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by
Thomas Hagedorn, Till Kösters, Sebastian Specht
and Jan Wessel

Institute of Transport Economics Münster
Working Paper
No. 39
November 2023

living.knowledge

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**Address**
Institut für Verkehrswissenschaft
Am Stadtgraben 9
D 48143 Münster, Germany

**Telephone**
+49 251 83-22 99 4

**E-Mail**
verkehrswissenschaft@uni-muenster.de

**Website**
http://www.iv-muenster.de



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# No Need for Speed: Fuel Prices, Driving Speeds, and the Revealed Value of Time on the German Autobahn

*By* Thomas Hagedorn*
Till Kösters*
Sebastian Specht*†
Jan Wessel*

*We estimate the relationship between fuel prices and driving speeds on the German Autobahn. The speed price elasticities are higher on sections without a speed limit ($-0.047$) than on those with a limit ($-0.033$), thus underlining the distortionary effect of speed limits on previously estimated elasticities. We also find higher elasticities when drivers are alone on the road, for high prices, and slower drivers. Based on the undistorted speed price elasticities, we estimate the short-run fuel demand elasticity and the revealed value of time (20.71 Euro/h; 83 % of gross wage), hence providing valuable input for policymakers and infrastructure planning.*

*Keywords: fuel prices, speed price elasticity, no speed limit, short-run fuel demand elasticity, value of time, German Autobahn.*
*JEL: R41, R48, Q41.*

## I. Introduction

"No matter how fast you're driving in Germany, someone is driving faster than you", Tom Hanks told show host David Letterman about his experiences on the German Autobahn. Indeed, the absence of a general speed limit allows for an almost completely free speed decision on many Autobahn sections – at least when they are not congested – so that the word "Autobahn" is regarded around the world as synonymous with freedom from restrictions (Gross, 2020). However, one factor that could still limit this speed decision is the fuel price, which constitutes a crucial determinant of car travel costs, and therefore impacts on travel behavior. One simple way to reduce these monetary travel costs – without scaling back travel activity or switching to other modes of transport – is to reduce driving speed. In this paper, we therefore explore several dimensions of the relationship between fuel prices and driving speeds on Autobahn sections.

The individual speed decision is influenced by various exogenous factors such as traffic regulations (e.g. speed limits) and driving conditions (e.g. road characteristics, traffic volume, weather and visibility), which drivers cannot influence. What drivers can influence, however, are their driving costs. If the fuel price $P$ increases, drivers can reduce their driving speed $S(P)$, and thereby save money through lower fuel consumption $f(S(P))$. This also lowers their accident risk $acc(S(P))$, but they accrue additional travel time costs as their travel time $t(S(P))$ increases.

* University of Münster, Institute of Transport Economics, Am Stadtgraben 9, 48143 Münster, Germany
† Corresponding author. E-Mail: sebastian.specht@uni-muenster.de

In accordance with Wolff (2014), we formalize this trade-off in a suitable driving cost function

$$C(S(P)) = P \times f(S(P)) + VOT \times t(S(P)) + acc(S(P)), \tag{1}$$

where VOT is the individual value of time. In this paper, we contribute to the literature by analyzing three important components of Equation 1 for the unique setting of the German Autobahn: the impact of fuel prices on driving speeds $S(P)$, the impact of fuel prices on fuel consumption $f(S(P))$, and the revealed VOT. In contrast to previous research, our findings are not distorted by speed limits, since there is no general speed limit on the German Autobahn, and people can drive as fast as they want on many sections. Moreover, our fine-grained data allows us to analyze the individual speed decisions of drivers who are alone on the road, and thus not affected by any other vehicles. Hence, this setting enables us to shed light on the true relationships between fuel prices and driving speeds, fuel consumption and the revealed VOT.

### A. *Speed Price Elasticity*

In Section II, we empirically estimate the relationship between fuel prices and driving speeds on the German Autobahn, which is denoted by $S(P)$ in Equation 1. Previous research on this relationship is rather scarce and has important limitations that we discuss below.

Blomquist (1984) and Dahl (1979) find a negative correlation between gasoline prices and traffic speed, which is confirmed by three more recent studies. Austin (2008) finds a speed price elasticity of $-0.05$ at the median speed, using hourly speed data on weekends at three locations on highways in California from 2003 to 2006. Both Watkins and Wolff (2013) and Wolff (2014) use hourly data to estimate a negative elasticity for rural freeways in Washington State, with a particular focus on elasticities for different speed ranges, i.e. average and fast drivers. By contrast, Burger and Kaffine (2009) find non-significant or even positive elasticities, differentiating between peak and off-peak hours. During peak hours, the speed price elasticity at the mean is 0.16, but it is not significant during off-peak hours. The authors argue that higher prices would lower traffic demand, and therefore ease congestion.

Previous research on the general relationship between fuel prices and speed is limited by a lack of comprehensive consideration of factors influencing the individual speed decisions, especially speed limits and traffic volumes. The above research was conducted only for a few US Highways, all of which have a speed limit.[1] If the actually desired driving speed lies above the speed limit, this speed limit could easily distort the observable speed reaction to increasing fuel prices.[2] Moreover, the above research does not explicitly account for traffic volumes[3],

[1] In Burger and Kaffine (2009), Watkins and Wolff (2013), and Wolff (2014) speed limits are 65 mph ($\sim$ 104.6 kph) and 70 mph ($\sim$ 112.7 kph), respectively. Summary statistics show that the average driving speed is below the posted speed limit. Maximum driving speeds are not more than 10 % higher than the posted speed limits, indicating that drivers adhere to the limit.

[2] To illustrate this with an arbitrary example, consider a cost-minimizing individual who would like to drive 105 kph, based for example on driving conditions, monetary and time costs. Due to an exogenous speed limit of 100 kph, however, she actually drives at 100 kph in order not to risk a ticket. Now, let us assume that a fuel price increase would reduce her ideal speed by 8 kph to 97 kph. The observable reduction in actual driving speed is 3 kph and thus 5 kph lower than it would be on sections without a limit.

[3] Austin (2008) does not control for traffic volume. Watkins and Wolff (2013) argue that drivers are not

which are, however, an important determinant of driving speed (Van Aerde and Rakha, 1995). Given these shortcomings of the literature, Wolff (2014) states that "the ideal situation to observe the effect of gas price on vehicle speed would be a freeway with no speed limit in a location with no congestion".

Against this backdrop, we are the first to analyze the undistorted relationship between fuel prices and driving speeds by exploiting the absence of a general speed limit on the German Autobahn. We explore how drivers respond to fuel price changes if they are not restricted by a speed limit, and compare this to their responses on selected Autobahn sections with a speed limit. For our analysis, we use per-minute speed and traffic data from 50 measuring stations on the German Autobahn between 2017 and 2022. Among these, 43 stations have no speed limit ("non-limit sections"), while 7 have a limit ("limit sections"). By utilizing a fixed effect regression model and accounting for driving condition variables like traffic volume, weather, and visibility, we gauge the impact of fuel prices on driving speed.

We find a speed price elasticity of $-0.047$ for Autobahn sections without a speed limit, which is indeed higher than and statistically significantly different from the speed price elasticity of $-0.033$ for sections with a speed limit. Our robust results confirm the hypothesis of lower speeds at higher prices, and they additionally suggest that previously estimated elasticities might be distorted downward by speed limits. To completely eliminate congestion effects and any interferences from other vehicles, we additionally analyze observations where only one car passes the measuring station, and we find that speed price elasticities for this "single driver" subsample are higher for both limit ($-0.036$) and non-limit ($-0.060$) sections, if individuals are alone on the road. Furthermore, we find heterogenous responses to price changes with respect to the fuel price level and the driving speed level. The estimated speed price elasticities are significantly higher when fuel prices are above €2 per liter, and we find that faster drivers react more inelastically.

### *B. Short-Run Fuel Demand Elasticity*

In Section III, we focus explicitly on the fuel consumption function $f(S(P))$ of Equation 1 and analyze how fuel price changes affect fuel demand. In the short-run, shifts in fuel demand due to price increases could be achieved by a decrease in travel frequency, a decrease in travel distance, or more fuel-efficient driving, for example, by reducing speed.[4] According to Austin (2008) and Hughes et al. (2006), drivers would rather focus on improving fuel efficiency than altering their travel habits when fuel prices rise. Thus, we do not consider fuel-consumption savings from scaling back travel activity or switching transport modes, but focus solely on fuel consumption savings that result from deliberate speed changes.

We find a short-run fuel demand elasticity of $-0.060$ on non-limit sections. Accordingly, a 10 % fuel price increase decreases speed by 0.59 kph, thereby saving about 0.04 l/100 km or €0.069/100 km. Our short-run fuel demand elasticity, while at the lower end, still aligns with previous findings ranging from $-0.03$ to

influenced by other vehicles, since traffic density in their observations is low. Wolff (2014) uses hourly fixed effects to control for traffic volume, and Burger and Kaffine (2009) introduce the unemployment rate and argue that it would be an appropriate control variable to control for the transportation demand during rush hours. However, none of the aforementioned studies control for any actual observed data on traffic volume.

[4] Further examples of fuel efficiency in the short-run are car maintenance, slower acceleration or reducing weight (Knittel and Tanaka, 2021; Thomas et al., 2017). In the medium-to-long run, people purchase more modern and efficient cars in order to optimize driving costs (Busse et al., 2013).

−0.51 (Dahl and Sterner, 1991; Espey, 1998; Goodwin et al., 2004). In addition, we use our findings to evaluate the implications of the proposed $CO_2$ tax increases for Germany. An increase in the $CO_2$ price from €30 to €65 per ton, as planned by 2026, would increase the fuel price by €0.104 compared to 2022. This could save 37.4 million liters of fuel per year, corresponding to 92,598 tons of $CO_2$, or the annual emissions of 44,506 cars in Germany.

### *C. Value of Time*

In Section IV, we estimate the revealed VOT for non-limit sections on the German Autobahn. The VOT quantifies the monetary valuation of travel-time changes and is an important concept for assessing infrastructure investments or policies (Small, 2012). This concept is rooted in the microeconomic theory of time allocation by Becker (1965) and DeSerpa (1971), and a recent overview can be found in Small and Verhoef (2007) or Wardman et al. (2016).

In general, there are two primary approaches to estimating the VOT. First, stated preferences (SP) experiments are used to gauge individual willingness to pay for travel time (Shires and de Jong, 2009). Second, revealed preferences (RP) models exploit observable real-world choices while traveling, such as opting for a tolled but faster lane over a congested route (e.g. Small et al., 2005). By comparison, results for VOT determined by SP are significantly lower than corresponding results for VOT based on RP. One reason for this difference could be a hypothetical bias in SP experiments (Brownstone and Small, 2005; Hensher, 2010; Small and Verhoef, 2007; Small et al., 2005). According to Small and Verhoef (2007), RP-based VOT should be preferred over SP-based VOT, especially for the evaluation of policies.

Moreover, most previous studies calculated the VOT on the extensive margin, i.e., by discrete choices. This approach, however, does not reveal any information on how individuals behave within the chosen option, e.g. how fuel efficiently they drive when choosing the car. Furthermore, decisions can be critically affected by heterogeneous preferences among individuals. Failing to control for these preferences could easily lead to omitted variable bias. To address these concerns, we follow Wolff (2014) and estimate the VOT on the intensive margin by using real-world traffic data, i.e. by relying on the continuous speed choice of drivers on the road. When fuel prices rise, rational drivers adjust their individual driving speed such that the marginal benefits from fuel savings and the lower accident risk equal the cost of the marginal travel time increase. To quantify this trade-off, we then use the estimated speed reactions and the subsequent fuel savings.

One drawback of Wolff (2014), however, is the presence of speed limits that could distort observable speed decisions. Hence, we contribute to the literature by estimating a revealed VOT on the intensive margin for the German Autobahn, where speed decisions are not distorted by speed limits. We find a revealed VOT on non-limit Autobahn sections of €20.71/h, which is equivalent to 83 % of the average hourly gross wage. Thus, our value is within the range of 50 % to 90 % found in the literature (Brownstone and Small, 2005; Small and Verhoef, 2007).

### *D. Implications*

The main implications of our paper are threefold. First, our results indicate that price signals are incorporated into drivers' short-term speed decisions. Hence, pricing instruments such as a carbon dioxide ($CO_2$) emission tax would enable policymakers to pursue desirable goals such as climate protection and lower accident risk.

Second, we provide a refined estimate of the VOT on the German Autobahn, that is based on revealed preferences at the intensive margin. This estimate can therefore enrich cost benefit analysis (CBA) for infrastructure projects relating to the German Autobahn. Moreover, the outlined approach for estimating the VOT could easily be applied to different road types.

Third, our results contribute to the ongoing debate on implementing a general speed limit on the German Autobahn. We provide empirical evidence that higher fuel prices reduce average driving speed on the German Autobahn, hence confirming the value of market-based pricing instruments as an alternative policy instrument to introducing a general speed limit.

## II. Estimating the Impact of Fuel Prices on Speed

### *A. Empirical Strategy*

To identify the impact of fuel prices on driving speed, we exploit the substantial variation in fuel prices. Similar to the literature, we argue that fuel price variation is exogenous to individual drivers, who act as price-takers with respect to fuel prices (Gillingham, 2014). Drivers alone cannot influence the fuel price, which is primarily determined by supply and demand in the world market. As a consequence, drivers have to optimize their driving behavior based on these exogenously given prices. In a later robustness check, we relax this assumption and use the crude oil price as an instrument for fuel prices in order to control for potential fuel price endogeneity.[5]

We also include critical control variables that can impact on driving conditions, and subsequently on driving speed. One crucial determinant of driving conditions is the weather; hence, we include variables for precipitation, wind speed, and temperatures. Moreover, we explicitly control for the presence of snow. As driving conditions are also influenced by visibility, we include information on daylight or twilight.

In addition, the number of other vehicles on the road impacts on driving speed, because more vehicles lead to congestion and thus to a reduction in average driving speed. Consequently, we control for traffic volume, which is measured at the same location and within the same temporal scale as the average driving speed. Here, we also distinguish between the number of cars and the number of trucks. Since trucks require more space and usually drive slower than cars, the number of trucks may have a stronger impact on the average speed of cars. To account for a potentially quadratic relationship between traffic flow and traffic speed (Van Aerde and Rakha, 1995), we include both linear and quadratic terms in our re-

[5] Gillingham (2014) argues that localized fuel demand shocks seem unlikely, as evidenced by the very limited variation in fuel prices across Californian counties. We do, however, relax the assumption of no localized fuel demand shocks as a robustness check. This is done by instrumenting the local fuel price through the global West Texas Intermediate (WTI) crude oil price, similar to Goetzke and Vance (2021) or Zhang and Burke (2020). While the global price of crude oil is the most important determinant of local fuel prices in Germany (Pearson Correlation of 0.94), its global scope suggests that it is unaffected by localized fuel demand shocks. As WTI crude oil is sourced from U.S. oil fields, it is quite removed from localized shocks in Germany (Gillingham and Munk-Nielsen, 2019). Also, it is plausible that the global crude oil price does not impact directly on driving behavior, but only through local fuel prices; hence, the exclusion restriction would hold and our instrument is relevant and valid.

gression. Other control variables are Covid-19 restrictions, holidays, the consumer price index (without energy) and the unemployment rate.

Furthermore, individual driving behavior is influenced by the driver's characteristics. Unfortunately, we do not have access to individual driver characteristics, but we approximate different groups of drivers via locational and temporal differentiation. For example, the group of drivers commuting to work might be different from the group of Sunday drivers. For temporal differentiation, we include fixed effects for the hours of the day, which we also interact with the different days of the week. For locational differentiation, we include fixed effects for the measuring station, which also control for characteristics of the road section (e.g. number of lanes, location). Additionally, we include fixed effects for months and years, in order to account for seasonal and cyclical trends.

This rich set of control variables and fixed effects controls for potential confounders of the relationship between fuel prices and driving speed. The resulting log-log regression model[6] for estimating the direct impact of fuel prices on driving speed can then be formalized as follows:

$$(2)\quad log(Speed_{i,t}) = \beta_1 \times log(Fuel\ Price_{d(t)}) + \mathbf{x}'\boldsymbol{\eta} + \lambda_i + \lambda_{h(t)\times w(t)} + \lambda_{m(t)} + \lambda_{y(t)} + \epsilon,$$

where $log(Speed_{i,t})$ is the logarithm of the average driving speed per minute for measuring station $i$. The logarithm of the average fuel price at date $d(t)$ is denoted as $log(Fuel\ Price_{d(t)})$.[7] The coefficient $\beta_1$ indicates the speed price elasticity. Control variables are denoted by $\mathbf{x}'$, and the various fixed effects by $\lambda$ for hour times weekday $h(t) \times w(t)$, month $m(t)$ and year $y(t)$; $\epsilon$ denotes the error term.

### B. Data

#### Speed and Traffic Volume

The speed and traffic volume data is from the Autobahn GmbH des Bundes[8] and covers from January 2017 to December 2022 for 50 measuring stations, including 22 station pairs measuring in both travel directions, and six measuring only in one direction. As illustrated in Figure 1, each station is located at a German Autobahn in North Rhine-Westphalia, the most populous state encompassing 30 % of the national Autobahn network. To minimize the influence of road characteristics on speed, the measuring stations were selected so that they are not located in curves or close to freeway ramps. Traffic volume and average driving speeds are recorded by induction loops under the surface on a per-minute basis, separately for cars and trucks. As depicted in Figure 1, our sample consists of 43 measuring stations without any speed limit, and 7 with a speed limit equal to or below the German highway guideline speed of 130 kph.

[6] A non-linear relationship between fuel prices and driving speeds is regularly assumed in the literature (e.g. Watkins and Wolff, 2013; Wolff, 2014). To confirm our results, we additionally compare the hereby estimated elasticites to those of a lin-lin regression model in Section II.D.

[7] According to Ellwanger and Snudden (2023), oil prices follow a random walk. Consequently, rational drivers would base their price expectations on the most recently observed prices (Bordalo et al., 2013), which we assume to correspond to the fuel price of the respective date, i.e. the date when driving speeds are recorded.

[8] Provision of raw data by Autobahn GmbH des Bundes, branch office Rheinland, further processing and presentation of results by the authors.

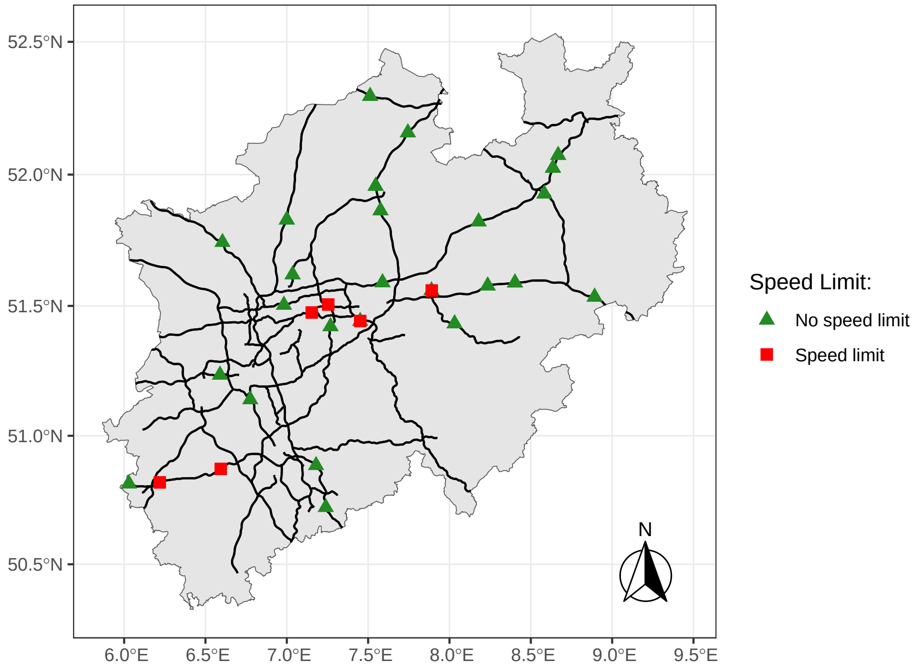


Figure 1. : Measuring Stations

To ensure that speed decisions in our data are not affected by external anomalies, we exclude traffic breakdowns, e.g. due to heavy snow fall or accidents, as well as observations during permanent or daytime construction sites[9]. In addition, we exclude all observations with an average speed below 70 kph, which Brilon et al. (2005) define as the free-flow speed threshold on German highways. In total, our final data set consists of 117 million per-minute observations, reflecting more than 2.1 billion cars and 460 million trucks.

## Fuel Prices

We use fuel price data from *Tankerkönig*, which is a fuel price comparison website that provides access to the data of the Market Transparency Unit for Fuels. For our study, we calculated the weighted daily average fuel price of Diesel, E5, and E10 in North Rhine-Westphalia, based on their respective shares in car fuel consumption per year.[10] We do not consider charging costs for battery electric cars, as they accounted for only 0.07 % of all passenger cars in Germany in 2017, and 1.27 % in 2022 (BMVI, 2023).

## Data on Control Variables

To account for the effect of weather conditions on traffic speed, we use hourly data on air temperature, precipitation and wind speed provided by the Deutscher

[9] This information is provided by the Straßeninformationsbank Nordrhein-Westfalen.

[10] E5 is the regular gasoline in Germany and contains up to 5 % of bioethanol, whereas E10 contains up to 10 % bioethanol. The shares of Diesel and E5 in total fuel consumption decreased slightly over the years, while the share of E10 increased. In 2022, the last year of our sample, Diesel accounted for 43.45 %, E5 for 46.88 % and E10 for 9.67 % of total fuel consumption.

Wetterdienst. According to Möllers et al. (2022), we classified precipitation intensity by creating two dummy variables, *Light Rain* (0 mm $<$ precipitation $<$ 2.5 mm) and *Rain* (precipitation $\geq$ 2.5 mm). The weather data are obtained from the weather stations nearest to each measuring station. In addition to weather conditions, drivers also adjust their speed according to visibility. Therefore, the share of minutes per hour of daylight and twilight is calculated via the R package "suncalc".[11]

To control for the effects of the Covid-19 pandemic and subsequent government intervention on mobility, we introduced the Covid Stringency Index of Mathieu et al. (2020). Furthermore, data on the unemployment rate of North Rhine-Westphalia is from the Federal Employment Agency (2023) and the consumer price index (without energy) from the Federal Statistical Office (2023b). Additional dummy variables account for school and public holidays.

## Summary Statistics

Summary statistics for the relevant variables in the data set are displayed in Table 1. The overall average speed in our data is 123.0 kph, with a lower average speed on sections with a speed limit (112.0 kph) and a correspondingly higher average speed on sections without a speed limit (124.9 kph).

Table 1—: Summary Statistics

| Variables | Observations | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Speed, Traffic, and Fuel Price* | | | | | | | | |
| Speed Cars | 117,515,005 | 123.04 | 14.85 | 70.00 | 114.12 | 123.61 | 132.10 | 253.00 |
| No limit | 100,390,225 | 124.92 | 14.07 | 70.00 | 116.33 | 125.00 | 133.33 | 253.00 |
| Limit | 17,124,780 | 112.02 | 14.46 | 70.00 | 101.00 | 112.97 | 122.90 | 252.00 |
| Volume Cars | 117,515,005 | 17.60 | 14.67 | 1.0 | 5 | 14 | 26 | 127 |
| No limit | 100,390,225 | 16.84 | 13.82 | 1 | 5 | 14 | 25 | 116 |
| Limit | 17,124,780 | 22.07 | 18.27 | 1 | 6 | 18 | 35 | 127 |
| Volume Trucks | 117,515,005 | 3.90 | 4.00 | 0 | 1 | 3 | 6 | 56 |
| No limit | 100,390,225 | 4.03 | 4.07 | 0 | 1 | 3 | 6 | 56 |
| Limit | 17,124,780 | 3.11 | 3.47 | 0 | 0 | 2 | 5 | 53 |
| Fuel Price | 117,515,005 | 1.45 | 0.26 | 1.10 | 1.29 | 1.35 | 1.52 | 2.27 |
| *Weather Indicators* | | | | | | | | |
| Temperature | 117,515,005 | 11.31 | 7.35 | −20.40 | 5.70 | 10.90 | 16.50 | 41.20 |
| Precipitation | 117,515,005 | 0.08 | 0.48 | 0.00 | 0.00 | 0.00 | 0.00 | 53.00 |
| Wind Speed | 117,515,005 | 3.48 | 2.08 | 0.00 | 1.90 | 3.10 | 4.60 | 22.10 |
| Snow | 117,515,005 | 0.005 | 0.07 | 0 | 0 | 0 | 0 | 1 |
| *Economic Indicators* | | | | | | | | |
| Unemployment Rate | 117,515,005 | 7.06 | 0.48 | 6.40 | 6.70 | 7.00 | 7.50 | 8.20 |
| Consumer Price Index | 117,515,005 | 2.50 | 2.18 | 0.30 | 1.30 | 1.60 | 3.10 | 9.50 |
| *Others* | | | | | | | | |
| School holidays | 117,515,005 | 0.27 | 0.44 | 0 | 0 | 0 | 1 | 1 |
| Holidays | 117,515,005 | 0.03 | 0.18 | 0 | 0 | 0 | 0 | 1 |
| Daylight | 117,515,005 | 0.54 | 0.50 | 0 | 0 | 1 | 1 | 1 |
| Twilight | 117,515,005 | 0.06 | 0.23 | 0 | 0 | 0 | 0 | 1 |
| Covid Stringency Index | 117,515,005 | 24.77 | 28.83 | 0.00 | 0.00 | 14.81 | 49.54 | 85.19 |

On average, 17.6 cars and 3.9 trucks pass the measuring stations per minute, with less traffic at night and more in the morning and afternoon rush hours. The weighted daily average fuel price fluctuated between €1.10 and €2.27 per liter during the observation period, with a mean value of €1.44 per liter.

[11] For a more detailed description, we refer to Wessel (2022).

### C. Descriptive Analysis

We begin our analysis by visually exploring the relationship between fuel prices and driving speeds. Accordingly, we depict the course of the fuel prices in the upper part of Figure 2. From January 2017 to mid-2021, average fuel prices were more or less constant, with the exception of a price drop induced by the Covid-19 pandemic in the spring of 2020. From mid-2021 onwards, the price rose steadily. In February 2022, the Russian invasion of Ukraine and the corresponding energy crisis in Germany caused a sharp increase in fuel prices. Between February and April, fuel prices exceeded the threshold of €2 per liter (equivalent to $8 per gallon) for the first time ever, and reached an all-time high at €2.27 on March 10, 2022. To counter the high fuel prices, the government introduced a temporary fuel discount of around €0.35 per liter for E5 and E10, and €0.17 per liter for Diesel between June and August 2022. Subsequently, fuel prices decreased below the €2 threshold, but rose again above €2 after the end of fuel discount.

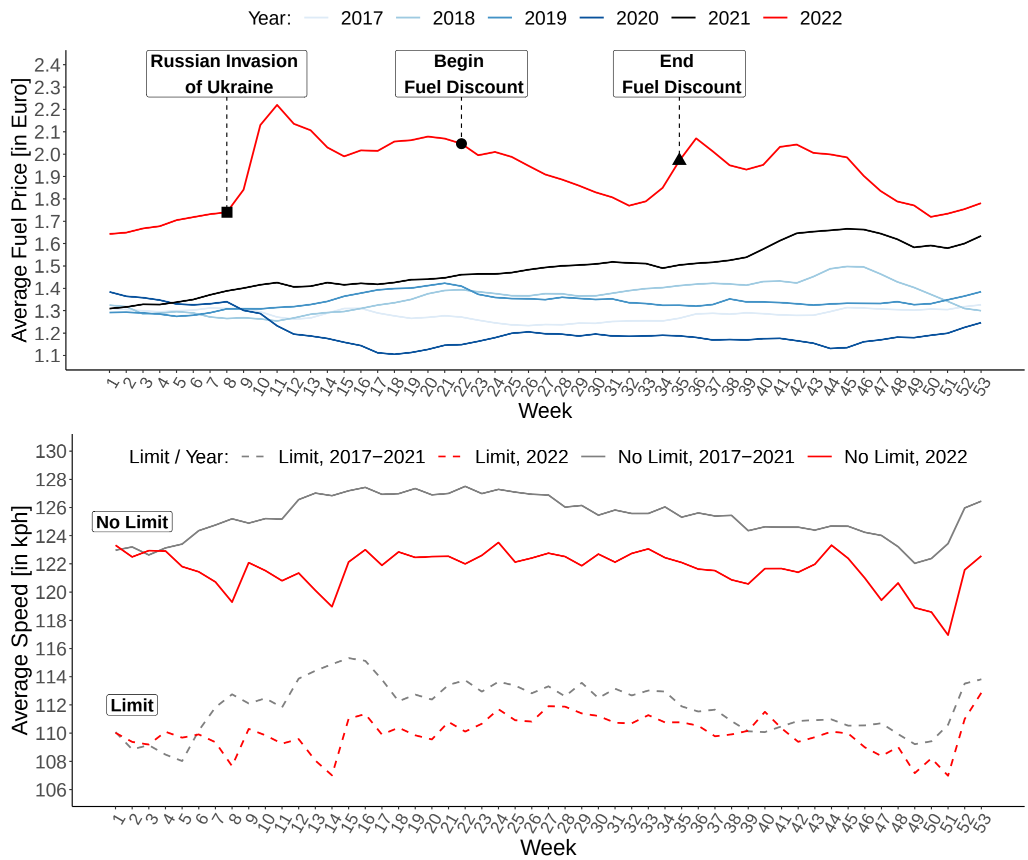


Figure 2. : Relationship Between Fuel Price and Average Speed

In order to relate these fuel prices to the observed driving speeds, we plot the average driving speeds for limit and non-limit Autobahn sections in the lower part of Figure 2. For the sake of visibility, we aggregate the years from 2017 to 2021, where driving speeds were relatively similar and followed a clear seasonal trend, with faster speeds due to better driving conditions in summer months. In 2022, however, driving speeds diverge from this trend and do not increase in spring, but even appear to drop on non-limit sections. This coincides with the sharp increase in fuel prices, hence indicating that fuel prices might impact on driving speeds. In line with this, driving speeds increase slightly during the fuel discount period, whereas they previously decreased in the same period. The phase-out of the fuel discount and the subsequently increasing fuel prices lead again to slightly decreasing speeds.

Furthermore, Figure 2 shows that the difference in driving speeds between 2022 and the previous years is more pronounced and stable on non-limit sections. On limit sections, however, driving speeds in the second half of 2022 approach those of the previous years.

Hence, we conclude that drivers on the German Autobahn appear to respond to fuel price changes by adjusting their driving speed. This response appears to be different for limit and non-limit sections. We continue in the next section by analyzing this relationship with a regression model.

### *D. Regression Analysis: Limit vs. No Limit*

#### Standard Regression

So far, the literature only reports speed price elasticities for sections with a speed limit. Our descriptive analysis, however, suggests that a speed limit might distort the impact of fuel prices on driving speed decisions. Hence, we contribute to the literature by exploiting the unique setting of the German Autobahn, where we have both limit and non-limit sections, and use the regression model outlined in Equation 2 to empirically analyze this hypothesis. We can thereby gain valuable insights into how drivers respond to fuel price increases when their speed decision is not affected by a speed limit. An overview of the relevant results is provided in Table 2, and the detailed results are outlined in Table 6 in Appendix VI.A.

Table 2—: Regression Results for Standard Regressions

| Dependent Variable: | log(Speed) | | | |
|---|---|---|---|---|
| Model: | OLS | | IV | |
| | Limit | No Limit | Limit | No Limit |
| log(Fuel Price) | -0.0331*** | -0.0470*** | -0.0226** | -0.0338*** |
| | (0.0069) | (0.0046) | (0.0085) | (0.0073) |
| Control Variables | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 17,124,780 | 100,390,225 | 17,124,780 | 100,390,225 |
| $R^2$ | 0.5933 | 0.3350 | 0.5933 | 0.3350 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

We find negative and statistically significant speed price elasticities for both sections types. This confirms that higher fuel prices result in lower driving speeds (Austin, 2008; Wolff, 2014). At sections with a speed limit, the speed price elasticity is −0.033 for the ordinary least squares (OLS) regression, implying that a 10 % increase in fuel prices reduces driving speeds by 0.33 %. At the mean price of €1.44, this would translate into a speed reduction of 0.37 kph. In contrast, the speed price elasticity for non-limit sections is −0.047, which translates into a speed reduction of 0.59 kph. A z-test confirms that these two estimates are indeed statistically different from each other (Clogg et al., 1995).[12] Hence, we confirm our hypothesis that a speed limit distorts the impact of fuel prices on drivers' speed decisions. As driving speeds are generally higher on non-limit sections, there is a greater scope for cost savings due to the non-linear relationship between driving speeds and fuel consumption compared to limit sections.

To mitigate the potential endogeneity concerns outlined in Section II.A, we use the WTI oil price as an instrument for fuel prices in an instrumental variable (IV) regression. The coefficients are slightly lower than the OLS estimates, but still statistically different from each other. Hence, this confirms the notion that speed limits distort speed decisions. For the sake of clarity, however, we continue by following the literature and focussing on OLS regressions (Austin, 2008; Gillingham, 2014; Wolff, 2014).

### Single Drivers

There are two points of concern with aggregated speed data, which are also considered in all other papers related to this topic. First, each observation reflects the average speed across several drivers, so that individual speed decisions are not measured directly. This implies that one cannot draw conclusions about individual behavior. Second, individual speed decisions might be distorted by other vehicles on the road. Psychological research indicates that drivers underestimate their own speed, and overestimate the speed of other vehicles. Hence, the presence of other vehicles on the road pressures them to speed up and they drive faster to keep up with the traffic flow (Åberg et al., 1997; Fleiter et al., 2010).[13] To mitigate these concerns, it would be necessary to analyze data at the individual level without the presence of other vehicles. Against this backdrop, we select only observations with one car and zero trucks passing the measuring station per minute. For these observations, which we define as *single drivers*, the recorded driving speed per one-minute-interval is the individual driving speed of one particular driver.

First, we observe that the average driving speeds of single drivers on limit and non-limit sections is about 4.39 kph and 3.06 kph lower, respectively, compared to the average speeds of the entire data sample.[14] Moreover, the elasticities in Table 3 confirm both the hypothesis of slower speeds in response to higher fuel prices, and a statistically significant difference between limit (−0.036) and non-limit sections (−0.059). We attribute the higher coefficients in our single driver

[12] The estimated coefficients of a corresponding lin-lin regression model are −3.966 for non-limit sections and −2.607 for limit sections. Accordingly, a fuel price increase of €1 reduces driving speeds by 3.966 kph and 2.607 kph, respectively. The corresponding elasticities are −0.0457 for non-limit sections and −0.0335 for limit sections, which is quite similar to our log-log estimates.

[13] On single-lane roads, it is possible that a single slow-driving vehicle would slow down the subsequent vehicles, because overtaking is not feasible. In such a case, fuel price changes would affect the driver's speed decision exclusively through the slow-driving vehicle in front, hence leading to an overestimation of speed price elasticities. However, since all Autobahn sections in our sample have at least two lanes in each direction and the "Rechtsfahrgebot" applies, this phenomenon is rather uncommon on Autobahn sections and therefore negligible in our analysis.

[14] This difference in average speeds persists when we compare the single driver subsample and the entire data for night hours (10 p.m. to 6.a.m.) only, and day hours only.

Table 3—: Regression Results for the Single Driver Subsample

| Dependent Variable: | log(Speed) | |
|---|---|---|
| Model: | Limit | No Limit |
| log(Fuel Price) | -0.0357** | -0.0593*** |
| | (0.0113) | (0.0067) |
| Control Variables | Yes | Yes |
| Fixed Effects | Yes | Yes |
| Observations | 471,674 | 2,683,113 |
| $R^2$ | 0.1530 | 0.1117 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

regression to the absence of other vehicles, allowing individual drivers to adhere to their true preferred speeds, without external pressure to keep up with the flow. Consequently, the coefficients in Table 3 show the undistorted individual speed responses to fuel price increases, whereas the results in Table 2 reflect the observed speed responses of overall traffic. The difference in estimated elasticities could then be interpreted as empirical evidence supporting the "keeping up with the flow" tendency reported in Fleiter et al. (2010).

### *E. Heterogeneity in Responsiveness*

#### Price Ranges

In our previous analyses, we examined the general speed effects of fuel price increases, irrespective of the price level. The price level, however, might influence the impact of fuel prices on driving speeds. For example, when prices rose above €2 for the first time, this was accompanied by a great deal of media interest and public debate (e.g. BILD, 2022; Tagesschau, 2022). As a consequence of this unexpected fuel price increase, the salience of fuel prices in people's everyday lives might have been increased and consumers may have become more price sensitive (Bordalo et al., 2013; Hastings and Shapiro, 2013). Accordingly, the most visible declines in driving speeds in Figure 2 coincided with prices above €2, in particular on Autobahn sections with no speed limit. To test for this assumed heterogeneity in speed price elasticities, we now run separate regressions both for prices below €2 and above €2, both for the entire sample and single drivers. The respective results are shown in Table 4.

First, we look at the results for the entire sample. For prices below €2, we only find a statistically significant speed elasticity for sections without a speed limit ($-0.012$). For prices above €2, we find statistically significant speed price elasticities on both section types, but with much higher values for non-limit sections ($-0.110$ vs. $-0.063$). Again, the coefficients for sections with a limit and with no limit differ significantly.

The single driver results confirm higher speed price elasticities (i) for non-limit sections, (ii) for fuel prices above €2 and (iii) for single drivers, i.e. when they are free to choose their driving speed. In particular, we find the highest speed price elasticity for single drivers on non-limit sections and prices above €2 ($-0.22$).

Table 4—: Overview of Regression Results for Heterogeneity in Responsiveness

| Data | Limit | Fuel Price | Speed/Lane | Coefficient | Std. error |
|---|---|---|---|---|---|
| *Price Ranges, All Data* | | | | | |
| All Data | Limit | Fuel Price < €2 | | −0.0097 | (0.0080) |
| All Data | No Limit | Fuel Price < €2 | | −0.0119** | (0.0056) |
| All Data | Limit | Fuel Price ≥ €2 | | −0.0628* | (0.0276) |
| All Data | No Limit | Fuel Price ≥ €2 | | −0.1102*** | (0.0137) |
| *Price Ranges, Single Drivers* | | | | | |
| Single Drivers | Limit | Fuel Price < €2 | | 0.0021 | (0.0086) |
| Single Drivers | No Limit | Fuel Price < €2 | | −0.0337*** | (0.0105) |
| Single Drivers | Limit | Fuel Price ≥ €2 | | −0.1020 | (0.0564) |
| Single Drivers | No Limit | Fuel Price ≥ €2 | | −0.2191*** | (0.0552) |
| *Speeds, All Data* | | | | | |
| All Data | Limit | | Right Lane | −0.0362*** | (0.0053) |
| All Data | No Limit | | Right Lane | −0.0555*** | (0.0056) |
| All Data | Limit | | Left Lanes | −0.0251*** | (0.0064) |
| All Data | No Limit | | Left Lanes | −0.0283*** | (0.0600) |
| *Speeds, Single Drivers* | | | | | |
| Single Drivers | No Limit | | Speed < 130 kph | −0.0352*** | (0.0066) |
| Single Drivers | No Limit | Fuel Price < €2 | Speed < 130 kph | −0.0160** | (0.0075) |
| Single Drivers | No Limit | Fuel Price ≥ €2 | Speed < 130 kph | −0.1447*** | (0.0435) |
| Single Drivers | No Limit | | Speed ≥ 130 kph | −0.0007 | (0.0056) |
| Single Drivers | No Limit | Fuel Price < €2 | Speed ≥ 130 kph | 0.0016 | (0.0067) |
| Single Drivers | No Limit | Fuel Price ≥ €2 | Speed ≥ 130 kph | −0.0398 | (0.0349) |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.
More detailed regression results can be found in Tables 7 to 10 in Appendix VI.A.

### Speeds

Next, we analyze whether slower drivers react differently to fuel price increases than faster drivers. To explore this relationship, we outline two separate approaches below.

First, we exploit the "Rechtsfahrgebot" on the German Autobahn. This law requires drivers to adhere to the rightmost lane if traffic flow permits, in order to allow for easier and safer overtaking in the left lanes. Accordingly, average driving speeds on non-limit Autobahn sections are 114 kph in the right lane and 135 kph in the left lanes. The respective speeds for limit sections are 103 kph and 124 kph. Running separate regressions for each lane type, we find that the slower right-lane drivers react more strongly to higher fuel prices than the faster left-lane drivers (see Table 4). This difference is statistically significant for both limit and non-limit sections.

Second, we use the single driver subsample to analyze the driving speeds at the individual level. This enables us to distinguish between *slow* and *fast* drivers through the threshold of 130 kph, i.e. the guideline speed on the German Autobahn. Since the highest possible speed limit is 130 kph, we focus on sections without speed limits, so as to retain sufficient observations above 130 kph. The results in Table 4 confirm that slow drivers are affected by fuel price increases and, again, the highest elasticity is found above €2 (−0.145). Fast drivers, however, display no significant response.

The results of both regressions suggest that slower drivers reduce their speed as a result of higher fuel prices, whereas faster drivers appear to react less or not at all – thus supporting Tom Hanks' experiences on the German Autobahn, because there will be speedsters no matter what the price. This behavior may be attributed to their preference for driving fast, potentially related to a high value of time due to high salaries or the urgency of reaching their destination on time, or simply impatience. Additionally, drivers whose fuel expenses are fully covered by their employers, e.g. by fuel cards, have no financial incentive to improve their fuel economy by adjusting their speed when fuel prices rise.

## III. Estimating the Short-Run Fuel Demand Elasticity

### *A. Calculation*

In our next step, we calculate the short-run fuel demand elasticity $\epsilon_d$. To do so, we require information on the relationship between fuel prices and speed ($S(P)$), as well as information on the influence of driving speed on fuel consumption ($f(S(P))$). The former was estimated in Section II, and the latter can be approximated with data from HBEFA (2022). They report the fuel consumption for the average car fleet and occupancy rate, different speeds and free-flowing traffic on the German Autobahn. The underlying relationship can best be specified by

$$(3) \qquad f(S(P)) = 1.71553 - 0.00507 \times S(P) + 0.00006 \times (S(P))^2,$$

which allows us to calculate the fuel demand elasticity for a price increase from $P_0$ to $P_1$ as

$$(4) \qquad \epsilon_d = \frac{\frac{\Delta f(S(P))}{f(S(P))}}{\frac{\Delta P}{P}},$$

with $\Delta f(S(P)) = f(S(P_1)) - f(S(P_0))$ and $\Delta P = P_1 - P_0$.

We then use Equation 4 to calculate the short-run demand elasticity for five different scenarios, each based on previously used subsamples. In each scenario, we assume that the average fuel price of the respective sample increases by 10 %, and we predict the subsequent changes in driving behavior in order to calculate the fuel savings and thereby the short-run fuel demand elasticity. The results are outlined in Table 5.

We begin by focusing on non-limit sections in Scenarios 1 to 4. In Scenario 1, we use all of our sample data and find a short-run fuel demand elasticity of −0.060, implying that a 10 % increase in fuel prices reduces fuel consumption by 0.05 l/100 km, which is solely due to a reduction in driving speed. The short-run demand elasticity is thus slightly higher than the corresponding speed price elasticity, indicating that the reductions in speed lead to slightly higher reductions in fuel consumption. In Scenario 3, we find that the short-run demand elasticity for single drivers (−0.071) is slightly higher than for all drivers, which could again be explained by the absence of interference from other vehicles. Scenarios 2 and 4 focus on the time periods during which fuel prices were above €2. The corresponding short-run fuel demand elasticities are significantly higher for all drivers (−0.13) and single drivers (−0.25), which is in accordance with the higher speed price elasticities during these time periods.

Previous meta studies report short-run fuel demand elasticities that range from −0.03 to −0.51, averaging between −0.24 and −0.26 (Dahl and Sterner, 1991; Espey, 1998; Goodwin et al., 2004). These elasticities are mostly based on country-

Table 5—: Short-Run Fuel Demand Elasticities for Five Scenarios

| Variable | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 | Scenario 5 |
|---|---|---|---|---|---|
| *Setting* | | | | | |
| Data | All Data | All Data | Single Driver | Single Driver | All Data |
| Speed Limit | No | No | No | No | Yes |
| Fuel Price | All Prices | $\geq$ €2 | All Prices | $\geq$ €2 | All Prices |
| Speed Price Elasticity | -0.0474*** | -0.1102*** | -0.0593*** | -0.2191*** | -0.0331*** |
| Old Price (€; sample average) | 1.44 | 2.06 | 1.44 | 2.06 | 1.44 |
| New Price (10 % increase) | 1.58 | 2.27 | 1.58 | 2.27 | 1.58 |
| Old Speed (kph; sample average) | 124.90 | 122.00 | 122.65 | 121.70 | 112.04 |
| New Speed (kph) | 124.31 | 120.66 | 121.92 | 119.03 | 111.63 |
| *Results* | | | | | |
| Fuel Savings (l/100 km)[1] | 0.045 | 0.096 | 0.053 | 0.186 | 0.021 |
| $CO_2$ Savings (gram/100 km)[1,2] | 112.71 | 238.08 | 131.53 | 462.11 | 52.99 |
| Fuel Costs Savings (€/100 km)[1] | 0.072 | 0.218 | 0.084 | 0.423 | 0.034 |
| Short-Run Fuel Demand Elasticity | -0.060 | -0.129 | -0.071 | -0.252 | -0.032 |

[1] Per vehicle.
[2] Based on the weighted average fuel consumption we previously used for the mixed fuel price, we can calculate a $CO_2$ equivalent of 2.48 kg per liter (Helmholtz-Gemeinschaft, 2022).

level fuel consumption data that encompass a broader spectrum of effects of fuel price changes, such as a reduction in travel activity and substitution to other modes of transportation. Our calculated elasticities, however, only account for fuel consumption reductions that are due to slower driving, thereby explaining why our elasticities are at the lower end of elasticities reported in literature.

From a methodological perspective, our results are more comparable to Austin (2008), who also estimates the short-run fuel demand elasticity from driving speed reactions only. However, he uses only data from road sections with a speed limit, and estimates smaller elasticities than ours for non-limit sections. In Scenario 5, we similarly estimate a short-run fuel demand elasticity for limit Autobahn sections, and find that it is lower than for non-limit sections. This again underlines that speed limits distort the impact of fuel price increases.

### B. *Policy Implications*

Figure 3 illustrates the impact of fuel prices on driving speeds, and subsequently on fuel consumption for the German Autobahn. Based on the the average fuel price of €1.91 and the average driving speeds in 2022, i.e. the most recent year of our sample, we use the speed price elasticities from Table 2 and calculate how fuel prices change the driving speeds on limit and non-limit Autobahn sections. These changes in driving speeds are depicted by the solid and dotted lines in Figure 3, respectively. The changes are then used to derive the subsequent changes in fuel consumption, for which we again rely on Equation 3. With the annual passenger car mileage on the German Autobahn in 2022 of 202.7 billion km[15], as well as the share of sections without a speed limit of 70 % (Bauernschuster and Traxler, 2021; Löhe, 2016), we can derive the annual changes in total fuel consumption

[15] We multiply the annual vehicle mileage on all German roads in 2022 of 721 billion km (Schönebeck et al., 2022) with the share of passenger car miles of 85.2 %. Since values for 2022 are not available, we calculated the average share of passenger car miles from 2017 to 2021 (Eisenmann et al., 2022). Then, these 614.2 billion km vehicle kilometers traveled by passenger cars are multiplied by the share of kilometers traveled on the German Autobahn, that is, 33 % (Matthey and Bünger, 2019), which results in our annual passenger car mileage of 202.7 billion km on the Autobahn.

for car traffic on the German Autobahn. These fuel consumption changes result purely from the changes in driving speeds, and they are depicted by the stacked areas on the secondary y-axis on the right in Figure 3. Darker areas refer to fuel consumption changes on non-limit Autobahn sections, and lighter areas to changes on limit sections.

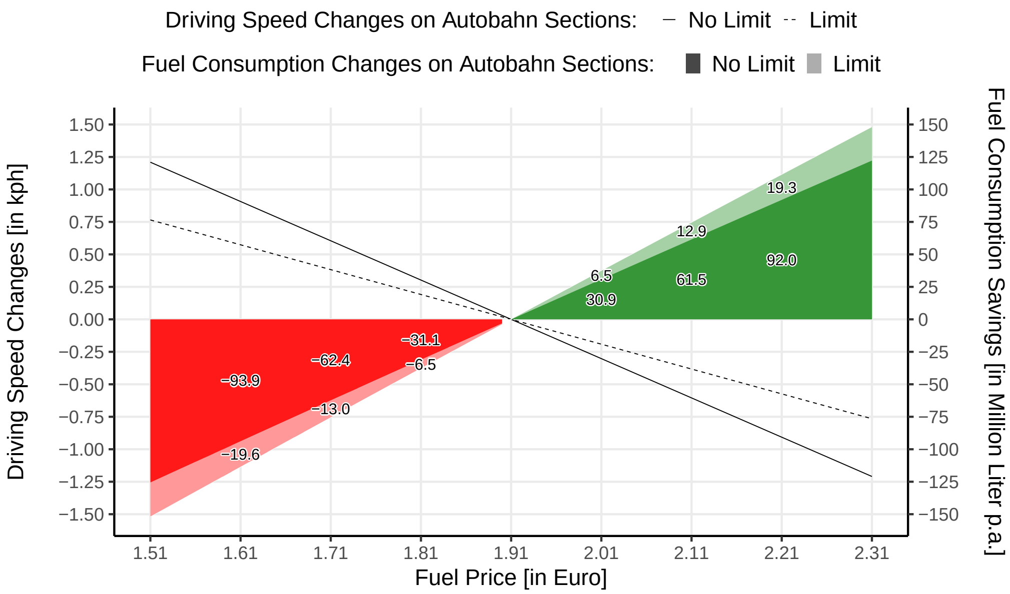


Figure 3. : Fuel Prices, Driving Speeds and Fuel Consumption Savings on the German Autobahn

The changes in total fuel consumption on the German Autobahn should be viewed as lower-bound estimates for two reasons. First, we do not consider changes in fuel consumption that result from potential changes in travel activity. Second, we use the baseline speed price elasticities, although the results in Table 4 suggest that the elasticities are higher for higher prices.

Our findings are relevant for policymakers, because they show that increasing fuel prices reduce fuel consumption and thereby $CO_2$ emissions – without the need to reduce travel activity or switch to other modes of transportation. In Germany, the fuel price in 2022 included a $CO_2$ tax of €30 per emitted ton. With the average $CO_2$ emissions of the German car fleet and the additional VAT of 19 %, this $CO_2$ tax amounted to roughly €0.088 per liter. In the upcoming years, the German government is planning to increase the $CO_2$ tax to €35 in 2024, €45 in 2025, and €65 per ton in 2025. Hence, the $CO_2$ tax will amount to roughly €0.192 per liter in 2026, a gross fuel price increase of €0.104 compared to 2022. This would then result in annual fuel consumption savings of 6.5 million liters for limit and 30.9 million liters for non-limit sections. In total, 37.4 million liters of fuel can be saved, corresponding to 92, 598 tons of $CO_2$ or the average annual $CO_2$ emissions of 44, 506 cars. This confirms that increasing fuel prices is indeed a viable policy instrument for achieving significant $CO_2$ savings, solely by reducing driving speed and without scaling back travel activity.

## IV. Estimating the Value of Time

### A. Calculation

In this section, we estimate the revealed VOT for drivers on non-limit sections on the German Autobahn. Similar to Wolff (2014), we use our speed price elasticities to estimate the VOT on the *intensive* margin. This approach takes into account the continuous choice of travel speed on the road, and is hence fundamentally distinct from former approaches, in which choices are limit to discrete options on the *extensive* margin. In contrast to Wolff (2014), who uses hourly data from Californian highways with a speed limit that might distort drivers' individual speed choice, we can estimate the undistorted VOT on Autobahn sections without any speed limit.

To estimate the VOT, we analyze the trade-off a driver faces when minimizing her overall driving costs. When fuel prices increase, rational drivers decrease their speed $S$ in such a way that the marginal benefit from fuel-cost savings $(\partial fc(S(P))/\partial S(P))$ and the marginal benefit from a lower accident risk $(\partial acc(S(P))/\partial S(P))$ are equal to marginal cost from a longer travel time $(\partial t(S(P))/\partial S(P) \times VOT)$. By totally differentiating Equation 1, the revealed VOT can be derived by:

$$VOT = -\Bigg(\underbrace{\frac{P \times \partial fc(S(P))/\partial S(P)}{\partial t(S(P))/\partial S(P)}}_{\text{fuel cost component}} + \underbrace{\frac{\partial acc(S(P))/\partial S(P)}{\partial t(S(P))/\partial S(P)}}_{\text{travel safety component}}\Bigg) \tag{5}$$

The *fuel cost component* of the VOT describes the ratio of marginal changes in fuel costs to marginal changes in travel time. To calculate the *fuel cost component*, we use the findings from our standard speed price elasticity in Table 2. A 10 % fuel price increase reduces driving speed by 0.59 kph on non-limit sections, thereby reducing fuel consumption by €0.072 per 100 km and vehicle (see Table 5). The corresponding travel time increase is about 20.6 seconds per 100 km and vehicle.[16] Then, the *fuel cost component* is €12.59/h.

The *travel safety component* of the VOT describes the ratio of marginal changes in accident costs to marginal changes in travel time. For a speed change from $S(P_0)$ to $S(P_1)$, the former is €0.046 per 100 km and vehicle, and can be calculated as

$$\partial acc(S(P), Y) = 100 \times \left(\sum_i (r_i(S(P_1), Y) - r_i(S(P_0), Y)) \times iac_i\right). \tag{6}$$

Here, $iac_i$ are the internalized accident costs for accident type $i$. The accident risk $r_i$ is influenced by the driving speed $S$ and exogenous factors $Y$, such as road characteristics. For further information we refer to Appendix VI.B. In relation to the travel time increase of 20.6 seconds, the *travel safety component* is then €8.12/h.

In sum, the revealed VOT on non-limit Autobahn sections then is €12.59/h + €8.12/h = €20.71/h. This revealed VOT reflects about 83 % of the average

[16] The time loss of 13.7 seconds needs to be multiplied by the average occupancy rate in Germany of $n = 1.5$ (Nobis and Kuhnimhof, 2018) to obtain the time loss per 100 km and vehicle $t(S(P)) = (100 \times 1.5)/(S(P))$.

hourly gross wage in Germany, which was €24.87/h in 2022 (Federal Statistical Office, 2023a). The revealed VOT for the single driver subsample on non-limit sections is €11.52/h + €7.53/h = €19.04/h and thus 77 % of the gross wage. It is lower than the revealed VOT for the entire data sample. One potential reason for this might be the lower share of business trips in periods when drivers are alone on the road, i.e. during night times.

### *B. Discussion*

According to Small and Verhoef (2007), the VOT ranges from 20 % to 90 % of the average gross wage. Moreover, they report that RP data tends to yield a higher VOT than SP data. Specifically, RP-based estimates range from 50 % to 90 % of the gross wage (Brownstone and Small, 2005; Small and Verhoef, 2007). Our findings based on RP data indicate a VOT of 77 to 83 % on non-limit Autobahn sections, which is in the upper range of reported values in the literature. In contrast to Wolff (2014), who identifies a VOT on the *intensive* margin ranging from 45 % to 57 % of the gross wage, our results for non-limit sections are significantly higher. If we similarly calculate the VOT for limit sections only, we obtain a value of €7.61/h + €5.27/h = €12.88/h. This is 52 % of the gross wage and similar to Wolff (2014).[17] Hence, this difference between the VOT for limit and non-limit sections can be explained by the absence of speed limits and the subsequently undistorted speed decisions.

The literature regarding the VOT in Germany is relatively limit and there is no research on non-limit Autobahn sections. In a comprehensive meta-analysis, Wardman et al. (2016) estimate a VOT of €9.61/h for urban free flow commuting.[18] Obermeyer et al. (2013) find a VOT range of €11.31/h to €16.01/h for urban motorized traffic in the city of Dresden. In the CBA framework for assessing infrastructure projects in Germany, a combined SP and RP model based on both hypothetical and actual choices from survey respondents is used (Axhausen et al., 2014; BMVI, 2016).[19] This framework yields a VOT of €11.05/h, but does not incorporate changes in accident costs. Hence, it is comparable to our estimated *fuel cost component* of €12.59/h, both with respect to scope and magnitude. Consequently, our approach appears to produce fairly similar estimates for travel time valuation on the German Autobahn.

## V. Conclusion

In this paper, we analyze the relationship between fuel prices and driving speeds on the German Autobahn. The previous literature concerning this relationship lacks an analysis of speed decisions made in the absence of speed limits and

[17] In Wolff (2014), the VOT components for a change in fuel consumption and the difference in accident costs for a speed reduction have a value of $11.52/h, which is 51.7 % of the average hourly gross wage of $22.32 in the State of Washington. Thus, the value is comparable and almost similar to our VOT for limit sections.

[18] For better comparability, all monetary values are adjusted to 2022 prices.

[19] Axhausen et al. (2014) provide standardized VOTs for different travel purposes and travel distances for the Bundesverkehrswegeplan (BMVI, 2016), which is the German national framework for assessing transport infrastructure investments. As their reported VOTs do not take into account accident costs, their values actually correspond to our *fuel cost component* of the VOT. To calculate one final value from the multitude of their reported VOTs, assumptions about average trip lengths and the share of private and business trips on the German Autobahn are necessary. We follow Goldmann and Sieg (2021) and use an average travel distance of 45 km for private and 100 km for business-related trips, with the former accounting for 88 % and the latter for 12 % of total trips.

without the influence of other vehicles. Thus, previously estimated speed price elasticities may be distorted. To tackle these concerns, we exploit the unique setting of there being no general speed limit on the German Autobahn. Furthermore, our data sample comprises per-minute speed and traffic flow data, which enables us to analyze individual speed decisions when no other vehicles are on the road.

Our results from the regression analysis are fourfold. First, we find that drivers significantly reduce their driving speed in response to fuel price increases, and thus confirm the findings of Austin (2008) and Wolff (2014). Second, drivers on Autobahn sections without a speed limit react significantly more strongly to higher fuel prices ($-0.047$) than drivers on limit sections ($-0.033$). This finding suggests that speed limits distort the extent to which drivers adjust their driving speed when fuel prices increase. Third, we find that the speed price elasticity for drivers who are alone on the road is higher than those for drivers influenced by the presence of other vehicles. We thereby support the findings of Fleiter et al. (2010), indicating that drivers experience pressure from other vehicles to drive faster than their own preferences, in order to keep up with the traffic flow. Fourth, our sensitivity analyses explore heterogenous responses and indicate higher speed price elasticities when prices are high and for slower drivers.

We then use our undistorted speed price elasticity estimators to quantify the impact of a price change on short-term fuel demand resulting from speed adjustments alone. In accordance with Austin (2008), who also considers solely the response of driving speeds due to higher fuel prices – although only for limit sections – we estimate a short-run fuel demand elasticity in the range between $-0.060$ and $-0.071$.

On this basis, we analyze the trade-off of a driver's speed decision to determine the revealed VOT at the *intensive* margin on non-limit Autobahn sections. Higher fuel prices lead to speed reductions, which on the one hand, lower fuel costs and accident risk, but on the other hand increase travel time. The revealed VOT on non-limit Autobahn sections is €20.71/h and thus 83 % of the average hourly gross wage. In contrast to the literature on revealed VOT, our value is in the upper range.

Our findings then enable deriving relevant policy implications. First, drivers respond to price signals and adjust their speed to reduce fuel consumption. Therefore, implementing governmental pricing instruments, such as the $CO_2$ tax in Germany, can be an impactful measure to reduce driving speeds and thereby lower fuel consumption and emissions, without the need to reduce travel activity. For instance, a targeted $CO_2$ price of €65 per ton in 2026 would reduce annual fuel demand by 37.4 million liters, equivalent to $92,598$ tons of $CO_2$, or the annual emissions of about $44,506$ cars in Germany. Second, the revealed VOT highlights a trade-off between factors such as fuel costs, accident risk, and travel time. Hence, policymakers need to carefully weigh up these considerations when making decisions about road infrastructure and pricing strategies. Our estimated *fuel cost component* of the VOT closely corresponds to the time value used in the Bundesverkehrswegeplan (Axhausen et al., 2014; BMVI, 2016), which assesses infrastructure investments in Germany. This suggests that the findings of this study align well with existing policy frameworks. However, our approach could serve as a valuable input for future infrastructure planning and investment decisions, by additionally considering the *travel safety component* of the VOT, i.e. the interdependencies between accident risk and driving speed. Third, our results contribute to the on-going debate on implementing a general speed limit on the German Autobahn. Our finding that drivers react to fuel price changes validates the fact that fuel prices serve as an effective market-based instrument for influencing driving speeds, and could therefore be considered as an alternative policy instrument to a general speed limit.

**Acknowledgements**

The authors would like to thank Edita Selimaj, Maria Kennel and Lars Rödermund for their valuable research assistance; Gernot Sieg and Johannes Becker for helpful comments; and Brian Bloch for his editing of the English. Finally, we would like to thank the participants of the 2023 International Transportation Economics Association Conference, and especially Erik T. Verhoef, for their helpful comments in improving this paper.

# VI. Appendix

## A. Regression Results

Table 6—: Detailed Regression Results for Standard Regressions

| Dependent Variable: | log(Speed) | |
|---|---|---|
| Model: | Limit | No Limit |
| *Variables* | | |
| log(Fuel Price) | -0.0331*** | -0.0470*** |
| | (0.0069) | (0.0046) |
| Traffic Volume Cars | -0.0011 | 0.0004* |
| | (0.0009) | (0.0002) |
| Traffic Volume Cars$^2$ | $-1.5 \times 10^{-5}$ | $-4.56 \times 10^{-5}$*** |
| | $(1.43 \times 10^{-5})$ | $(6.37 \times 10^{-6})$ |
| Traffic Volume Trucks | -0.0038** | -0.0079*** |
| | (0.0015) | (0.0008) |
| Traffic Volume Trucks$^2$ | 0.0001 | 0.0002*** |
| | (0.0001) | $(3.36 \times 10^{-5})$ |
| Daylight | 0.0402*** | 0.0381*** |
| | (0.0060) | (0.0013) |
| Twilight | 0.0191*** | 0.0174*** |
| | (0.0043) | (0.0007) |
| Wind Speed | -0.0009 | -0.0019*** |
| | (0.0005) | (0.0002) |
| Temperature | 0.0005*** | 0.0006*** |
| | (0.0001) | $(6.29 \times 10^{-5})$ |
| Light Rain | -0.0462*** | -0.0434*** |
| | (0.0040) | (0.0013) |
| Rain | -0.0799*** | -0.0775*** |
| | (0.0091) | (0.0023) |
| Snow | -0.0411** | -0.0387*** |
| | (0.0123) | (0.0024) |
| School Holidays | 0.0049*** | -0.0005 |
| | (0.0012) | (0.0005) |
| Holidays | 0.0140*** | 0.0042*** |
| | (0.0035) | (0.0013) |
| Unemployment Rate | -0.0014 | -0.0011 |
| | (0.0012) | (0.0013) |
| Consumer Price Index | 0.0007 | -0.0011*** |
| | (0.0009) | (0.0004) |
| Covid Stringency Index | $5.93 \times 10^{-5}$ | $-9.3 \times 10^{-5}$*** |
| | $(6.57 \times 10^{-5})$ | $(2.77 \times 10^{-5})$ |
| *Fixed Effects* | | |
| Station | Yes | Yes |
| Hour × Weekday | Yes | Yes |
| Month | Yes | Yes |
| Year | Yes | Yes |
| *Fit Statistics* | | |
| Observations | 17,124,780 | 100,390,225 |
| $R^2$ | 0.59327 | 0.33499 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 7—: Regression Results for Price Ranges and Entire Data

| Dependent Variable: | log(Speed) | | | |
|---|---|---|---|---|
| Model | Fuel Price < €2 | | Fuel Price ≥ €2 | |
| | Limit | No Limit | Limit | No Limit |
| log(Fuel Price) | -0.0097 | -0.0119** | -0.0628* | -0.1102*** |
| | (0.0080) | (0.0056) | (0.0276) | (0.0137) |
| Control variables | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 15,916,212 | 93,201,535 | 1,208,568 | 7,188,690 |
| $R^2$ | 0.5915 | 0.3324 | 0.6206 | 0.3554 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 8—: Regression Results for Price Ranges and Single Driver Subsample

| Dependent Variable: | log(Speed) | | | |
|---|---|---|---|---|
| | Fuel Price < €2 | | Fuel Price ≥ €2 | |
| | Limit | No Limit | Limit | No Limit |
| log(Fuel Price) | 0.0021 | -0.0337*** | -0.1020 | -0.2191*** |
| | (0.0086) | (0.0105) | (0.0564) | (0.0552) |
| Control Variables | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 440,703 | 2,512,535 | 30,971 | 170,578 |
| $R^2$ | 0.1544 | 0.1091 | 0.1415 | 0.1573 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 9—: Regression Results for Left and Right Lane

| Dependent Variable: | log(Speed) | | | |
|---|---|---|---|---|
| Model: | Left Lanes | | Right Lane | |
| | Limit | No Limit | Limit | No Limit |
| log(Fuel Price) | -0.0251*** | -0.0283*** | -0.0362*** | -0.0555*** |
| | (0.0064) | (0.0600) | (0.0053) | (0.0056) |
| Control Variables | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Observations | 19,979,718 | 113,469,200 | 16,930,658 | 93,449,852 |
| $R^2$ | 0.6035 | 0.4434 | 0.5926 | 0.3644 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 10—: Regression Results for Speed Ranges for Non-Limit Sections

| Dependent Variable: | log(Speed) | | | | | |
|---|---|---|---|---|---|---|
| Model: | Speed < 130 kph | | | Speed ≥ 130 kph | | |
| | All Prices | Fuel Price < €2 | Fuel Price ≥ €2 | All Prices | Fuel Price <€2 | Fuel Price ≥ €2 |
| log(Fuel Price) | -0.0352*** | -0.0160** | -0.1447*** | -0.0007 | 0.0016 | -0.0398 |
| | (0.0066) | (0.0075) | (0.0435) | (0.0056) | (0.0067) | (0.0349) |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,868,483 | 1,747,898 | 120,585 | 814,630 | 764,637 | 49,993 |
| $R^2$ | 0.0623 | 0.0613 | 0.0807 | 0.0348 | 0.0320 | 0.0831 |

Clustered (measuring station) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

## B. *Calculating the Travel Safety Component of the VOT*

The road safety literature reports a strong and positive relationship between driving speed and accident risk, especially for motorways (Elvik, 2009, 2013). To calculate the *travel safety component* of the VOT, we thus require information on the changes in accident costs per vehicle and 100 kilometers if driving speed changes. Tscharaktschiew (2016) is the first to estimate accident costs for different driving speeds on the German Autobahn. Accordingly, our calculations and assumptions are closely related to those in Tscharaktschiew (2016), to which we refer for more detailed explanations.

As outlined in the main text, the *travel safety component* of the VOT is defined as

$$\text{(7)} \qquad \textit{travel safety component} = \frac{\partial acc(S(P))/\partial S(P)}{\partial t(S(P))/\partial S(P)}.$$

We are now interested in the differences in the accident costs $\partial acc(S(P))$ per vehicle and 100 kilometers, which are modeled by

$$\text{(6)} \qquad \partial acc(S(P), Y) = 100 \times \left( \sum_i (r_i(S(P_1), Y) - r_i(S(P_0), Y)) \times iac_i \right).$$

This equation multiplies the internalized accident costs $iac_i$ for accident type $i$ with the corresponding difference in accident risk $r_i(S(P), Y)$ that results from a driving speed change from $S(P_1)$ to $S(P_2)$. In our analysis, we generally distinguish between four different accident types: $i = 1$ for fatal injuries, $i = 2$ for severe injuries, $i = 3$ for slight injuries, and $i = 4$ for property damage only. The total accident costs per kilometer are then calculated as the sum of these accident-type-specific expected costs. The multiplication by 100 ensures that the costs are per 100 kilometer. Below, we describe the accident risk $r_i(S(P), Y)$ and the internalized accident costs $iac_i$ in more detail.

The accident risk $r_i(S(P), Y)$ per vehicle kilometer and accident type $i$ is defined according to the "Power Model" outlined and specified in Elvik (2009, 2013):

$$\text{(8)} \qquad r_i(S(P), Y) = \pi_i(Y) \times \left( \frac{S(P)}{\overline{S}} \right)^{\Theta_i}.$$

This depends on the individual driving speed $S(P)$ and exogenous factors such as road characteristics or weather conditions, which are denoted by $Y$. The first term on the right of Equation 8, i.e. $\pi_i$, reflects the reference accident rate per kilometer of accident type $i$. With data from Federal Statistical Office (2021), we can calculate the values for $\pi_i$ on the German Autobahn. Not surprisingly, the reference accident rate is highest for property-damage-only accidents and lowest for fatal accidents (see Table 11). The second term on the right then models how the accident risk changes if driving speed changes. The reference accident rates $\pi_i$ were measured at the actual driving speeds, so we set the reference speed level $\overline{S}$ to 121.1 kph, which is the average driving speed across both limit and non-limit sections in our data weighted by the real-world share of the respective sections. The values for the accident-speed elasticities $\Theta_i$ are from Elvik (2009, 2013) and specify the relationship between driving speed changes and accident risk changes.

Not all accident costs are internalized by vehicle occupants (e.g. Link et al., 2007; Tscharaktschiew, 2016), so we calculate the internalized accident costs $iac_i$ of accident type $i$ as

$$iac_i = \phi_i \times \delta_i + \chi_i \times \sigma_i \times \xi_i. \tag{9}$$

Here, the accident-type-specific value of safety $\phi_i$ is multiplied by the internalization rate $\delta_i$, and the costs of property damage $\chi_i$ are adjusted by the internalization rates for property damages $\sigma_i$ and by guilt assignment $\xi_i$. We use the values of safety $\phi_i$ from Schoeters et al. (2021), which is the most recent data available. It should be noted that they report higher monetary values than used by Tscharaktschiew (2016). Depending on the accident type $i$, about 15 % to 25 % of injuries or fatalities involve people outside of the car. Hence, we use internalization rate values for $\delta_i$ provided by Tscharaktschiew (2016) and Link et al. (2007). Per definition, $\delta_4$ for property-damage-only accidents is set to zero. The monetary values for the costs of property damage $\chi_i$ are from Baum et al. (2010). Since insurance companies bear part of the property damages, $\sigma_i$ is assumed to be 80 % for all accidents. In addition, we assume that only in half of the cases is the driver under consideration the one who is assigned the guilt for the accident, i.e. $\xi_i = 0.5$.

Further information on the parameter values and their respective sources are presented in Table 11. All monetary values are converted to 2022 prices. Finally, we can plug in the speeds for different prices in Equation 6 and obtain a monetized value for the change in accident risks. For a fuel price increase of 10 %, this value accounts for €0.046 per 100 km on non-limit sections, €0.055 for single drivers on non-limit sections, and €0.023 for all drivers on limit sections.

Table 11—: Parameters for Accident Data

| Description | Symbol | Value | Dimension |
|---|---|---|---|
| *Accident Risk (Federal Statistical Office, 2021)* | | | |
| Accident Risk ($i = 1$) | $\pi_1$ | $1.4 \times 10^{-8}$ | risk/km |
| Accident Risk ($i = 2$) | $\pi_2$ | $2.1 \times 10^{-8}$ | risk/km |
| Accident Risk ($i = 3$) | $\pi_3$ | $9.3 \times 10^{-8}$ | risk/km |
| Accident Risk ($i = 4$) | $\pi_4$ | $5.7 \times 10^{-7}$ | risk/km |
| *Power Parameter (Elvik, 2009, 2013)* | | | |
| Exponents Power Function ($i = 1$) | $\Theta_1$ | 4.1 | – |
| Exponents Power Function ($i = 2$) | $\Theta_2$ | 2.6 | – |
| Exponents Power Function ($i = 3$) | $\Theta_3$ | 1.1 | – |
| Exponents Power Function ($i = 4$) | $\Theta_4$ | 1.5 | – |
| *Internalization and Guilt (Link et al., 2007; Tscharaktschiew, 2016)* | | | |
| Internalization Rate ($i = 1$) | $\delta_1$ | 0.74 | % |
| Internalization Rate ($i = 2$) | $\delta_2$ | 0.80 | % |
| Internalization Rate ($i = 3$) | $\delta_3$ | 0.85 | % |
| Internalization Rate ($\forall i$) | $\sigma_i$ | 0.80 | % |
| Guilt Assignment ($\forall i$) | $\xi_i$ | 0.50 | % |
| *Monetary Values (Baum et al., 2010; Schoeters et al., 2021)* | | | |
| Value of Safety ($i = 1$) | $\phi_1$ | 7,350,000 | € |
| Value of Safety ($i = 2$) | $\phi_2$ | 1,100,000 | € |
| Value of Safety ($i = 3$) | $\phi_3$ | 73,500 | € |
| Property Damage ($i = 1$) | $\chi_1$ | 33,147 | € |
| Property Damage ($i = 2$) | $\chi_2$ | 15,931 | € |
| Property Damage ($i = 3$) | $\chi_3$ | 10,149 | € |
| Property Damage ($i = 4$) | $\chi_4$ | 4,753 | € |

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