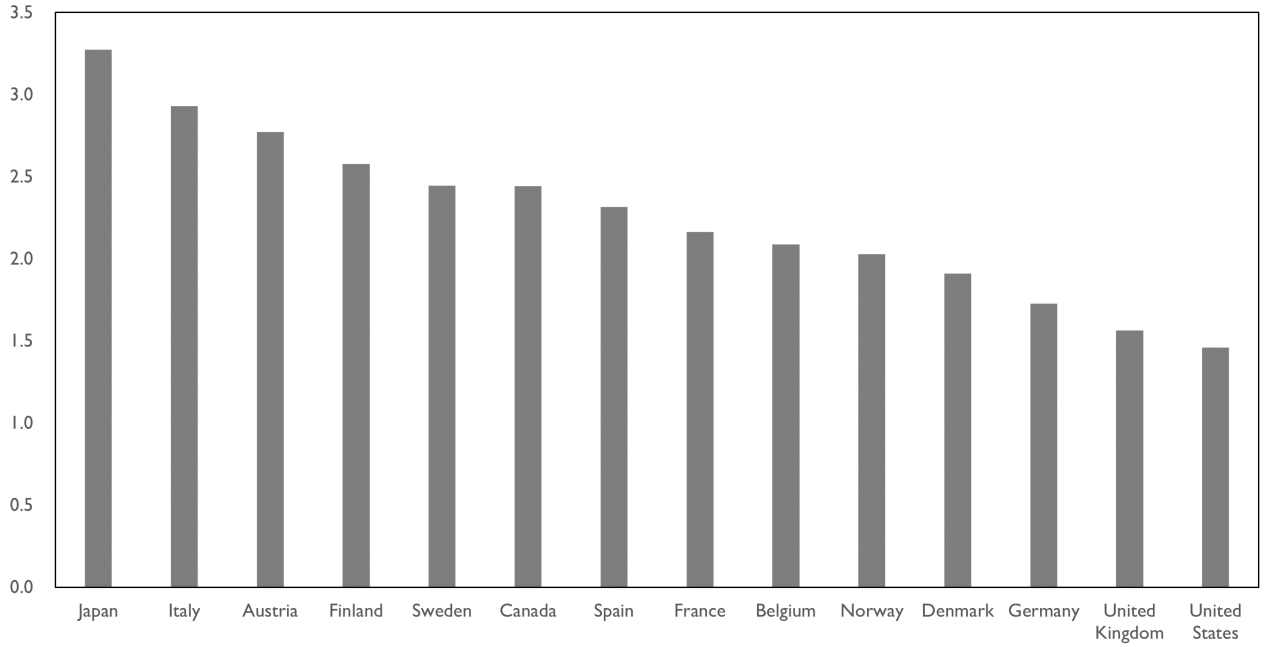


Figure B.3 displays the share of value added coming from the Land transport sector across a selection of OECD countries. Source: OECD.

Figure B.4: Transportation work in the heavy duty vehicle sector by commodity group

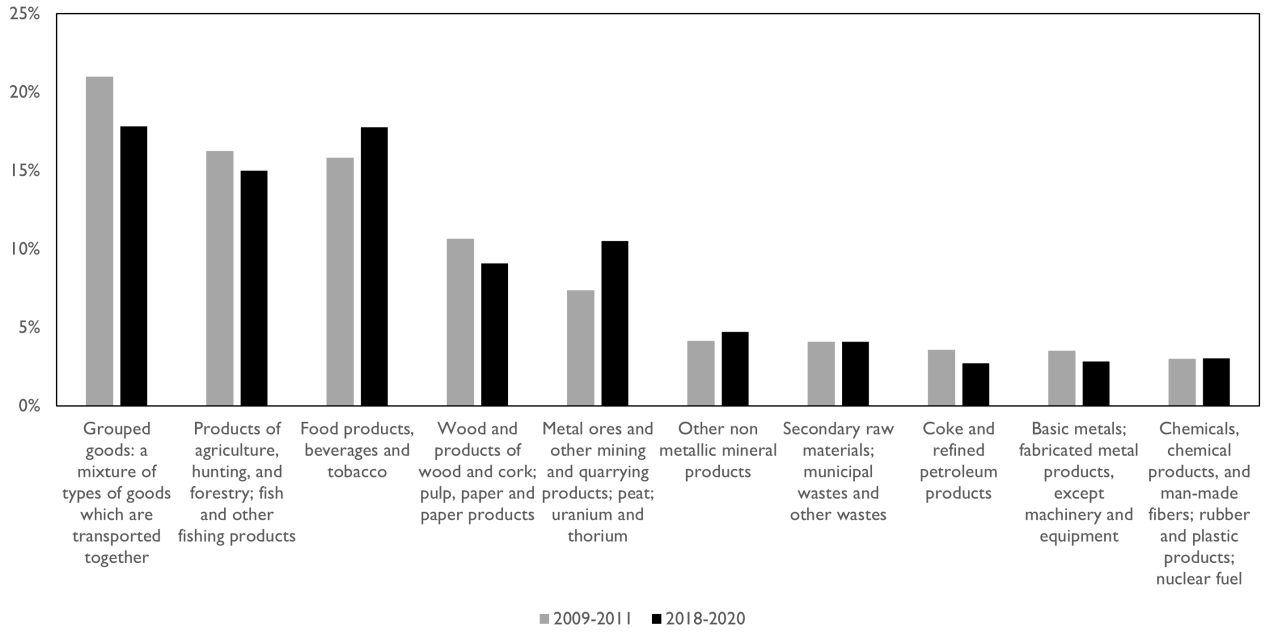
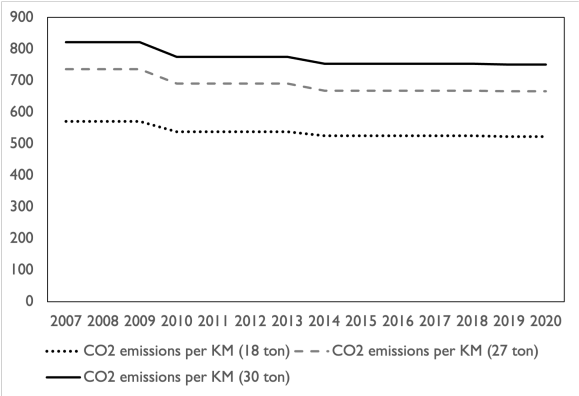


Figure B.4 displays the share of (actual transportation work for the ten most important commodity groups (NST2007) averaged over 2009–2011 (gray bar) and 2018–2020 (black bar). Source: *Lastbilsundersökningen*.

Figure B.5: Emission classes of heavy duty vehicles

(a) Emission classes



(b) Actual emissions per VKT

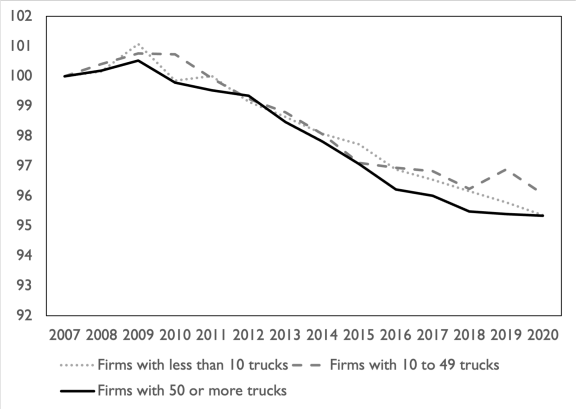
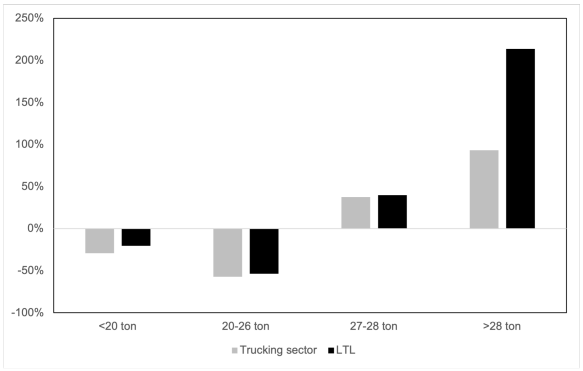


Figure B.5 displays changes in emission class standards (expressed as CO_2 per kilometer for a truck weighing in 18 ton (gray dotted line), weighing 27 ton (gray dashed line) and weighing 30 ton (solid black line) in (a) and actual CO_2 per kilometer in the Swedish heavy duty vehicles sector divided by fleet size (firms with less than 10 trucks (gray dotted line), firms with 10-49 trucks (gray dashed line) and firms with 50 or more trucks (solid black line)) in (b).

Figure B.6: Percent change of trucks and VKT by weight class

(a) Share of trucks by weight class



(b) Share of VKT by weight class

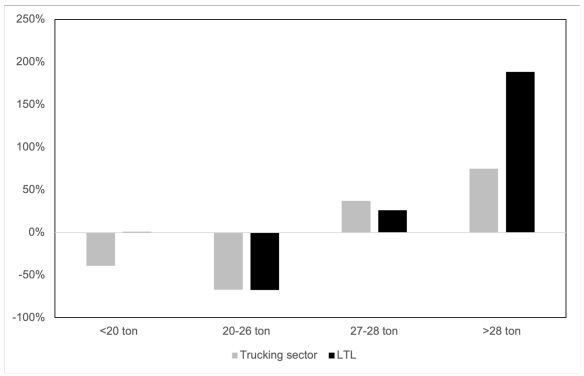


Figure B.6 displays the percent change from 2007–2020 in the share of heavy trucks (a) and VKT (b) for each of the four weight classes for all trucking firms (gray bars) and the firms with 50 or more trucks that have all four weight classes of heavy duty vehicles (black bars).

Figure B.7: Generate emission factors (g/km) for heavy trucks

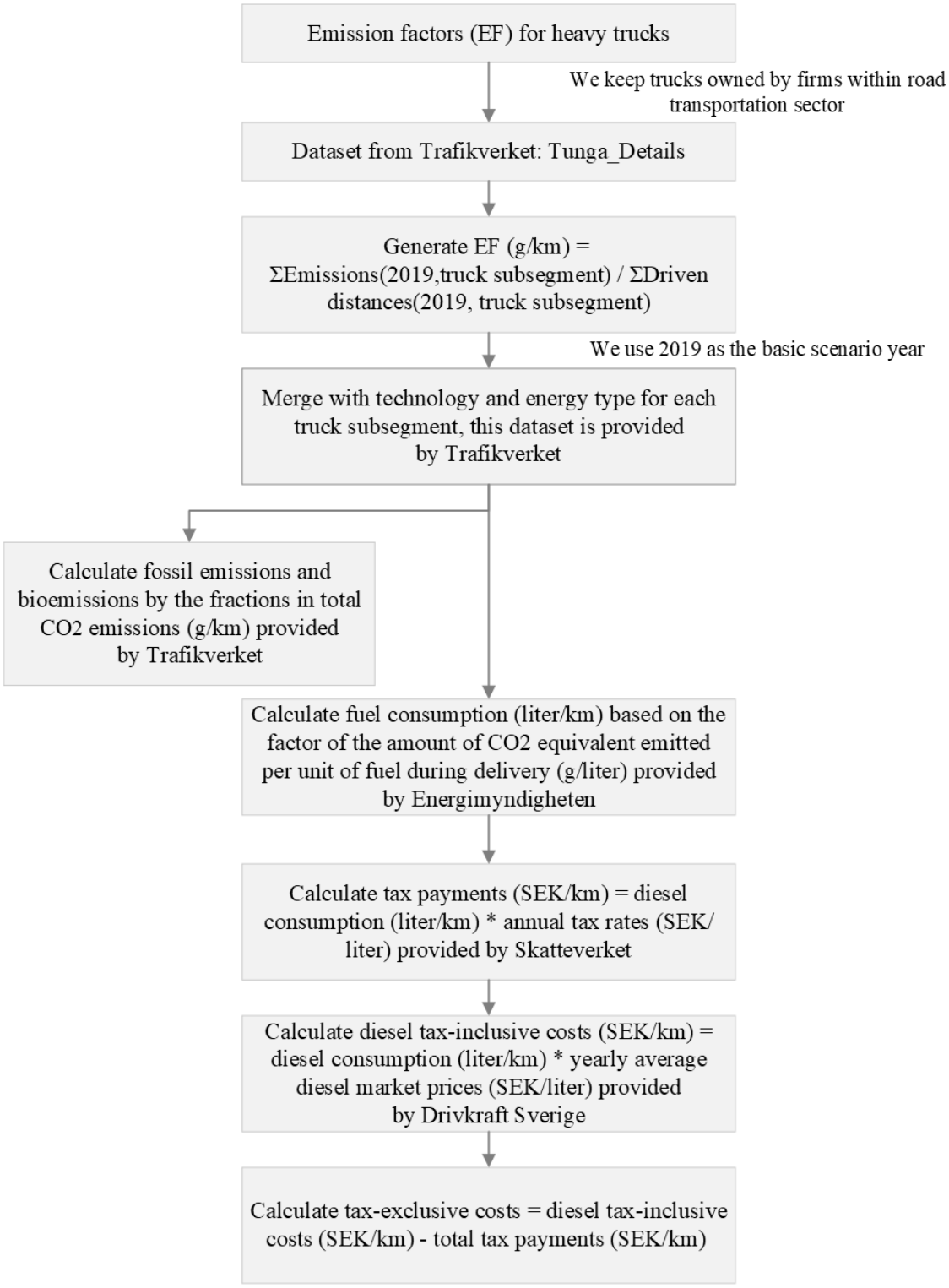


Figure B.7 displays the process of generating emission factors for heavy trucks. The calculation way is described in Consortium (2022).

Figure B.8: The fraction of renewable shares in diesel (%) by years

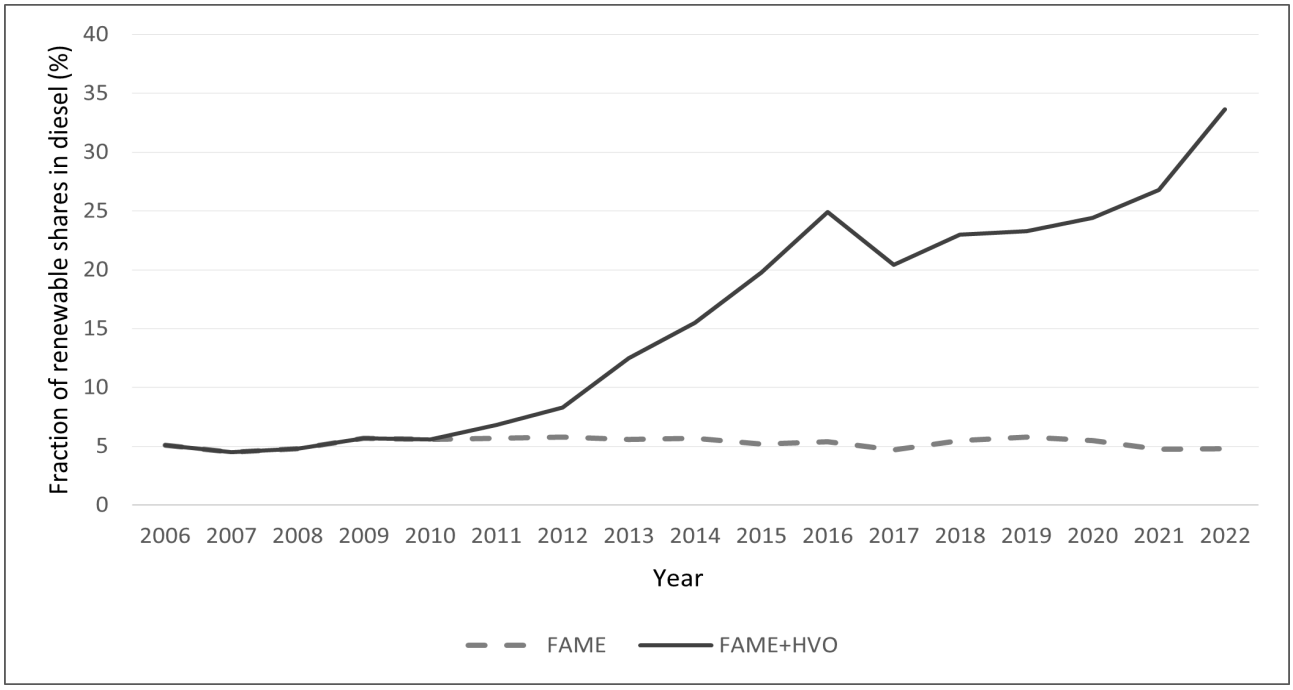


Figure B.8 displays the fraction of renewable shares blended into diesel from 2006 to 2022. Source: *miljobarometern*.

Table B.1: Fuels of heavy duty vehicles in Sweden

	Total	**≤ 20 ton**	**>20–28 ton**	**>28 ton**
Gasoline	58,779	58,641	115	23
Diesel	1,846,258	880,090	713,852	252,316
Electric	69	32	35	2
Natural gas	10,665	4,410	6,064	191
Kerosene	14	14		0
E85	514	254	260	0
Total	1,916,299	943,441	720,326	252,532

Table B.1 reports number of truck-year observations of all heavy duty vehicles in Sweden during 2007–2020.

Table B.2: Tax inclusive fuel cost and vehicle kilometers traveled: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	**<10**	**10–49**	**≥50**	**All**	**<10**	**10–49**	**≥50**
$\ln(FC)_{i,t}$	-0.618***	-0.571***	-0.899**	-0.752***				
	(0.073)	(0.076)	(0.416)	(0.201)				
$\ln(FC–Policy)_{i,t}$					-0.596***	-0.364*	-0.700**	-0.888***
					(0.131)	(0.192)	(0.326)	(0.266)
$\ln(FC–Price)_{i,t}$					-0.025	-0.206	-0.242	-0.343***
					(0.123)	(0.193)	(0.180)	(0.088)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,921	43,782	7,130	711	51,917	43,778	7,130	711
Adjusted R^2	0.841	0.756	0.902	0.921	0.842	0.756	0.902	0.926

Table B.2 reports OLS estimates of Equation 1. $ln(VKT)_{v,t}$ is the dependent variable. *VKT* is the vehicle kilometers traveled by vehicle v in year t. *FC* is fuel cost per transport work (in KM–Ton) for vehicle v in year t. *FC–Policy* is fuel cost per transport work (in KM–Ton) due to the policy component of the tax inclusive fuel cost for firm i in year t. *FC–Price* is fuel cost per transport work (in KM–Ton) due to the fossil diesel price component of the tax inclusive fuel cost for firm i in year t. The sample comprises heavy duty vehicles in the freight transport by road sector (NACE 4941) with at least four consecutive observations during 2007–2020. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.3: Tax inclusive fuel cost and firm level adjustments: VKT by weight class – all firms

	(1)	(2)	(3)	(4)
	<20 ton	**20–26 ton**	**27–28 ton**	**>28 ton**
$\ln(FC)_{i,t}$	1.425***	1.047***	-0.619***	-0.931***
	(0.179)	(0.235)	(0.121)	(0.102)
$\ln(FC)_{i,t-1}$	-0.079	0.154	-0.003	0.008
	(0.098)	(0.118)	(0.060)	(0.048)
$\ln(FC)_{i,t-2}$	0.293***	0.155*	-0.093*	0.004
	(0.095)	(0.087)	(0.050)	(0.042)
$\ln(FC)_{i,t-3}$	-0.037	-0.133	-0.031	0.066
	(0.076)	(0.090)	(0.056)	(0.046)
$\sum\ln(FC)$	1.602	1.223	-0.746	-0.985
	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes
Observations	2,685	17,939	30,870	25,950
Adjusted R^2	0.866	0.692	0.657	0.757

Table B.3 reports OLS estimates where $ln(VKT_{c,i,t}/VKT_{i,t})$ is the dependent variable. $VKT_{c,i,t}$ is the vehicle kilometers traveled by vehicles across four weight class groups c for firm i in year t and $VKT_{i,t}$ is the vehicle kilometers traveled for firm i in year t. The four weight class groups are for trucks under 20 tons (c=1); trucks 20–26 tons (c=2); trucks 27–28 tons (c=3); trucks more than 28 tons (c=4). FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.4: Tax inclusive fuel cost and firm level adjustments: VKT by weight class – firms owning less than 10 trucks

	(1)	(2)	(3)	(4)
	<20 ton	**20–26 ton**	**27–28 ton**	**>28 ton**
$\ln(FC)_{i,t}$	1.307***	1.081***	-0.504***	-0.831***
	(0.223)	(0.266)	(0.140)	(0.101)
$\ln(FC)_{i,t-1}$	-0.088	0.133	0.049	0.022
	(0.107)	(0.139)	(0.069)	(0.051)
$\ln(FC)_{i,t-2}$	0.303***	0.150	-0.079	0.016
	(0.107)	(0.099)	(0.057)	(0.041)
$\ln(FC)_{i,t-3}$	-0.040	-0.195*	-0.046	0.061
	(0.074)	(0.100)	(0.060)	(0.042)
$\sum\ln(FC)$	1.122	1.169	-0.581	-0.732
	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes
Observations	1,129	11,673	23,282	21,334
Adjusted R^2	0.816	0.671	0.626	0.654

Table B.4 reports OLS estimates where $ln(VKT_{c,i,t}/VKT_{i,t})$ is the dependent variable. $VKT_{c,i,t}$ is the vehicle kilometers traveled by vehicles across four weight class groups c for firm i in year t and $VKT_{i,t}$ is the vehicle kilometers traveled for firm i in year t. The four weight class groups are for trucks under 20 tons (c=1); trucks 20–26 tons (c=2); trucks 27–28 tons (c=3); trucks more than 28 tons (c=4). FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020 owning less than 10 trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.5: Tax inclusive fuel cost and firm level adjustments: VKT by weight class – firms owning 10 to 49 trucks

	(1)	(2)	(3)	(4)
	<20 ton	**20–26 ton**	**27–28 ton**	**>28 ton**
$\ln(FC)_{i,t}$	1.981***	1.017**	-1.593***	-2.108***
	(0.297)	(0.450)	(0.313)	(0.419)
$\ln(FC)_{i,t-1}$	-0.127	0.343	0.048	-0.091
	(0.374)	(0.257)	(0.117)	(0.149)
$\ln(FC)_{i,t-2}$	0.012	0.114	-0.109	0.079
	(0.312)	(0.210)	(0.133)	(0.293)
$\ln(FC)_{i,t-3}$	-0.217	0.300	0.061	-0.280
	(0.293)	(0.233)	(0.164)	(0.265)
$\sum\ln(FC)$	1.649	1.774	-1.593	-2.398
	(0.008)	(0.003)	(0.001)	(0.000)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes
Observations	1,156	5,330	6,607	4,026
Adjusted R^2	0.860	0.677	0.737	0.765

Table B.5 reports OLS estimates where $ln(VKT_{c,i,t}/VKT_{i,t})$ is the dependent variable. $VKT_{c,i,t}$ is the vehicle kilometers traveled by vehicles across four weight class groups c for firm i in year t and $VKT_{i,t}$ is the vehicle kilometers traveled for firm i in year t. The four weight class groups are for trucks under 20 tons (c=1); trucks 20–26 tons (c=2); trucks 27–28 tons (c=3); trucks more than 28 tons (c=4). FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020 owning between 10 and 49 trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.6: Tax inclusive fuel cost and firm level adjustments: VKT by weight class – firms owning 50 or more trucks

	(1)	(2)	(3)	(4)
	<20 ton	**20–26 ton**	**27–28 ton**	**>28 ton**
$\ln(FC)_{i,t}$	2.302	0.883	-1.179**	-0.951
	(1.622)	(0.833)	(0.502)	(1.381)
$\ln(FC)_{i,t-1}$	0.311	0.004	-0.190	-2.878**
	(1.353)	(0.588)	(0.337)	(1.236)
$\ln(FC)_{i,t-2}$	0.860	0.895*	-0.420	1.035
	(0.757)	(0.478)	(0.350)	(1.183)
$\ln(FC)_{i,t-3}$	1.579	0.226	0.208	0.259
	(1.073)	(0.542)	(0.266)	(1.154)
$\sum\ln(FC)$	5.052	2.008	-1.581	-2.535
	(0.141)	(0.092)	(0.057)	(0.399)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes
Observations	350	696	704	422
Adjusted R^2	0.821	0.767	0.870	0.632

Table B.6 reports OLS estimates with $ln(VKT_{c,i,t}/VKT_{i,t})$ as the dependent variable. $VKT_{c,i,t}$ is the vehicle kilometers traveled by vehicles across four weight class groups c for firm i in year t and $VKT_{i,t}$ is the vehicle kilometers traveled for firm i in year t. The four weight class groups are for trucks under 20 tons (c=1); trucks 20–26 tons (c=2); trucks 27–28 tons (c=3); trucks more than 28 tons (c=4). FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020 owning 50 or more trucks. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.7: Tax inclusive fuel cost and firm level adjustments: Type of truck company – Distance driven

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		<10		10–49		≥50	
	All	Not all	All	Not all	All	Not all	All	Not all
	(LTL)	(TL)	(LTL)	(TL)	(LTL)	(TL)	(LTL)	(TL)
$\ln(FC)_{i,t}$	-0.995***	-0.221**	-0.930***	-0.177*	-1.054	-0.623*	-0.876***	-0.726*
	(0.180)	(0.091)	(0.179)	(0.095)	(0.641)	(0.329)	(0.285)	(0.428)
$\ln(FC)_{i,t-1}$	0.159*	-0.445***	0.070	-0.446***	-0.079	-0.107	-0.228	0.262*
	(0.085)	(0.070)	(0.084)	(0.073)	(0.108)	(0.123)	(0.221)	(0.150)
$\ln(FC)_{i,t-2}$	0.000	-0.120	0.094	-0.102	0.160	0.157	-0.385*	-0.817***
	(0.106)	(0.091)	(0.102)	(0.076)	(0.179)	(0.112)	(0.215)	(0.292)
$\ln(FC)_{i,t-3}$	-0.128	0.044	-0.185**	0.014	-0.179*	-0.035	-0.171	0.460
	(0.080)	(0.063)	(0.075)	(0.052)	(0.107)	(0.119)	(0.134)	(0.326)
$\sum\ln(FC)$	-0.964	-0.742	-0.951	-0.711	-1.152	-0.608	-1.660	-0.821
	(0.000)	(0.000)	(0.000)	(0.000)	(0.057)	(0.051)	(0.000)	(0.245)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,768	43,153	4,814	38,968	3,309	3,821	540	171
Adjusted R^2	0.885	0.816	0.751	0.755	0.900	0.904	0.931	0.901

Table B.7 reports OLS estimates where $ln(VKT)_{i,t}$ as the dependent variable, where VKT is the vehicle kilometers traveled by firm i in year t. FC is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.8: Tax inclusive fuel cost and firm level adjustments: Type of truck company – Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		**<10**		**10–49**		**≥50**	
	All	**Not all**	**All**	**Not all**	**All**	**Not all**	**All**	**Not all**
	(LTL)	**(TL)**	**(LTL)**	**(TL)**	**(LTL)**	**(TL)**	**(LTL)**	**(TL)**
$\ln(FC)_{i,t}$	0.844***	0.168***	0.844***	0.137*	0.795**	0.572*	0.797**	0.064
	(0.115)	(0.081)	(0.126)	(0.083)	(0.377)	(0.347)	(0.316)	(0.647)
$\ln(FC)_{i,t-1}$	-0.236***	0.307***	-0.196**	0.325***	-0.271***	-0.223	0.287	-0.673**
	(0.089)	(0.058)	(0.098)	(0.061)	(0.101)	(0.254)	(0.253)	(0.322)
$\ln(FC)_{i,t-2}$	-0.057	-0.017	-0.064	-0.039	-0.030	-0.323***	0.240	0.759***
	(0.089)	(0.049)	(0.108)	(0.044)	(0.094)	(0.120)	(0.239)	(0.268)
$\ln(FC)_{i,t-3}$	0.117*	-0.097**	0.163**	-0.084**	0.039	0.108	0.104	-0.298
	(0.066)	(0.044)	(0.079)	(0.041)	(0.085)	(0.103)	(0.216)	(0.296)
$\sum\ln(FC)$	0.668	0.361	0.747	0.339	0.533	0.134	1.428	-0.148
	(0.000)	(0.000)	(0.000)	(0.000)	(0.076)	(0.527)	(0.029)	(0.827)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,768	43,151	4,814	38,966	3,309	3,821	540	171
Adjusted R^2	0.717	0.601	0.673	0.595	0.872	0.831	0.922	0.951

Table B.8 reports OLS estimates with *ln(Sales per VKT)*$_{i,t}$ as the dependent variable, where *Sales per VKT* is PPI adjusted sales per VKT by firm i in year t *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum$ln(FC) present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.9: Tax inclusive fuel cost and firm level adjustments: Type of truck company – Profitability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		**<10**		**10–49**		**≥50**	
	All	**Not all**	**All**	**Not all**	**All**	**Not all**	**All**	**Not all**
	(LTL)	**(TL)**	**(LTL)**	**(TL)**	**(LTL)**	**(TL)**	**(LTL)**	**(TL)**
$\ln(FC)_{i,t}$	-0.004	-0.016	-0.020	-0.020	0.066	0.047	0.036	0.167***
	(0.031)	(0.022)	(0.028)	(0.022)	(0.107)	(0.038)	(0.054)	(0.047)
$\ln(FC)_{i,t-1}$	-0.002	0.005	-0.005	0.010	-0.255	-0.201	0.081*	-0.093
	(0.022)	(0.019)	(0.025)	(0.020)	(0.209)	(0.172)	(0.045)	(0.070)
$\ln(FC)_{i,t-2}$	-0.018	-0.022	0.071**	-0.025	0.019	0.078	0.028	0.025
	(0.073)	(0.023)	(0.030)	(0.024)	(0.091)	(0.054)	(0.026)	(0.057)
$\ln(FC)_{i,t-3}$	0.028	0.016	-0.020	0.016	0.020	0.058	0.084***	-0.034
	(0.040)	(0.019)	(0.024)	(0.020)	(0.016)	(0.076)	(0.027)	(0.038)
$\sum\ln(FC)$	0.004	-0.017	0.026	-0.019	-0.150	-0.018	0.229	0.065
	(0.921)	(0.554)	(0.498)	(0.528)	(0.263)	(0.832)	(0.005)	(0.672)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,753	43,079	4,805	38,893	3,306	3,821	539	171
Adjusted R^2	0.284	0.405	0.314	0.410	0.406	0.423	0.540	0.746

Table B.9 reports OLS estimates with *EBIT to sales*$_{i,t}$ as the dependent variable in panel C, where *EBIT to Sales* is earnings before interest and taxes divided sales for firm i in year t. *FC* is fuel cost per transport work (in KM–Ton) for firm i in year t. The sample comprises firms in the freight transport by road sector (NACE 4941) during 2007–2020. All regressions include firm and year fixed effects and a set of firm control variables: ln(total assets), ln(firm age) and debt to assets. $\sum\ln(FC)$ present an F-test of joint significance. The standard errors are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table B.10: Emission factors for heavy duty vehicles (g/km)

Year	Vehicle type	Emission factor (g/km)
2007		431.26
2010		433.11
2013	**HGV<10 tons**	425.53
2016		413.71
2020		398.61
2007		568.30
2010		560.25
2013	**HGV 10-20 tons**	549.60
2016		538.51
2020		525.69
2007		721.63
2010		714.06
2013	**HGV 20-27 tons**	703.53
2016		694.82
2020		687.83
2007		741.29
2010		735.27
2013	**HGV 27-29 tons**	720.84
2016		703.58
2020		685.68
2007		838.14
2010		826.44
2013	**HGV >=29 tons**	808.37
2016		785.90
2020		766.56

Table B.10 displays the changes in annual average emission factors (g/km) among five weight categories of heavy-duty vehicles from 2007 to 2020. The amount of CO_2 emitted per km shows a declining tendency for all weight groups. Trucks weighing above 29 tons had the highest reduction in emission factor at 8.54% over time, while trucks weighing 20 to 27 tons have the least reduction at 4.70%. Calculations based on model from Trafikverket and Consortium (2022).