Can our large cars make us bad drivers? Analysis of complete national records of vehicle weight and its association with risky driving behavior

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Cite as:
Rosenzweig Stav, Steren Aviv, Rubin Ofir (2024), Can our large cars make us bad drivers? Analysis of complete national records of vehicle weight and its association with risky driving behavior. *Proceedings of the European Marketing Academy*, (122549)

Paper from EMAC Regional Conference, Lisbon, Portugal, September 25-27, 2024

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Abstract

There is a clear trend of consumers' preference for larger, heavier vehicles, fueling an "arms race". While these vehicles better protect consumers in the event of a car crash, theory suggests that consumers' perceived increased safety will lead to risky behavior. Using complete national car fleet data and police-issued speeding tickets over a calendar year, we examined the association between vehicle mass and risky behavior in terms of speeding tickets. Controlling for consumers' choice of car, we find a positive association between vehicle mass and speeding tickets. The findings replicate for deviation, safety, and traffic signal violations.

Keywords: *vehicles, risky behavior, speeding*

1. Introduction

Over the last dozen years, a clear trend has developed of shifting towards larger, heavier, and more powerful passenger vehicles. Whereas car mass fell within each vehicle category (i.e., sedan, SUV, minivan etc.), market trends led to an increase in the average mass of new vehicles, indicating a shift in demand towards larger and heavier categories (US Environmental Protection Agency, 2021). For instance, the share of sport utility vehicles (SUVs) out of all new passenger vehicles sold in the US has tripled in the last 40 years (Winston & Yan, 2021), and is expected to account for 78% of the US market by 2025 (Voelk, 2020).

On top of pollution concerns, experts and consumers argue that much more than regular size vehicles, the ever more popular large vehicles, such as crossovers, SUVs, and pickups, pose increased danger to pedestrians and cyclists (Schmitt, 2021). Heavier vehicles are also usually higher than lighter vehicles and are, thus, likely to impact other non-motorists road users on their bodies and heads rather than their legs, thereby causing more serious injuries (White, 2004). Individual and social considerations are at play: the accentuated presence of large passenger vehicles fuels what has been described as an "arms race", in which consumers purchase larger and heavier vehicles for comfort and self-protection (White, 2004), which, in turn, enhances preference towards these vehicles (Thomas & Walton, 2008). From a societal perspective, smaller vehicles would have been advantageous because of the lower threat posed to others in the event of a collision (Bento et al., 2017; Mu &, Yamamoto 2019).

Consumers might use products in risky ways. Vehicles provide a valuable and promising arena for consumer behavior research (Tomaino et al., 2020), especially in understanding how products influence behavior in safety-related contexts. Identifying the root causes of risky driving behavior is crucial for preventing or mitigating harm to drivers and their surroundings. Given the potential implications, this concern is pertinent for consumers, marketers, and policymakers alike. A critical concern stems from consumer preference for larger, heavier vehicles, which may foster a false sense of safety, potentially leading to behavioral adaptation and increased risk seeking. Consumer behavioral adaptation in the form of increased risk seeking is evident in a variety of situations. For example, climate affects mood and thus risky behavior because individuals seek arousal to repair their mood (Parker & Tavassoli, 2000). Individuals experiencing loss adapt their behavior and increase risk taking in gambling (Andrade & Iyer, 2009), and individuals experiencing safety in their location choose riskier products (Esteky, 2022).

Specifically in the realm of private vehicles, to fit their desired level of risk, individuals strive to counteract any external safety gain by adapting their behavior to compensate for the gain, in an attempt to recapture *homeostasis* (Wilde, 1982). As a result, behavioral adaptation of heavy vehicle drivers is likely to reduce the benefit of the vehicle's greater objective safety for its occupants (Hedlund, 2000).

The present study aims at investigating the association between vehicle mass and risky driving behavior, taking advantage of complete national level data for the entire car fleet and police-issued speeding tickets during one year. We postulate that the larger and heavier the vehicle, the safer it feels, which enhances behavioral adaptation. Therefore, controlling for vehicle choice, drivers of large and heavy vehicles might be more prone to risky driving and thus pose more threat to others than might be expected.

2. Literature Review

2.1 Enhanced safety and consumer behavior

The complexity of human behavior in response to enhanced safety and the way it might lead to risky behavior, feeds an ongoing discussion in the literature. Iyer and Singh (2018) suggest that consumers exert less effort to reduce the probability of accidents, when they perceive the product (e.g., automobiles) as a high-safety one. Bolton et al. (2006) find that products and services that mitigate risk by reducing its likelihood or severity can backfire and increase risky behavior, seriously impairing consumer welfare. For example, drugs for weight management both lowered the perceived risk of gaining weight and decreased the motivation to engage in preventive activity (Bolton et al., 2008, 2015). That is, a remedy for a risk decreases individuals' motivation to act to prevent the potential risk. Soleymanian et al. (2019) suggest that immediate and periodic feedback on risky driving behavior can contribute to a safer driving. A meta-analysis showed that cues, such as warning labels, do indeed cause consumers to modify their behavior and promote safe usage (Purmehdi et al., 2017). However, a different meta-analysis demonstrated that in more than 20% of cases, behavior was modified in the opposite direction: cues informing that usage could be risky drove reckless behavior (Cox et al., 1997). A third meta-analysis that specifically examined the effects of threat-based messages on risky driving indicated that when driving is a source of self-esteem for drivers, death-related appeals provoked defensive responses that increased risky driving (Carey et al., 2013).

2.2 Enhanced safety in large vehicles

Several studies have shown that drivers feel safer in large vehicles. Drivers perceive larger vehicles to be safer and indicated that the primary reason for purchasing them was considering their own safety (Axsen & Long, 2022; Thomas & Walton, 2008). Accordingly, SUV drivers were found to have higher perceived safety compared with other car drivers (Thomas & Walton, 2007), in line with recent research indicating that an elevated viewpoints increased individuals' risk taking primarily due to an increased sense of control (Jami, 2019).

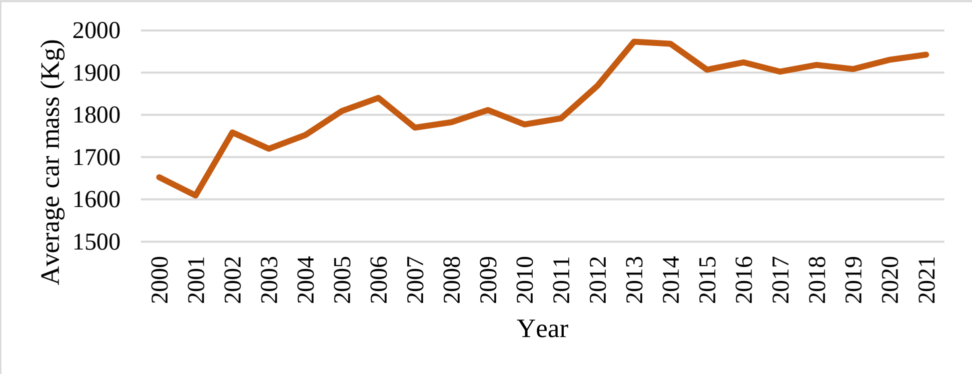
2.3 Measuring risky driving behavior

To study risky driving, a prime measure in the literature is speeding tickets (e.g., Melman et al., 2017; Vertlib et al., 2023). An increase of the vehicle's speed decreases the driver's response time, increases the probability of involvement in a collision, and increases the severity of injury of the driver and other road users (Hedlund, 2000). Moreover, speeding is specifically associated with behavioral adaptation (Smiley & Rudin-Brown, 2020). Therefore, if indeed a larger vehicle is associated with behavioral adaptation of more risky driving, speeding violations are expected to reflect this linkage.

2.4 Research context - the car market in Israel

Our research context is the private car market in Israel, with 2.98 million privately owned passenger vehicles at the end of the studied period (CBS, 2021), of which about 262,000 were newly purchased (Israel Ministry of Transport and Road Safety, 2022). Similar to other countries, the composition of the Israeli car market demonstrates a steady increase in the volume and share of SUVs and other large passenger vehicles (Steren et al., 2022), where the average mass of newly sold vehicles increased by 17.6% from 1,653Kg in 2000 to 1,943Kg in 2021 (Figure 1). Fatal car crashes caused an annual average of 38.9 deaths per 1 million inhabitants in Israel, somewhat lower than Canada, higher than the United Kingdom, and similar to Germany (OECD, 2022). The car market in Israel is different from other countries in that there are no local car manufacturers, thus all vehicles are imported. Durig the studied period, the Israel Police issued 685,175 traffic violation tickets, of which 134,392 were for speeding.

Fig. 1 Average car mass of newly sold vehicles in Israel (authors' calculations, based on Israel Ministry of Transport and Road Safety, 2022)



3. Methodology

3.1 Data

We use data of the Ministry of Transport and Road Safety in Israel, which include records of all passenger vehicles that were active in 2018. To these data, we matched all speeding tickets issued by police vehicles in 2018 obtained from Israel Police. Our data allows us to account for all vehicles with speeding violations and all those without speeding violations active during an entire calendar year. Additional advantages include that the data is a census rather than a sample, with the strong external validity of real-world data and the data was collected by authorities, whereas self-report measures of mileage and violations are unreliable (af Wåhlberg & Dorn, 2015). Moreover, these real-world data reflect actual actions of drivers in their actual environment which is affected by other drivers (Jacobsen, 2013).

Each observation in our database represents a specific vehicle configuration and includes brand and model, mass, horsepower, propulsion technology, fuel type, gear type etc., and the number of speeding tickets issued in 2018 to drivers of this particular vehicle configuration. For each vehicle configuration, the number of active vehicles in 2018 functioned as weighting factors in the estimation, such that overall, we analyze the entire Israeli car fleet, which included 3,095 unique configurations, representing 2,162,525 vehicles.[1] Whereas this data structure does not enable identifying a specific vehicle or driver conduct within vehicle configurations, it has two meaningful advantages: (1) it enables a focus on the effect of the type of vehicle and its attributes, that is above and beyond any individual driver or driving characteristics, and (2) it provides an aggregate level perspective that is currently limited in consumer research on risky behavior.

3.2 Modelling and estimation approach

[1] We excluded from the analysis rare models of which less than 50 cars were sold due to privacy considerations (0.4% of cars), and configurations first introduced in 2018, for which there is no record of kilometers traveled (14% of cars).

In studying risky driving behavior, endogeneity is associated with vehicle size: riskier drivers may prefer to purchase larger vehicles. We therefore use a two-stage least-squares (2SLS) regression model, predicting the endogenous variable using an instrumental variable in the first stage, and then using the predicted value to estimate its effect on the dependent variable in the second stage (Steren et al., 2016; Wooldridge, 2015):

$$\begin{aligned} \ln(m_i) &= \alpha_0 + \alpha_1 \ln(p_i) + \sum\nolimits_{k=2}^{K} \alpha_k X_{ik-1} + \sum\nolimits_{l=K+1}^{L} \alpha_l B_{il-K} + \omega_i \\ s_i &= \beta_0 + \beta_1 \widehat{\ln(m_i)} + \sum\nolimits_{k=2}^{K} \beta_k X_{ik-1} + \sum\nolimits_{l=K+1}^{L} \beta_l B_{il-K} + \epsilon_i \end{aligned} \tag{1}$$

where vehicle mass, m_i, is a proxy for vehicle size, as vehicle size and vehicle mass are highly correlated (Whitefoot & Skerlos, 2012), and s_i are observed speeding tickets for configuration i divided by the number of units of this configuration). X_i are control variables, including horsepower, gear type, fuel type, propulsion technology, number of seats, safety score and average kilometers traveled by vehicles of this configuration, to control for the presence on the road. We also control for the location (urban or interurban) and time of day (day: 6:00-17:00; evening: 17:00-00:00; night: 00:00-6:00) of the violation. Finally, B_i are brand (manufacturer) fixed effects, accounting for features that might appeal to consumers characterized by certain levels of tendency to risky driving.

$\widehat{ln(m_i)}$ are the predicted natural log of vehicle mass values from the first stage. We use the weighted average price of each configuration over all model years, p_i, as an instrumental variable, because the assemblage of a large vehicle is more costly than that of a small vehicle (Anderson & Auffhammer, 2014). There is no direct association between vehicle price and driving behavior. Vehicle price is associated with income level, and prior literature is inconclusive regarding the association between income level and driving behavior, where high-income individuals could be less sensitive to fines, but the probability of collecting the fine is higher for high income individuals (Garoupa, 2001), which could decrease proneness to speeding violations. Moreover, risky driving behavior can result in crashes, and high-income individuals are less likely to be involved in these (La et al., 2013). Finally, losing means of commuting due to vehicle seizure or license suspension is a deterrent for low-income individuals who depend on their vehicle for their livelihood (Shams et al., 2011), but, on the other hand, has a higher alternative cost for high-income individuals. For these reasons, one can predict driving behavior neither based on income level, nor the value of one’s vehicle. We offer and test an additional instrumental variable below.

4. Results

Our sample includes 3,095 unique vehicle configurations comprising 2,162,525 passenger vehicles. Table 1 provides a summary of the statistics relating to key variables. The average vehicle mass is 1,743 kg and it has 121 horsepower. The average vehicle costs NIS 131,412 (~$37,800) and it travels 20,228 kilometers annually. The average annual number of speeding tickets per vehicle is 0.06. Table 2 presents the 2SLS estimation results. The first stage estimation indicates a significant association between the instrumental variable of vehicle price and vehicle mass. The coefficient of vehicle mass in the second stage is positive, indicating that drivers in larger, heavier vehicles are more prone to speeding violations. Our results suggest that a 1% increase in vehicle mass increases the expected number of speeding tickets per vehicle by 0.024.

We conducted the following robustness tests. First, in addition to speeding tickets issued by police cars, we use speeding violations data recorded by traffic enforcement cameras (Column 2 in Table 3). Police cars and enforcement cameras are significantly different enforcement methods in terms of technology and usage. During 2018, these cameras issued 54,153 speeding tickets (compared with 134,392 issued by police cars). Results are robust for these two enforcement methods. We also examined the following violations as alternative dependent variables: deviation violations (e.g., lane deviation), safety violations (e.g., phone usage while driving or failure to fasten seatbelts), and disobeying traffic signals (e.g., not stopping at red light). We observe consistent results with each of these DVs (Columns 3-5 in Table 3).

Table 1 – Summary of statistics[a] (N=2,162,525)

	Mean	Std. deviation	Minimum	Maximum
Vehicle mass (kg)	1,743	289	980	3,300
Horsepower	121	34	60	455
Average vehicle price (NIS*)	131,412	52,726	53,990	1,065,000
Average kilometers traveled per vehicle (km/annum)	20,228	9,540	2,751	161,096
Average safety score	1.08	1.80	0	10.5
Automatic gear (=1, otherwise=0)	0.94	0.23	0	1
Number of seats	5.09	0.50	2	9
Diesel (=1, otherwise=0)	0.05	0.21	0	1
Hybrid (=1, otherwise=0)	0.03	0.16	0	1
Electric (=1, otherwise=0)	0.0003	0.02	0	1
4×4 drive (=1, otherwise=0)	0.06	0.24	0	1
Speeding tickets per vehicle	0.06	0.05	0	2.18
% of violations in interurban roads	0.45	0.12	0	0.88
% of violations at day time	0.72	0.13	0	1
% of violations at evening time	0.23	0.10	0	1
% of violations at night time	0.05	0.05	0	0.38

* NIS 1 ≈ $0.3

[a] Values are weighted averages accounting for the number of vehicles in each configuration.

Table 2 – Regressions results (standard errors)

	First stage	Second stage
	ln(vehicle mass) (kg)	Speeding tickets per vehicle
ln(vehicle mass) (kg)		0.024 (5.736e-04)***
Average kilometers traveled per vehicle (km/annum)	-9.54e-07 (8.205e-09)***	7.15e-07 (3.446e-09)***
Horsepower	0.004 (3.530e-05)***	2.62e-04 (1.928e-06)***
Safety score	0.001 (3.863e-06)***	0.003 (1.491e-05)***
Automatic gear (=1, otherwise=0)	-0.058 (2.788e-04)***	-0.003 (1.111e-04)***
Diesel (=1, otherwise=0)	0.037 (3.685e-04)***	0.028 (1.628e-04)***
4×4 drive (=1, otherwise=0)	-1.68e-04 (2.915e-04)	-0.011 (1.229e-04)***
Hybrid (=1, otherwise=0)	0.004 (3.943e-04)***	0.007 (1.670e-04)***
Electric (=1, otherwise=0)	-0.051 (3.460e-03)***	0.015 (1.460e-03)***
Number of seats	0.053 (1.288e-04)***	-0.002 (6.716e-05)***
% of violations in interurban roads	0.009 (5.474e-04)***	0.089 (2.307e-04)***
% of violations at evening time	0.006 (7.949e-04)***	0.125 (3.349e-04)***
% of violations at night time	0.145 (1.709e-03)***	0.221 (7.178e-04)***
Brand fixed effects	✓	✓
ln (average price) (NIS[a])	0.390 (5.300e-04)***	
Constant	2.622 (5.631e-03)***	-0.238 (3.871e-03)***
R^2	0.759	0.472
Number of observations	2,162,525	2,162,525

[a] NIS 1 ≈ $0.3, *** p<0.01

To explore potential variations in result across car categories, we segmented our data into 10 distinct car categories, each representing typical usage patterns. This aligns with the notion that consumers first select the car category that suits their needs, forming a consideration set, and then choose from the available car products within this set (Giannetti & Srinivasan, 2021). We use classifications of a leading local vehicle website[2]: minivan, family vehicle, small family vehicle, SUV, luxury, executive, sports, commercial, supermini, and mini. Results are consistent in 8 out of 10 categories, suggesting that the observed effects are not confined to a general scope but rather extend to specific car categories.

Table 3 – Regressions results by enforcement type and violation type (standard errors)

	(1)	(2)	(3)	(4)	(5)
	Speeding (Police-car issued)	Speeding (Camera issued)	Police-car issued		
Variable			Deviation	Safety	Traffic signals
ln(vehicle mass) (kg)	0.024***	0.012***	0.019***	0.096***	0.0003***
	(5.736e-04)	(2.675e-04)	(3.214e-04)	(9.205e-04)	(5.845e-05)
Vehicle characteristics (X_i)	✓	✓	✓	✓	✓
Brand fixed effects (B_i)	✓	✓	✓	✓	✓
Constant	-0.238***	-0.117***	-0.147 ***	-0.694***	-0.003***
	(3.871e-03)	(1.805e-03)	(2.169e-03)	(6.212e-03)	(3.945e-04)
R^2	0.472	0.409	0.261	0.148	0.268
Number of observations	2,162,525	2,162,525	2,162,525	2,162,525	2,162,525

[a] NIS 1 ≈ $0.3, *** p<0.01

Finally, to further demonstrate robustness, we tested a model using an alternative instrumental variable: the vehicle's towing capacity. Regulated towing capacity is correlated with larger vehicle mass, but there is no apparent theoretical relationship between towing capacity and driver behavior. Our findings remain consistent under this identification strategy.

5. Discussion

We take advantage of complete national level data of speeding tickets during a single calendar year to show that drivers of heavier vehicles are associated with a higher number of speeding tickets. Examining a single entire year means that enforcement level, economic and infrastructure conditions are consistent across all observations and potential seasonal effects are reflected in the data. After accounting for vehicle choice, the positive association between vehicle mass and speeding tickets is above and beyond any vehicle attribute, including vehicle brand. These results remain robust across significantly different enforcement methods and different traffic violations, indicating that drivers of larger, heavier vehicles tend to drive more recklessly. They support the view that behavioral adaptation occurs in response to the perceived level of risk (Iyer & Singh, 2018), potentially in an attempt to regain homeostasis (Hedlund, 2000; Wilde, 1982).

Behavioral adaptation in response to vehicle physical characteristics can emerge in several ways. For example, Vertlib et al. (2023) demonstrated that advanced safety systems in automobiles can provoke risky driving behavior, despite not being emphasized in the vehicle's appearance. Furthermore, factors unrelated to physical risk can influence risk perception (Slovic, 2016). For instance, Ma et al. (2019) contended that luxury brands instill a sense of protection even without functional safety features. In the context of vehicles, this perception may arise from a sense of superiority, potentially leading individuals to disregard safety regulations. This notion aligns with Baz et al. (1999), who suggest that consumers are more inclined to take risks with stronger brand names. Some of our analyses can offer insights into these potential alternative mechanisms. For instance, violations such as phone usage, seatbelt neglect, and disobeying traffic signals are unlikely to be affected by drivers' sense of stability

[2] https://www.icar.co.il

or perceived friction. Yet, we find that such violations are still associated with mass. Moreover, examining brand fixed effects in our model, we find no systematic association between luxury brands and violations. For example, brands linked with speeding violations included Lexus, Audi, and BMW (all considered luxury brands on the local market), but also less luxurious brands such as Citroen, Fiat, and Kia. Similarly, brands negatively associated with speeding included Buick and Cadillac, as well as less luxurious brands such as Suzuki and Mitsubishi.

The present study has the following limitations. First, we use national records at the vehicle configuration level, because the Israel Police and the Ministry of Transportation report traffic violations at this level. This level of analysis has two meaningful advantages. (1) This level of data allows investigating the effect of vehicle's characteristics on behavior, regardless of specific driver characteristics, thus providing a comprehensive perspective on the effect of one's vehicle on risky driving; and (2) it provides an aggregate level perspective that is currently limited in consumer research on risky behavior. However, the aggregate nature of the data might mask individual behaviors, which could limit our conclusions' generalizability. Driver-level data could have been instrumental in addressing unobserved heterogeneity when explaining risky driving behavior, as aggregation may obscure individual behavior. Future research could further explore the impact of mass on risky driving behavior by examining both individual and aggregate levels simultaneously. Second, our cross-sectional data cover a period of one year, representing a specific car fleet composition. It is possible that the effect that we assess will be different under other car-fleet compositions, with respect to the distribution of vehicle sizes, road conditions and infrastructure in other countries.

Consumers' desire to purchase increasingly larger and heavier vehicles because these vehicles provide a sense of safety is documented in the literature. To mitigate potential inclination toward risky driving behavior, policymakers should find means of internalizing this externality, such as by restricting large and heavy vehicles from busy urban areas (Diekhoff, 2019; Zipper, 2022) or imposing high insurance rates to account for their drivers' higher tendency of risky behavior. Policymakers should also find ways to educate consumers regarding a potential tendency to risky behavior in heavier vehicles. They should also engage marketers in educating consumers about safer driving in heavy vehicles that they market.

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