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Pump or pedal? The impact of fuel prices on cycling in Germany

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ABSTRACT

We analyze the relationship between fuel prices and cycling in Germany. The estimated cross-elasticity is positive and significant for utilitarian traffic, and increased in 2022 when prices became more salient. To derive our results, we exploit fuel-price variations caused by the Russian invasion of Ukraine, among other factors. Cross-elasticities are then estimated by running both OLS and IV regression models on hourly bicycle counts from 72 automated counting stations. While cross-elasticities have been estimated for low-cycling countries such as the U.S. or Australia, our results provide valuable insights for transport planning and sustainable policy making in higher-cycling countries.

1. Introduction

Cycling is widely regarded as an important cornerstone for a more sustainable transportation system because of its many positive attributes. It neither emits greenhouse gases nor other pollutants (Pucher et al., 2010), can improve physical and mental health (Martin et al., 2014; Götschi et al., 2016), is relatively cheap (Gössling et al., 2019), and can even improve living quality in cities (Gehl, 2013). Hence, the promotion of cycling has received considerable attention in recent years (Pucher and Buehler, 2017), and the effectiveness of various policy instruments for promoting cycling is evaluated in Rietveld and Daniel (2004). They conclude that there are essentially two ways to increase bicycle usage: reducing the generalized (i.e. monetary and non-monetary) costs of cycling, and increasing the generalized costs of transport alternatives. The former, for example, could be achieved by improving cycling infrastructure and thereby reducing the generalized costs of cycling. The latter can be achieved by increasing fuel costs, which would reduce the relative attractiveness of cars and thereby increase that of bicycles. Against this backdrop, we analyze the impact of fuel prices on cycling flows in Germany.

While there is some literature on the effect of fuel prices on cycling, it mainly relates to North America and Australia. Pucher and Buehler (2006), Buehler and Pucher (2012) show that the modal shares of cycling and cycling to work in North American cities are higher in those cities with higher gasoline prices. Noland and Kunreuther (1995) conduct a survey in Philadelphia, U.S., and find that a 1% increase in the perceived automobile costs increases the probability of cycling by roughly 0.3%. Rashad (2009) use data from individual-level travel surveys in the U.S. between 1990 and 2001 and find that if gasoline prices increase by $1, the probability of cycling in the past month increases by 4.3 to 4.7 percentage points for men and by 2.9 to 3.5 percentage points for women. He et al. (2020) analyze bike-sharing in three U.S. metropolises and find that a 1% increase in gasoline prices increases the total duration of bike-share trips by 1.2% and the total frequency by 1.6%. Smith and Kauermann (2011) analyze hourly bicycle counts in Melbourne, Australia, from December 2005 to June 2008. They find that higher petrol prices increase cycling volumes, with cross-elasticities of approximately 0.3.

The above research comes with the caveat that the results only apply to countries with a very low modal share of cycling, i.e. 1% for the U.S. and 1.4% for Canada and Australia (Buehler and Pucher, 2021). It is therefore questionable whether these results would

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apply in countries with significantly higher modal shares of cycling, e.g. European countries such Belgium (8%), Sweden (9%), Germany (11%), Denmark (14%), and the Netherlands (28%). Following Wardman et al. (2018), we can write the relationship between cross-elasticities and mode shares as

$$\eta_{ij} = -\eta_{jj}\frac{V_j}{V_i}\delta_{ji}, \tag{1}$$

where i refers to the bicycle mode of transport and j to the car mode of transport, η_{ij} is the cross-elasticity of cycling flows with respect to fuel prices, η_{jj} is the elasticity of car flows with respect to fuel prices, V_i and V_j are the respective volumes of demand for the two transport modes, and δ_{ji} is the diversion factor that reflects the proportion of car users who switch to cycling. Hence, a higher modal share of cycling would c.p. imply a reduction of V_j/V_i, and thereby also reduce the cross-elasticity η_{ij}. This underlines that cross-elasticities from countries with a lower modal share of cycling could easily be different from countries with a higher modal share.

The literature on fuel-price cross-elasticities in higher-cycling countries is rather scarce. The mode choice models studying these countries often do not treat fuel costs as an explicit cost component, so that no fuel-price cross-elasticities can be derived (e.g. Börjesson and Eliasson, 2012, 2014; Wardman et al., 2007; Ton et al., 2019). To the best of our knowledge, only Frondel and Vance (2017) explicitly analyze the relationship between fuel prices and cycling for one of these countries, i.e. Germany. In particular, they use household-level survey data from 1999 to 2013 and find that a €1 increase in fuel prices increases the probability of choosing the bicycle for non-recreational trips by 14.4 percentage points in urban areas, but not in non-urban areas. However, their findings relate only to the probability of choosing the bike for a trip, but not to the absolute number of cycling trips.

We then contribute to the literature by explicitly estimating the cross-elasticity of overall cycling flows with respect to fuel prices for a country with a higher modal share of cycling, i.e. where cycling is a more established mode of transport. To estimate this cross-elasticity, we use hourly bicycle counts from 72 automated counting stations in 9 German cities and districts between 2018 and 2022, and combine them with daily fuel prices. As part of our identification strategy, we can exploit the strong and arguably exogenous variations in fuel prices that resulted from the Russian invasion of Ukraine and a three-month fuel discount in Germany. Also, we control for weather, calendar, pandemic, and cyclical effects.

We find that the estimated cross-elasticities from an ordinary least squares (OLS) regression model are positive, but slightly lower to those of an instrumental variable (IV) regression model, in which we instrument the German consumer fuel price through the world-market price of Brent crude oil. Our results also show that the positive cross-elasticities are only statistically significant at utilitarian counting stations, but neither at recreational nor mixed counting stations. The estimated cross-elasticity at utilitarian counting stations, which is 0.35 for the OLS and 0.46 for the IV regression, is relatively constant between weekdays and weekend days, as well as between peak and off-peak hours. In 2022, when fuel prices became more salient due to historically high prices and stronger price variations, the cross-elasticity was considerably higher than in previous years.

The estimated cross-elasticity and our additional findings provide important information for traffic modeling, and can thus be helpful for traffic planners and policy makers (Litman, 2022). Moreover, the results suggest that raising fuel taxes to optimal levels, as outlined by Tscharaktschiew (2014), would additionally increase cycling flows and thereby contribute to a more sustainable transportation system.

The remainder of this paper is structured as follows. In Section 2, the methodology and data are outlined. Section 3 presents the results of the regression analysis, which are further discussed in Section 4.

2. Methodology and data

2.1. Methodology

To identify the impact of fuel prices on cycling flows, we exploit the variation in fuel prices. In general, we follow Gillingham (2014) and argue that individuals act as price-takers, because fuel prices are primarily determined by supply and demand in the world market. This was especially evident in 2022, when the Russian invasion of Ukraine led to a very strong increase in fuel prices. Hence, we assume that individuals have to optimize their travel decisions based on these exogenously determined prices.

To check the robustness of our results, however, we also relax this assumption and use the Brent crude oil price as an instrument for the consumer prices. The crude oil price would only impact on cycling flows through gasoline prices and nothing else (Gillingham, 2014; He et al., 2020). This allows us to control for potential endogeneity of fuel prices, similar to He et al. (2020).

We also include control variables that are generally found to be important determinants of cycling (Rietveld and Daniel, 2004). This includes information on weather, public holidays, school holidays, and semester breaks within the respective cities. Additionally, the Covid-19 pandemic, the fear of infection, and the associated government intervention affected mobility in general and cycling flows in particular (e.g. Möllers et al., 2022), so that we also control for the stringency of government intervention. We complement these control variables with various fixed effects. To address systematic differences between counting stations, we include fixed effects for these stations. To account for temporal effects, we include fixed effects for the hours of the day, interacted with the different days of the week. Additionally, we include monthly fixed effects to account for seasonal trends.

The control variables and fixed effects outlined above account for potential confounders of the relationship between cycling flows and fuel prices. The final regression model can then be written as:

$$log(Cyclists_{it}) = \beta_1 \cdot log(Real\ Fuel\ Price_{d(t)}) + \mathbf{x}'_{it}\boldsymbol{\eta} + \lambda_i + \lambda_{w(t)\times h(t)} + \lambda_{m(t)} + \epsilon_{it}, \tag{2}$$

Table 1
Summary statistics.

Variable	Observations	Mean	St. Dev.	Min	Q25	Median	Q75	Max
Cyclists	2,295,528	172.23	209.74	0	25	100	237	2,919
Precipitation [in mm]	2,295,528	0.07	0.45	0.00	0.00	0.00	0.00	47.80
Temperature [in °C]	2,295,528	12.12	7.96	−17.30	5.90	11.60	18.00	40.00
Windspeed [in m/s]	2,295,528	3.67	2.06	0.00	2.10	3.30	4.80	22.10
Humidity [in %]	2,295,528	71.27	19.27	10	57	74	88	100
Cloudiness [in eights]	2,295,528	5.45	2.78	0	3	7	8	8
Public Holiday	2,295,528	0.03	0.17	0	0	0	0	1
School Holiday	2,295,528	0.46	0.50	0	0	0	1	1
Semester Break	2,295,528	0.14	0.35	0	0	0	0	1
Covid Stringency Index	2,295,528	0.28	0.29	0.00	0.00	0.15	0.55	0.85
Fuel Price [in €]	2,295,528	1.46	0.26	1.10	1.30	1.38	1.58	2.27
Real Fuel Price [in €]	2,295,528	1.37	0.18	1.06	1.28	1.34	1.46	2.01
Brent Crude Oil Price [in €]	2,295,528	0.39	0.13	0.05	0.33	0.37	0.43	0.78
CPI	2,295,528	1.06	0.05	1.00	1.03	1.04	1.08	1.20

where $log(Cyclists_{it})$ is the logarithm of hourly bicycle counts at counting station i and time t.[1] The logarithm of the average real fuel price on date $d(t)$ is denoted as $log(Real\ Fuel\ Price_{d(t)})$. The corresponding regression coefficient β_1 indicates the cross-elasticity of cycling with respect to fuel prices. In order to control for other factors that impact on cycling flows, we include a factor variable for different precipitation levels, a linear and quadratic term for air temperature, linear variables for windspeed, cloudiness, and humidity, dummy variables for public holidays, school holidays, and semester breaks, as well a variable indicating the stringency of government intervention during the Covid-19 pandemic. These control variables are denoted by $\mathbf{x}'_{it}$ and described in more detail in Section 2.2. To control for all locational factors that are constant over time, we include fixed effects for counting stations, denoted by λ_i. Additionally, we control for daily and seasonal traffic patterns via fixed effects that are denoted by $\lambda_{w(t)\times h(t)}$ for weekday times hour, and $\lambda_{m(t)}$ for the month. The error term is denoted by ϵ_{it}.

2.2. Data sources

Our observation period spans the years from 2018 to 2022. The hourly bicycle counts are from automated counting stations in 8 German cities or districts (72 stations): Berlin (15), Bremen (8), Dresden (5), Freiburg (4), Hanover (9), Heidelberg (8), Münster (8), Rhein-Kreis Neuss (5), Rhein-Sieg-Kreis (10). All counting stations were installed by Ecocounter, rely on below-surface induction loops, and have a self-reported accuracy of 95%. Similar data is used regularly in current research (e.g. Miranda-Moreno and Nosal, 2011; Wessel, 2020; Kraus and Koch, 2021). In our analysis, we only consider the daytime hours 5:00 to 22:59, so that 2,295,528 observations remain in our final dataset.

Fuel prices are from Tankerkönig, a website that provides access to the underlying data of the official Market Transparency Unit for Fuels. Similar to Hagedorn et al. (2023), we first use the posted consumer fuel prices of all gas stations in Germany and calculate daily average consumer fuel prices for Diesel, E5 gasoline, and E10 gasoline. We then calculate one daily average consumer fuel price by weighting those daily average prices of Diesel, E5 gasoline, and E10 gasoline by the consumption shares of each fuel type in each year of the sample. The daily price for Brent crude oil is from the U.S. Energy Information Administration, and converted from Dollars per Barrel to Euros per Liter. For our analysis, we then transform all nominal monetary values to real monetary values based on the German consumer price index (CPI), as advised by Litman (2022).

Weather data is from the nearest weather stations of the German Meteorological Service. In particular, we use the temperature (in Celsius), the windspeed (in m/s), cloudiness (in eighths of the sky that is covered in clouds), and humidity (in %). For temperature, we include both a linear and a squared term to account for non-linear effects. Precipitation is given in millimeters, but we convert it to a factor variable indicating different degrees of precipitation intensity.[2]

The dummy variables for public holidays, school holidays, and semester breaks are based on information from publicly available sources. The Oxford Covid-19 Government Response Tracker accounts for the stringency of government intervention during the Covid-19 pandemic (Hale et al., 2021). It is used in many studies to control for the impact of the Covid-19 pandemic on mobility (e.g. Vannoni et al., 2020; Schulte-Fischedick et al., 2021). Summary statistics for all variables are outlined in Table 1.

2.3. Descriptive statistics

We begin our descriptive analysis by looking closer at the course of the fuel prices, which are illustrated in Fig. 1. The average nominal fuel price fluctuated between €1.10 and €1.50 between 2018 and mid-2021. It began to increase in the second half of

[1] We follow the literature and use $log(Cyclists_{it}+1)$ for non-missing zeros (e.g. Nosal and Miranda-Moreno, 2014; Wali et al., 2024; Wali and Frank, 2024). For the whole sample, this amounts to 3.5% of all observations, which is within the range of values reported in other studies (e.g. Nosal and Miranda-Moreno, 2014) and thus acceptable (Wooldridge, 2012).

[2] We follow Wessel (2020), so that this factor variable indicates light drizzle (precipitation < 0.5 mm/h), strong drizzle (0.5 mm/h $\leq$ precipitation < 1 mm/h), light rain (1 mm/h $\leq$ precipitation < 2 mm/h), moderate rain (2 mm/h $\leq$ precipitation < 5 mm/h), heavy rain (5 mm/h $\leq$ precipitation < 10 mm/h), and very heavy rain (10 mm/h $\leq$ precipitation).

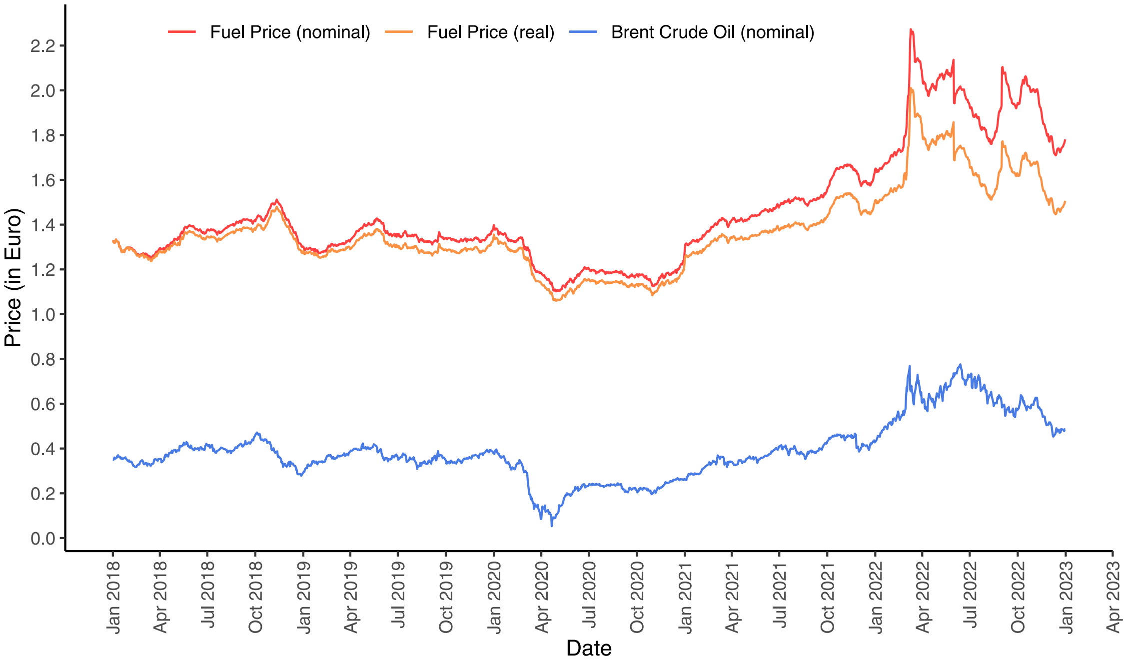

Fig. 1. Prices.

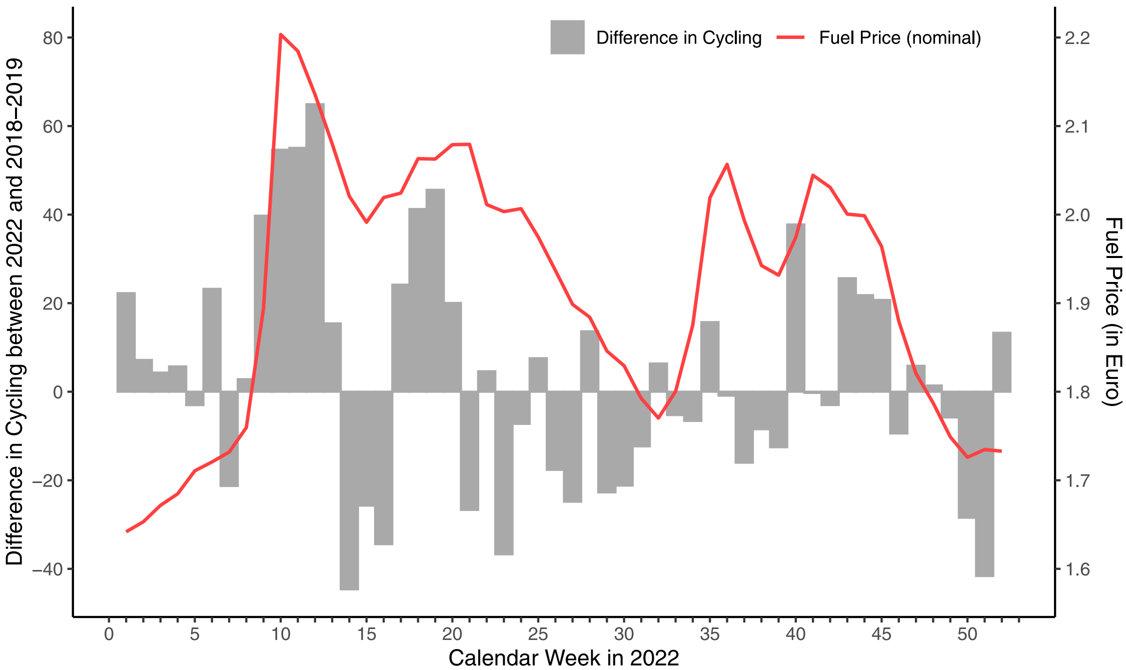

Fig. 2. Fuel prices and cycling in 2022.

2021 and peaked in March 2022, which can be attributed to the Russian invasion of Ukraine. The fuel price remained rather high, but the general uncertainty and a three-month fuel discount (ca. €0.35 per liter gasoline and €0.17 per liter Diesel between June and August 2022) led to greater variation in the course of the fuel price.

Next, we explore whether there is a visible relationship between fuel prices and cycling flows. As cycling flows are generally strongly seasonal, we focus our visual analysis on the difference between weekly cycling flows in 2022, i.e. when the fuel price variation was highest, and the average weekly cycling flows from 2018 to 2019, i.e. the sample years before the Covid-19 pandemic. This reduces visual distortion from seasonal effects, and the resulting differences in cycling flows are depicted by the gray bars in Fig. 2. The red line illustrates the course of the nominal fuel price in 2022.

We find that the extreme increase in fuel prices in Weeks 9 and 10 indeed corresponded to strong increases in cycling flows in 2022. In Weeks 17 to 20, high fuel prices again correspond to higher cycling flows. The fuel discount in Weeks 22 to 35 reduced fuel prices, and cycling flows were, on average, slightly lower than in previous years. The subsequent increase in fuel prices from Week 35 onward corresponded to increases in cycling flows, and the fuel price decrease in the last weeks of 2022 corresponded to below-average cycling flows.

Of course, irregular weather or calendar events can still affect these differences. For example, Weeks 14, 37, 39, and 51 were affected by the highest precipitation levels of 2022; Weeks 15 and 16 by the Easter holidays; and Weeks 41 and 42 by autumn holidays in some states. These weather or calendar events can thus explain why cycling flows in the respective weeks were lower than in previous years, despite relatively high fuel prices. Therefore, Fig. 2 leads us to conclude that a positive relationship between fuel prices and cycling flows appears likely.

3. Analysis

3.1. The impact of fuel prices on cycling flows

In order to estimate the cross-elasticity between fuel prices and cycling flows, we first run the standard regression model from Eq. (2). An overview of the result of the OLS regression is provided in Column (1) of Table 2, and the full regression output is reported in Table 7 in the Appendix. The estimated cross-elasticity of this regression is 0.29, implying that a 10% increase in fuel prices increases cycling flows by 2.9%.

Table 2
Standard regressions.

	OLS (1)	IV (2)
log(*Real Fuel Price*)	0.2902***	0.3694***
	(0.0677)	(0.0737)
Control Variables	Yes	Yes
Station Fixed-Effects	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes
Monthly Fixed-Effects	Yes	Yes
Observations	2,295,528	2,295,528
R^2	0.86906	0.86903

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

As outlined in Section 2.1, we address potential endogeneity concerns by running an additional IV regression, for which we use the logarithm of Brent crude oil prices as an instrument for the logarithm of local fuel prices. The second stage of the IV regression is reported in Column (2), and with a first-stage F-statistic of $12,041,693$, we can reject the null hypothesis of weak instruments with a p-value of 0.000. The estimated cross-elasticity of the IV regression is 0.36, and thus rather similar to the OLS estimate. Hence, the IV regression confirms the positive and significant cross-elasticity between fuel prices and cycling flows in Germany.

3.2. Impact heterogeneity

In order to test the robustness of the point estimates outlined above for cross-elasticities that were estimated using the entire sample, we now run separate regression models on selected subsets to explore potential dimensions of heterogeneity.

First, we analyze whether the estimated cross-elasticity varies between different types of traffic. To identify these different types of traffic, we classify our counting stations according to the method outlined in Wessel (2020). As a result, 48 counting stations are classified as measuring mainly utilitarian traffic, with more cyclists during morning peak hours than noon hours on weekdays, and more cyclists on weekdays than on weekend days. 13 stations are classified as measuring mainly recreational traffic, with fewer cyclists during morning peak hours than noon hours on weekdays, and fewer cyclists on weekdays than on weekend days. The 11 remaining stations are classified as measuring mixed traffic. This classification enables us to run separate regressions for each type of traffic, and the respective results are outlined in Table 3. It becomes evident that only utilitarian traffic is significantly affected by changes in fuel prices, and the estimated cross-elasticities are slightly higher than those from the regression models for the entire sample in Table 2. For mixed and recreational traffic, on the other hand, we do not find a significant effect of fuel prices on cycling flows. Thus, the cross-elasticities from our standard regression models in Table 2 appear to be driven mainly by the utilitarian counting stations, which is why we will focus on these stations in the following.

Second, we check whether cycling flows at different weekdays or times of day are differently affected by changes in fuel prices. Our findings suggest that the cross-elasticity is relatively similar between days during the week and days on the weekend (see Table 4), as well as between peak hours (7:00–8:59 and 16:00–18:59) and off-peak hours during the week (see Table 5).

Third, we analyze whether the cross-elasticity is constant over time (see Table 6). We find that it was close to our originally estimated value between 2018 and 2021. In 2022, however, the cross-elasticity took on a much higher value, and a 10% increase in fuel prices in 2022 led to an increase in cycling flows of roughly 14% to 16%, depending on the regression model.

Table 3
Heterogeneity by station type.

	Utilitarian		Mixed		Recreational	
	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
log(*Real Fuel Price*)	0.3505*** (0.0578)	0.4579*** (0.0616)	0.0259 (0.2853)	0.0953 (0.2981)	0.2959 (0.1701)	0.3503 (0.1987)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Station Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,540,909	1,540,909	339,122	339,122	415,497	415,497
R^2	0.82828	0.82819	0.87954	0.87952	0.74307	0.74305

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 4
Heterogeneity by weekday type for utilitarian traffic.

	Weekday		Weekend	
	OLS (9)	IV (10)	OLS (11)	IV (12)
log(*Real Fuel Price*)	0.3383*** (0.0594)	0.4642*** (0.0639)	0.3620*** (0.0580)	0.4144*** (0.0615)
Control Variables	Yes	Yes	Yes	Yes
Station Fixed-Effects	Yes	Yes	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes	Yes	Yes
Monthly Fixed-Effects	Yes	Yes	Yes	Yes
Observations	1,101,610	1,101,610	439,299	439,299
R^2	0.80145	0.80130	0.85012	0.85010

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 5
Heterogeneity by times of day for utilitarian traffic.

	Peak		Off-Peak	
	OLS (13)	IV (14)	OLS (15)	IV (16)
log(*Real Fuel Price*)	0.3266*** (0.0629)	0.4773*** (0.0685)	0.3427*** (0.0585)	0.4594*** (0.0626)
Control Variables	Yes	Yes	Yes	Yes
Station Fixed-Effects	Yes	Yes	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes	Yes	Yes
Monthly Fixed-Effects	Yes	Yes	Yes	Yes
Observations	305,911	305,911	795,699	795,699
R^2	0.73788	0.73757	0.80144	0.80130

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

4. Discussion and conclusions

In summary, we run OLS and IV regression models and find positive cross-elasticities of cycling flows with respect to fuel prices. This relationship is statistically significant only for utilitarian trips, i.e. when the main purpose of the trip is to reach a specific destination. In such a case, the transport mode is of lesser importance, and individuals might be more willing to switch to cycling in order to reduce travel costs. For recreational trips, on the other hand, utility is often generated by the travel activity itself, so that individuals might be more committed to a particular transport mode. This could be one reason why we do not find a statistically significant impact of fuel prices on cycling flows for recreational stations.

The estimated cross-elasticity for utilitarian bicycle traffic is relatively constant between weekdays and weekend days, as well as between peak and off-peak hours. This also holds for the different years of our observation period, with the exception of 2022. In that year, fuel prices reached an all-time high and generally fluctuated much more than in previous years. In combination with the increased media attention devoted to those high fuel prices (BILD, 2022; Tagesschau, 2022), it is reasonable to assume that fuel prices became more salient and subsequently were a more important determinant of travel decisions. This would be in line with the theory outlined in Hastings and Shapiro (2013) and Bordalo et al. (2013), who show that consumers react more strongly

Table 6
Heterogeneity by observation periods for utilitarian traffic.

	2018–2021		2022	
	OLS (17)	IV (18)	OLS (19)	IV (20)
log(*Real Fuel Price*)	0.3284*** (0.1014)	0.6994*** (0.0900)	1.400*** (0.1156)	1.595*** (0.2064)
Control Variables	Yes	Yes	Yes	Yes
Station Fixed-Effects	Yes	Yes	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes	Yes	Yes
Monthly Fixed-Effects	Yes	Yes	Yes	Yes
Observations	1,228,424	1,228,424	312,485	312,485
R^2	0.82953	0.82905	0.84175	0.84173

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

to unexpected price increases, because they make prices more likely to become salient. As predicted by the theory, the estimated cross-elasticity for 2022 is indeed significantly higher than in previous years. Similar observations for the own-price elasticity of fuel are also reported in Gillingham (2014), Dahl (2012).

The main goal of our analysis was to estimate the impact of fuel prices on cycling flows for a country with a higher modal share of cycling. Therefore, we can now relate our results to those from countries with a lower modal share of cycling. We do so by focusing on Smith and Kauermann (2011), who are probably closest to our analysis, as they also use data from automated bicycle counting stations. For Melbourne, Australia, they find cross-elasticities of approximately 0.3 when considering all counting stations, and around 0.4 when considering only counting stations in the central business district. Hence, their findings are quite similar to our results for all counting stations and only utilitarian counting stations, respectively. This indicates that individuals in low-cycling and higher-cycling countries appear to have quite similar cross-elasticities of cycling flows with respect to fuel prices.[3]

In the only other study on the impact of fuel prices on cycling in higher-cycling countries, Frondel and Vance (2017) find a positive impact of fuel prices on the probability of choosing the bicycle for a trip in an urban environment in Germany. For trips in more rural areas, however, the effect is not statistically significant. This is in line with our findings, because the utilitarian counting stations in our sample are located in more urban areas, and the mixed and recreational counting stations are located in more rural areas.

Moreover, our results complement those of Frondel and Vance (2017), who focus on the impact of fuel prices on the probability of using the bicycle for a trip. This probability, however, does not necessarily correspond to changes in overall cycling flows. For example, if higher fuel prices did not impact on cycling flows and reduced car trips, then the probability of choosing the bike would already increase, even though cycling flows would remain constant. Hence, our estimated cross-elasticity contributes to the literature by estimating the impact on overall cycling flows in higher-cycling countries.

While our paper focuses on the cross-elasticity between fuel prices and cycling flows, Wardman et al. (2018) conduct a meta-analysis on the impact of fuel prices on other modes of transport. The estimated fuel-price cross-elasticities are 0.19 for bus ridership, 0.27 for rail ridership, 0.15 for light rail transit, 0.14 for metro ridership, and 0.11 for walking. This suggests that fuel-price increases lead to larger percentage increases for cycling flows than for other modes of transport.

The estimated cross-elasticities have useful policy implications for higher-cycling countries. While previous research found that higher fuel prices reduce fuel consumption itself (Alberini et al., 2022), we can now confirm that they also increase cycling flows. As cycling is associated with a positive social net benefit (Gössling et al., 2019), higher fuel prices would therefore contribute to a more sustainable transportation system in two different ways. This is especially important considering the findings from Tscharaktschiew (2014), who calculates the optimal gasoline tax for Germany using an optimal tax approach within a general equilibrium framework that considers externalities such as congestion, accidents, noise, local air pollution, and global climate-change costs. He finds that the optimal gasoline tax in Germany is 0.96 €/liter and thus 46% higher than the actual gasoline tax, with various sensitivity analyses confirming that the current gasoline tax in Germany is very likely to be too low. Raising the gasoline tax to its optimum would thus not only address all externalities associated with car driving, but also contribute to society by boosting cycling flows.

CRediT authorship contribution statement

Jakob Findenegg: Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization. **Jan Wessel:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization.

[3] Against the backdrop of Eq. (1), we can approximate the diversion factor δ_{ji} for Australia and Germany. Recent estimates for the fuel price elasticity are -0.04 for Australia (Zhang and Burke, 2020) and -0.26 for Germany (Alberini et al., 2022). The term V_j/V_i was approximately 60 in Australia (Hensher et al., 2022) and $0.43/0.11 = 3.9$ in Germany (Nobis and Kuhnimhof, 2018) before the pandemic. With similar cross-elasticities $\eta_{ij} \approx 0.3$, the diversion factor δ_{ji} would be 0.13 in Australia and 0.30 in Germany, implying that German car users are more likely to switch to bicycles than Australian car users. Moreover, Eq. (1) suggests that the fuel-price cross-elasticity and the diversion factor must be very similar for Germany, given $\eta_{jj} = -0.26$ and $V_j/V_i = 3.9$.

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Appendix

Table 7
Standard regressions (full output).

	OLS (21)	IV (22)
log(*Real Fuel Price*)	0.2902***	0.3694***
	(0.0677)	(0.0737)
Light Drizzle	−0.2101***	−0.2100***
	(0.0097)	(0.0097)
Strong Drizzle	−0.3096***	−0.3094***
	(0.0143)	(0.0143)
Light Rain	−0.3643***	−0.3640***
	(0.0158)	(0.0158)
Moderate Rain	−0.4219***	−0.4222***
	(0.0227)	(0.0227)
Heavy Rain	−0.2810***	−0.2821***
	(0.0201)	(0.0201)
Very Heavy Rain	−0.1720***	−0.1729***
	(0.0283)	(0.0284)
Temperature	0.0461***	0.0461***
	(0.0022)	(0.0022)
Temperature^2	−0.0009***	−0.0009***
	(5.8×10^{-5})	(5.81×10^{-5})
Windspeed	−0.0423***	−0.0423***
	(0.0029)	(0.0029)
Cloudiness	−0.0175***	−0.0176***
	(0.0013)	(0.0013)
Humidity	−0.0053***	−0.0053***
	(0.0006)	(0.0006)
Public Holiday	−0.6716***	−0.6707***
	(0.0494)	(0.0493)
School Holiday	−0.1276***	−0.1348***
	(0.0112)	(0.0115)
Semester Break	−0.1074***	−0.0996***
	(0.0125)	(0.0120)
Covid Stringency Index	0.0108	0.0254
	(0.0400)	(0.0391)
Station Fixed-Effects	Yes	Yes
Weekday×Hour Fixed-Effects	Yes	Yes
Monthly Fixed-Effects	Yes	Yes
Observations	2,295,528	2,295,528
R^2	0.86906	0.86903

Standard errors are clustered by counting station.
Significance Codes: ***: 0.01, **: 0.05, *: 0.1.

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