Peer Effects in Electric Car Adoption: Evidence from Sweden

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Abstract

I study peer effects in the diffusion of electric cars in Sweden. To identify peer effects, I use a shift-share IV design that links the renewal of elapsing individual-level, car leasing contracts (i.e., shift) with the propensity to acquire an electric car based on individual traits (i.e., share). I study three different peer groups: co-workers, family members, and neighbors. One new electric car causes, in the next quarter, an additional .077 new electric car acquisitions in the workplace, .014 in the family, and .111 in the neighborhood. These peer effects generate persistent shifts in the demand for electric cars rather than pulling forward future planned purchases. I show that the new electric cars obtained by peers largely crowd out diesel and petrol cars and that peer effects are associated with the transmission of information. Peer effects reduce carbon emissions by encouraging peers to acquire electric and cleaner cars, drive less, and lower the number of cars. Finally, I document how the empirical findings alter the design of optimal environmental policies.

JEL codes: O33, D12, Q58, L91, C45

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I Introduction

How to promote a shift toward new environmentally-friendly technology is a central issue in economic and policy debates over the green energy transition. The transport industry accounts for about a quarter of Europe's greenhouse gas emissions and is the only sector where emissions have not decreased since 1990. Reducing transport emissions is pivotal to meeting the EU's emissions targets and ensuring progress toward its 2050 objective of climate neutrality. To transition to low-emission mobility, Europe plans to replace vehicles powered by the combustion of fossil fuels with electric vehicles. However, the market penetration of electric vehicles remains relatively low and insufficient to reach the set EU emission targets (Figure A1).

A key mechanism in the diffusion of new technologies and practices is social interactions with peers (Griliches, 1957; Bass, 1969).[1] Early adopters of new technologies can generate positive externalities among their peers, which impacts the technology's diffusion process. Therefore, environmental policies that aim to stimulate the diffusion of new, environmentally-friendly technologies must incorporate how peer effects influence the adoption decision in social networks.[2]

My primary contribution is to provide causal estimates of peer effects on adopting a crucial new green technology – electric cars[3] – within peer groups that span essential aspects of life: workplace, family, and neighborhood.[4] The peer effects are substantial and economically meaningful: On average, one new electric car causes, in the next quarter, an additional .077 new electric car acquisitions in the workplace, .014 in the family, and .111 in the neighborhood. The estimated peer effects for electric cars are considerably stronger than for petrol or diesel cars, highlighting the significance of peer effects of new technologies

[1]Social learning has been established as an essential determinant of early technology adoption in numerous economic settings, primarily in developing countries. Agriculture (Foster & Rosenzweig, 1995; Conley & Udry, 2010), deworming programs (Kremer & Miguel, 2007), new crop choices (Bandiera & Rasul, 2006), and fertilizer adoption (Duflo et al., 2011) are a few examples.

[2]The literature studying the effects of government intervention on environmental technology adoption (Sallee, 2011; Boomhower & Davis, 2014; Hughes & Podolefsky, 2015) does not analyze how financial incentives for new environmentally-friendly technologies are influenced by peer effects.

[3]I aggregate hybrid electric, plug-in, and electric cars into one outcome variable and refer to these as "electric cars" throughout the paper.

[4]The idea that people learn from their peers has been examined in settings ranging from education (Sacerdote, 2001; Graham, 2008; List et al., 2020), consumption behavior (De Giorgi et al., 2020; Bailey et al., 2022), participation in welfare programs (Dahl et al., 2014; Hesselius et al., 2009), to criminal behavior (Bhuller et al., 2018; Dustmann & Landerso, 2021), and charitable giving (DellaVigna et al., 2012). In the environmental realm, peer effects have been identified in the adoption of solar photovoltaic panels (Bollinger & Gillingham, 2012; Graziano & Gillingham, 2015), hybrid vehicles (Narayanan & Nair, 2013; Heutel & Muehlegger, 2015; Zhu & Liu, 2013; Jansson et al., 2017; Chakraborty et al., 2022), and water conservation (Bollinger et al., 2020).

in the automobile market. The results are robust to alternative functional specifications, sample restrictions, placebo tests, and peer group dynamics.

To address whether the results correspond to a substitution from other vehicle fuel types, I estimate how one new peer electric vehicle influences the adoption of new petrol and diesel cars relative to a peer group that did not receive a new electric car at the renewal threshold.[5] The results show that new electric cars initiated through peer effects pull demand from diesel and petrol cars, while some incremental demand is newly generated. This implies that peer effects accelerate the adoption of new electric cars and reduce the demand for competing technologies (such as fossil fuel cars). The estimated peer effects, however, may result from individuals pulling forward planned electric car purchases. I find that peer effects generate persistent shifts in demand for electric cars and do not merely reflect intertemporal substitution. One exogenous new electric car increases the electric car take-up for four quarters in the workplace, eight quarters in the family, and two quarters in the neighborhood and the peer effect on the uptake of electric vehicles shows no sign of turning negative.

Peer effects can influence people's electric car take-up through several mechanisms. I provide suggestive evidence for information transmission early along the adoption curve, about financial incentives, and exposure to electric cars. In particular, peer effects are greater for the first adopter in a peer group, during high subsidy periods, and in neighborhoods with single-family homes than those with apartment buildings.[6] In contrast, there is no lack of information regarding leasing contracts and the public charging infrastructure. If the key mechanism driving the peer effects is spreading information, then information campaigns about the costs and benefits of owning an electric car (especially for low-adopting peer groups) may be a complementary policy tool to increase electric car diffusion.[7]

Next, I examine how peer effects influence the car-related carbon emissions of an individual. Adding up the different sources of emission reduction, the cumulative impact of peer effects on carbon emissions extends far beyond the electric car adoption decisions of peers. An additional new electric car encourages co-workers to adopt cleaner cars, drive less, and reduce the number of owned cars. The total carbon net effect induced through the peer adoption of an electric car equals 3.8% of the average carbon emission of an individual, which is due to a 1.6% reduction in the average carbon emission per kilometer driven, a .5%

[5]Approximately two-thirds of the contract renewals in the control group result in no new car adoption, and one-third in either a new petrol or diesel car.

[6]This relates to a growing literature that tries to understand the economic channels behind peer effects (Dahl et al., 2014; Bursztyn & Jensen, 2015; De Giorgi et al., 2020).

[7]Heterogeneities in the transmission of peer effects across demographic characteristics have additional repercussions for analyzing the efficacy of interventions, which target a small set of early adopters who can generate follow-on demand through peer effects. Specifically, I find that people below 45, having a high-school degree, with higher income, and within smaller groups are particularly influential.

reduction by driving less, and a 1.7% reduction in the number of cars. While around half of the decrease in average carbon emission is explained by adopting electric cars, the rest is due to non-adopters choosing cleaner fossil fuel cars. The peer effect results are illustrated in Section IV.

To shift the electric car adoption of peers, my identification strategy exploits the fact that many individuals in Sweden lease their cars and replace them on a fixed three-year schedule. Specifically, I use the timing of the leasing contract renewal as an exogenous shock to peer car adoption. Taken alone, the lease timing instrument shifts the adoption of new cars in general, instead of exclusively new electric cars. To isolate exogenous shocks to peers' electric car adoption, I link the timing of the peers' leasing contract renewal with an individual prediction of their probability of adopting a new electric car, which I constructed using machine learning techniques. Notably, the variation in electric car adoption is not driven by differences in the composition of peer groups, as the sum of probabilities to lease a new electric car is controlled for across groups.

A key question for policymakers is how to optimally design subsidies for new emerging green technologies. In the classic Pigou paradigm, the optimal subsidy equals the difference between the externalities that arise from adopting the electric car and the car that would otherwise have been purchased. Externalities in the electric car market include a reduction in carbon emission, industrial learning-by-doing, network externalities related to charging infrastructure, and the undervaluation of future energy savings (Rapson & Muehlegger, 2021). Peer effects amplify these externalities. Intuitively, the decision does not only disregard their externalities but also those of their peers, whom they will influence to get an electric car. The policymaker should scale the optimal subsidy with the peer effect. The policy implications are discussed in Section V.

Peer effects do not only influence the optimal level of subsidies, but also their trajectory. To internalize the dynamics of peer interactions, I allow the peer effects to vary at different stages in the adoption. I provide suggestive evidence that predominantly early adopters lead to additional demand for electric cars, which implies that the policymaker should front-load subsidies to early adopters.

The literature on peer effects in early technology adoption has evolved along three dimensions. One is related to identifying peer effects, which requires addressing the endogeneity of the peer's behavior. This has proven difficult given the well-known econometric issues of reflection, correlated unobservables, and endogenous group membership (Manski, 1993; Brock & Durlauf, 2001b; Moffitt et al., 2001). Recent work studies narrow settings by using distinct visual features or a particular type of car (Toyota Prius) as instruments.[8]

[8]The identification strategy in Heutel and Muehlegger (2015) exploits whether initial exposure to a low-

Besides these identification issues, a central challenge in studying peer effects is to construct appropriate peer groups and access data which matches members of a peer group. Previous work treated all past adopters in surrounding geographic entities as the reference group, missing out on interpersonal influences along other dimensions. A third challenge is to identify how economic incentives influence peer effects and derive implications for optimal environmental policies in the presence of peer effects. Even though a few studies have estimated this relationship empirically (La Nauze, 2021; Bollinger et al., 2020), the existing research lacks a theoretical framework that characterizes how peer effects alter the optimal incentives setting.

This paper advances the state of research along all three lines. First, my methodological contribution is to demonstrate how econometric techniques from the recent shift-share instrumental variables (SSIV) literature can be applied to estimate peer effects (Adao et al., 2019; Borusyak et al., 2022), which unlocks a wide range of potential future applications. To address the econometric concerns inherent in measuring peer effects, I link the timing of the leasing contract renewal with a measure of each individuals's probability of adopting a new electric car. This identification approach mirrors a shift-share research design that sums up the estimated probabilities (i.e., exposure shares) among all peers at the leasing contract renewal (i.e., shifts). Section III presents the empirical specification to measure peer effects and explains the identification strategy.

To give a concrete example of the identification strategy, suppose that there are two similar peer groups (A and B), each with a single leaser whose contract expires in a given quarter. While the probability that the new car is electric is high for the person in peer group A, it is low for the person in peer group B. The identification strategy then compares the subsequent electric car adoption of other people in the peer group that experienced an elapsing car leasing contract by someone who was *ex-ante* predicted to be likely to adopt an electric car (peer group A) relative to a peer group that had someone exposed who was unlikely (peer group B). Consequently, any differences in peer group electric car adoption in the quarters following the peers' contract renewal are informative about the role of peer effects. The variation in the electric car adoption is determined by which individual in the peer group is randomly induced to the elapsing leasing contract, while both peer groups have the same predicted probabilities of adopting a new electric car on average.

Second, I combine several rich administrative data sets spanning the whole population

quality (Honda Insight) versus a high-quality product (Toyota Prius) affects the likelihood of purchasing a hybrid vehicle. Narayanan and Nair (2013) estimate the peer effect using the adoption of hybrid vehicles that are exact versions of their non-hybrid counterpart (Honda Civic) as an instrument for the network adoption of the Toyota Prius in California. The identifying assumption is that adopting a hybrid car is not subject to social effects if a virtual identical combustion engine car exists.

of Sweden and all vehicle ownership and purchase records to construct comprehensive peer groups along workplaces, families, and neighborhoods. The final data set consists of an extensive list of individual socio-demographic characteristics, peer group characteristics, car attributes, charging infrastructure, and the financial implication of all vehicle reforms in Sweden from 2012 to 2020. This rich administrative data allows me to study whether peer effects matter for the electric car take-up among co-workers, relatives, and neighbors. Section II summarizes the data set construction and the peer group preparation.

Third, I show how government policy – namely environmental subsidies – interacts with peer effects and how this can inform the design of optimal environmental policies.[9] Specifically, by deriving a modified dynamic form of Pigouvian subsidy, I characterize optimal policies in the presence of peer effects. Finally, I discuss how different mechanisms of the observed peer effects alter the dynamics of the optimal Pigouvian subsidy. This is related to a burgeoning literature that studies the interplay of individual and social motives (Bursztyn et al., 2014; Bursztyn & Jensen, 2017; Cantoni et al., 2019; Jia & Persson, 2021).

II Data

II.A Data Construction

1. *Data Sources.* The primary data sources are the Swedish vehicle register (*Fordonsregistret*), the longitudinal integrated database for health insurance and labor market studies (*LISA*), the occupational register (*Yrkesregistret*), the population and housing census (*Folk- och bostadsräkningar*), the Swedish business register (*Företagsregister*), and the geographic database (*Geografidatabasen*) for the period 2012 to 2020 provided by Statistics Sweden. In addition, I merge this data with information on the charging station network and the financial implications of vehicle reforms enacted by the Swedish government.

The vehicle register entails data on all vehicles owned by Swedish residents. The data includes information on the car's general status (registration date, owner type, whether it is leased, when the car became the property of the current owner, in use or not, etc.), the vehicle specification (make, model, and trim), and numerous car characteristics (service weight, odometer reading, fuel type, fuel efficiency, particle filter, carbon emission, etc.). Each registration also records a vehicle identification number and a social security number equivalent,

[9] This relates to a significant body of research on the optimal design of policies with behavioral agents. Prominent examples of behavioral phenomena include social reputation (Benabou & Tirole, 2006, 2011), salience (Chetty et al., 2009), inattention (Farhi & Gabaix, 2020), social norms (Allcott, 2011), nudges (Allcott & Taubinsky, 2015; Allcott & Kessler, 2019), social-image concerns (Bursztyn et al., 2014; Bursztyn & Jensen, 2017), and non-standard decision making (Bernheim & Taubinsky, 2018).

which uniquely identifies all individuals in Sweden except for Swedes living abroad. The vehicle identification number allows me to track the ownership of vehicles over time.[10]

To match individuals to their cars, I link the vehicle registry through the social security number equivalent to the LISA data, which merges several administrative and tax registers for the universe of Swedish individuals aged 18 and above. LISA contains a list of socio-demographic information (such as gender, age, family situation, income, education, and employment status). I supplement the data with the geographic location of the residence and the workplace, measured by $125m$ grid cells in all urban areas or $500m$ squares in rural parts. To add occupational status, I link the data to the Swedish occupational register, which includes information on the gross salary, employment status, workplace industry code, and duration of employment on an annual basis. Similarly for firms, I add information on the universe of Swedish firms using the business register. This includes a rich set of information on the firm (the number of employees, net revenue, personnel cost, and social contribution cost).

The charging infrastructure is supplemented through data from ChargeX (*Uppladdning.nu*). It includes information on the number of charging points and available plug-in spaces in Sweden by their opening date and location coordinates. Charger characteristics include the operator's name, the connector type of each outlet, and the charging power. *Uppladdning* has collected and maintained the charging station database of Sweden since 2008.[11]

I obtain information on government incentives from the Swedish Tax Authority (*Skatteverket*), the Swedish Transport Agency (*Transportstyrelsen*), and Statistics Sweden (*Statistiska centralbyrån*). Information on the financial benefits of vehicle rebates stems from the government bills from the Ministry of the Environment (2007, 2011, 2017). The Swedish Parliament's decision on annual road tax relief for cars in certain environmental classes and preferential taxation of green benefit cars comes from the Ministry of Finance (2005b, 1999, 2001). Data on price and tax components for various fuel types is acquired from tax calculation conventions *(Beräkningskonventioner)* by the Swedish Ministry of Finance (2005a, 2010, 2015, 2020).

II.B Peer Groups

A pervasive challenge in studying peer effects is to construct appropriate peer groups and access data which matches members of a peer group. This comprehensive administrative

[10] Appendix C provides additional details on the data preparation, variable construction, and imputation techniques.

[11] Figure A2 depicts the geographic location of all active and publicly available charging stations. The map reveals that the charging infrastructure is mainly established in large cities and along major highways.

data allows me to examine whether peer effects matter for the adoption of electric cars along three dimensions: workplaces, families, and neighborhoods.[12] These groups are a significant source of social influence, as their cars are visible to co-workers, relatives, and neighbors, and they engage in frequent social encounters.[13]

The first social domain is assumed to be co-workers who work in the same workplace (address of the firm). Because co-workers are more likely to interact directly in small- and medium-sized firms, I restrict the sample to workplaces with at least 5 and up to 150 employees.[14] 40.5% of the overall population is employed by small and medium-sized businesses.

Using the multi-generational register (*Flergenerationsregistret*) that connects individuals to their parents and siblings, I define the family as all first- and second-degree relatives. A first-degree relative includes the individual's parents, (half-)siblings, and children, while second-degree relatives refer to the individual's grandparents, grandchildren, aunts, uncles, nephews, and nieces.

The third social group is the neighborhood, which follows an extensive literature defining networks through geographic entities (Topa, 2001; Arzaghi & Henderson, 2008; Bell & Song, 2007; Manchanda et al., 2008; McShane et al., 2012; Narayanan & Nair, 2013; Kuhn et al., 2011; Agarwal et al., 2017). Using the geographic coordinates of residences, I define all individuals living within the same $125m$ radius in urban and $500m$ in rural areas as the neighborhood population.

As peer effects are (more easily) measurable across individuals, I exclude cars owned by legal entities (as opposed to private individuals) throughout the entire empirical analysis. In addition, I limit the sample to the three most frequently driven cars based on vehicle kilometers traveled per person.[15]

[12] Despite the fact that these peer groups include a range of vital facets of life, peer effects pertinent to car adoption can also be anticipated from other social groups (e.g., high-school or university friends).

[13] For instance, cars are visible to colleagues when parked outside offices and are likely topics of discussion among co-workers (Jansson, 2011; Johansson-Stenman & Martinsson, 2006). In residential neighborhoods, vehicle selection is indicative of the driver's social standing (Johansson-Stenman & Martinsson, 2006).

[14] As some individuals receive compensation from multiple employers, the workplace is the company that pays the greatest annual compensation. This also indicates the length of stay at a specific plant. I do not impose this restriction on the family or neighborhood peer groups.

[15] Extensive ownership of cars is mainly linked to individuals using the registered cars for firm purposes or illegal tax avoidance reasons.

II.C Descriptive Statistics

1. *Individual and Car Attributes.* Table A1 presents summary statistics of individuals and their cars between 2012 and 2020.[16] Panel A summarizes socio-demographic statistics on the individual-by-year level for Swedes above 18. The average Swede is 47 years, with around 12 years of education, and earns a disposable family income of around 253 thousand SEK ($\approx$ \$26,894) conditional on being employed.[17] 57% of individuals are married or live with a cohabitant, 45% have at least one child, and around 41% own at least one car. Around 67% of people commute, with an average distance of 24 kilometers. The sample represents an annual average of 7,903,549 Swedes.

Panel B of Table A1 highlights the descriptive statistics on the Swedish vehicle registry data, which are at the vehicle-by-year level. The average car is around 11 years old, travels around 11,994 kilometers per year, and emits 147.69 grams CO_2 per kilometer. The Swedish fleet comprises an average of 3,859,775 private cars.

2. *Peer Group Characteristics.* Table A3 lists the aggregated characteristics of workplaces, families, and neighborhoods between 2012 and 2020. The average individual has 45 co-workers, 5 relatives, and 260 neighbors, who have registered 6.92, .55, and 27.79 new cars, respectively, between 2012 and 2020. The total number of new electric car registrations per peer group, the outcome of interest, is equal to .48 in the workplace, .04 in families, and 1.38 in neighborhoods. For all panels, the bottom row displays how many people have elapsing leasing contracts, which serves as an instrument for new car adoption. The total number of co-workers, relatives, and neighbors that were at the three-year leasing renewal between 2012 and 2020 equals .64 in workplaces, .05 in families, and 2.52 in neighborhoods. The sample consists of 198,471 unique plants, 6,990,298 families, and 147,955 neighborhoods.

II.D Swedish Car Market

1. *Evolution of Alternative Fuel Cars.* Historically, the Swedish vehicle fleet mainly consisted of cars that run on petrol or diesel. Since 2005, however, alternative fuel cars have gradually penetrated the Swedish market. Figure I displays the number of monthly new cars

[16] To gain a better perspective on who adopts electric cars, Table A2 compares the demographic and charging infrastructure variables of three types of car owners (i.e., all car owners, flex-fuel, and electric) and the entire population in 2020. Relative to the population and car owners, people who own electric cars are generally much more likely to be male, wealthier, less likely to be unemployed, more likely to be married, and considerably more educated. Most strikingly, electric car owners have around one more year of education and 120,000 SEK more annual disposable income than the average person. In terms of charging availability, electric car owners have slightly more active, publicly available charging stations and plug-ins, although it is not different in power wattage.

[17] I convert Swedish kronor to US dollars using the exchange rate from January 1, 2020 (.1063 USD/SEK).

registered by individuals for each alternative fuel type between 2005 and 2020.[18] Between 2007 and 2010, the registrations of ethanol-powered cars increased rapidly in Sweden, making them the first alternative-fuel type to reach the market.

The uptake of electric, plug-in, and hybrid electric cars began around 2012.[19] Since there has been a steady increase in sales of new (partly-) electric cars annually, from 861 units in 2012 to 21,951 in 2020. This equals a 19.7% market share of electric cars relative to all new registrations in 2020.[20] The majority of electric cars sold were hybrid electric, accounting for 65.8% of new (partly-) electric cars, while electric and plug-in hybrid electric cars represented 12.6% and 21.6%, respectively. In total, private individuals have registered 81,588 electric cars since 2005.[21]

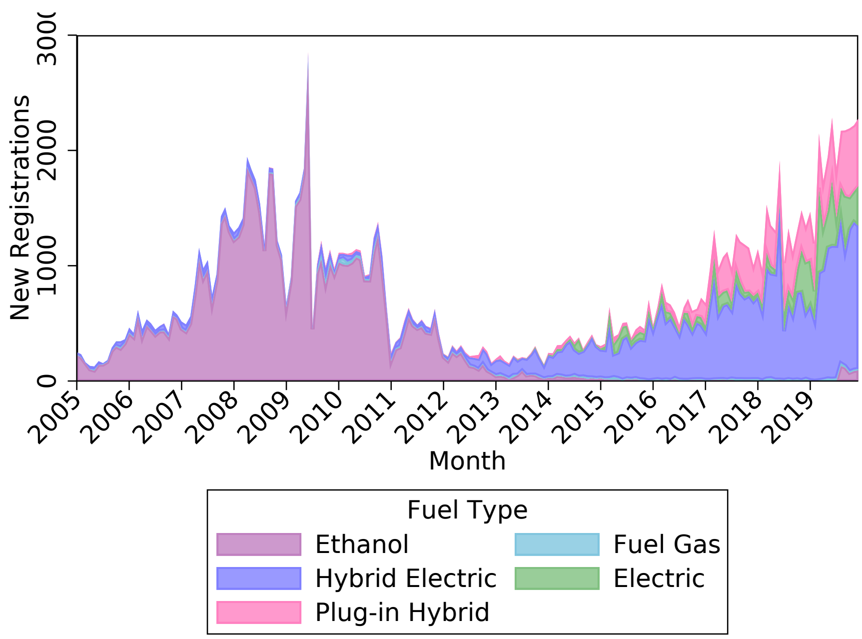


Figure I: New Registrations of Alternative Fuel Cars

Notes: The figure displays the number of monthly new registrations of alternative fuel cars that were registered by private individuals in the Swedish vehicle market between 2005 and 2020.

[18]Alternative fuel cars can partly or fully run on alternative fuels rather than gasoline and diesel. Among the most common are different types of electric cars (i.e., hybrid electric, electric, plug-in hybrid), but vehicles that run on ethanol, compressed natural gas, or LPG are also available to the consumer.

[19]A hybrid electric car combines a conventional internal combustion engine system with an electric propulsion system. An electric hybrid cannot be charged with electricity from the mains but uses the internal combustion engine to charge the electric motor's battery while driving. A plug-in hybrid electric car can be recharged from an external source of electricity and another fuel to power an internal combustion engine. An electric car is powered by one electric motor that only runs on electricity from a battery.

[20]The corresponding market shares of newly registered cars are illustrated in Figure A3.

[21]Figure A4 illustrates the geographic adoption patterns of electric cars in Sweden.

2. *Leasing Market.* The Swedish automobile market has two striking features that I exploit to identify peer effects. First, a substantial portion of new cars is leased (as opposed to purchased). The share of newly leased cars in relation to the total number of new car registrations in Sweden has increased from 3.8% in 2012 to 45.4% in 2020 (Figure A5). One explanation for the high proportion of leased cars is the low interest rates, which reduce the taxable vehicle fringe benefit (Appendix B.2).

Secondly, leasing contracts are typically renewed, and cars are exchanged on a fixed three-year schedule. First introduced by Volvo in the late 1960s, car manufacturers in Sweden usually offer a warranty for the first three years on new cars. Since then, car leasing contracts are usually set up for this period. To validate this timing in leasing renewal, Figure II plots the probability of leasing a new car against the number of quarters since the current leased car's registration. The probability of leasing a new car spikes when the current car age crosses the three-year threshold (the gray area).[22] More than 40% of all leased cars are replaced exactly 12 quarters after their first registration.[23] Given the large market for newly leased cars and the fact that around 40% of these leased cars are exchanged after precisely three years, the timing of the peer's leasing contract renewal reflects a strong exogenous take-up of new cars.

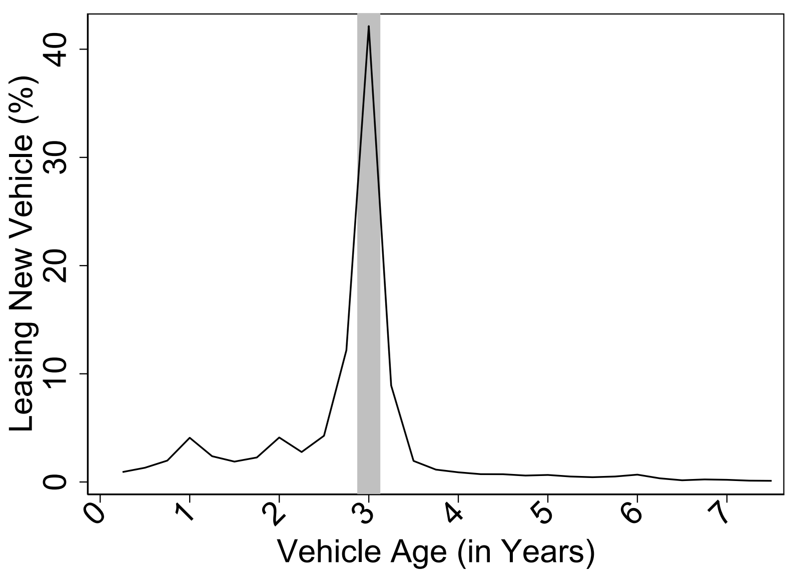


Figure II: Leasing Contract Renewal Probability

Notes: The figure illustrates the contract renewal probability of leased cars with respect to the time in the current car contract (i.e., quarters since first registration).

[22] There are also spikes after one and two years, indicating that some car contracts entail different renewal lengths.

[23] I confirm this with an event study analysis in Figure H2.

III Empirical Methodology and Identification

III.A Peer Effect Specification

To empirically estimate the size of the peer effects for electric cars in the Swedish vehicle market, the equation of interest (1) is given by a regression of whether individual i adopts a new electric car in quarter q on the number of newly registered electric cars in the previous quarter q_{-1} in peer group p, conditional on all individual and peer group characteristics:[24]

$$V_{i,q}^{e} \ = \ \alpha + \ \theta^{e} V_{p_{-i},q_{-1}}^{e} + \ \gamma \overline{X}_{p_{-i},q} \ + \ \delta X_{i,q} \ + \ \phi_{q} \ + \ \varepsilon_{i,q}, \tag{1}$$

where i indexes the individual, p the peer group of size N excluding individual i, q the quarter and superscript e indicates electric cars. The dependent variable, $V_{i,q}^{e}$, is an indicator of whether individual i acquires a new electric car in quarter q. The peer influence variable equals the sum of all electric car registrations per peer group in the previous quarter q_{-1} excluding individual i: $V_{p_{-i},q_{-1}}^{e} = \sum_{j\epsilon N, j\neq i} V_{j,p,q_{-1}}^{e}$. The vector $X_{i,q}$ represents a rich set of individual demographic variables, residential charging infrastructure, and previous car attributes.[25] To control for the underlying peer group characteristics, $\overline{X}_{p_{-i},q} = \sum_{j\epsilon N, j\neq i} \frac{X_{j.q}}{N-1}$ includes the average characteristics of the peer group using the same set of demographic variables excluding individual i. The quarter fixed effect ϕ_q captures time-varying factors such as nationwide incentives for cars, gas price shocks, or the introduction of a new model. $\varepsilon_{i,q}$ captures individual i's error term.

The peer coefficient (θ^e) measures the effect of the number of new electric cars in the peer group in the previous quarter ($V_{p_{-i},q_{-1}}^{e}$) on whether the person adopts a new electric car in the current quarter ($V_{i,q}^{e}$).

This empirical specification makes two implicit assumptions: First, it assumes a lag of up to one quarter in the transmission of peer effects. Second, it assumes a linear-in-sums model such that peers are influenced by the total number of new car registrations in peer groups while controlling for the number of peers.[26] Alternative functional forms include the share of peers that acquired new electric cars (linear-in-means) or whether any peer bought

[24] This follows the notation of Moffitt et al. (2001) by assuming linearity of the relationship in peer effects.

[25] The demographic control variables include age, gender, disposable family income, gross salary, employment status, self-employment dummy, being married or cohabitant, having at least one child, years of education, commuting distance, number of peers, and being at the contract renewal. The residential charging infrastructure captures the installation of a charging point, the number of plug-ins and charging stations, charging time, and charging capacity. The previous vehicle and driving attributes account for vehicle kilometers traveled, owning an alternative fuel or electric car, the total number of cars, average carbon emission, engine power, service weight, and fuel efficiency averaged over the previous year.

[26] Controlling for network size in a linear-in-sum model is crucial as people with more friends are more frequently exposed to peer effects (Bramoullé et al., 2020).

a new electric car. The results are robust to these alternative functional forms and varying transmission time of peer effects (Section IV.G).

III.B Identification

1. *Identification Concerns.* The model specification in equation (1) implies that individuals belonging to the same peer group may have similar car choices due to three distinct types of effects: (i) *endogenous* interactions: the direct influence of peers' new electric cars on individual car adoption, which implies genuine peer influences (θ^e); (ii) *exogenous* (or contextual) interactions: the indirect influence on individual electric car adoption from average exogenous characteristics of the peer group (γ); (iii) *correlated* effects: the influence of a common set of unobservables on both individual and peers' car adoption (ε). The main empirical challenge is to disentangle the causal relationship of peer influence on electric car adoption from the exogenous and correlated effects. As only the endogenous peer effects give rise to a social multiplier, correct identification of endogenous peer effects is essential to guide policy.

Three main concerns arise in the identification of endogenous peer effects in equation (1): reflection, endogenous group membership, and correlated unobservables (Manski, 1993; Brock & Durlauf, 2001a; Moffitt et al., 2001). The first problem is the reflection problem, which implies that just as peers may affect the individual, the individual may also affect peers. Consequently, it is difficult to disentangle whether an individual's action is the cause or the effect of a peer's influence. This hinders identifying the endogenous from the exogenous effect, even in the absence of correlated effects. The latter two are concerned with the differentiation between the social environment (endogenous and exogenous interactions) and non-social, correlated effects. Endogenous group membership emerges if individuals with similar characteristics self-select into groups, and these characteristics are important determinants of the dependent variable.[27] Correlated unobservables arise from common unobserved factors that may affect the individual and the peer group.[28]

2. *Exogenous Peer Car Take-up.* I exploit exogenous variation in the adoption probability of electric cars for some individuals in a group and measure how other group members' car decisions change subsequently (referred to as the partial population approach in Moffitt

[27] For instance, family-friendliness in workplaces is a relevant driver of many women's employment decision (Herr & Wolfram, 2009; Goldin & Katz, 2012), and if, at the same time, family-friendliness is related to the car purchasing decision, this may increase the electric car adoption within the workplace in the absence of any peer effects.

[28] For example, targeted marketing campaigns within neighborhoods or vehicle fleet policy changes in the workplace influence the car take-up of the entire peer group and are likely to be unobserved, correlated within groups, and crucial for the car decision.

et al. (2001)).[29] To illustrate how this approach solves the identification concerns, suppose that a peer group is composed of only two people: individual 1 and 2. Suppose now that the electric car adoption of individual 1 in quarter q_{-1} is exogenously shocked by a variable $Z_{1,q_{-1}}$. The system of simultaneous equations in this peer group equals:

$$V_{1,q_{-1}} = \alpha_1 + \theta_1^e V_{2,q_{-1}} + \gamma_1 X_{1,q_{-1}} + \delta_1 X_{2,q_{-1}} + \beta Z_{1,q_{-1}} + \varepsilon_{1,q_{-1}} \quad (2)$$

$$V_{2,q} = \alpha_2 + \theta_2^e V_{1,q} + \gamma_2 X_{2,q} + \delta_2 X_{1,q} + \varepsilon_{2,q} \quad (3)$$

This model captures the idea that individual 1's electric car choice is affected by the electric car choice of individual 2, and vice versa. It also allows individual 1's choice to depend on his own characteristics (X_1), and the characteristics of individual 2 (X_2). The model captures the idea that a shock to individual 1 increases the probability of adopting a new electric car and this may change the probability of individual 2 through peer effects (if $\theta^e \neq 0$), but notably not through the common group effect shared by 1 and 2. If the exogenous shock to the subset of the peer group is uncorrelated with X_1, X_2, ε_1 and ε_2 and individual 2's car choice is made after individual 1, the peer effects can be consistently estimated by regressing $V_{2,q_{-1}}$ on $V_{1,q}$ and scaling it by the first stage.

The research design solves the reflection problem through the presence of an excluded variable that appears in individual 1's outcome equation but not in that of individual 2 and by using lagged, but not contemporaneous, adoption by peers.[30] As peer groups are determined before the exogenous shock, endogenous group membership does not pose a threat to the identification. Peer group changes that happen after the exogenous shock are

[29] This approach exploits exogenous variation within endogenously formed groups through the introduction of a policy or program that exogenously shifts the average price of some peers' decisions (Dahl et al., 2014), or by exogenous characteristics of distant 2-nodes, who are not direct peers (Bramoullé et al., 2009; De Giorgi et al., 2010, 2020). Another set of approaches attempts to address the identification challenges by finding contexts in which individuals are exogenously assigned to new social environments. Examples of exogenous assignments into peer groups include classroom variation in the gender and racial mix (Hoxby, 2000; Lavy & Schlosser, 2011; Lu & Anderson, 2015), randomly assigned school or college roommates (Sacerdote, 2001; Zimmerman, 2003; Duncan et al., 2005; Carrell et al., 2009; Shue, 2013), and squadrons of freshman at the Air Force Academy (Carrell et al., 2013). However, this cannot address how peer effects within naturally occurring, self-chosen peer groups unfold. Without a clear source of exogenous variation, researchers have developed structural frameworks to address the identification challenges related to peer effects. With the objective to account for network endogeneity, structural frameworks attempt to combine a model of peer effects with a model of network formation. Goldsmith-Pinkham and Imbens (2013), for instance, first proposed a structural approach that was designed to capture observed and unobserved homophily. Yet, naturally occurring peer groups are constantly changing, making network endogeneity hard to capture in this setting.

[30] Overcoming the reflection problem through prior peer group decisions follows numerous papers in the literature (Towe & Lawley, 2013; Bollinger & Gillingham, 2012; Bailey et al., 2022).

either the causal result of the instrument or orthogonal to it. Under the assumption that the instrument is orthogonal to all observed and unobserved covariates, correlated unobservables do not bias the estimates.

III.C Shift-Share IV Design

To implement the partial-population approach, a successful instrument needs to be as good as randomly assigned ("independence") and shift the electric car adoption probability of an individual's peer ("relevance") without influencing the car decision through any other channel than the peer effect ("exclusion restriction"). To construct an instrument that meets these requirements, I link the timing of the leasing contract renewal (as an exogenous shock to the car take-up) with a measure of each individual's probability of adopting a new electric car. This identification strategy corresponds to a shift-share (or Bartik) research design (Adao et al., 2019; Borusyak et al., 2022),[31] where the exogenous component comes from the timing of elapsing individual-level, car leasing contracts and the non-random exposure shares from heterogeneity in the adoption probability of electric cars at the renewal threshold.[32]

1. *Intuition for Identification Strategy.* To conceptualize how the identification strategy measures peer effects, assume that there are two similar peer groups, and we want to measure how the car choices of peers influence the individual in the red dashed circle (Figure III). Each peer group contains four peers, two of whom have a high probability of adopting an electric car (green), and two have a low probability (brown). Suppose that in a given quarter, the lease contract for one individual in each group expires. While the lease expires for someone who is unlikely to adopt an electric car in the top peer group, it expires for someone who is likely to go for an electric car in the bottom peer group. The identification strategy then compares the subsequent electric car adoption in the peer group that experienced a leasing renewal by someone who was *ex-ante* predicted to be likely to adopt an electric car relative to a peer group that had someone exposed who was unlikely. Consequently, any differences in peer group electric car adoption in the quarters following the contract renewal are informative about the role of peer effects. The variation in the electric car is not driven by differences in the composition of the peer groups as the sum of adopting a new electric

[31] The shift-share design has been used in numerous settings, such as firms that are differentially exposed to foreign market shocks (Hummels et al., 2014; Berman et al., 2015), immigration shocks (Tabellini, 2020; Fouka et al., 2021; Derenoncourt, 2022; Card, 2001), trade (Kovak, 2013), individuals facing different national income trends (Boustan et al., 2013), or countries that are differentially exposed to the U.S. food aid supply shocks (Nunn & Qian, 2014).

[32] The recent literature on shift-share instruments stresses two separate paths for identification: exogenous shocks versus exogenous shares. As individuals are not randomly choosing electric cars at the renewal threshold, I leverage exogenous variation from the timing of the leasing contract renewal, while allowing the variation in exposure shares to be non-random.

car among leasers is identical across per groups; rather, it is the contract renewal timing that selects different people to lease a new electric car.

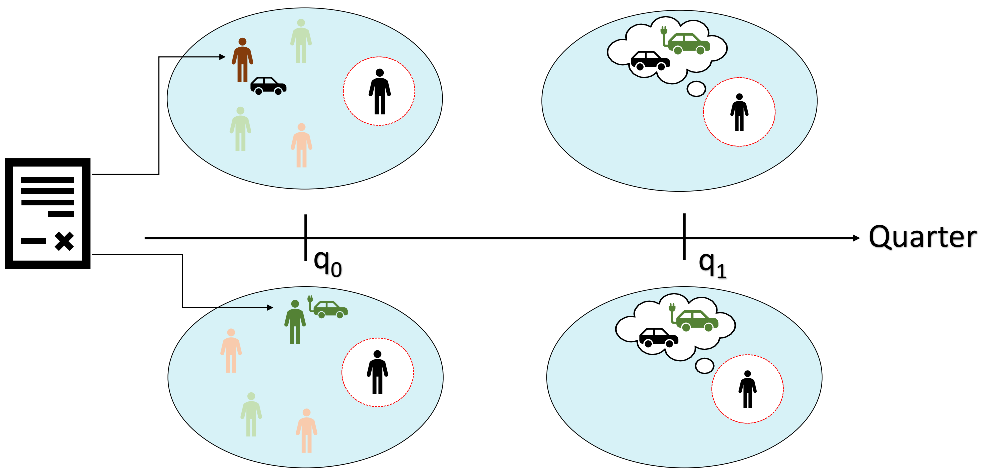


Figure III: Graphical Intuition for Identification Strategy

2. *Leasing Contract Renewal.* The exogenous component of the SSIV-design is based on the idea that car leasing contracts are frequently renewed, and cars are exchanged after three years in the Swedish vehicle market. The exogenous variation exploits the timing of the leasing renewal contract as an exogenous shock to the peer car adoption.[33] This instrument, however, would shift the adoption of all general cars instead of exclusively electric cars. Hence, I do not solely use how many peers are at the contract renewal in a given quarter, but also what type of peers and their likelihood to buy electric cars.

3. *Electric Car Adoption Propensity.* To operationalize a research design that only shifts peer electric car adoption, I interact the peer leasing contract renewal with a measure of each individual's probability of adopting a new electric car at the contract renewal.

For the non-random exposure shares, I develop a measure of each individual's probability of adopting a new electric car. I view the estimation of whether the individual at the leasing renewal adopts an electric car as a pure prediction problem, which follows a growing literature that proposes to use machine learning estimation to fit the first stage in an instrumental variable context when the number of instruments is large (Belloni et al., 2014; Mullainathan

[33]The growing number of contract renewal shocks over time may pose a possible source of concern (Figure A5). However, as long as the shocks demonstrate idiosyncratic variation in the type of person at the contract renewal while controlling for the number of individuals at the contract renewal, the validity of the instrument remains even if the number of shocks in peer groups increases.

& Spiess, 2017; Peysakhovich & Eckles, 2018; Athey, 2018; Chernozhukov et al., 2018).[34] Under the assumption that the peer contract renewal timing is random, what type of peer faces this renewal must also be plausibly random. In this context, I use information about individual demographics, peer group characteristics, charging infrastructure, and past car attributes (summarized as X) to estimate a single propensity of adopting a new electric car for each individual who leases a three-year-old car.[35] As the relationship between the features and the demand for electric cars is likely to be complicated and non-linear, I fit a neural network to predict these propensities. Equation (4) gives the functional form of the neural network:

$$\widehat{Pr}(V^e \mid V^{3y}_{i,q-1} = 1)_q \; = \; \sum_{m \epsilon M} g_m(\omega_m^T X_{q-1}). \tag{4}$$

Let ω_m be a unit vector of unknown parameters and g_m an unspecified function estimated using a flexible smoothing method. Figure D1 illustrates that the estimated propensities accurately reflect the actual electric car take-up of individuals at the renewal cutoff. Appendix D.1 provides additional details on the design of the neural network and the performance of the estimation.

To give some concrete examples, Figure IV plots the probability of adopting an electric car at the renewal threshold for four different characteristics. It reveals substantial heterogeneity in the adoption probability of electric cars in the renewal quarter and that years of education, annual salary, vehicle usage, and the previous engine size indicate whether an individual chooses an electric car. Panel A, for instance, indicates that the probability of adopting an electric car at the renewal for people with less than 12 years of education is only around 3%, while it amounts to over 10% for people with a Ph.D. For salary, in Panel B, we observe a high adoption probability for top-income groups. Furthermore, the adoption probability of electric cars is inversely related to the vehicle's traveled kilometers. Finally, a car with a smaller previous engine is generally related to higher electric car adoption. I predict a single propensity using the heterogeneity of all of these rich background characteristics.

[34] This empirical strategy fits the applied setting particularly well as multiple instruments can be utilized to determine peer adoption and the rich, individual-level Swedish data can precisely forecast endogenous variation in electric car take-up at the renewal decision.

[35] For the remainder of the paper, I refer to these as "propensities."

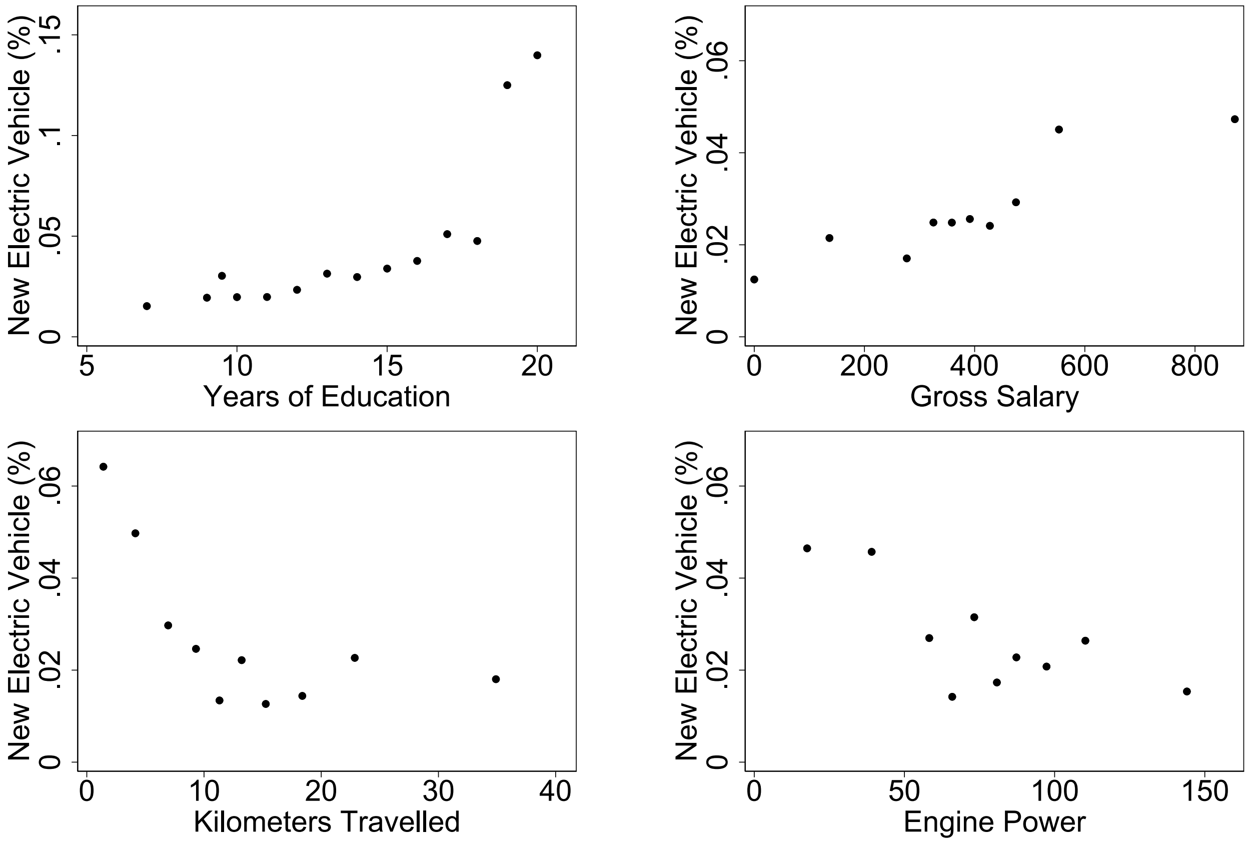


Figure IV: New Electric Car Probability by Background Characteristics

Notes: The figures illustrate the probability of leasing a new electric car at the three-year leasing contract renewal for four different characteristics: Years of education (Panel A), gross salary in thousand SEK (Panel B), vehicle kilometers traveled (Panel C), and previous engine power (Panel D).

III.D Estimating Equations

To construct the SSIV for the adoption of electric cars in peer groups, I interact a dummy indicating if the individual is at the three-year contract renewal ($V^{3y}_{j,q-1}$) with the individual's estimated propensity ($\widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1)$). The exogenous variation comes solely from the interaction of these two terms but not from the number of peers at the contract renewal or their propensities. The instrument then equals the sum of all propensities across all peers at the three-year leasing renewal threshold in a given quarter.[36] The first stage (5) and reduced form equation (6) of the SSIV can be implemented by the following two-equation system:

[36]This can be interpreted as an instrumental variable regression that uses the propensity-weighted sum of peer contract renewal as shocks (Borusyak et al., 2022).

$$V^{e}_{p-i,q-1} \;=\; \alpha^{e} \sum_{j\epsilon N} V^{3y}_{j,q-1} \;\cdot\; \widehat{Pr}(V^{e} \mid V^{3y}_{j,q-1} = 1) + \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q}$$
$$+\; \delta_1 \, V^{3y}_{p-i,q-1} \;+\; \delta_2 \, \overline{Pr}(V^{e} \mid V^{l}_{j} = 1)_{q-1,j} + u_{i,q-1} \tag{5}$$

$$V^{e}_{i,q} \;=\; \beta^{e} \sum_{j\epsilon N} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^{e} \mid V^{3y}_{j,q-1} = 1) \;+\; \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q}$$
$$+\; \delta_1 \, V^{3y}_{p-i,q-1} \;+\; \delta_2 \, \overline{Pr}(V^{e} \mid V^{l}_{j} = 1)_{q-1,j} + u_{i,q-1}. \tag{6}$$

Equation (5) states the first stage relationship between the shift-share instrument and the number of new electric cars in that peer group. The reduced form equation (6) indicates how the shift-share instrument in the previous quarter affects the individual's electric car acquisition. θ^{e} then corresponds to the total number of new electric cars in quarter q that are induced by the instrument (β^{e}) scaled by the first stage estimate (α^{e}). For all main results, I report the OLS ($\widetilde{\theta}^{e}$), first stage (α^{e}), and the two-stage least squares (α^{e}/β^{e}) coefficients.

The average of the estimated propensities is not constant across peer groups, placing the SSIV in the "incomplete shares" class with panel data (Borusyak et al., 2022). To control for the composition of peer groups and their car preferences, I add two key control variables that capture these differences in propensities across peer groups. First, I additionally control for the number of contract renewals in each peer group in a given quarter ($V^{3y}_{p-1,q-1}$). Second, I add a control for the average propensity to lease a new electric car for all leasing peers (l) within a peer group ($\overline{Pr}(V^{e} \mid V^{l}_{j} = 1)_{q-1,j}$). This accounts for a potential direct relationship between the average peer group probability and the individual probability of adopting a new electric car in a given quarter. This follows the recent shift-share literature (Borusyak et al., 2022) to control for the sum of the exposure shares when the sum varies across groups.

1. *Identifying Assumptions and Validity Checks.* Validity of the SSIV requires two assumptions to be fulfilled: instrument validity and instrument relevance. The strength of the instrument is verified in Figure V. Following the framework of Borusyak et al. (2022), the exclusion restriction can formally be stated as follows:

$$E\left[\sum_{i} (\sum_{j\epsilon N} V^{3y}_{j,q-1} \;\cdot\; \widehat{Pr}(V^{e} \mid V^{3y}_{j,q-1} = 1)_{j}) \;\cdot\; \varepsilon_{i} \mid X_{i,p_{-i}}\right] \;=\; 0 \tag{7}$$

Equation (7) expresses that propensity-weighted shocks and the error term are orthogonal. This is satisfied as long as the shocks are as-good-as-randomly assigned, mutually uncorrelated, large in number, and sufficiently dispersed in terms of their average exposure, conditional on the control vector. Applied to this context, the propensity-weighted number of peers at the leasing renewal must be orthogonal to omitted characteristics that are correlated with the individual electric car adoption, after conditioning on the specified baseline characteristics.[37] Although this assumption is inherently untestable, I examine the plausibility of the many conditionally uncorrelated shocks assumption by analyzing the distribution of shocks and using balance tests to corroborate the plausibility of the conditionally exogenous shock assignment assumption (Appendix D.2).

2. *Inference.* As discussed in Adao et al. (2019), standard inference procedures in the case of shift-share research designs become complicated as observed and unobserved shocks may induce dependencies between the instrument and the residual across observations with similar exposure shares.[38] Intuitively, there might be a correlation between residuals in peer groups with similar propensities because these individuals may be exposed to similar combinations of unobserved demand or supply shifters. However, my standard errors are almost identical when moving from standard errors clustered at the peer group level to the shift-share correlated standard errors of Adao et al. (2019) (Figure D3). This implies that across-individual residual dependencies do not substantially influence statistical inference in error terms relative to peer group level clustering. Hence, I cluster standard errors at the peer group level throughout the empirical analysis.[39]

3. *First Stage Results.* To provide evidence for the relevance of the instrument, I begin with a graphical depiction of the first stage. Figure V displays the point estimates and 95%-confidence intervals of the first stage equation (5) for all three peer groups. The x-axis is the value of the shift-share instrument, which I group into 10-percentile bins. The y-axis plots peer electric car adoption, which has been residualized on the full set of baseline controls and quarter-fixed effects. The slope of the regression line is equivalent to the α^e coefficient from equation (5). The figure shows that one additional person at the contract renewal predicted to adopt an electric car implies roughly one additional electric car in that peer group, exactly as we should expect, given the way the instrument is constructed. The first stage F-statistics for the workplace (146.24), family (3140.76), and neighborhood (29237.14) exceed the conventional threshold values for instrument relevance.

[37]One possible concern is that the timing of leasing contract renewal is correlated among peers, resulting in re-occurring simultaneous car decisions in the absence of any peer effects. To address such concerns, I directly control for whether the person is in the car leasing renewal quarter such that the variation purely stems from the leasing renewal of peers.

[38]This relates to Moulton's (1986) standard error clustering problem, in which the residual and the instrument are correlated across observations within predetermined clusters. In the presence of SSIV, there is the additional complication that every pair of observations with overlapping shares may be correlated.

[39]Appendix D.3 discusses statistical inference and standard error construction.

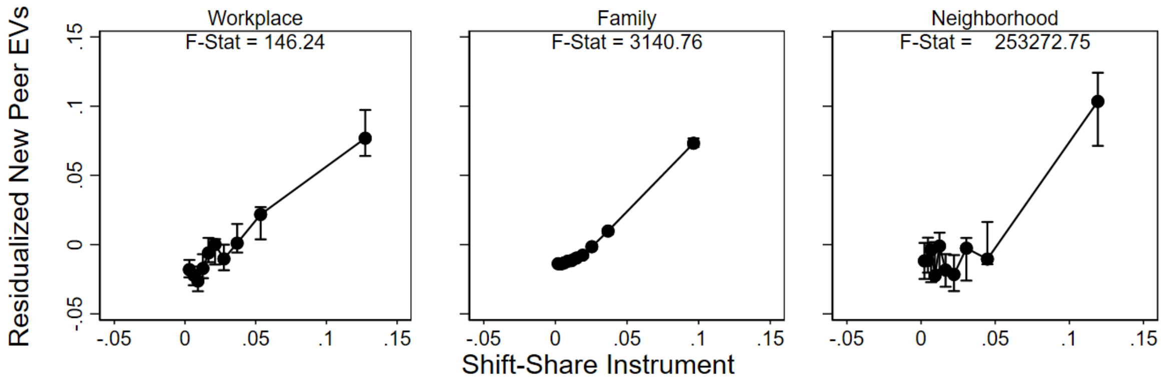


Figure V: First Stage Binned Scatterplots

Notes: These figures present binned scatterplots of the first stage in the workplace (Panel A), family (Panel B), and neighborhood (Panel C) of the first stage in equation (5) (using the Stata package binsreg). The shift-share instrument along the x-axis is defined as the interaction between the number of peers at the three-year car leasing contract renewal and their propensities to adopt an electric car. The right-hand side variable is grouped into 10 bins (10 percentiles each) for all groups that experienced a contract renewal in a given quarter. Both relationships are residuals of the set of control variables in equation (1): individual-demographic variables, peer group characteristics, chargins insfrastructure, peer group demographic control variables, past cars choices and quarter-fixed effects.

4. *How to Interpret Treatment Effect Estimates.* The identification strategy compares the electric car adoption of two similar peer groups, where one peer group received a new electric car (i.e., the treatment group) relative to a peer group that did not receive a new electric car at the renewal threshold (i.e., the control group). Instead, the control group either acquires a new petrol or diesel car, or does not renew the leasing contract. On average, 63% to 65% of individuals in the control group do not adopt a new car at the three-year threshold, whereas 31 to 33% lease a new petrol and 4% a new diesel car (Table D5). Hence, the peer coefficient must be interpreted relative to the subsequent electric car adoption of a peer group in which about two-thirds of contract renewals result in no new car adoption, and one-third in either a new petrol or diesel car.[40]

IV Main Results

[40]Figure D4 illustrates the share of new petrol cars, diesel cars, and non-renewals for individuals at the leasing contract renewal who do not adopt a new electric car. Notably, the propensity to adopt a new petrol or diesel car during the leasing renewal quarter has remained steady, indicating that the interpretation of the control group remains the same between 2012 and 2020.

IV.A Regression Results

Table I estimates peer effects on new electric cars by co-workers (Panel A), relatives (Panel B), and neighbors (Panel C). The coefficients in columns (1) and (3) indicate how the adoption of one new electric car influences the total number of new electric cars in the peer group in the next quarter. In column (4), I divide those total effects by the size of the peer group, which gives an estimate of the peer effect "per capita."[41] These coefficients imply how one new peer electric car affects the electric car adoption of one co-worker, relative, or neighbor in the next quarter.

The OLS results from equation (1) in column (1) of Table I indicate sizable interpersonal influences of electric car adoption in all peer groups. In the next quarter, one new electric car is associated with .027 new electric cars in the workplace, .006 in families, and .059 in neighborhoods through peer effects.

The first stage estimates in column (2) corroborate that the shift-share instrument is a strong predictor of electric car take-up in peer groups. In particular, a predicted increase of one percentage point in leasing a new electric car translates into an increase of approximately one percentage point in the number of electric cars in each peer group.

The 2SLS estimates indicate strong evidence for peer effects. The peer coefficient in column (3) can be interpreted as follows: On average, one new electric car causes, in the next quarter, an additional .077 new electric car acquisitions in the workplace, .014 in the family, and .111 in the neighborhood. Put differently, approximately one in 13 electric cars in the workplace, 71.4 in the family, and 9 in the neighborhood trigger a subsequent electric car adoption in the following quarter due to peer effects.[42]

Although the estimated peer effects are largest in the neighborhood in absolute terms, column (4) indicates that the peer effects per co-worker and relative are larger than those per neighbor. Specifically, each new electric car causes, in the next quarter, .0027 new electric cars per relative, and .0017 per co-worker, while the corresponding effect is .0004 per neighbor. One explanation is that the ties among relatives and co-workers are closer than among neighbors.

The observed peer effects, however, may be present for new cars in general. To identify peer effects for new cars (rather than solely electric cars), I use the leasing contract renewal as an instrumental variable for the adoption of new cars (Appendix H). In comparison, the peer effects for new electric cars are considerably stronger than for all new cars (Table H1),

[41]The average person has 45 co-workers, 5 relatives, and 260 neighbors (Table A3).

[42]Most relatedly, Narayanan and Nair (2013) estimate that 100 Toyota Prius in the zip code result in one incremental purchase through peer effects. Given the arguably stronger ties of co-workers, relatives, or immediate neighbors (relative to previous adopters in large geographic groups), the observed peer effects are considerably larger than the prior estimates for hybrid electric vehicles.

suggesting that peer groups are more relevant for adopting new, early technologies such as electric cars.

The second stage estimates exceed the OLS estimates in all peer groups. This is surprising, as we expect an upward bias due to similar preferences, facing similar environments, or experiencing common shocks of peer groups. The most likely explanation is that the SSIV estimates represent a local average treatment (LATE) for the subset of people with peers at the leasing contract renewal threshold. Relative to the average population, people leasing cars differ in demographic characteristics.[43] Consequently, the observed peer effects with frequent contract renewals may be higher than the average effect in the population. Given the high prevalence of leased cars, especially among individuals who are likely to be early adopters of electric cars, the LATE corresponds to the population we expect to be most influential early in the adoption process. In the mechanism Section IV.E, I provide evidence that peer effects diminish as the level of adoption grows.

IV.B Substitution

An important question is whether the observed peer effects correspond to newly generated demand or are pulled from other vehicle fuel types. To answer this, I measure how a peer's electric car adoption influences the subsequent adoption of three fuel types (petrol, diesel, and electric) and new cars. To operationalize this analysis, I regress the individual adoption of new petrol, diesel, electric, and new cars of any fuel type on the peer electric car uptake in the previous quarter in the respective peer group.

Figure VI illustrates the peer effect estimate of an additional new peer electric car on new petrol, diesel, electric, and new cars in each peer group. First, the top bar in each panel (mirroring the results in Table I) indicates that an additional peer electric car increases the probability of adopting an electric car in the next quarter. However, the peer electric car adoption simultaneously reduces the probability of adopting new diesel and petrol cars in all peer groups. Specifically, one additional new electric car in the peer group results in a reduction of .043 new diesel cars in the workplace, .001 in the family, and .038 in the neighborhood. This suggests that peers do not only accelerate the adoption of electric cars but also crowd out the adoption of diesel and petrol cars. Hence, the take-up of new technologies accelerates future adoption through positive peer effects but also reduces the

[43]Table A4 reports car owners' average individual and car characteristics and the entire population, pooling the years from 2012 until 2020. Compared to the population, people who lease cars are relatively younger, more likely to be male, more wealthy, less likely to be unemployed, and more likely to be married or cohabitant. Most strikingly, an individual leasing a car has, on average, around 100 SEK more disposable income and .75 years more education. Generally, leasers own more fuel-efficient cars, have smaller engines, lower carbon emissions, and are more likely to be electric.

Table I: Peer Effects in Electric Car Adoption

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Peer Coefficient	.0274***	1.1319***	.0771***	.0017***
	(.0061)	(.0816)	(.0281)	(.0006)
%-Effect	194.32	8033.43	546.92	546.92
Mean Dep. Variable	.014	.014	.014	0
B.Family Network				
Peer Coefficient	.0060***	1.1695***	.0140***	.0027***
	(.0005)	(.0169)	(.0049)	(.0010)
%-Effect	413.69	80945.65	966.66	966.66
Mean Dep. Variable	.001	.001	.001	0
C.Neighborhood Network				
Peer Coefficient	.0594***	1.4960***	.1114***	.0004***
	(.0023)	(.1029)	(.0298)	(.0001)
%-Effect	80.26	2022.11	150.64	150.64
Mean Dep. Variable	.074	.074	.074	0

Notes: This table presents the regression estimates of peer effects in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The %-effect and the mean dependent variable are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

acquisition of old technologies (such as fossil fuel cars).

Second, the peer adoption of electric cars results in a reduction of new cars in workplaces and families, but an increase in new cars in neighborhoods relative to a peer group that does not receive an exogenously-arriving new electric car. This suggests that peer effects in workplaces and families correspond to a substitution from other fuel types as the incremental demand for electric cars is pulled from diesel and petrol cars. However, in neighborhoods the additional demand for electric cars is only partially offset by reduced demand from other fuel types, indicating that peer effects resulted in a complementary electric car adoption rather than a substitution from different fuel types.

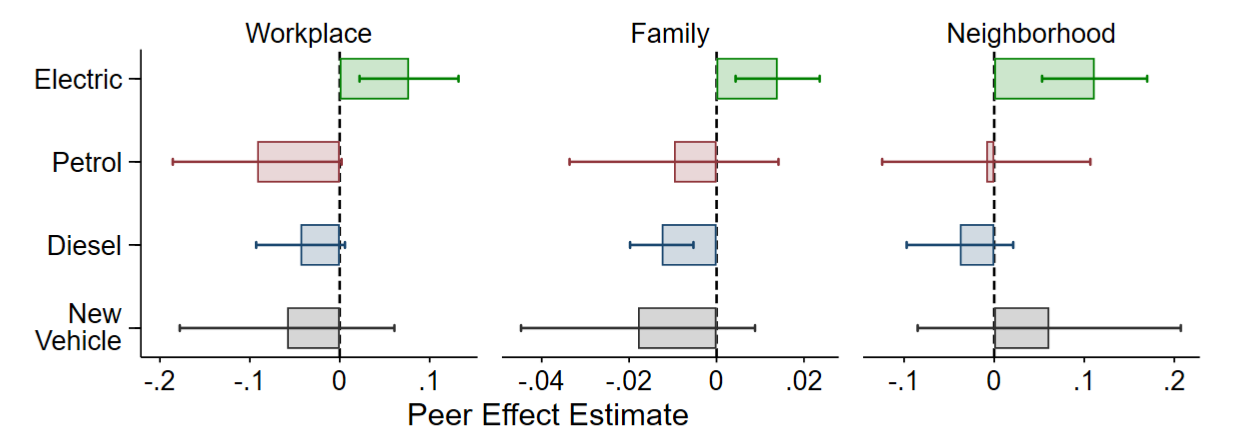


Figure VI: Peer Effects by Vehicle Fuel Types

Notes: The plots present regression estimates of peer effects across three different motor fuel types (petrol, diesel, and electric) and all new car registrations for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable measures the number of new petrol (red), diesel (blue), electric (green), or any new cars (grey) in the peer group. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C. The corresponding coefficients and percentage effects are shown in Table F1.

IV.C Dynamics

Having estimated the peer effects after one quarter, I next explore the dynamics of peer effects over longer periods. This answers how long the social influence of the peer electric car adoption lasts and whether these peer effects generate additional demand for electric cars or merely reflect an intertemporal substitution of already planned future purchases.

The interpretation of longer-horizon peer effects becomes more complicated as second-degree effects gradually emerge. For example, an individual's new electric car in quarter q

may affect a mutual peer's acquisition in quarter $q+1$, influencing another peer's purchasing decision in quarter $q+2$. The estimated LATE coefficients capture both the direct effect of the initial peer acquisition and all higher-order indirect effects by common peers caused by the initial electric car adoption.

Figure VII displays the total peer effect coefficients (θ^e_τ) four quarters prior and up to eight quarters following the peer electric car adoption in quarter $q = -1$ across the three peer groups.[44] The dashed line refers to the peer electric car adoption period, which resembles the first stage regression corresponding to equation (5). The dynamics reveal that the peer effects of electric cars affect the car choice for the first four quarters in the workplace, eight quarters in the family, and two quarters in the neighborhood.[45] After that, the aggregate effect converges toward zero in all groups. Importantly, the peer effect on the uptake of electric cars shows no sign of turning negative.[46] This indicates that interpersonal influences generate additional demand for electric cars and are not merely intertemporal substitution. Aggregating the observed peer effect over three years, I find that one additional electric car in the peer group adds .35 new electric cars in the workplace, .29 in the family, and .95 in the neighborhood. Although the parallel trends assumption is inherently untestable, Figure VII documents that the trends in electric car adoption before the leasing renewal quarter for a peer group that received a new electric car and a peer group that did not receive a new electric car at the renewal threshold ($\theta^e_\tau \approx 0$) suggest that the assumption is likely to hold.

Notably, the peer effect in families persists over the entire horizon, whereas the influence in the neighborhood is short-lived. This implies that new electric cars have a lasting impact on future adoption patterns among families, whereas the peer effect is only temporary in workplaces and neighborhoods. One potential explanation for the shorter-lived peer effects among co-workers and neighbors is that individuals may change workplaces or neighborhoods. In Figure F1, I restrict the sample to individuals who worked in the same plant or

[44] This dynamic model is related to the social multiplier model in Glaeser et al. (2003) and the snowball effect model by Dahl et al. (2014). The main difference is that peer effects are only measured whenever a peer adoption occurs instead of a constant period, implying that peer effects can be temporally distant and rely on parametric assumptions. The social multiplier effect model in Glaeser et al. (2003) identifies social multipliers under the assumption that the peer effect of the most recent electric car is the largest, but the effect decays at a constant rate. The snowball effect model by Dahl et al. (2014) assumes that the first electric car has the largest social influence on all subsequent peer car decisions, but the effect decays over time. Instead of imposing a parametric assumption on the decay rate, I estimate each period's total peer effect (i.e., direct and indirect) using an elapsing leasing renewal contract in period $q = -1$.

[45] The waiting times for electric cars provide one possible explanation for peer effects over longer periods. Individuals at the contract renewal make their car selection before the renewal date so that the new car's arrival coincides with the leasing renewal. If the individual at the renewal threshold exerts peer effects, waiting periods will delay the adoption of new electric cars, and peer effects will appear in subsequent periods.

[46] In contrast, the peer effect dynamic for all new general cars shows a reverse trend of car adoption (Figure H3), suggesting that intertemporal substitution is more prevalent for new cars.

lived in the same neighborhood for the duration of the study. The empirical results reveal persisting peer effects for constant peer groups, indicating that switching jobs or moving diminishes the magnitude of the peer effect.

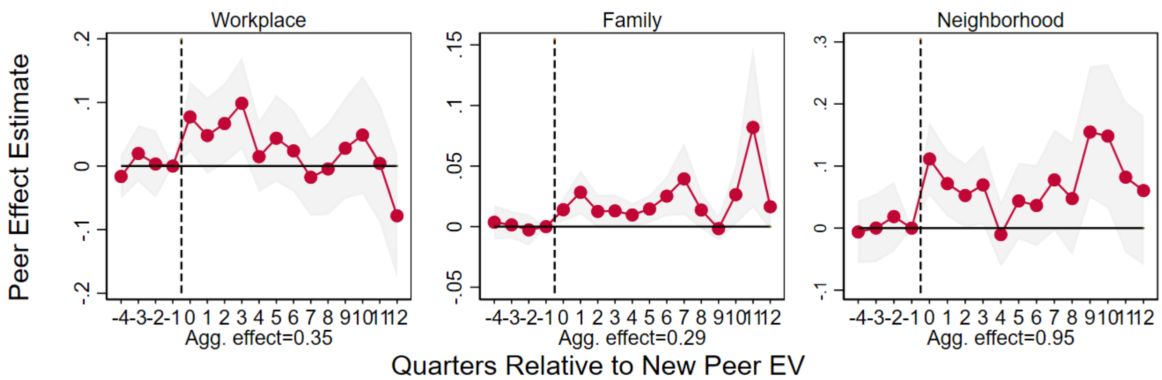


Figure VII: Peer Effect Dynamics

Notes: The figure displays regression estimates of peer effects at various horizons in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group up to four quarters prior and up to eight quarters following the initial electric car adoption of peers. The underlying regression specifications of the peer effect dynamics are documented in Section E.1. The dashed line between period -1 and 0 refers to the peer electric car adoption period, which resembles the first stage regression in equation (5). The coefficients capture the total peer effect induced by SSIV in quarter q=-1. 95%-confidence intervals are indicated through the error bars.

IV.D Heterogeneity

Identifying characteristics of socially influential individuals that foster the electric car take-up is vital for policymakers to predict future adoption rates and target financial incentives towards socially influential groups. This Section explores heterogeneity in the transmission of peer effects in electric cars. The heterogeneity analysis contributes to this research by documenting demographic attributes indicative of sizable social peer effects in adopting electric cars.

Figure F2 explores heterogeneity in the transmission of peer effects, separating people at the leasing renewal along demographic characteristics. The results indicate that an individual's age, education, income, and peer group size are significant predictors of the strength of peer effects. In particular, the peer effects of adopting a new electric car are enhanced in smaller workplaces and neighborhoods. This finding suggests that small groups are particularly valuable in increasing the vehicle fleet turnover as the peer effects progress faster. In addition, the size of the peer effect for different levels of education varies across peer groups, indicating no monotonic pattern for education. Lastly, I find that peer effects increase with income and are stronger for younger people in all peer groups.

IV.E Mechanisms

Peer effects can influence people's electric car take-up through several mechanisms. Peer effects may serve as a source of information, and individuals are therefore affected through "social learning" about electric cars (Moretti, 2011; Dahl et al., 2014; Herskovic & Ramos, 2020). Although it is difficult to assess what type of information transmission drives the estimated peer effects without data on individual information sets, I empirically test whether the information is transmitted at different stages of the adoption curve, about financial incentives, the leasing details, the public charging infrastructure, and through exposure or experience with electric cars.[47]

As information about a new technology is typically scarce at the beginning, I expect peer interactions with early adopters of electric cars to carry more informational value and generate larger peer effects on their peer groups. To test this hypothesis, I estimate the strength of peer effects for each individual in the peer group's diffusion curve. Figure F3 reveals that peer effects are stronger for early adopters and diminish along the adoption curve, which suggests that early adopters may diffuse more information about electric cars.[48]

A second possible learning mechanism is that peer groups provide information about the financial incentives for adopting a new electric car. Since the penetration of electric cars is still low, there may be a lack of information about the financial incentives of adopting a new electric car. To test whether peer effects transmit information about financial incentives, I separate the sample into three periods: a low-subsidy period (from January 2012 to June 2018); a medium-subsidy period (July 2018 to December 2019); a high subsidy period (from January 2020).[49] Figure F4 reveals that the peer effects increase with higher financial incentives for electric cars. As a result, peers are a potential source of information about the financial incentives for electric cars.[50]

A third learning channel is that peers may share information about how to lease a new car. If information about leasing is a key driver of the observed peer effects, I expect to also detect peer effects from any newly leased cars. To empirically test this idea, I regress whether an individual adopts a new electric car on the number of newly leased petrol and diesel cars in the peer group. Figure F5 documents that peer effects are absent for new non-electric cars. This implies that social learning is specific to leasing new electric cars, and

[47] The underlying regression specifications to measure various peer effects mechanisms are illustrated in Appendix E.

[48] The importance of the information channel also aligns with the fact that the peer effects are considerably larger in small peer groups, where the transmission of information is straightforward.

[49] For each period, the financial incentives of the vehicle subsidies with respect to the CO_2 emission level are shown in Figure B1.

[50] An alternative explanation is that individuals are at a different adoption level in higher subsidy periods and the demand elasticities are more responsive to peer's electric car adoption.

does not solely operate through information about leasing contracts.

A fourth plausible social learning channel driving the observed effects could be learning from peers about the availability of the charging infrastructure.[51] This includes sharing information about the closest residential charging station, recharge time and cost, and available parking spots with plug-ins. Exposure to charging stations in the residential neighborhood is likely associated with being more informed about the charging infrastructure. To test this hypothesis, I break up the peer effect estimates from neighborhoods with and without public charging stations in Figure F6. The results reveal that the take-up of electric cars is not constrained by a lack of information about charging stations and is not a key mechanism for the estimated peer effects.

A peer that has tried a new technology more frequently may be able to provide more detailed information about its characteristics. To assess whether the experience with electric cars drives information transmission, I compare the strength of peer effects for electric cars driven more frequently ($>$ 12.000 km annually) to those driven less frequently ($< 8000km$ annually) in Figure F7. Consistent with this experience channel, I find that the estimated peer effects are greater among peers who drive their electric cars more, which suggests that information emerges due to the peer's experience with electric cars.[52]

Immediate exposure to electric cars may serve as a mediator for information transmission. If this is the primary driver, then the visibility of electric cars may play a key role in peer effects.[53] For instance, electric cars in an individual's driveway have stronger visibility and attributability than those parked near apartment buildings. To test this idea, I estimate the peer effects in neighborhoods that predominantly consist of houses or apartments. Figure F8 shows stronger peer effects for neighborhoods with single-family homes compared to those with apartment buildings, which suggests that the visibility of electric cars is a mediating factor of peer effects.[54]

In addition to the purely informational value, peers' electric car adoption may also

[51] The availability of charging station infrastructure at home and at work has been argued to play a crucial role in the electric vehicle decision. Using a two-sided market with endogenous charging station entry and electric vehicle adoption, Springel (2021) shows a positive connection between charging station subsidies and electric vehicle purchases in Norway. In a similar framework, Li (2016) provides evidence that mandating compatibility in charging standards would increase the size of the electric vehicle market in the US.

[52] Notably, the distinction between low and high usage is most pronounced in neighborhoods where exposure to electric cars is expected to influence peer effects the most.

[53] The observability of new technologies or practices has been shown to play a pivotal role in peer effects (Mas & Moretti, 2009; Bursztyn & Jensen, 2015), and has undergirded economic theories of peer effects (Bernheim, 1994; Benabou & Tirole, 2006). Previous research has argued that one potential determinant of the relatively high market share of the Toyota Prius was its design, which made it more visible in the neighborhood community (Kahn, 2007; Ozaki & Sevastyanova, 2011).

[54] This is consistent with the notion that the peer effects are significantly larger in rural than in urban neighborhoods (Table F3).

directly enter the individual's utility function through a "preference channel" (Mas & Moretti, 2009; DellaVigna et al., 2016; Bursztyn et al., 2018). Peer effects can, for example, serve as an instrument for enforcing norms through social reputation concerns, which directly enter an individual's utility function (Benabou & Tirole, 2011; Jia & Persson, 2021). Social reputation in adopting an electric car can operate through the honor of being an early adopter or the fear of being shamed for driving a gas guzzler. The empirical results in Figure F4, however, indicate that the peer effects are particularly large when there are subsidies for electric cars. This contradicts the fact that peer effects drive social reputation concerns, as financial incentives would reduce the social reputation from adopting an electric car and lower peer interactions.

Assuming that social norms operate through conforming to the average car type of peers in the utility function (Akerlof, 1997; Kandel & Lazear, 1992; Bernheim, 1994), deviating from the average carbon emission of peers becomes more costly in a conformity model. Hence, I split the sample into peer groups with a low- and high-carbon emitting vehicle fleet in Figure F9. The peer effects in low- and high-carbon emission car fleets are not substantially different, indicating that conformity to social norms is not a primary motivator behind peer effects.

IV.F Effects on Carbon Emissions & Behavioral Changes

To establish whether peer effects contribute to a cleaner transport sector or reflect an increase in pollution, I compute how adopting an electric car in peer groups affects an individual's car-related carbon emissions. These are equal to the product of the average carbon emission per kilometer ($\overline{V_{i,q}^{CO_2}}$), the average kilometers traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$).[55] To determine the change in an individual's carbon emission through peer effects, I differentiate the total carbon emission of each individual with respect to the impact of one new electric car in the peer group. Equation (8) displays the carbon emission change that arises through the peer adoption of an electric car for the next six quarter $q = 0, ..., 6$:

$$\begin{aligned} \triangle CO_{2_{i,q}} \;=\; & \sum_{q=0}^{6} \underbrace{\theta^{e}_{CO_2} \cdot \overline{KM_{i,q}} \cdot N_{i.q}}_{\triangle CO_2} + \underbrace{\theta^{e}_{KM} \cdot \overline{V_{i,q}^{CO_2}} \cdot N_{i.q}}_{\triangle Driving} \\ & + \underbrace{\theta^{e}_{N} \cdot \overline{V_{i,q}^{CO_2}} \cdot \overline{KM_{i,q}}}_{\triangle Vehicle}. \end{aligned} \tag{8}$$

[55] I only account for the end-of-pipe emissions of vehicles, not their carbon emissions throughout production.

The peer coefficients $\theta^e_{CO_2}$, θ^e_{KM}, and θ^e_N indicate how one new peer electric car influences the average carbon emissions, the kilometers traveled and the number of cars, respectively.[56] Appendix E.3 describes the derivation of the carbon emission model and the underlying regression specifications.

Equation (8) implies that the carbon emission change ($\triangle CO_{2_{i,q}}$) resulting from the adoption of a peer electric car is equal to the sum of three effects: changes in (i.) average carbon emissions, (ii.) kilometers traveled, and (iii.) the number of cars. Figure VIII illustrates how the addition of one new electric car affects the per-person carbon emissions in the workplace by encouraging co-workers to adopt cleaner cars ("vehicle emission"), drive less ("kilometers traveled"), and reduce the number of owned cars ("number of vehicles"). The effect is relative to the average carbon emission of a person in the workplace, which equals .38 tons of carbon quarterly. Figure F10 illustrates how peer effects influence the total carbon emission in families and neighborhoods.

One new peer electric car reduces, in the next quarter, the average carbon emissions of a co-worker's car by .47 grams. To link this to the change in carbon emissions purely caused by electric cars, one new peer electric car results in an additional .0017 new electric car acquisitions per co-worker in the next quarter. By multiplying the peer coefficient on electric car adoption by the emission reduction induced by adopting a new electric car (about 85 grams of carbon), I estimate that a new electric car reduces the carbon emissions by around .145 grams in the next quarter. This implies that around half of the reduction in car emissions is explained by adopting electric cars; the rest is due to non-adopters choosing cleaner fossil fuel cars.

To quantify the total effect on car emissions, I multiply the peer coefficient on carbon emissions ($\theta^e_{CO_2}$) by the individuals' kilometers traveled ($\overline{KM_{i,q}}$) and the number of cars ($N_{i.q}$). Carbon emissions fall by around .2% by triggering co-workers to adopt cleaner cars in the next quarter. If we extend this effect over the next six quarters, the total impact on average carbon emissions decreases to approximately 1.6% per co-worker relative to the initial period. This is driven by a 1% reduction in carbon emissions due to the adoption of new electric cars and a .6% decrease due to the adoption of cleaner fossil fuel cars.

The cumulative impact of peer effects, however, extends far beyond the adoption decisions of peers: Figure VIII indicates a substantial and economically meaningful reduction in kilometers traveled and the number of cars. One new peer electric car reduces the average kilometers traveled by around 28 kilometers per person (θ^e_{KM}) in the next quarter, showing

[56] The carbon assessment of peer effects excludes "ripple" effects on the second-hand car market and outside the peer group. In Table F6, I find that peer effects do not matter for adopting used electric cars. However, cars that leave peer groups following the expiration of a lease contract are typically cleaner than the average car in the population.

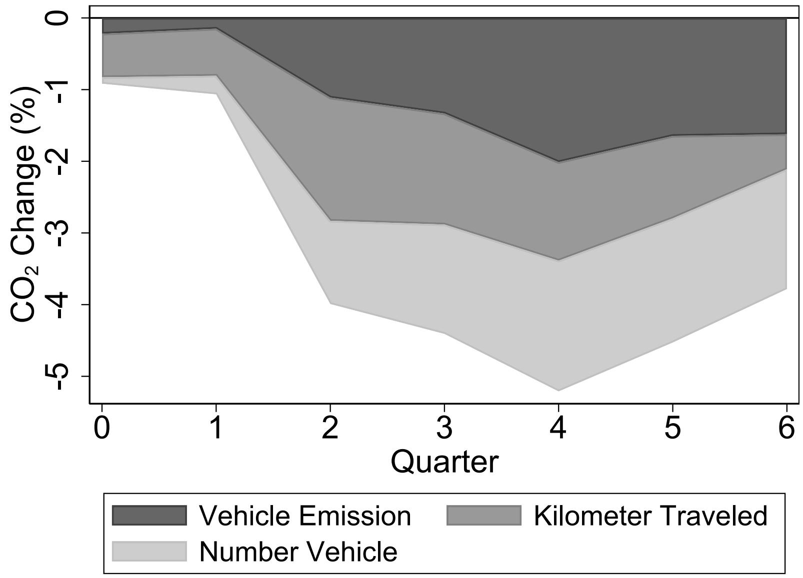
no indication of a "rebound effect."[57] Multiplying the peer effect on kilometers traveled by the average carbon emissions and the number of cars, I find that one new electric car induces a .5% carbon reduction through changes in driving behavior after six quarters. In addition, one new peer electric car reduces the total number of cars by .0015 in the next quarter (θ_N^e). Multiplying this peer coefficient on the number of cars by the average carbon emission and the kilometers traveled, the carbon emission effect of a change in the number of cars is around 1.7%. The empirical evidence that people are driving fewer cars and traveling less frequently by car may indicate a transition to alternative modes of transportation.

The total carbon emission changes caused by peer effects amount to approximately 3.8% after six quarters, which comes from a 1.6% reduction in car emissions, a .5% reduction by driving less, and a 1.7% reduction in the number of cars.[58] The empirical results suggest that peer effects facilitate the transition to a greener transport sector and expand the scope of peer effects by revealing that the total carbon emissions of electric cars are significantly greater than the adoption decision of electric cars. While the electric car adoption by peers accounts for about one-seventh of the total carbon emission effect, moving to cleaner cars in general, lowering the kilometers driven, and the number of owned cars, account for the majority of carbon savings. In addition to the effect on carbon emissions, the peer effects of electric cars also lead individuals to adopt lighter cars with smaller engines and greater fuel efficiency (Table F5).

Aggregating the total carbon emission changes through the peer electric car adoption over the first six quarters decreases carbon emissions by 1.18 tons in the workplace. To convert the carbon emission changes into a monetary equivalent, I multiply the carbon emission savings with the Swedish carbon tax rate (as an approximation for the social cost of carbon), which is currently set to \$126 per ton of CO_2. The total monetary value of carbon emission reductions attributable to the adoption of one new electric car is thus approximately \$149 in the workplace.

[57] This is subject to a voluminous literature (Borenstein, 2015; Chan & Gillingham, 2015; Gillingham et al., 2020).

[58] Figure F11 confirms that the peer effect results on the total carbon emission (normalized to one at the peer electric car adoption) are equivalent to the sum of the carbon emission changes through these three margins.



(a) Workplace

Figure VIII: Carbon Emission Changes

Notes: The figure displays how one additional new electric car in the workplace causes reductions in the per-person carbon emissions by (i.) triggering co-workers to adopt cleaner cars ("vehicle emission"), (ii.) driving less ("kilometers traveled"), and (iii.) reducing the number of cars they own ("number of vehicles"). The effect is relative to the average carbon emission of a person in the workplace, which equals .38 tons of carbon quarterly. The underlying regression specifications of the carbon emission model are documented in Section E.3. About half of the reduction in vehicle emissions is explained by adopting electric cars; the rest is due to non-adopters choosing cleaner fossil fuel cars. The corresponding coefficients are illustrated in Table F4.

IV.G Robustness Checks

In this Section, I test the stability of the estimated peer effect coefficients to various alternative specifications. The results remain robust across various alternative functional specifications, sample restrictions, peer group structure, placebo tests, machine learning techniques, and dynamics.

In Table G1, I first apply a probit estimation model to estimate the individual electric car take-up, and there is virtually no change in the estimates. Instead of using the total number of peer electric cars as a measure of social impact, I estimate the results using the proportion of peers and a binary indicator denoting whether a peer has adopted a new electric car. Applying these functional forms as peer influence has little effect on the outcomes. Next, I explore what happens if I exclude people who lease themselves or are at the contract renewal threshold. Excluding leased cars as an outcome causes the coefficients to become insignificant, implying that peer effects primarily influence the take-up of new leased electric cars, but have little effect on the purchase of electric cars. The second stage estimates omitting peers at the renewal threshold are marginally smaller, yet the results remain significant. Finally, I restrict the sample to peer groups that experienced at least one leasing renewal to mitigate the concerns regarding disparities between peer groups with and without leasing peers. However, the peer effects of the restricted sample remain unaltered.

As peer groups are overlapping, such that co-workers may reside in the same neighborhood or are related, the peer coefficients may capture potential interdependencies between peer groups. In Table G2, I evaluate each peer group independently by subtracting members of other peer groups from the reference group. In families, for example, I exclude relatives working at the same plant (e.g., family-owned businesses) or living in the same neighborhood. The findings reveal that the workplace and neighborhood effects diminish marginally, while the family effect shrinks by around 25%. A fraction of the peer effect in families is caused by co-workers or neighbors that are relatives.

As a validity check, I also run two series of placebo tests. The first tests the results for placebo peer groups, while the second assigns false renewal thresholds. To provide further evidence that the estimated peer effects reflect actual social influences, I check whether the estimated peer effects for placebo co-workers and neighbors vanish. The placebo co-workers I consider are: 1. Firm-level co-workers: These are co-workers employed in the same firm, two-digit industry, and municipality, but they do not work in the same plant; 2. Future co-workers: This placebo co-worker group consists of future co-workers that switch into the individual's workplace. The placebo neighbors I consider are distant neighbors living in the same demographic statistical area ($DeSO$), but I exclude neighbors within the $125m$ radius. Table G3 verifies that there are no peer effects among both groups of placebo co-workers. As there is no apparent tie between these placebo peer groups, this confirms that the estimated peer effects do not simply reflect a spurious relationship induced by unobserved factors. Similarly, the impact for the distant neighbor becomes significantly smaller, which indicates that the peer effects are largely transmitted among immediate neighbors.

A potential threat to the underlying estimation strategy is that individuals with peers at the renewal threshold inherently differ from peer groups without leasing renewals. To mitigate this concern, the second placebo test assigns a false contract renewal threshold to the exogenous part of the shift-share design. For this purpose, I group the false contract renewal eight quarters prior to and past the actual three-year contract renewal and interact it with the estimated propensities. The placebo peer coefficients in Table G4 indicate that having peers leasing a car before or after the renewal threshold does not imply a higher probability of adopting a new electric car.[59]

[59]This is based on the "recentering" method described in Borusyak and Hull (2020), which draws counterfactual shocks from the assignment process and recomputes the instrument. Following their idea, the

I perform an additional robustness check regarding the dynamics of peer effects, which is concerned with the transmission time of peer effects. As opposed to assuming a quarter for the transmission of peer effects, Table G5 extends the transmission to 2, 3, and 4 quarters. The results stay significant, but the empirical specifications with a longer transmission time are slightly smaller and have larger standard errors.

V Policy Implications

A key question for policymakers is how to design subsidies for emerging green technologies.[60] The classic economic approach is to make polluters internalize the external costs they generate (Pigou, 1920): taxes should equal the marginal externality at the optimal resource allocation. Externalities occur when the adoption of a new product has a direct, uninternalized (i.e., not through prices) impact on the welfare of another individual.

The externalities of electric cars must be measured relative to the car that would otherwise have been purchased (i.e., the "counterfactual" car). The total value of externalities for electric cars e then equals the difference between each externality that arises from adopting the electric car $e_j(V^e)$ and the externality from the counterfactual car $e_j(V^c)$ (Muehlegger & Rapson, 2020).[61] Externalities in the electric car market include a reduction in global and local pollution externalities, industrial learning-by-doing, network externalities related to charging infrastructure, and the undervaluation of future energy savings (Rapson & Muehlegger, 2021). Equation (9) states the externality calculation for electric cars:

$$e \;=\; \sum_{j=1}^{J}[e_j(V^e) - e_j(V^c)]. \tag{9}$$

The optimal Pigouvian subsidy would advise setting the upfront subsidy τ for electric cars equal to the sum of externalities ($\tau^* = e$) in the absence of peer effects. The subsidy corrects for the positive externalities of adopting the electric car relative to the counterfactual car.

counterfactual shock corresponds to peers nearby the leasing renewal, which I interact with the estimated propensities.

[60]There is a large body of literature that analyzes the impact of government policies such as subsidies, tax credits, tax rebates, or the US 2009 Cash for Clunkers Program on the adoption of hybrid and electric vehicles (Mian & Sufi, 2012; Beresteanu & Li, 2011; Chandra et al., 2010; Gallagher & Muehlegger, 2011; Muehlegger & Rapson, 2018). However, it remains unknown how peer interactions that stimulate the subsequent adoption in peer groups impact the evaluation of these programs.

[61]Intuitively, an individual who switches to an electric car will generate large environmental benefits if it replaces a gas guzzler and small environmental benefits if it replaces an environmentally-friendly car. Importantly, to assess emissions savings, it is insufficient to observe what car is sold, exchanged, or retired when an individual purchases an electric car, as this does not likely reflect the "counterfactual."

An economically meaningful marginal benefit of electric car adoption is the impact on the peer group's electric car decision. As peer effects generate an additional θ^e follow-on purchases of electric cars, the externalities are amplified by the peer effect $\theta^e(e_j(V^e) - e_j(V^m))$. Intuitively, the electric car adoption does not only disregard their externalities, but also those of their peers, whom they will influence to get an electric car.

The peer effects do not only influence the optimal level of subsidies but also their trajectory. As peer effects are stronger for early adopters and diminish along the adoption curve (Figure F3), I allow the peer effects to vary along the adoption curve. This is essential for internalizing the dynamics of peer interactions at different stages of the adoption. $\theta^e(v^*)$ captures the size of peer effects as a function of the number of electric cars in the peer group ($v^* = \sum_{j\epsilon N, i\neq j} V_j^e$).

Proposition 1. *(modified Pigou) Assume that a policymaker sets a standard Pigouvian subsidy τ that equals the sum of all externalities e according to equation (9). Relative to a standard Pigouvian subsidy that does not internalize peer effects, the socially optimal Pigou $\tau^*(\theta)$ equals the sum of externalities e scaled by the size of the peer effects at the current level of the adoption $\theta^e(v^*)$:*

$$\tau^*(\theta) \;=\; e \,\cdot\, [1 + \theta^e(v^*)]$$

Proposition 1 characterizes the optimal Pigouvian subsidy $\tau^*(\theta)$ relative to a standard subsidy τ that does not internalize peer interactions.[62] I made two implicit assumptions to derive the optimal Pigouvian subsidy in Proposition 1. First, peer effects solely change the demand for electric cars, but do not affect the adoption of fossil fuel cars. Second, adopting a new electric car has no direct effect on peer's welfare.

Figure IX presents the trajectory of the optimal Pigouvian subsidy along the adoption curve $\tau^*(\theta)$ relative to a first-best Pigouvian subsidy without any peer effects. Across all peer groups, the modified subsidy for electric cars shifts upward for early adopters in the presence of peer effects, but decreases along the adoption curve. This is because early adopters create a larger follow-on adoption of electric cars, which scales the marginal benefit of individual electric car adoption. This implies that optimal policies should front-load subsidies to early adopters to capture the higher marginal benefits of peer effects at the beginning of the adoption curve.

[62]The derivation of the optimal modified Pigouvian subsidy in the presence of peer effects is illustrated in Appendix I.

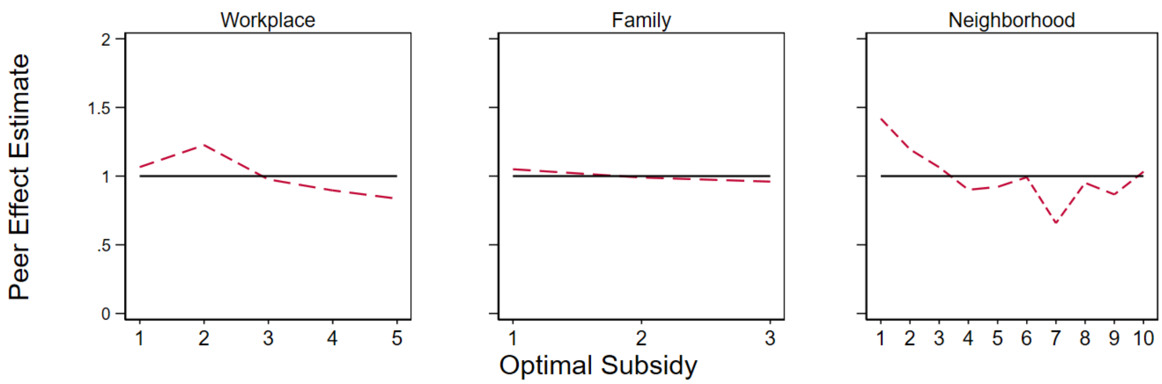


Figure IX: Pigouvian Subsidy with Peer Effects

Notes: The figure displays the trajectory of the optimal Pigouvian subsidy along the adoption curve in the presence of peer effects (red dashed line) relative to the optimal Pigou without peer effects (black line) for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The optimal Pigou without peer effects equals the difference between each externality that arises from adopting an electric car and the externality from the counterfactual car according to equation ((9)). The underlying regression specifications to estimate peer effects along the adoption are documented in Section E.4.

Assumption 1. To capture the crowding out of petrol and diesel cars discussed in Section IV.B, I incorporate how a peer electric car changes the adoption of new fossil fuel cars θ^c. This substitution reduces the positive externality from electric car adoption by the magnitude of the peer effect on new fossil fuel cars $-\theta^c(e_j(V^e) - e_j(V^m))$. As a result, the modified Pigouvian subsidy that accounts for this substitution effect in equation (32) increases as new electric cars also reduce the externalities from the adoption of fossil fuel cars in peer groups.

Assumption 2. There are various mechanisms through which the adoption of electric cars may influence peer's welfare. To relax this assumption, I discuss how three mechanisms of the observed peer effects may alter the welfare of electric cars and how this affects the dynamics of the Pigouvian subsidy. First, the information provided by peers may reduce the uncertainty about the characteristics or the usage of electric cars, which increases the welfare of adopting a new electric car (Moretti, 2011; Dahl et al., 2014). As early adopters in peer groups primarily diffuse information, optimal policies should compensate for the additional welfare that future adopters derive from the information. Thus, information transmission gives an additional justification for front-loading electric vehicle subsidies.

Second, a peer electric car may affect individuals' welfare through social reputation (Benabou & Tirole, 2006, 2011). Suppose that early adopters of electric cars reap social honor from adopting electric cars, while inflicting an equal social stigma on non-adopters. As a result, adopting a new electric car crowds out social honor and thereby reduces welfare for subsequent adopters in the peer group. This implies that the optimal subsidy lessens for early adopters due to social reputation concerns, but rises as the adoption curve progresses.

Third, the subsidy's imposition may affect the strength of peer effects. Empirical evidence suggests that financial incentives crowd out peer effects in water conservation practices (Bollinger et al., 2020) and green power consumption La Nauze (2021).[63] If the subsidy discourages peer interactions for electric cars, then the optimal subsidy decreases, while the subsidy increases if the subsidy crowds-in peer effects.

VI Concluding remarks

The paper provides evidence for substantial peer effects in adopting electric cars in workplaces, families, and neighborhoods. On average, one new electric car causes, in the next quarter, an additional .077 new electric car acquisitions in the workplace, .014 in the family, and .111 in the neighborhood. The peer-driven adoption of electric cars largely crowds out the demand for diesel and petrol cars. The peer effects reflect incremental demand for electric cars rather than intertemporal substitution of future planned purchases. The peer effects for new electric cars are considerably stronger than for all new cars, suggesting that peer groups are more relevant for adopting new, early technologies such as electric cars. Adding up the different sources of emission reduction, the cumulative impact of peer effects on carbon emissions extends far beyond the electric car adoption decisions of peers. Adding one new electric car encourages co-workers to adopt cleaner cars, drive less, and reduce the number of owned cars.

Peer effects have clear policy implications for optimal subsidy levels and dynamics for emerging green technology. As peer effects enhance externalities on those peers, whom they will influence to acquire an electric car, a policymaker should scale subsidies in accordance with peer effects. In addition, because peer effects are negatively sloped along the adoption curve, policymakers should favor early adopters for subsidies. Finally, information campaigns about financial incentives for electric cars (especially for low-adopting peer groups) may be an effective complementary policy, as the empirical findings align with an information transmission mechanism of early adopters, about financial incentives, and exposure to electric cars.

[63] This is supported by empirical evidence that financial incentives discourage prosocial behavior (Gneezy & Rustichini, 2000a, 2000b; Mellström & Johannesson, 2008).

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Appendix

Peer Effects in Electric Car Adoption:
Evidence from Sweden

Sebastian Tebbe

A Additional Summary Statistics

Table A1: Individual Descriptive Statistics

	Mean	Std. dev.	Min	Max	Obs.
A.Socio-Demographic Data					
Age	47.09	18.15	18	117	65,277,131
Female	0.50	0.50	0	1	65,277,131
Annual Gross Salary (in tho.)	323.61	265.32	0	81,443	65,277,131
Family Disposable Income (in tho.)	231.38	619.74	0	1,039,452	65,277,131
Annual Unemployment Days	5.06	31.69	0	366	65,277,131
Self-Employment (in %)	0.07	0.26	0	1	65,277,131
Number of Retire	0.20	0.40	0	1	65,277,131
Married or Cohabitant (in %)	0.57	0.50	0	1	65,277,131
At Least 1 Child (in %)	0.45	0.50	0	1	65,277,131
Years of Education	12.10	2.62	7	20	64,001,852
Commuting Distance	23.86	85.56	0	1,738	65,277,131
Share Commuting	0.67	0.47	0	1	65,277,131
At least 1 Vehicle (in %)	0.41	0.49	0	1	65,277,131
Average Number of Vehicles	0.49	0.67	0	3	65,277,131
B.Vehicle Data					
Vehicle Kilometer Travelled	11993.95	7674.94	0	497,937	32,288,962
Leased Vehicles (%)	0.02	0.15	0	1	32,288,962
Vehicle Age	10.73	8.67	0	116	32,288,939
Service Weight (kg)	1470.42	264.37	0	17,910	32,288,962
Engine Power (KW)	102.52	38.09	0	1,777	32,288,962
Vehicle Fuel Efficiency (l/100km)	5.97	3.08	0	66	32,288,962
Vehicle Carbon Emission (g/km)	147.69	73.97	0	500	32,288,962
C.Charging Infrastructure Data					
Charging Station	0.33	1.45	0	57	1,885,835
Charging Station Installation	0.04	0.19	0	1	1,885,835
Number of Plug-in	1.16	8.87	0	555	1,885,835
Power Wattage (kWh)	17.26	19.20	.43	350	1,885,835

Notes: Panel A presents individual socio-demographic statistics on the individual-by-year level from 2012 to 2020. Panel B presents descriptive statistics on the Swedish vehicle registry data, which are at the vehicle-by-year level. Panel C presents descriptive statistics for the charging infrastructure based on the residential location of individuals at the neighborhood-by-year level between 2012 to 2020. All incomes, revenues, and costs are expressed in 2020 Swedish Kroner (SEK).

Table A2: Summary Statistics for the Population and EV Owners

	Population		Vehicle Owner		
	Mean	Std. Dev.	Car Owner	Flex-Fuel	Electric
A.Socio Demographic Variables					
Age	47.48	18.29	49.77	48.74	49.70
Female	0.50	0.50	0.39	0.36	0.35
Gross Salary (in tho.)	317.63	260.17	361.27	353.73	439.20
Disposable Income (in tho.)	226.91	628.19	243.43	224.45	309.45
Annual Unemployment Days	8.91	41.76	6.63	7.26	6.00
Self-Employment (in %)	0.07	0.26	0.05	0.04	0.07
Married or Cohabitant (in %)	0.56	0.50	0.64	0.67	0.74
At Least 1 Child (in %)	0.44	0.50	0.36	0.36	0.34
Years of Education	12.16	2.62	12.30	12.50	13.16
Share Commute (in %)	0.67	0.47	0.73	0.76	0.78
Distance Commute	26.03	91.50	26.70	26.22	29.24
B.Charging Network					
Number of Charging Stations	3.23	5.71	2.54	2.42	2.74
Charging Station Installations	0.15	0.36	0.13	0.13	0.14
Number of Plug-in	16.87	43.02	11.63	11.09	13.77
Power Wattage (kWh)	9.78	17.38	8.99	8.99	8.67
Number of Observation	7,475,707		3,163,052	184,930	121,447

Notes: This table reports descriptive statistics on socio-demographic variables (Panel A) and the public charging network (Panel B) computed for the Swedish working-age population (18 or older) and for three types of car owners: all car owner, flex-fuel car owner, and (hybrid) electric car owner in 2020.

Table A3: Peer Group Statistics

	Mean	Std. dev.	Min	Max	Obs.
A.Workplace Network					
Number of Co-worker	45.25	37.55	5	150	98,068,936
New Car Registrations	6.92	8.02	0	183	98,068,936
New EV Registrations	0.48	1.06	0	63	98,068,936
Contract Renewal	0.64	1.23	0	22	98,068,936
B.Family Network					
Number of Relatives	5.10	4.04	1	171	231,971,072
New Car Registrations	0.55	1.01	0	27	231,971,072
New EV Registrations	0.04	0.21	0	10	231,971,072
Contract Renewal	0.05	0.26	0	9	231,971,072
C.Neighborhood Network					
Number of Neighbors	260.28	327.01	5	2,853	243,356,013
New Car Registrations	27.79	30.48	0	303	243,356,013
New EV Registrations	1.85	2.67	0	26	243,356,013
Contract Renewal	2.52	3.58	0	41	243,356,013

Notes: The table presents summary statistics for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C) summed over all periods. The time period reaches from 2012 until 2020.

Table A4: Summary Statistics for the Population and Leaser

	Population		Vehicle Owner		
	Mean	Std. Dev.	Owner	New Vehicle	Leased Vehicle
A.Socio Demographic Variables					
Age	47.10	18.13	51.11	50.75	44.39
Female	0.50	0.50	0.38	0.36	0.42
Gross Salary (in tho.)	324.05	266.23	373.65	431.55	430.09
Disposable Income (in tho.)	231.62	622.78	249.17	311.98	266.09
Annual Unemployment Days	5.07	31.70	3.66	1.90	2.65
Self-Employment (in %)	0.07	0.26	0.05	0.06	0.04
Married or Cohabitant (in %)	0.57	0.50	0.66	0.71	0.67
At Least 1 Child (in %)	0.44	0.50	0.35	0.34	0.40
Years of Education	12.10	2.62	12.17	12.46	12.82
Share Commute (in %)	0.67	0.47	0.71	0.76	0.88
Distance Commute	23.88	85.54	24.10	26.47	30.25
B.Vehicle Attributes					
Vehicle Carbon Emission (g/km)	60.49	83.75	147.39	132.73	121.28
Engine Power (KW)	41.60	54.48	101.38	103.81	91.66
Vehicle Fuel Efficiency (l/100km)	2.45	3.42	5.98	5.42	5.10
Service Weight (kg)	601.34	737.62	1465.34	1495.75	1407.88
Electric Vehicle	0.01	0.08	0.02	0.07	0.06
Vehicle Kilometer Travelled	6053.96	9777.47	14752.31	10730.68	15599.27
Number of Observation	65,546,382		26,898,528	1,218,648	699,114

Notes: This table reports descriptive statistics on socio-demographic variables (Panel A) and car attributes (Panel B) computed for the Swedish working-age population (18 or older), and for car owners. car owners are divided into three categories: people owning cars, people buying new cars, and people leasing cars. A person is included once each year, so the observation number is larger than the number of unique individuals.

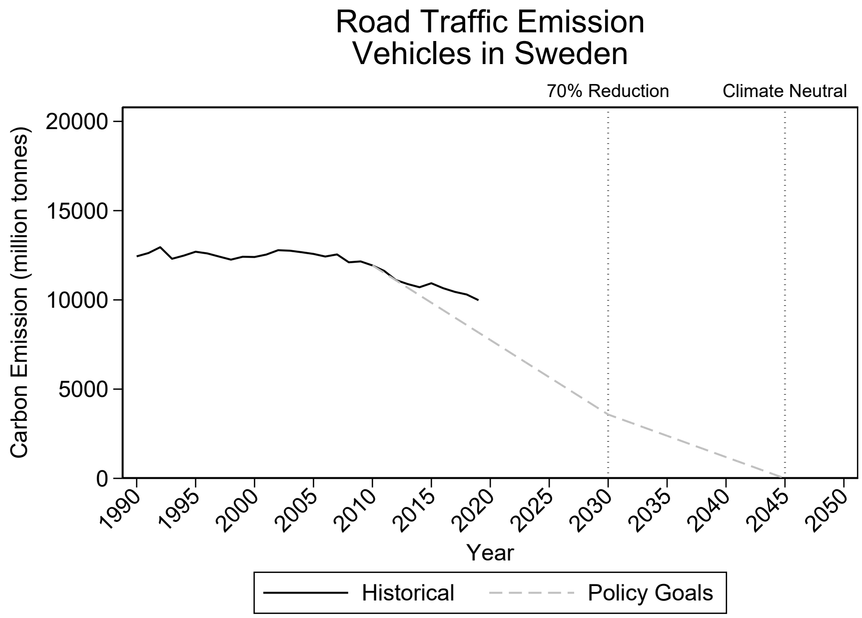


Figure A1: Road Traffic Emission in Sweden

Notes: The figure plots the total carbon emission (in million tons) in the road traffic sector in Sweden from 1990-2020. The first dotted line on the x-axis corresponds to the goal to lower greenhouse gas emissions from domestic transport by 70% in 2030 relative to the 2010 levels, while the second line indicates the zero emission target in 2045. The dashed grey line then depicts the linear reduction relative to 2010 levels of carbon in the road traffic sector necessary to reach the stated policy goals.

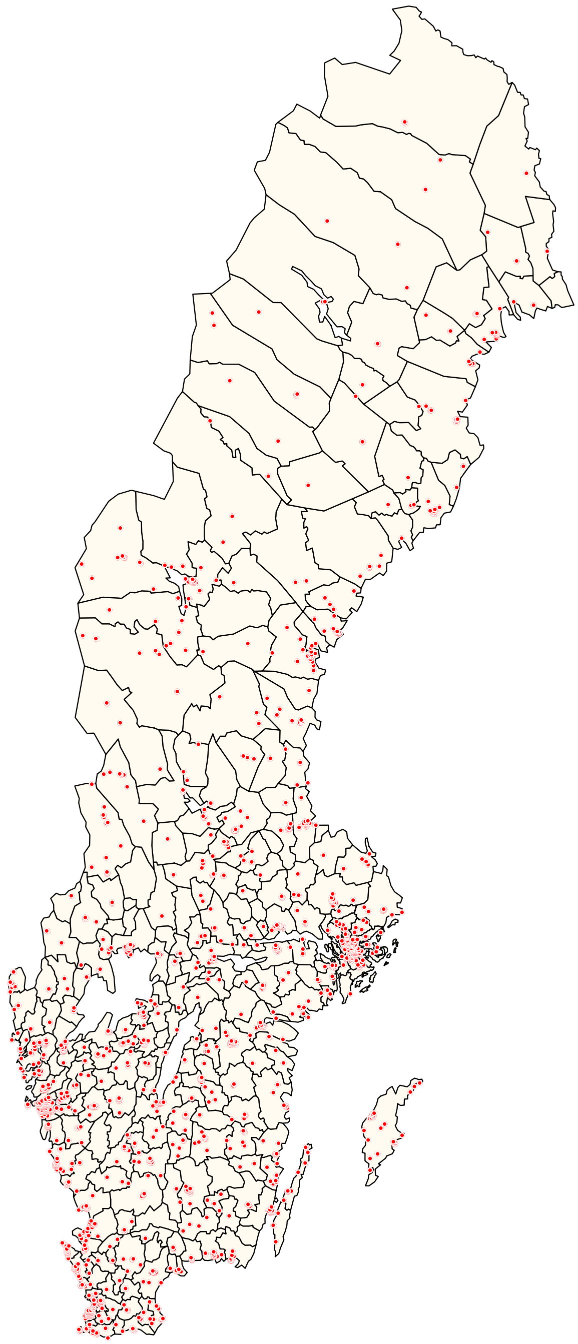


Figure A2: Location of Charging Station in Sweden (2020)

Notes: The figure displays the geographic location of all publicly-available, active charging stations in Sweden by 2020. The Swedish map is divided into 291 municipalities. The charging infrastructure is based on data from ChargeX (Uppladdning.nu) and includes the exact geographic coordinates of each charging point and its status.

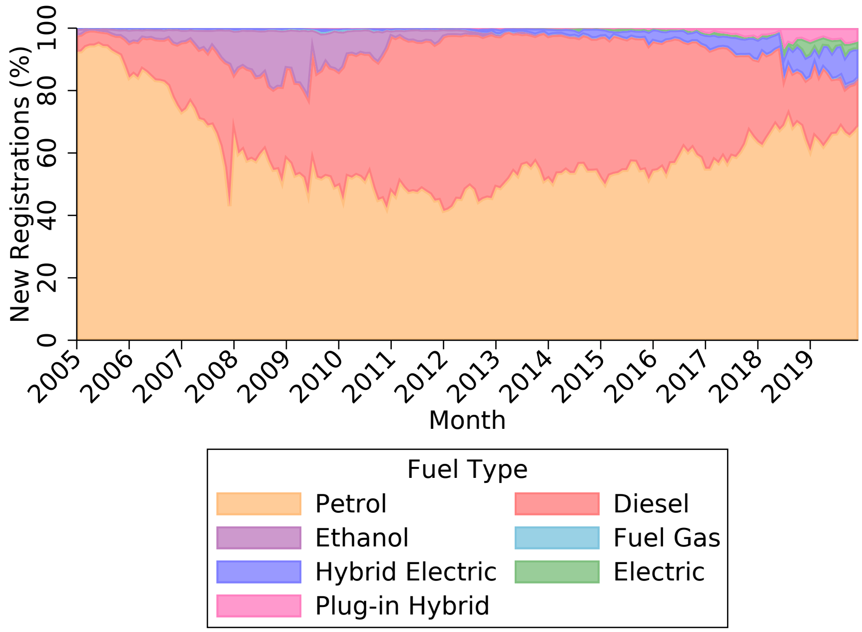
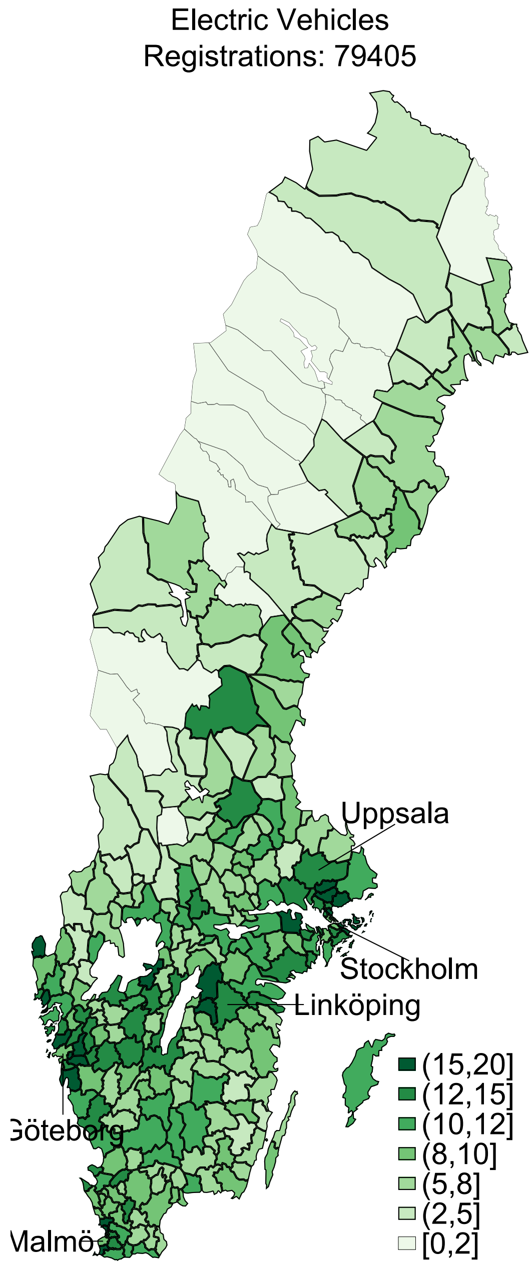
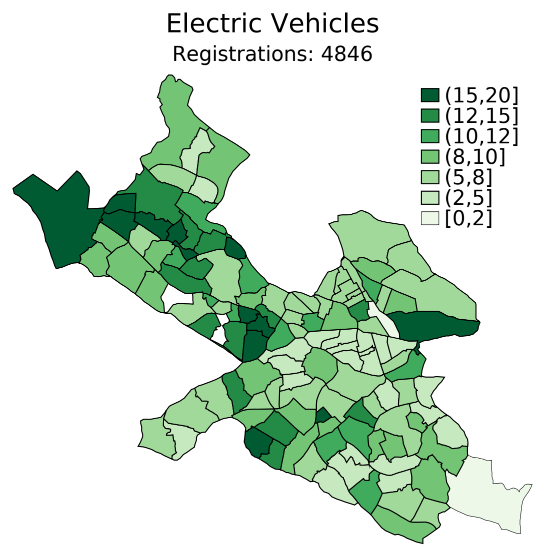


Figure A3: Market Shares of New car Types

Notes: The figure displays the monthly market share of all newly registered cars by individuals for each car fuel type in the Swedish vehicle market between 2005 and 2020.



(a) Sweden



(b) Stockholm

Figure A4: Location of Electric cars in Sweden (2020)

Notes: The figure reports the total number of electric cars per 1000 capita in 2020 across municipalities in Sweden (Panel A) and neighborhoods in Stockholm (Panel B). Darker green shades are related to a higher share of electric cars.

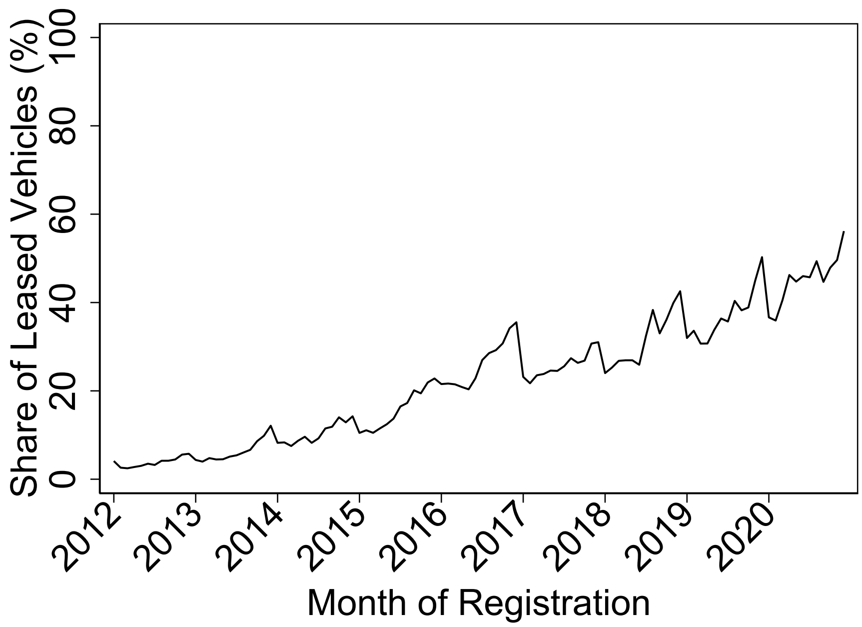


Figure A5: Share of Leased cars

Notes: This figure displays the monthly share of all newly leased cars relative to the total number of new registrations by individuals in the Swedish vehicle market between 2012 and 2020.

B Swedish Vehicle Reforms

B.1 Vehicle Subsidies

The subsidy of "green" vehicles came into effect through three policies: the green car premium ("*miljöbilspremie*") from April 2007 to June 2009, the super green car premium ("*supermiljöbilspremie*") from January 2012 to June 2018, and the climate bonus ("*klimatbonus*") as part of the bonus-malus system in July 2018. The government declared its main purpose to increase sales and use of new cars with low climate impact, to contribute to lower carbon dioxide emissions and a fossil-independent vehicle fleet. The Swedish government declared its main purpose to increase sales and use of new cars with low climate impact, to contribute to lower carbon dioxide emissions and a fossil-independent vehicle fleet. The financial incentives of the vehicle subsidies with respect to the CO_2 emission level is shown in Figure B1.

Table B1: Conditions for Green Car Subsidy

	Green Car	Super Green Car	Climate Bonus
Target Group	Households	Households & firms	Households & firms
CO_2 (g/km^3)	≤ 120	≤ 50	$\leq 60(70)$
Premium (SEK)	10,000	20,000-40,000	10,000-60,000
Payment	6 months after purchase	When ordering the vehicle	6 months after purchase

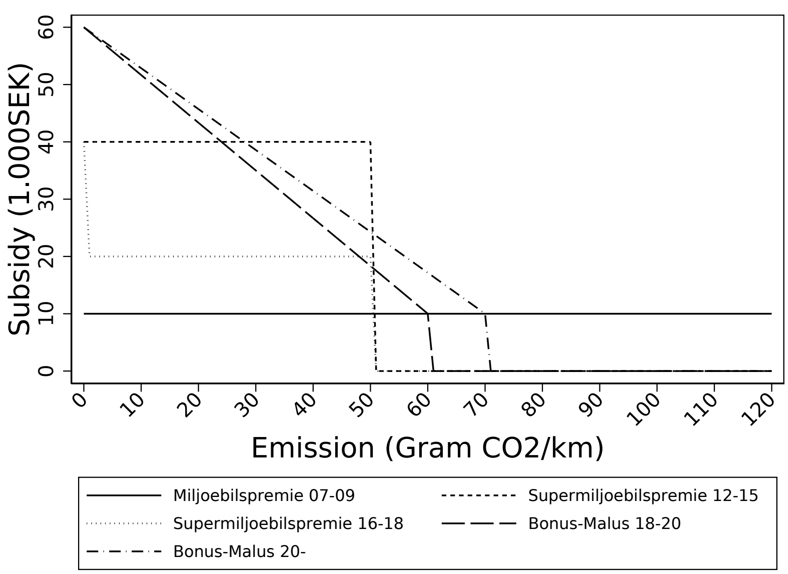


Figure B1: Swedish Vehicle Subsidies

1. *The Green Car Rebate ("Miljöbilspremie").* The Swedish "Green Car Rebate" was passed in parliament and publicly announced in March 2007 (Ministry of the Environment, 2007). Effectively starting in April 2007, the car rebate consisted of a $10,000$ SEK transfer to all private individuals six months after buying a vehicle that is classified as "green". To qualify as green vehicle and be eligible for the subsidy, vehicles have to comply with certain emission criteria depending on their fuel type. Vehicles are either classified as fossil-fueled (petrol, diesel) or alternatively-fueled. Vehicles running on fossil fuels qualify as "green" cars if the CO_2 emission level does not exceed 120 g/km. Diesel cars must additionally have a particulate emission of less than 5 mg/km. For flex fuel vehicles (E85, CNG and LPG), the carbon emission threshold to be considered as green is 218 gCO_2/km. In addition, cars running on alternative fossil fuels qualify only if the fuel consumption is lower than 9.2 $litre/100km$ using petrol, 8.4 $litre/100km$ using diesel or 9.7 $m^3/100km$ using CNG. Fully-electric cars qualify as green if the energy consumption per $100km$ is lower than 37 kwh. Legal entities, however, are excluded from the green car rebate.

2. *The Super Green Car Rebate ("Supermiljöbilspremie").* In September 2011, the Swedish government approved the "Super Green Car Rebate" with a budget of 200 million SEK, which effectively started in January 2012 (Ministry of the Environment, 2011). Irrespective of the fuel type, the rebate was provided to those vehicles with emission levels below $50g/km^3$ of CO_2. Private households as well as legal entities qualified for the subsidy. Between 2012 and 2015, individuals received a subsidy of 40,000 SEK for new vehicles fulfilling the emission threshold. The premium for legal entities was calculated as 35% of the price difference between the super green car and a corresponding petrol or diesel car. The maximum premium, however, was set to 40,000 SEK. Between 2016 and June 2018, the highest premium applied only to cars with zero emissions, while the purchase of new cars with emission level between 1-$50g/km^3$ was rewarded with 20,000 SEK. For legal entities, the maximum rebate of cars with zero CO_2 emissions remained at 40,000 SEK. For cars with CO_2 emissions between 1-$50g/km$, the premium was calculated as 17.5% of the price difference between the green car and a comparable petrol or diesel car with a maximum of 20,000 SEK.

3. *Climate Bonus ("Klimatbonus").* The Swedish Government issued an ordinance in December 2017 about a climate bonus rebate as part of the new bonus-malus system. The amendment applies from July, 2018 and only affects new vehicles registered in the Road Traffic Register as of that date (Ministry of the Environment, 2017). The climate bonus applies to vehicles that emit a maximum of 60 g/km^3 of CO_2. From January 2020, the CO_2 limit for new registrations to receive a climate bonus has been increased to 70 g/km^3. For purely electric cars and hydrogen cars with zero emissions, the highest possible bonus

amount to 60,000 SEK. The bonus will then be reduced by 833 SEK for every gram of CO_2 emitted per kilometer. From 2020 onward, the reduction per additional CO_2emission was replaced by 714 SEK. CNG cars and light trucks/buses will receive a bonus of 10,000 SEK independent of the CO_2 emission. The bonus can not exceed 25% of the price charged for the new car when the car model was first introduced on the Swedish market. Similar to the super green car rebate, the premium of the climate bonus program for legal entities can not exceed 35% of the difference between the new price of the vehicle and the price of a comparable petrol or diesel vehicles.

B.2 Private Use of a Company Car

A vehicle fringe benefit applies when an employer makes a vehicle they own or lease available for the private use of an employee. The fringe benefit value is calculated on the basis of the new car price, the price base amount, a government loan interest rate, extra equipment and ownership taxes. Since the Swedish government's decision in 1999 regarding preferential taxation of green benefit cars (Ministry of Finance, 1999) and the decision on the reduction in the benefit value for certain green cars in 2001 (Ministry of Finance, 2001), the benefit value is reduced under certain conditions. First, it is lowered to the benefit value of a comparable petrol or diesel cars. Second, an additional reduction of 20% to 40% with a maximum of 8,000 to 16,000 SEK can apply depending on the fuel type and vintage of the vehicle.

Employers may provide a car fringe benefit if they make available a car they own or lease to an employee for their private use. Vehicles used exclusively for work-related purposes do not incur fringe benefits taxation in Sweden if they are used for private purposes less than 1000 km and fewer than 10 times annually purposes. The fringe benefit value is added to the employee's gross total income with tax paid accordingly.[64] The fringe benefit value is calculated as

$$Fringe\ Benefit\ Value = p \cdot 0.09 \ + \ \%PBV \ + \ 0.75 \cdot GB \cdot p \tag{10}$$

if the price p was less than $7.5PBV$, where PBV refers to the price base value, and GB to the Government Bond interest rate. The fringe benefit value equals a certain percentage of the price base amount, 75% of the government loan interest rate at the end of November by the year before the income year multiplied with the new car price plus 9% of the new car price. Table B2 shows the price base value, its percentage and the government bond interest rate required to calculate the fringe benefit value for each year.

After 2016 and if the price was above $7.5PBV$, the following calculation was used,

[64] Up until 2019, company cars account for approximately 65% of all new electric car sales in Sweden.

adding a term at the right, which increases the value for more expensive cars

$$Fringe\ Benefit\ Value = p \cdot 0.09 + \%PBV + 0.75 \cdot GB \cdot p + 0.2 \cdot (p - 7.5 \cdot PBV) \quad (11)$$

If the price of the car when new is over $7.5PBV$, the price-related amount is calculated as 9% of $7.5PBV$ plus 20% of the price over $7.5PBV$.

Table B2: Fringe Benefit Values for Green Cars

Year	Price Base Value (SEK)	% of Price Base Value	Government Bond Interest Rate (%)
2005	39,400	30	3.95
2006	39,700	30	3.26
2007	40,300	30	3.54
2008	41,000	31.7	4.16
2009	42,800	31.7	2.89
2010	42,400	31.7	3.20
2011	42,800	31.7	2.84
2012	40,000	31.7	1.65
2013	44,500	31.7	1.49
2014	44,000	31.7	2.09
2015	44,500	31.7	0.90
2016	44,300	31.7	0.65
2017	44,800	31.7	0.50
2018	45,500	29	0.50
2019	46,500	29	0.51
2020	47,300	29	0.50

This approach, however, would favor petrol and diesel over electric cars, given their comparatively lower purchase price. The Swedish legislation allows reducing the benefit value represented by the private use of company cars if the vehicle runs on alternative fuels and therefore reduces the amount of income taxes that need to be paid on it. For alternative-powered vehicles, the taxable value of the car used for the personal income tax is reduced in two steps. First, the benefit value is reduced to the benefit value of comparable petrol or diesel cars. Secondly, the calculated benefit value is reduced by 20% to 40% with a maximum of 8,000 to 16,000 SEK depending on the fuel type and year. The permanent reduction of the benefit value down to the benefit value of a comparable petrol or diesel car is permanent for all alternative-fueled vehicles. The second step of a 20% to 40% with a maximum of 8,000 to 16,000 SEK reduction has changed for some fuel types. Table B3 summarizes the fringe benefit calculations for each fuel type.

- For electric cars, plug-in hybrids and cars driven by gas (not LPG) there is a reduction of the value for personal income taxation of 40% with a maximum of 16,000 SEK compared to the taxation value of the corresponding or comparable car driven by petrol or diesel. From 2017, the maximum reduction was decreased to 10,000 SEK.

- For hybrid electric cars the time-limited reduction of the benefit value by 40% with a maximum of 16,000 SEK was abolished in 2012.
- For cars driven by ethanol the reduction of the taxable value is 20% and the reduction can not exceed 8,000 SEK compared to corresponding petrol or diesel cars. The time-limited reduction of the benefit value by 20% with a maximum of 8.000 SEK was abolished in 2012.
- For cars driven by LPG, rapeseed oil, or other environmentally adjusted fuels the benefit value is the same as for the corresponding petrol or diesel car

If the employer pays for all the fuel, the employee must treat 120% of the value of the fuel used for private driving as personal income.

Table B3: Fringe Benefit Calculations

Fuel Type	Fringe benefit calculation in 2005
Gasoline	Eq. (10-11)
Diesel	Eq. (10-11)
Electric	as for comparable non-Green Car (Eq . (10-11), then reduced by 40%, but at most 16,000 SEK (10,000 SEK in 2017)
Plug-in	as for comparable non-Green Car (Eq . (10-11), then reduced by 40%, but at most 16, 000 SEK (10,000 SEK in 2017)
Hybrid	as for comparable non-Green Car (Eq . (10-11), then reduced by 40%, but at most 16,000 SEK (no benefit value reduction after 2012)
CNG bi-fuel	as for comparable non-Green Car (Eq . (10-11), then reduced by 40%, but at most 8,000 SEK (no benefit value reduction after 2012)
LPG bi-fuel	as for comparable non-Green Car (Eq . (10-11)
E85 flexi-fuel	as for comparable non-Green Car (Eq . (10-11), then reduced by 20%, but at most 8,000 SEK (no benefit value reduction after 2012)

C Data Preparation Notes

This Section describes the construction of the demographic variables, peer group characteristics, previous car attributes, and charging infrastructure. The variable's name appears in bold, while the variable's original name and data source appear in italics.

C.1 Demographic Variables.

- **Age** (*FodelseAr*; *LISA*). Indicates the person's age.
- **Gender** (*Kon*; *LISA*). Equals one if the person is female.
- **Years of education** (*SUN2000niva*; *Yrkesregistret*). The information of the LISA register has been translated into years of education in the following way: 7 for (old) primary school, 9 for (new) compulsory school, 9.5 for (old) post-primary school (*realskola*), 10 for less than two years of high school (or incomplete high school), 11 for short high school, 12 for long high school, 13 for less than two years of post-secondary education, 14 for short university, 15 for three years of university, 16 for four years of university, 17 for five or more years of undergraduate university studies (including magister), 18 licentiate, 19 research education and 20 for doctorate. The educational attainment of the Swedish population is reported by schools and universities. Information on schooling for people migrating to Sweden later in life is collected through surveys and categorized into Swedish standards.
- **Field of education** (*SUN2000Inr*; *Yrkesregistret*). The first two digits of the module represent the main focus of the education corresponding to the specialization in ISCED 97. The field of education is coded into nine groups following the categorization provided by Statistics Sweden: general education, pedagogy and teacher education, humanities and art, social sciences and law and trade and administration, mathematics and data, technology and manufacturing, agriculture and forestry and veterinary care, health and social care, services, and unknown.
- **Disposable income** (*DispInk*; *LISA*). This measure quantifies annual disposable income in 1000 Swedish kronor and is constructed from individual tax records (there is no joint family taxation). It includes all income sources and government transfers (wages and in-kind benefits from jobs, pensions, transfers and subsidies, business income, capital income, sickness and parental-leave benefits, etc.

- **Gross salary** (*LoneInk*; *LISA*). This measures the total annual gross salary in 1000 Swedish kronor provided by the employer and reported to the Swedish Tax Agency (*Skatteverket*).

- **Annual unemployment** (*ALosDag*; *LISA*). Represents the number of days per year in unemployment.

- **Self-employment** (*YrkStalln*; *Yrkesregistret*). Indicates whether the person is self-employed.

- **Married or cohabitant** (*FamSt*F; *LISA*). The family status code indicates each person's position in a family. This variable captures all individuals that are in a relationship (with or without joint children) and single parents living with their children.

- **At least one child** (*FamSt*F; *LISA*). Based on the family status code, this variable measures whether the person has at least one child.

- **Commute to work** (*XKOORDsw YKOORDsw*; *Geografidatabasen*). This variable indicates whether an individual commutes to work based on the geographic reference point of their residence and workplace. A person is assumed to commute to work if their place of residence is distinct from their place of employment.

- **Commute distance** (*XKOORDsw YKOORDsw*; *Geografidatabasen*). The commute distance is the distance in kilometers between the centroid of the person's residence and the centroid of their workplace. The commuting distance is set to zero for unemployed individuals and those who work within the same geographic area.

- **Car-leasing renewal** (*datovls; Fordonsregistret*). The car replacement quarter is based on the specific date when the car's latest change of ownership took place. For each person's car, the car replacement in quarters then equals the difference between the date of the first and latest change of car ownership for all leased cars. An individual is at the leasing contract renewal exactly 12 quarters after its registration.

- **Social security number** (*PersonNr*; *LISA*). Uniquely identifies each person in Sweden above 16.

- **Apartment type** (*HusTyp*; *Folk- och bostadsräkningar*). Indicates whether the house is a (semi-)detached house, a one- and two-family house or an apartment building. Aggregating the variable to the neighborhood-level, the final variable equals one if at least of the people live in apartment buildings, and zero if at least half live in any form of house.

C.2 Peer Group Characteristics.

The network structure spans along the following three dimensions:

- **Workplaces** (*CfarNr*; *LISA*). Uniquely identifies workplaces and follows them over time, even when the company changes legal identity.
- **Family** (*PersonNrFar, PersonNrMor*; *Flergenerationsregistret*). The multi-generational register contains information about people born from 1932 who have been registered since 1961 as well as their biological parents and possible adoptive parents. Using the personal identifier of parents and siblings, I define the families as all first- and second-degree relatives. A first-degree relative includes the individual's parents, (half-)siblings, and children, while second-degree relatives refer to the individual's grandparents, grandchildren, aunts, uncles, nephews and nieces.
- **Neighborhood** (*XKOORDsw, YKOORDsw*; *Geografidatabasen*). Using the geographic coordinates of individuals, I define all individuals living within the same $125m$ radius in urban and $500m$ in rural areas as the neighborhood.

The peer group characteristics reflect the average demographic variables of co-workers, relatives, and neighbors excluding individual i. Additionally, peer group characteristics include the size of workplaces, families, and neighborhoods.

C.3 Car Attributes.

- **Status** (*Status*; *Fordonsregistret*). Corresponds to the status of the car: in traffic, not in traffic or de-registered.
- **Owners** (*Agare*; *Fordonsregistret*). Indicates whether the car is privately owned or by a legal entity.
- **Engine power** (*Effekt*; *Fordonsregistret*). Indicates the engine power of the car in kilo Watt (kW).
- **Leas** (*Leas*; *Fordonsregistret*). Indicates whether the car is leased.
- **Electric car** (*drivmedel*; *Fordonsregistret*). The original variable indicates the car's fuel type and is classified into all electric cars (i.e., hybrid electric, plug-in and fully electric cars).
- **Service weight** (*totalvikt*; *Fordonsregistret*). Indicates the total weight of the car in kilogram.

- **Carbon emission** (*CO2Varde*; *Fordonsregistret*). Carbon dioxide emissions in grams per kilometer.

- **Fuel efficiency** (*BrForbr*; *Fordonsregistret*). Indicates the cars's fuel consumption in liter per 100 kilometer.

- **Vehicle kilometer traveled** (*Mätarställning*; *Fordonsregistret*). Indicate the vehicles's annual kilometer traveled and is based on the Swedish Transport Agency's information.

- **Vehicle identifier** (*LopNr_Fordon*; *Fordonsregistret*). Uniquely identifies each vehicle.

C.4 Charging Infrastructure.

- **New charging stations** (*Uppladdning.nu*). Equals the number of newly installed, publicly available active charging stations within a neighborhood per quarter.

- **Total charging stations** (*Uppladdning.nu*). Equals the total number of publicly available active charging stations within a neighborhood.

- **Number of plug-in** (*Uppladdning.nu*). Equals the total number of available plug-in charger within a neighborhood.

- **Average power** (*Uppladdning.nu*). Indicates the average power wattage of all available charging stations within a neighborhood.

- **Charging station capacity** (*Uppladdning.nu*). This equals the ratio of all electric and plug-in hybrid electric cars relative to all publicly available charging station within a neighborhood.

D Shift-Share Instrument

Section D.1 details the construction and evaluation of the neural network designed to predict the endogenous exposure shares. Section D.2 conducts validity checks of the shift-share instrument, and Section D.3 discusses the statistical inference of standard errors. Section D.4 provides additional details on the control group.

D.1 Neural Network Design

1. *Propensity Estimation.* This Section gives a detailed description of the neural network approach in equation (4) used to estimate a propensity of acquiring a new electric car for each individual who leases a three-year-old car ($V_{i,q}^{3y} = 1$). The neural network model is trained using a stratified training and testing split, where I train the model with 75% of the quarterly data and then use the model to predict propensities for 25% in the test data.[65] The deep learning neural network is trained using the stochastic gradient descent algorithm with momentum and an exponential decaying learning rate. The underlying learning rate parameter is initially set to $\eta = .01$, and the learning rate decreases exponentially. When the weights are updated, I include an exponentially weighted average of the previous updates ($\alpha = .8$). The model learns to best approximate the function using 50 training epochs and a batch size of 250. The neural network consists of two hidden layers with a layer sizes of 25 and 15. Batch normalization is used between the hidden layers to re-parametrize the model and make units always standardized. The classification metric to train the model is mean squared error. Both models use the complete set of control variables discussed in Section D as well as occupation- and municipality-fixed effects.

2. *Performance of Propensity Predictions.* Subsequently, I evaluate how the estimated purchasing propensities relate to the realized adoption probabilities of electric cars. To do this, Figure D1 displays the binscatter plots of the predicted against the realized probability of acquiring an electric car at the three-year renewal cutoff for both the hold-out test set ("Test Sample") and the actual training data set ("Train Sample") in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). Reassuringly, the predicted electric car adoption in the training and test data closely aligns with the 45-degree line. The finding suggests that the neural network prediction accurately reflects the actual electric car take-up decision of individuals at the renewal cutoff. The 5%-binned predicted probabilities to lease

[65] It is crucial to test on a held-out data set as training using in-sample data would run the risk of overfitting the neural network model. This would bias the coefficients of the shift-share design towards the OLS coefficients.

a new electric car at the renewal timing range between 0% and 40%. This highlights a large heterogeneity of individual electric car adoption that is exploited in the SSIV-design.

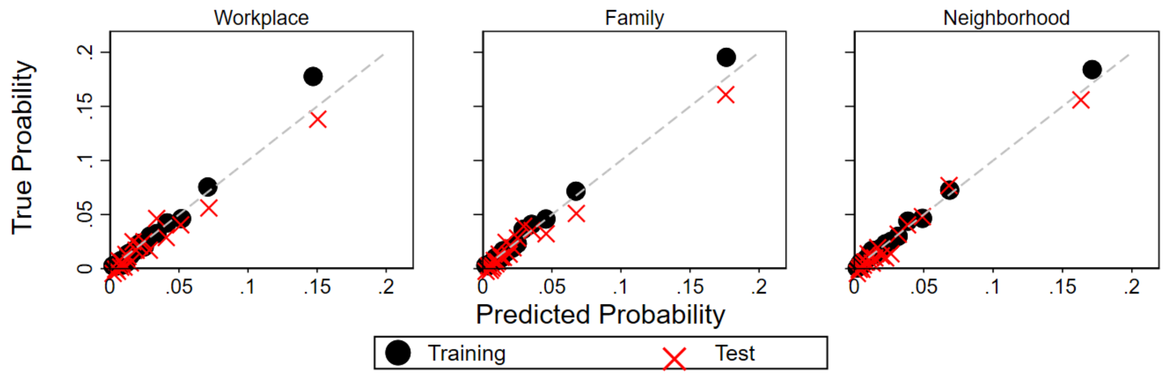


Figure D1: Propensity Predictions

Notes: The figures display binscatter plots of the predicted against the realized probability to acquire an electric car conditional on being at the three-year leasing renewal cutoff for both the hold-out test set ("Test Sample") and the actual training data set ("Train Sample") in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The y-axis plots the actual probability of electric car adoption within 5-percentile bins of predicted peer electric car adoption. All Panels include individuals at the three-year leasing contract renewal between 2012 and 2020.

Another common metric used in machine learning to assess the performance of a predictive model at various thresholds is the ROC-AUC curve. The Receiver Operator Characteristic (ROC) curve is a probability curve that plots the true positive rate (y-axis) against the false positive rate (x-axis) at various thresholds. The Area Under the Curve (AUC) score equals the area under the curve of the formed line and is the measure of a classifier to distinguish between classes. Intuitively, it corresponds to the probability that a classifier will rank a random positive example above a random negative one. When the AUC equals one, the classifier can perfectly distinguish between classes, while .5 reflects a meaningless model that is as good as random. Figure D2 shows the ROC curves for both the hold-out test set ("Test Sample") and the actual training data set ("Train Sample") in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The underlying AUC scores are displayed in Table D1. The trained model achieved a .76 ROC-AUC score in the workplace, .78 in the family, and .78 in the neighborhood on the test data set that was not used in the training model. This implies an approximately 78% chance I correctly classify whether the person acquires an electric or non-electric car at the renewal threshold.

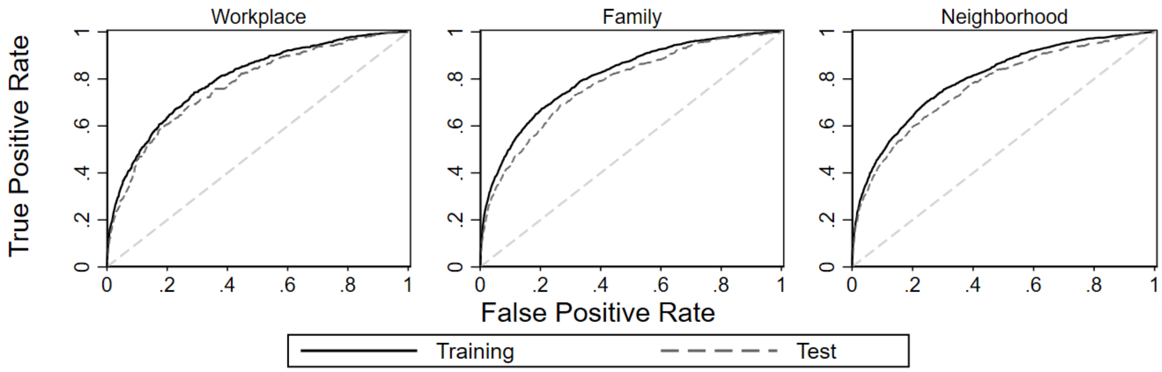


Figure D2: ROC-AUC Curves

Notes: The figures present Receiver Operating Characteristic (ROC) curves for the estimated probabilities of adopting a new electric car at the contract renewal in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The training set is indicated in solid lines, and the test set in dotted lines. All Panels include individuals at the three-year leasing contract renewal between 2012 and 2020.

Table D1: Propensity Evaluation

	Peer Groups		
	A.Workplace	B.Family	C.Neighborhood
ROC-AUC Score			
Train Sample	.8093	.8187	.8078
Test Sample	.7585	.7734	.7780
MSE			
Train Sample	.0245	.0239	.0243
Test Sample	.025	.0251	.0249

D.2 Validity Checks

To justify the assumption that there are many conditionally uncorrelated shocks, I first document that the average shock exposure converges to zero, which can be interpreted as requiring a large effective sample size. Table D2 reports summary statistics for the contract renewal shocks computed with predicted propensities across workplaces, families, and neighborhoods. The effective sample size, measured as the inverse of the Herfindahl index $(1/\sum_{j,q} Pr(V^e)^2_{jq})$, is indeed high: 358,077 across peer group-by-quarter, and the largest shock weight is below .00001% across peer group-by-quarter. The distribution of shocks also indicates a sufficient dispersion with a standard deviation of .0196 and an interquartile range of .0017. This implies a sizable degree of variation at the peer group level and a few particular peer groups do not drive the results. As a large number of shocks is key for the validity of the empirical strategy, the last row Table D2 indicates that the leasing contract renewal leverages above 50,000 shocks to the car adoption in all peer groups.

Table D2: Shock Summary Statistics

	Peer Groups		
	A.Workplace	B.Family	C.Neighborhood
Mean	0	0	0
Standard Deviation	.0196	.0142	.4438
Interquartile range	.0017	.0006	.3269
Effective sample size (1/HHI)			
Across peer groups and quarters	358,077	85,416	31,777,512
Largest weights			
Across peer groups and quarters	$<.0001$	$<.0001$	$<.0001$
Observation counts			
N(peer group shocks)	27,619	80,817	50,409
N(peer groups)	252,352	7,314,474	4,696

Notes: This table summarizes the distribution of contract renewal timings across workplaces (column 1), families (column 2), and neighborhoods (column 3). Shocks are measured as the total number of peers at the three-year leasing contract renewal. Shares are computed as the propensity of adopting a new electric car using a neural network, as described in equation (4). All statistics are weighted by the average exposure shares.

Besides the effective sample size condition, I provide evidence that the shocks are sufficiently mutually uncorrelated. To assess the plausibility of this assumption, I analyze the correlation patterns of shocks across peer groups and quarters. In particular, I compute intra-class correlation coefficients (ICCs) of shocks within peer groups. These ICCs come from a random effects model, providing a hierarchical decomposition of residual within-quarter shock variation:

$$g_{pq} = \mu_q + bsic2_{(p),q} + d_p + e_{pq}, \tag{12}$$

where μ_q are quarter fixed effects, d_p is a time-invariant peer group random effect, and $bsic2_{(p),q}$ denote time-varying (and possibly auto-correlated) random effects for each peer group. I estimate equation (12) as a hierarchical linear model by maximum likelihood, assuming Gaussian residual components. Table D3 reports estimated ICCs from equation (12), summarizing the share of the overall shock residual variance due to each random effect. These reveal that there is no evidence for clustering of shocks at the peer group level among all peer groups, which supports the assumption that shocks are serially uncorrelated across peer groups and quarters.

Table D3: Shock Intra-Class Correlations

	Peer Groups		
	A.Workplace	B.Family	C.Neighborhood
Shock ICCs			
Across peer groups	.0161	.0223	.0347
	(.022)	(.0408)	(.0561)

Notes: This table summarizes the distribution of contract renewal timings across workplaces (column 1), families (column 2), and neighborhoods (column 3). Shocks are measured as the total number of peers at the three-year leasing contract renewal. Shares are computed as the propensity of adopting a new electric car using a neural network, as described in equation (4). All statistics are weighted by the average exposure shares.

To assess the plausibility of the shock orthogonality assumption, I conduct two types of falsification checks: a peer group level balance test and a pre-trends analysis. In Table D4, I regress potential peer group level confounders on the SSIV-weighting by the average exposure shares. The possible confounding variables include average age, gender, salary, income, unemployment, being married, share having children and years of education. Broadly, these variables reflect the composition of a peer group. If the contract renewal timing is as-good-as-randomly assigned to peer groups across quarters, I expect the shocks not to predict these predetermined variables. Consistent with the shock orthogonality assumption, Table D4 shows that there is indeed no statistically significant correlation between shocks and the set of baseline characteristics. Overall, I fail to reject balance in 2 out of 30 potential confounders.

Table D4: Shock-Balance Test

	A. Workplace	B. Family	C. Neighborhood
	2SLS(1)	2SLS(2)	2SLS(3)
A.Socio-Demographics:			
Person Age	2.3817	84.3751	.1159
	(8.8859)	(71.6883)	(.1009)
Female	-.1139	-1.6481	.0001
	(.3044)	(2.4618)	(.0001)
Gross Salary	-.0000	-.0000	-.0000***
	(.0000)	(.0000)	(.0000)
Disposable Income	27.5184	108.7367	-3.4742
	(144.7592)	(555.6870)	(2.8974)
Unemployment Days	-5.9028	-.0000	-.5073**
	(25.6098)	(.0000)	(.2502)
Self-Employed	.0397	-1.0239	-.0003
	(.1022)	(1.4272)	(.0023)
Retired	-.1470	-1.1761	-.0010
	(.3050)	(1.3618)	(.0022)
Married	-.0000	1.6542	-.0018
	(.0000)	(2.1444)	(.0017)
Children	-.1042	-1.3137	.0015
	(.2953)	(1.8665)	(.0017)
Years Education	-.0592	.9610	-.0391*
	(.9206)	(10.0416)	(.0206)

Notes: The table reports coefficients from regressions of the peer group level covariates on the peer contract renewal timing weighted by the propensity across workplaces (column 1), families (column 2), and neighborhoods (column 3). The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.3 Statistical Inference of Standard Errors

As discussed in Section 2., I explore the robustness of statistical inference to alternative approaches of constructing standard errors. To account for potential across-observation interdependence in peer groups, I cluster standard errors at the peer-group level in accordance with Eckles et al. (2016) and Zacchia (2020). Adao et al. (2019) present an alternate method for constructing standard errors that accommodates for the shift-share structure (AKM henceforth). Another option that follows the shift-share design is to cluster the standard error on the shock-level, which accrues to the individual in this context. To understand how severe these dependencies are in the error term, I compare the heteroskedasticity-robust standard error and compare them to individual, peer-group, and AKM standard errors.

Figure D3 compares the magnitude of heteroskedasticity-robust standard errors to individual clustered, peer-group clustered, and AKM standard errors across the workplaces, families, and neighborhoods. Across all peer groups, individual-clustered standard errors are similar in size to the heteroskedasticity-robust standard errors, implying no spurious correlation across individuals. However, standard errors increase if they are either clustered on the peer-group level or following the clustering method in Adao et al. (2019). The AKM standard errors are at most 20% larger than the heteroscedasticity standard errors, while the peer-group standard error are 19% larger. Most importantly, there is no discrepancy between peer-group clustered and AKM standard errors. Across peer effects within peer groups and across observations with similar exposure shares are similar in size and do not confound the statistical inference in this setting after conditioning on all baseline controls. This suggest that residual across-individual dependencies do not considerably influence statistical inference in error terms within peer groups.

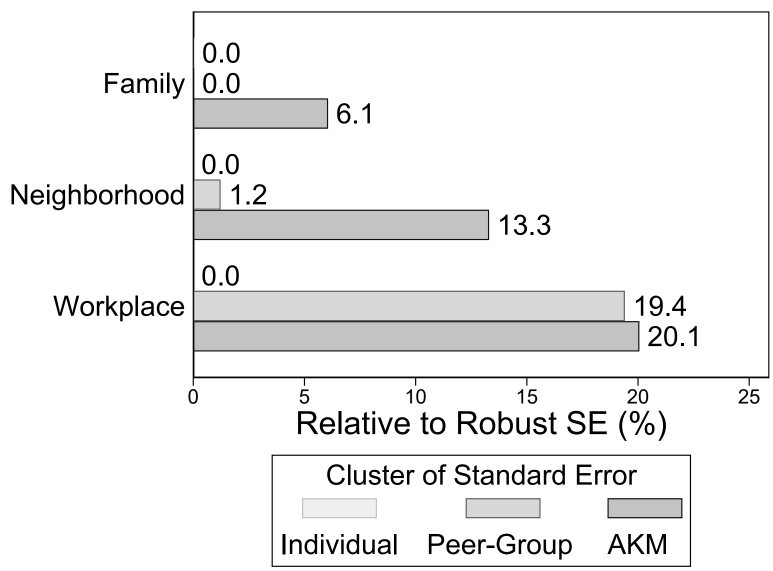


Figure D3: Comparison of Standard Errors

Notes: The figure compares standard errors using various clustering approaches to heteroskedasticity-robust standard errors for the shift-share IV corresponding to column (3) of Table I for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The top row uses standard errors clustered at the individual-level, the middle row uses standard errors clustered at the peer-group-level, and the bottom row uses AKM standard errors.

D.4 Control Group

Table D5: Probabilities of New Vehicles at Leasing Renewal

	Peer Groups		
	A.Workplace	B.Family	C.Neighborhood
Adoption Propensities at Leasing Renewal			
New Petrol car	32.87	30.79	32.62
New Diesel car	3.76	3.64	3.67
No New car	63.37	65.57	63.71

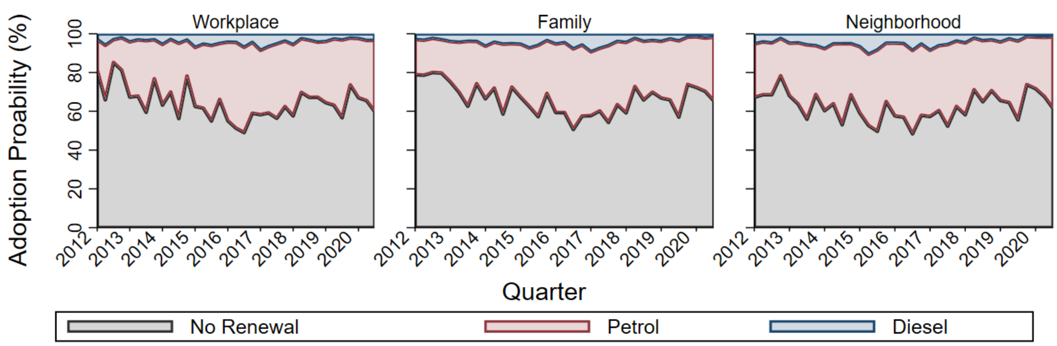


Figure D4: Probabilities of New Vehicles at Leasing Renewal

Notes: The figures present the car adoption probabilities for new petrol, diesel, and non-renewals in the leasing renewal quarter for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). All Panels include individuals at the three-year leasing contract renewal between 2012 and 2020.

E Regression Specifications

This Section documents the regression specifications to estimate the peer effects dynamics (Section E.1), heterogeneous effects (Section E.2), the carbon emission model (Section E.3), along the adoption curve (Section E.4), and in fossil fuel cars (Section E.5),

E.1 Peer Effect Dynamics

To estimate the dynamics of peer effects, I expand the horizon over which peer effects are measured to capture the exact timing of the peer effects. The dependent variable equals the individual electric car take-up four quarters prior and up to eight quarters following the initial peer electric car adoption: $V^e_{i,\tau}$ for $\tau = -4, ..., 8$. By defining the elapsing leasing contract in $q = -1$ as the reference quarter, the dynamic reduced form equation can be written as:

$$V^e_{i,q+\tau} \; = \; \alpha + \theta^e_\tau \sum_{j \epsilon N} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1) + \gamma \overline{X}_{p-i,q} + \delta X_{i,q} + \phi_q + \varepsilon_{i,q} \qquad \tau \in \{-4, ..., 8\}, \tag{13}$$

where θ^e_τ captures the dynamic peer effects four quarters prior and eight quarters following the peer electric car adoption. θ^e_τ accounts for peer effects' direct and indirect social forces and how they unfold over time. The first stage equation (5) remains unchanged as the exogenous variation comes solely from the contract renewal in $q = -1$.

The underlying model makes two key assumptions: sequential ordering and additive separability. The first assumption of sequential ordering implies that individuals who adopt a new electric car subsequently affect peers who acquire new electric cars, but not vice versa. Secondly, additive separability entails that peer effects do not have an interactive effect within the peer group.

E.2 Heterogeneity Models

To analyze heterogeneity in influence according to peer group demographic characteristics, I first design a mutually exclusive and exhaustive set of characteristics G. In Section IV.D, the set of characteristics G include age, education, income, and the size of the peer group. For example, one set of socio-demographic characteristics corresponds to peer ages, with three conditions capturing people aged below 45, between 45 and 60, and above 60.

Technically, the instrument, the propensity-weighted sum of control renewals, and the dependent variables, the number of new electric cars in the peer group are restricted to the peers captured by one of the conditions $g\epsilon G$. The propensity-weighted SSIV and the dependent variable for peers with characteristics g are calculated as follows:

$$\widehat{V}^g_{p,q-1} = \sum_{j\epsilon N} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^e \mid V^{3y}_{j,q-1} = 1) \cdot 1(Condition^g_{j,q-1})$$

$$V^{e,g}_{p,q-1} = \sum_{j\epsilon N} V^{e}_{j,q-1} \cdot 1(Condition^g_{j,q-1})$$

To control for the composition of peer groups and their car preferences within each condition, I change the two key control variables to account for differences in propensities across peer groups with different conditions. First, I control for the number of contract renewals in each peer group p who are members of group g in a given quarter ($V^{3y,g}_{p-1,q-1}$). Second, I add a control for the average propensity to lease a new electric car for all leasing peers who are part of group g within a peer group ($\overline{Pr}(V^e \mid V^{l,g}_j = 1)_{q-1,j}$). In addition, I directly control for the number of peers of individual i who are members of each group g.

Adding these conditions and new variables to the baseline peer effect specification, I estimate one first stage and second stage per condition for each peer group:

$$\begin{aligned} V^{e,g}_{p-i,q-1} &= \alpha^e \widehat{V}^g_{p,q-1} + \delta X_{i,q} + \gamma \overline{X}_{p-i,q} + \delta_1 V^{3y,g}_{p-i,q-1} + \delta_2 \overline{Pr}(V^e \mid V^{l,g}_j = 1)_{q-1,j} + u_{i,q-1} \\ &+ \delta_1 V^{3y,g}_{p-i,q-1} + \delta_2 \overline{Pr}(V^e \mid V^{l,g}_j = 1)_{q-1,j} + u_{i,q-1} \end{aligned} \tag{14}$$

$$\begin{aligned} V^e_{i,q} &= \beta^e \widehat{V}^g_{p,q-1} + \delta X_{i,q} + \gamma \overline{X}_{p-i,q} \\ &+ \delta_1 V^{3y,g}_{p-i,q-1} + \delta_2 \overline{Pr}(V^e \mid V^{l,g}_j = 1)_{q-1,j} + u_{i,q-1}. \end{aligned} \tag{15}$$

$$V^g_{p,q-1} = \alpha \hat{V}^{3y,g}_{p,q-1} + \delta X + \delta N^g_{i,q-1} + \bar{V}^{3y,g}_j + e_{i,q-1}$$

$$V_{i,q} = \theta V^g_{p,q-1} + \delta X + \delta N^g_{i,q-1} + \bar{V}^{3y,g}_j + \varepsilon_{i,q}$$

E.3 Carbon Emission Model

A person's total car-related carbon emissions in a given quarter ($CO_{2,i,q}$) is equal to the carbon emission of a vehicle ($V^{CO_2}_j$) multiplied by the vehicle kilometers traveled (KM_j), summed over all cars j. Equation (16) states the total carbon emission of person i in quarter q:

$$CO_{2,i,q} = \sum_{j\epsilon J} V^{CO_2}_{i,q,j} \cdot KM_{i,q,j} \tag{16}$$

This can be expressed as the product of the kilometer-weighted average carbon emission of vehicles ($\overline{V_{i,q}^{CO_2}}$), the average kilometer traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$) according to:

$$CO_{2,i,q} \;=\; \overline{KM_{i,q}} \cdot \overline{V_{i,q}^{CO_2}} \cdot N_{i.q} \tag{17}$$

To measure how peer effects in adopting a new electric car influence a person's carbon emission, I differentiate the total carbon emission of each person ($CO_{2,i,q}$) by the impact of one new electric car in the peer group ($V^e_{p-i,q-1}$) in the following equation (18):

$$\begin{aligned}\underbrace{\frac{\partial CO_{2,i,q}}{\partial V^e_{p-i,q-1}}}_{\triangle CO_{2,i,q}} \;=\; & \underbrace{\frac{\partial \overline{KM_{i,q}}}{\partial V^e_{p-i,q-1}}}_{\theta^e_{KM}} \cdot \overline{V_{i,q}^{CO_2}} \cdot N_{i.q} \;+\; \underbrace{\frac{\partial \overline{V_{i,q}^{CO_2}}}{\partial V^e_{p-i,q-1}}}_{\theta^e_{CO_2}} \cdot \overline{KM_{i,q}} \cdot N_{i.q} \\ & + \underbrace{\frac{\partial \overline{KM_{i,q}}}{\partial V^e_{p-i,q-1}}}_{\theta^e_{N}} \cdot \overline{KM_{i,q}} \cdot \overline{V_{i,q}^{CO_2}}\end{aligned} \tag{18}$$

Using the peer coefficients θ^e_{KM}, $\theta^e_{CO_2}$, and θ^e_N to represent the effect of one newly-arriving peer electric car on the kilometer-weighted average carbon emission of cars, the total kilometers traveled, and the number of cars, I can rewrite the change in carbon emissions ($\triangle CO_{2,i,q}$) as:

$$\begin{aligned}\triangle CO_{2,i,q} \;=\; & \underbrace{\theta^e_{KM} \cdot \overline{V_{i,q}^{CO_2}} \cdot N_{i.q}}_{\triangle Driving} \;+\; \underbrace{\theta^e_{CO_2} \cdot \overline{KM_{i,q}} \cdot N_{i.q}}_{\triangle CO_2} \\ & + \underbrace{\theta^e_{N} \cdot \overline{V_{i,q}^{CO_2}} \cdot \overline{KM_{i,q}}}_{\triangle Vehicle}\end{aligned} \tag{19}$$

Equation (19) implies that the change in carbon emissions resulting from the adoption of a peer electric car is equal to the sum of the changes in driving, average carbon emissions, and the number of cars. Changes in driving-related carbon emissions are equal to the effect of one new electric car on the average kilometers traveled in the peer group multiplied by the average carbon emission and the number of cars. Similarly, the average carbon emission-related changes equal the peer effect on the average carbon emission multiplied by the average kilometer traveled and the number of cars. Finally, the car-related carbon emission changes equal the peer effect on the number of new cars multiplied by the average carbon emission and the kilometers traveled.

To empirically estimate the peer effects on the carbon emissions $\theta^e_{CO_2}$, the vehicle kilometers traveled θ^e_{KM}, and the number of cars θ^e_N, I regress whether individual i adopts a new electric car in quarter q on the individual carbon emission per kilometer ($\overline{V_{i,q}^{CO_2}}$), the average kilometers traveled ($\overline{KM_{i,q}}$), and the number of cars ($N_{i.q}$), conditional on all individual and peer group characteristics. Equations (20), (21), and (22) state the underlying regression specifications:

$$\overline{V_{i,q}^{CO_2}} \;=\; \alpha + \;\theta_{CO_2}^{e} V_{p-i,q-1}^{e} + \;\gamma \overline{X}_{p-i,q} \;+\; \delta X_{i,q} \;+\; \phi_q \;+\; \varepsilon_{i,q}, \tag{20}$$

$$\overline{KM_{i,q}} \;=\; \alpha + \;\theta_{KM}^{e} V_{p-i,q-1}^{e} + \;\gamma \overline{X}_{p-i,q} \;+\; \delta X_{i,q} \;+\; \phi_q \;+\; \varepsilon_{i,q}, \tag{21}$$

$$N_{i.q} \;=\; \alpha + \;\theta_{N}^{e} V_{p-i,q-1}^{e} + \;\gamma \overline{X}_{p-i,q} \;+\; \delta X_{i,q} \;+\; \phi_q \;+\; \varepsilon_{i,q}, \tag{22}$$

E.4 Peer Effects along Adoption Curve

To empirically estimate the size of peer effects along the adoption curve, I regress whether individual i adopts a new electric car in quarter q on the number of newly registered electric cars in the previous quarter q_{-1} for every number of electric cars in the adoption curve. The first stage (23) and reduced form equation (24) can be implemented by the following two-equation system:

$$V_{p-i,q-1}^{e}(v^*) \;=\; \alpha^{e} \sum_{j\epsilon N} V_{j,q-1}^{3y} \cdot \widehat{Pr}(V^{e} \mid V_{j,q-1}^{3y} = 1)(v^*) + \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} + \varepsilon_{i,q-1} \tag{23}$$

$$V_{i,q}^{e} \;=\; \beta^{e} \sum_{j\epsilon N} V_{j,q-1}^{3y} \cdot \widehat{Pr}(V^{e} \mid V_{j,q-1}^{3y} = 1)(v^*) \;+\; \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} \;+\; \varepsilon_{i,q}, \tag{24}$$

where v^*indicates $v^* = \sum_{j\epsilon N, i\neq j} V_j^{e}$ indicates the number of electric cars in the peer group. Effectively, I estimate the strength of peer effects for every single number of electric cars in the adoption curve.

E.5 Fossil Fuel Peer Effects

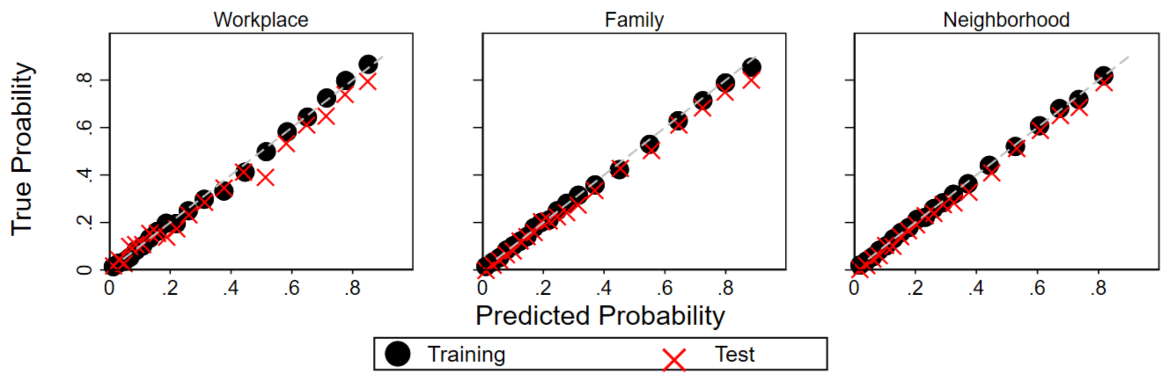
To estimate peer effects from petrol and diesel cars, I additionally fit models for each vehicle fuel type $m = \{Petrol, Diesel\}$. To construct the SSIV for the adoption of petrol and diesel cars in peer groups, I interact a dummy indicating if the person is at the three-year contract renewal ($V_{j,q-1}^{3y}$) with their estimated propensity to adopt one of these car fuel types in the renewal quarter ($\widehat{Pr}(V^{m} \mid V_{j,q-1}^{3y} = 1)$). I predict the adoption propensities for petrol and diesel cars using the same neural network from equation (4). Accordingly, I fit a first stage equation (25) and reduced form equation (26) including each car fuel type that a peer could have acquired at the leasing contract renewal:

$$V^m_{p-i,q-1} \;=\; \alpha^m \sum_{m\epsilon M}(\sum_{j\epsilon N} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^m \mid V^{3y}_{j,q-1} = 1)) + \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} + \varepsilon_{i,q-1} \tag{25}$$

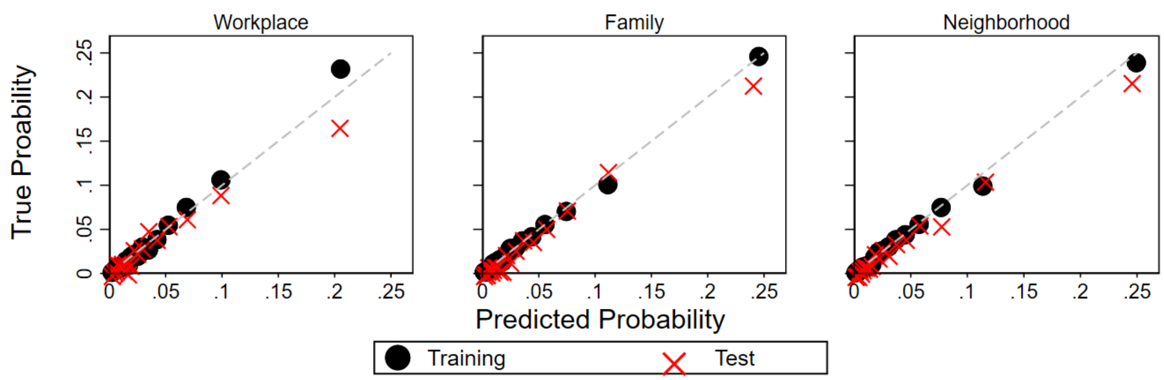
$$V^e_{i,q} \;=\; \beta^m \sum_{m\epsilon M}(\sum_{j\epsilon N} V^{3y}_{j,q-1} \cdot \widehat{Pr}(V^m \mid V^{3y}_{j,q-1} = 1)) \;+\; \delta X_{i,q} \;+\; \gamma \overline{X}_{p-i,q} \;++\; \varepsilon_{i,q} \tag{26}$$

The indicator variable $V^m_{i,q}$ captures whether individual i purchases a new car of vehicle fuel type m in quarter q. The peer effect coefficients θ^m capture the effect of a peer leasing a new car of fuel type m on the individual adoption of a new electric car in the next quarter. To control for the composition of people's peers and their car preferences, I add a control for the average propensity to lease a new car of each car fuel type m for all leasing peers (l) within a peer group $(\overline{Pr}(V^m \mid 1V^l_j = 1)_{q,j})$.

Figure E1 explores the performance of these predictors for petrol and diesel cars for both the hold-out test set ("Test Sample") and the actual training data set ("Train Sample") across all peer groups. The predicted car adoption for new petrol, and diesel cars is closely aligned with the realized car take-up. In fact, the predicted probabilities for petrol and diesel cars are spread out across the entire y-axis, indicating a useful and accurate source of variation. The findings suggest that the classification of petrol, and diesel cars can be quite accurately predicted using the neural network.



(a) Petrol



(b) Diesel

Figure E1: Propensity Score Prediction of Fossil Fuel Cars

Notes: The figures display the binscatter plots of the predicted against the realized probability to acquire new petrol (top columns) and new diesel cars (bottom columns) conditional on being at the three-year leasing renewal cutoff for both the hold-out test set ("Test Sample") and the actual training data set ("Train Sample") in the workplace, family, and neighborhood. The y-axis plots the actual probability of petrol and diesel adoption within 5-percentile bins of predicted peer petrol or diesel car adoption. All Panels include individuals at the three-year leasing contract renewal between 2012 and 2020.

F Additional Peer Effect Results

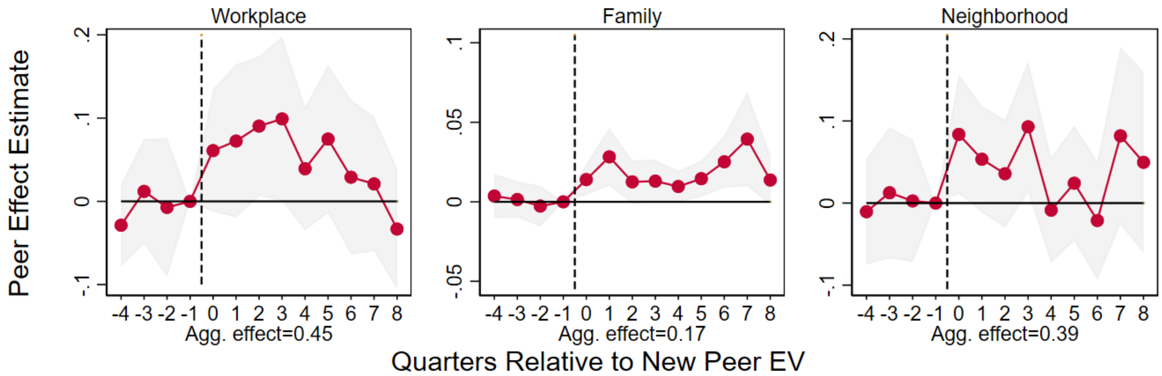


Figure F1: Peer Effects for Constant Groups

Notes: The figure displays regression estimates of peer effects for people who remained in the same peer group throughout the entire horizon in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The dashed line between periods -1 and 0 refers to the peer electric car adoption period. The underlying regression specifications of the peer effect dynamics are documented in Section E.1. The red lines capture the total effect of peer car adoption induced by the leasing contract renewal in quarter q=-1. 95%-confidence intervals are indicated through the error bars.

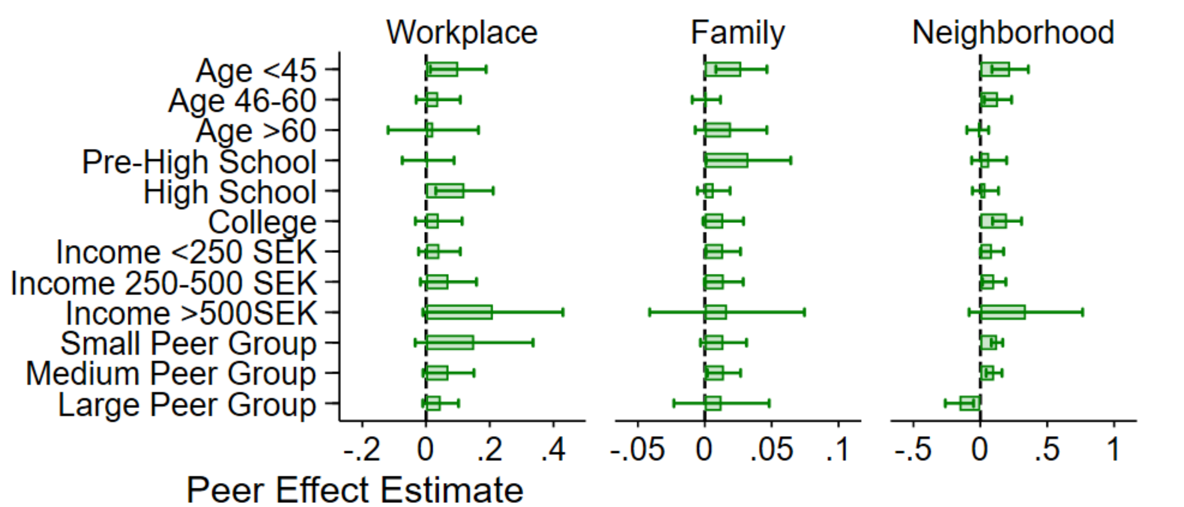


Figure F2: Peer Effect Heterogeneity by Demographic Characteristics

Notes: The figures display peer effects, split by demographic characteristics of the peer group, using the propensity-weighted leasing contract renewal instrument in equation (1) for the workplace (Panel A), family (Panel B), and the neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The underlying regression specifications used to estimate the peer effect heterogeneity are outlined in Section E.2. 95%-confidence intervals are indicated through the error bars.

Table F1: Peer Effects Across Motor Fuel Types

	Petrol	Diesel	Electric	All Vehicles
	(1)	(2)	(3)	(4)
A.Workplace Network				
Peer Coefficient	-.0918*	-.0436*	.0771***	-.0585
	(.0479)	(.0252)	(.0281)	(.0609)
%-Effect	-69.457	-67.84	546.924	-27.729
B.Family Network				
Peer Coefficient	-.0097	-.0013***	.0139***	.-.0089
	(.0085)	(.0004)	(.0049)	(.0131)
%-Effect	881.095	65.212	467.463	596.715
C.Neighborhood Network				
Peer Coefficient	-.0088	-.0381	.1114***	.0611
	(.0590)	(.0302)	(.0298)	(.0745)
%-Effect	-1.338	-11.418	150.636	5.708
Mean Dep. Variable	.659	.334	.074	1.07

Notes: This table presents the peer effects regression estimates across three different motor fuel types (petrol, diesel, and electric) and the sum of cars in workplaces. The dependent variable in columns (1), (2), (3), and (4) measures the number of new petrol, diesel, electric, or any new cars. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

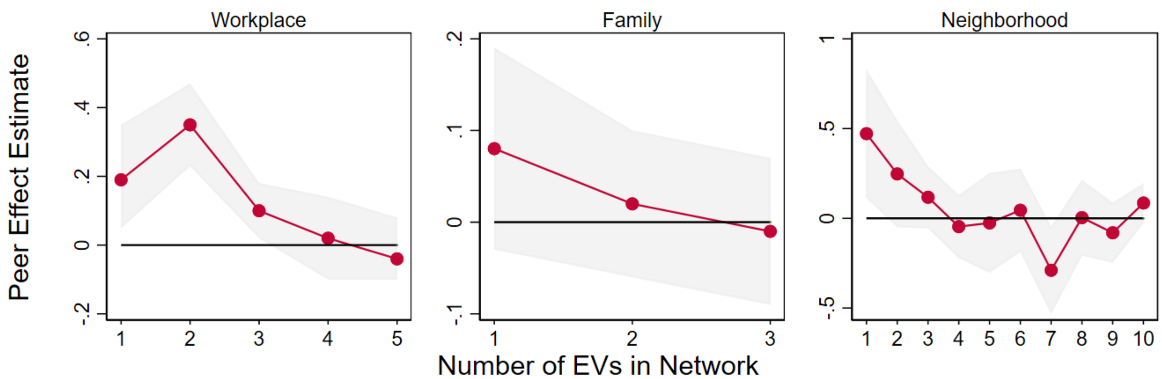


Figure F3: Peer Effects along Adoption Curve

Notes: This figure presents the peer effect results along the adoption curve for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The independent variable equals the number of new electric cars in the peer group in the previous quarter for each number of peers in the number of the adoptions curve. The underlying regression specifications to estimate peer effects along the adoption are documented in Section E.4. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C.

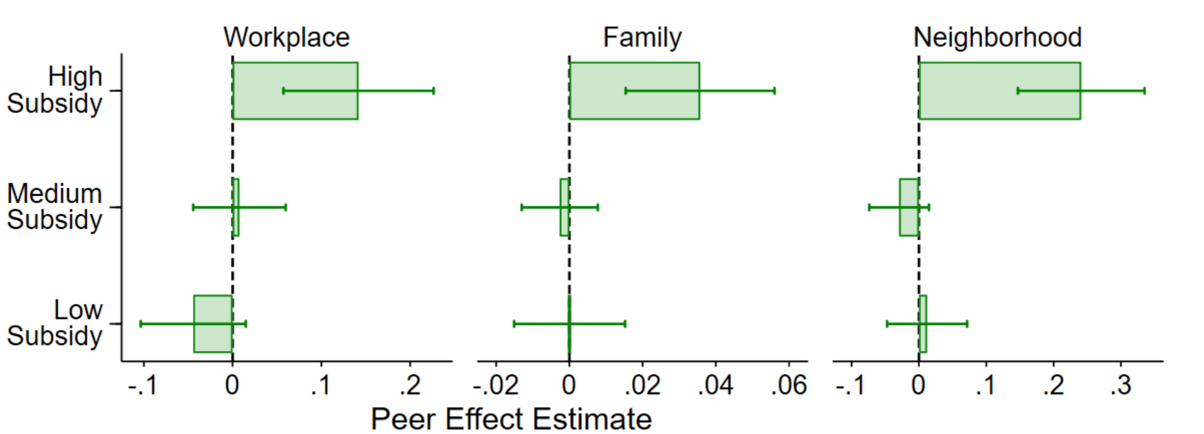


Figure F4: Peer Effects for Subsidy Period

Notes: This figure presents the peer effect results for three different subsidy periods for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I separate the sample into three periods: a low-subsidy period (from January 2012 to June 2018), a medium-subsidy period (July 2018 to December 2019), and a high-subsidy period (from January 2020). All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C.

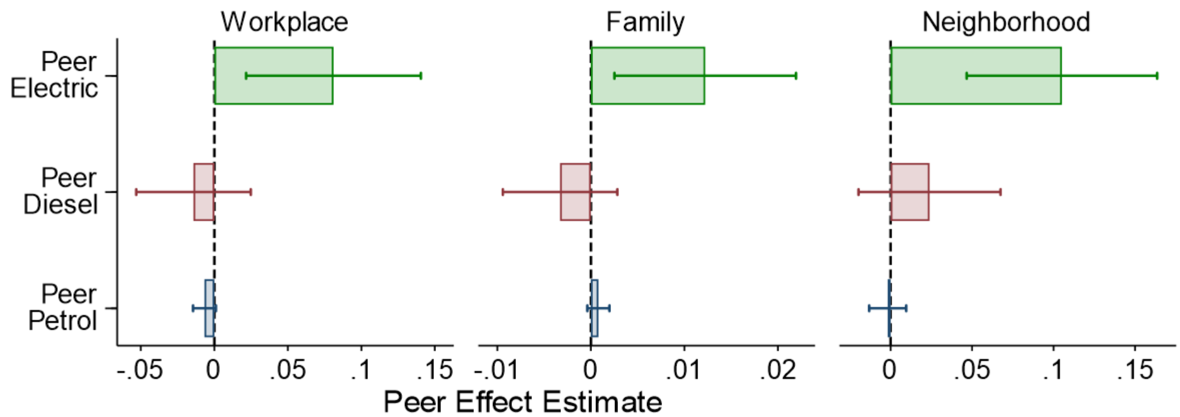


Figure F5: Peer Effects in Fossil Fuel Cars

Notes: This figure presents the peer effect results for petrol, diesel, and electric cars for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The independent variable measures the number of new petrol, diesel, and electric cars in the peer group in the previous quarter. The underlying regression specifications for peer effects in petrol, and diesel cars are documented in Section E.5. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C. The coefficients are illustrated in Table F2.

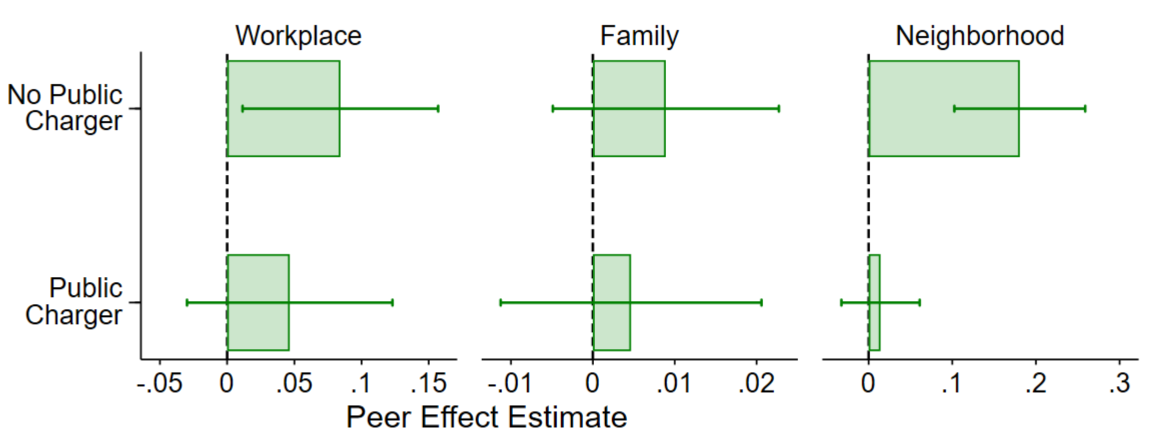


Figure F6: Peer Effects by Public Charging Infrastructure

Notes: This figure presents the peer effect results for peer groups with and without public charging infrastructure for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I separate the sample into peer groups with and without public residential charging stations. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C.

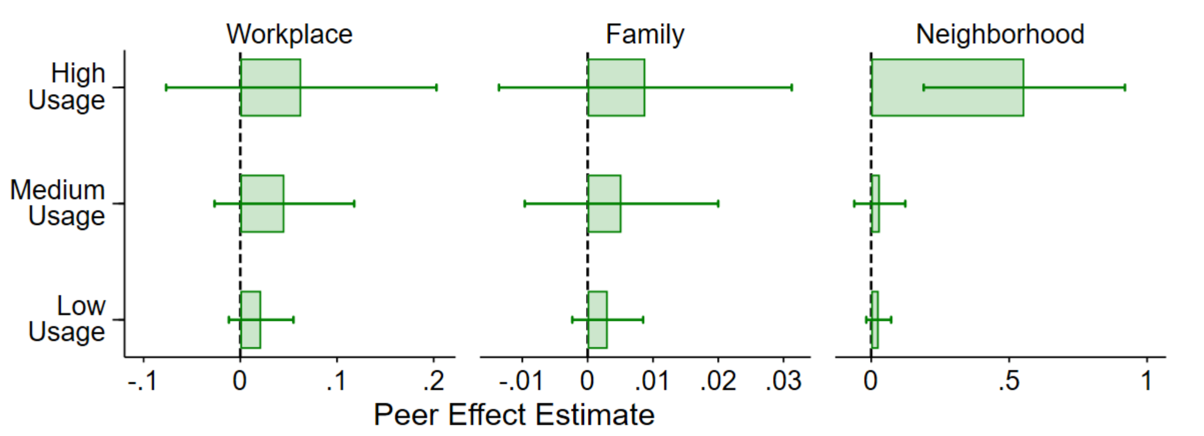


Figure F7: Peer Effects by Usage

Notes: This figure presents the peer effect results for different levels of usage for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I separate the independent car into electric cars with three levels of usage: low usage (<8.000km), medium usage (8.000-12.000km), and high usage (>12.000km). All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C.

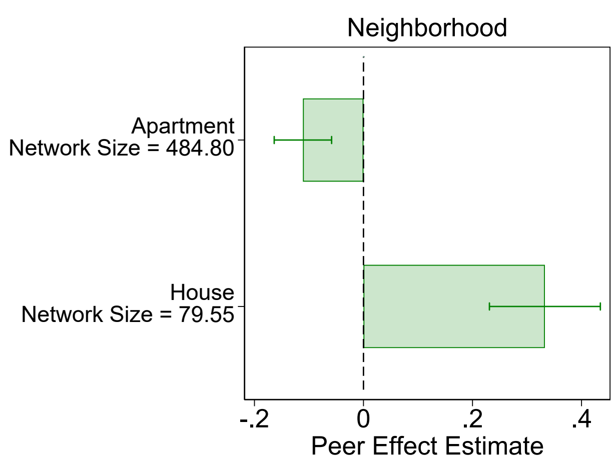


Figure F8: Peer Effects by Building Type

Notes: This figure presents the peer effect results for peer groups living in houses and apartments in neighborhoods. The dependent variable indicates the number of new electric cars in the peer group in a given quarter. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals reflect robust standard errors, clustered by plants.

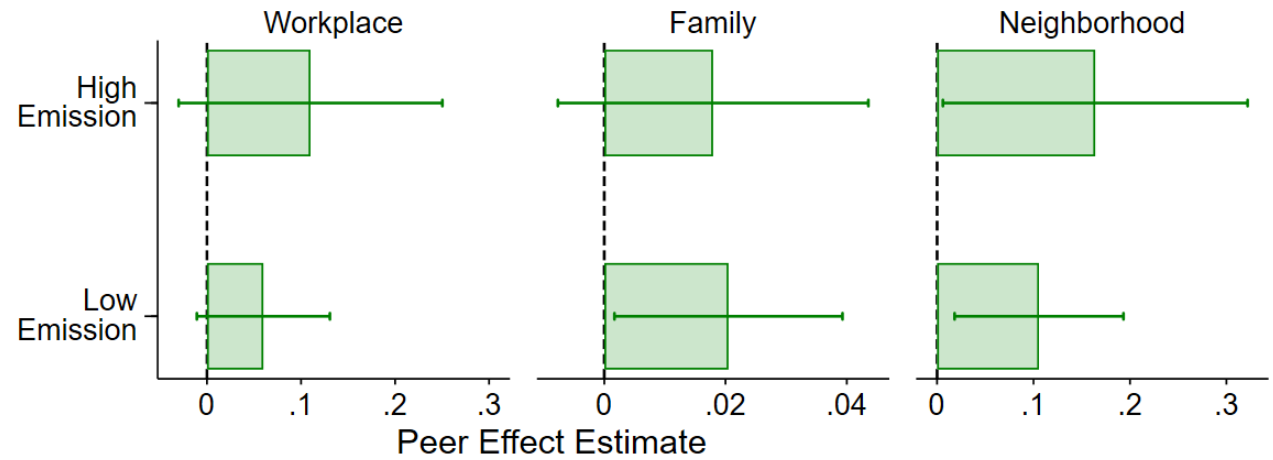


Figure F9: Peer Effects by Peer Group Emission

Notes: This figure presents the peer effect results for peer groups with low- and high-carbon emissions of the vehicle fleet for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. I split the sample into peer groups with a low and high average carbon-emitting vehicle fleet. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table F2: Peer Effects in Fossil Fuel Cars

	Petrol	Diesel	Electric	All Vehicles
	(1)	(2)	(3)	(4)
A.Workplace Network				
Peer Petrol	-.0497***	-.0142***	-.0067*	-.0708***
	(.0102)	(.0055)	(.0040)	(.0125)
Peer Diesel	-.0254	-.0785*	-.0142	-.1176
	(.0555)	(.0449)	(.0199)	(.0786)
Peer Electric	-.1443***	-.0776***	.0811***	-.1412**
	(.0499)	(.0277)	(.0303)	(.0642)
Mean Dep. Variable	.132	.064	.014	.211
B.Family Network				
Peer Petrol	.0197***	-.0020**	.0008	.0186***
	(.0020)	(.0008)	(.0006)	(.0022)
Peer Diesel	.0306***	.0142**	-.0033	.0414***
	(.0113)	(.0056)	(.0031)	(.0127)
Peer Electric	.0002	-.0157***	.0122**	-.0024
	(.0117)	(.0035)	(.0050)	(.0131)
Mean Dep. Variable	.013	.007	.001	.021
C.Neighborhood Network				
Peer Petrol	-.0486***	-.0461***	-.0018	-.0969***
	(.0165)	(.0083)	(.0058)	(.0204)
Peer Diesel	-.2372***	-.0596	.0239	-.2749***
	(.0675)	(.0372)	(.0222)	(.0830)
Peer Electric	-.0295	-.0146	.1051***	.0581
	(.0611)	(.0317)	(.0298)	(.0782)
Mean Dep. Variable	.659	.334	.074	1.07

Notes: This table presents the peer effect results for petrol, diesel, and electric cars for the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new electric cars in the peer group in a given quarter. The independent variable measures the number of new petrol, diesel, and electric cars in the peer group in the previous quarter. The underlying regression specifications for peer effects in petrol, and diesel cars are documented in Section E.5. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table F3: Peer Effects for Electric Cars by Area

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Urban	.0236***	1.2905***	.0709**	.0016**
	(.0025)	(.0939)	(.0332)	(.0007)
Rural	.0285***	1.1808***	.0746**	.0017**
	(.0029)	(.0100)	(.0352)	(.0008)
B.Family Network				
Urban	.0055***	1.2413***	.0130**	.0025**
	(.0007)	(.0232)	(.0060)	(.0012)
Rural	.0063***	1.0877***	.0065	.0013
	(.0006)	(.0241)	(.0083)	(.0016)
C.Neighborhood Network				
Urban	.0116***	1.9577***	.0722***	.0012***
	(.0023)	(.1145)	(.0242)	(.0002)
Rural	.0254***	2.2604***	.1369***	.0038***
	(.0031)	(.1921)	(.0396)	(.0002)

Notes: This table presents the regression estimates of peer effects in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table F4: Environmental Impact of Peer Effects

	Carbon Emission						
	q	q_1	q_2	q_3	q_4	q_5	q_6
A.New Electric Cars							
Co-worker New EV Registrations	9.3773	8.2135	7.8896	8.8683	-.2480	13.8281	10.4098
	(16.2479)	(12.6200)	(10.8633)	(12.8340)	(5.4046)	(20.6632)	(15.7001)
B.All New Cars							
Peer Coefficient	20.2953	3.5736	1.3951	16.7963	15.3991	499.1132	469.5317
	(47.0567)	(50.6930)	(37.5778)	(42.8834)	(35.6649)	(382.0479)	(357.7601)
Mean Dep. Variable	67.5	68.5	69.57	70.72	71.5	72.03	72.63
	Vehicle Kilometer Traveled						
	q	q_1	q_2	q_3	q_4	q_5	q_6
Peer Coefficient	-5.2e+02	-8.9e+02	-1.1e+03	-1.5e+02	461.5522	3.1e+03	6.2e+03
	(1.8e+03)	(1.7e+03)	(1.8e+03)	(1.0e+03)	(777.2449)	(4.0e+03)	(4.5e+03)
Mean Dep. Variable	1466.37	1484.49	1503.98	1526.16	1540.74	1550.48	1560.54
	Number of Vehicle						
	q	q_1	q_2	q_3	q_4	q_5	q_6
Peer Coefficient	-.5098	-.4093	-.2270	.1486	.3462	-.5809	.6515
	(.8365)	(.6786)	(.4611)	(.4194)	(.4159)	(1.8788)	(1.2823)
Mean Dep. Variable	.57	.57	.58	.59	.6	.61	.61

Notes: This table presents how one additional new peer electric car in the workplace influences the (i.) average carbon emission per kilometer, (ii.) the vehicle kilometer traveled, and (iii.) the number of owned vehicles over the next six quarters. The underlying regression specifications of the carbon emission model are documented in Section E.3. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

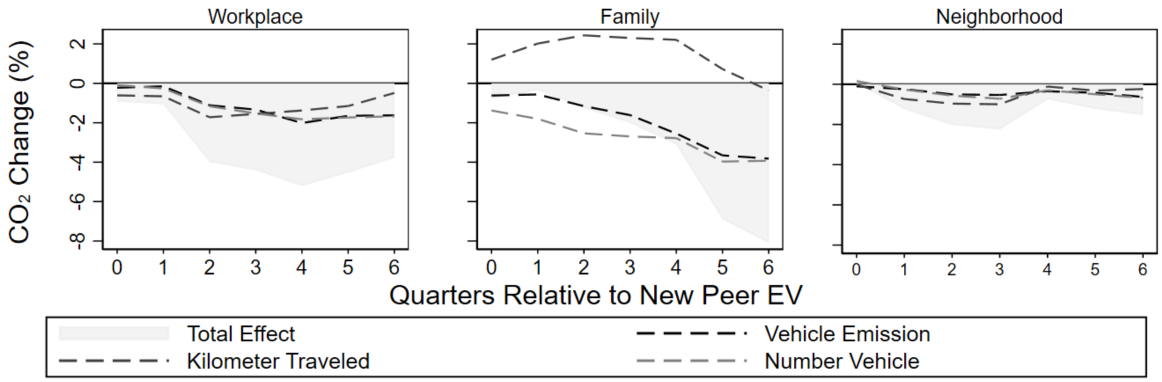


Figure F10: Carbon Emission Changes

Notes: The figure displays how one additional new electric car causes reductions in the per-person carbon emissions by (i.) triggering co-workers to adopt cleaner cars ("vehicle emission"), (ii.) driving less ("kilometers traveled"), and (iii.) reducing the number of cars they own ("number of vehicles") in families (Panel A) and neighborhoods (Panel B). The underlying regression specifications of the carbon emission model are documented in Section E.3. The effect is relative to the average carbon emission of a person in the workplace, which equals .38 tons of carbon quarterly. About half of the reduction in vehicle emissions is explained by adopting electric cars; the rest is due to non-adopters choosing cleaner fossil fuel cars.

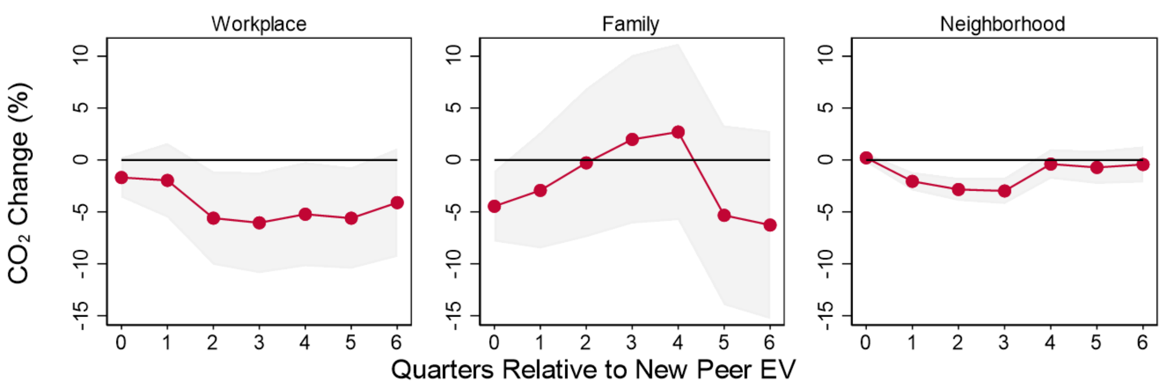


Figure F11: Peer Effects on Carbon Emissions

Notes: This figure presents the peer effect of one new electric car on the total carbon emission for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The dependent variable indicates the total carbon emission normalized to one in quarter zero. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. 95%-confidence intervals are indicated through the error bars.

Table F5: Alternative Outcomes of Peer Effects

	Vehicle Ownership		
	(1)Weight	(2)Engine	(3)Fuel
A.Workplace Network			
Peer Coefficient	-33.314***	-2.675***	-0.166***
	(9.995)	(0.752)	(0.040)
Mean Dep. Variable	645.82	44.96	2.66
B.Family Network			
Peer Coefficient	-68.875***	-4.915***	-.410***
	(18.437)	(1.342)	(.081)
Mean Dep. Variable	610.43	42.29	2.5
C.Neighborhod Network			
Peer Coefficient	-2.488	-.285	-.023**
	(2.590)	(.192)	(.011)
Mean Dep. Variable	589.72	40.82	2.42

Notes: This table presents the regression estimates of peer effects on three car characteristics for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). The outcome of interest is equal to three average car characteristics per person one year after the peer electric vehicle adoption: (1) weight [kilogram], (2) engine power [horsepower], and (3) fuel efficiency [liter/100km]. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table F6: Peer Effects for Second-Hand Electric Cars

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Peer Coefficient	.0115***	1.1319***	-.0010	-.0000
	(.0041)	(.0816)	(.0193)	(.0004)
%-Effect	78.97	7760.88	-6.9	-6.9
Mean Dep. Variable	.015	.015	.015	0
B.Family Network				
Peer Coefficient	.0021***	1.1695***	.0039	.0008
	(.0003)	(.0169)	(.0063)	(.0012)
%-Effect	152.37	86802.34	289.26	289.26
Mean Dep. Variable	.001	.001	.001	0
C.Neighborhood Network				
Peer Coefficient	.0219***	1.4960***	.0145	.0001
	(.0018)	(.1029)	(.0244)	(.0001)
%-Effect	30.03	2053.03	19.91	19.91
Mean Dep. Variable	.073	.073	.073	0

Notes: This table presents the regression estimates of peer effects on the adoption of second-hand electric cars in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The %-effect and the mean dependent variable are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

G Robustness Checks

Table G1: Alternative Specifications Checks of Peer Effects

	A. Workplace			B. Family			C. Neighborhood		
	OLS(1)	FS(2)	2SLS(3)	OLS(4)	FS(4)	2SLS(6)	OLS(7)	FS(8)	2SLS(9)
Peer Effect Estimate:									
Baseline	.0274***	1.1319***	.0771***	.0060***	1.1695***	.0140***	.0594***	1.4960***	.1114***
	(.0061)	(.0816)	(.0281)	(.0005)	(.0169)	(.0049)	(.0023)	(.1029)	(.0298)
Estimation Model:									
Probit	.1554***	1.1319***	.0896	.3602***	1.1695***	1.1134***	.1074***	1.4960***	.1059**
	(.0163)	(.0816)	(.1345)	(.0176)	(.0169)	(.1923)	(.0035)	(.1029)	(.0460)
Functional Form:									
Percentage Influence	.0060***	.9897***	.0394***	.0001***	1.122***	.0001***	.0887***	1.1767***	.0325***
	(.0014)	(.0743)	(.0105)	(.0000)	(.0327)	(.0000)	(.0023)	(.0758)	(.0150)
Binary Influence	.0098***	.9960***	.0021***	-.0037*	.9998***	-.0002	.0215***	.9829***	-.0118***
	(.0013)	(.0002)	(.0003)	(.0019)	(.0002)	(.0006)	(.0017)	(.0005)	(.0005)
Alternative Outcomes:									
Non-Leased	.0156***	1.1319***	.0133	.0036***	1.1695***	-.0016	.0355***	1.4960***	.0451**
	(.0031)	(.0816)	(.0160)	(.0004)	(.0169)	(.0028)	(.0017)	(.1029)	(.0214)
Non-Renewal	.0273***	1.1319***	.0742***	.0059***	1.1695***	.0150***	.0570***	1.4960***	.1032***
	(.0061)	(.0816)	(.0261)	(.0005)	(.0169)	(.0047)	(.0022)	(.1029)	(.0292)
Sample Restriction:									
Peer Leasing	.0404***	1.0937***	.0802*	.0087***	1.1469***	.0115	.0607***	1.4371***	.1419***
	(.0124)	(.0824)	(.0415)	(.0018)	(.0171)	(.0075)	(.0031)	(.1036)	(.0421)

Notes: This table presents the regression estimates of peer effects for various alternative specifications in workplaces (Panel A), families (Panel B,) and neighborhoods (Panel C). The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. Columns (1), (4), and (7) present OLS estimates, columns (2), (5), and (8) the first stage estimation, and colums (3), (6), and (9) the second state estimation using the shift-share instrument. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table G2: Peer Effects for Non-Overlapping Peer Groups

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Peer Coefficient	.0264***	1.1271***	.0747***	.0017***
	(.0060)	(.0816)	(.0278)	(.0006)
%-Effect	190.74	8142.2	539.8	539.8
Mean Dep. Variable	.014	.014	.014	0
B.Family Network				
Peer Coefficient	.0039***	1.1680***	.0092***	.0026***
	(.0003)	(.0170)	(.0034)	(.0010)
%-Effect	390.73	115713.58	912.12	912.12
Mean Dep. Variable	.001	.001	.001	0
C.Neighborhood Network				
Peer Coefficient	.0594***	1.4960***	.1114***	.0004***
	(.0023)	(.1029)	(.0298)	(.0001)
%-Effect	80.26	2022.11	150.64	150.64
Mean Dep. Variable	.074	.074	.074	0

Notes: This table presents the regression estimates of peer effects in non-overlapping peer groups for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The %-effect and the mean dependent variable are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table G3: Peer Effects for Placebo Peer Groups

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Firm Co-worker	-.0001	5.5945***	.0100	.0000
	(.0031)	(.8057)	(.0149)	(.0000)
%-Effect	-.09	4989.44	8.94	8.94
Mean Dep. Variable	.112	.112	.112	0
Future Co-worker	.0006	.8052**	-.0309	-.0051
	(.0005)	(.3979)	(.0216)	(.0035)
%-Effect	34.11	42337.59	-1626.53	-1626.53
Mean Dep. Variable	.002	.002	.002	0
C.Neighborhood Network				
Distant Neighbor	.0408***	1.4983***	.0595	.0001
	(.0039)	(.0869)	(.0540)	(.0001)
%-Effect	17.37	637.32	216.71	216.71
Mean Dep. Variable	.235	.235	.235	0

Notes: This table presents the regression estimates of peer effects for placebo peer groups in workplaces (Panel A) and neighborhoods (Panel C) using the contract renewal timing instrument. Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. The placebo co-workers are: 1. Firm-level co-workers: Individuals employed in the same firm, two-digit industry, and region, but work do not work in the same plant; 2. Future co-workers: Future co-workers that switch workplaces during the eight-year observation window. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table G4: Contract Renewal Timing Placebo Estimates

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Prior Renewal	.1482	-.8647	-.0107	-.0002
	(.0546)	(2.3967)	(.0281)	(.0004)
Past Renewal	.0559	-.0345	-.0082	-.001
	(.0421)	(.3644)	(.0115)	(.0002)
B.Family Network				
Prior Renewal	.0019	.0153	0.0058	.0000
	(.0055)	(.0008)	(.0359)	(.0311)
Past Renewal	.0200	.0609	-.0430	-.0057
	(.0126)	(.0036)	(.1305)	(.0172)
C.Neighborhood Network				
Prior Renewal	.0019	.0153	0.0195	.0000
	(.0055)	(.0008)	(.0239)	(.0311)
Past Renewal	.0200	.0609	-.0430	-.0057
	(.0126)	(.0369)	(.1305)	(.0172)

Notes: This table presents the regression estimates of peer effects for placebo contract renewals in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Prior and past placebo estimates use the contract renewal thresholds eight quarters before and after the actual three-year renewal timing. Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhood in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table G5: Varying Horizon of Peer Effects

	OLS	First Stage	Second Stage
	(1)	(2)	(3)
A.Workplace Network			
1 Quarter (baseline)	.0274***	1.1319***	.0772***
	(.0061)	(.0816)	(.0282)
2 Quarter	.0250***	1.3421***	.0534***
	(.0063)	(.0904)	(.0175)
3 Quarter	.0239***	1.5025***	.0489***
	(.0057)	(.1047)	(.0128)
4 Quarter	.0236***	1.6095***	.0506***
	(.0054)	(.1139)	(.0113)
B.Family Network			
1 Quarter (baseline)	.0060***	1.1695***	.0140***
	(.0005)	(.0169)	(.0049)
2 Quarter	.0054***	1.2424***	.0367***
	(.0003)	(.0171)	(.0069)
3 Quarter	.0052***	1.2871***	.0397***
	(.0003)	(.0178)	(.0056)
4 Quarter	.0051***	1.3246***	.0427***
	(.0002)	(.0183)	(.0049)
C.Neighborhood Network			
1 Quarter (baseline)	.0594***	1.4960***	.1115***
	(.0023)	(.1029)	(.0298)
2 Quarter	.0457***	1.7038***	.0784***
	(.0017)	(.1089)	(.0174)
3 Quarter	.0320***	1.9240***	.0592***
	(.0014)	(.1361)	(.0121)
4 Quarter	.0192***	2.0704***	.0523***
	(.0012)	(.1533)	(.0103)

Notes: his table presents the regression estimates of peer effects for varying time horizons in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (1), column (2) equals the first stage estimation of equation (5), and column (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new electric cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new electric car. All regressions include individual demographic, past car attributes, charging infrastructure, peer group demographic control variables, and quarter-fixed effects. The %-effect and the mean dependent variable are reported below the coefficients. The unit of observation is individual$\times$quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

H Peer Effects for General Cars

In Section H.2, I propose an instrumental variable that shifts the new car purchasing probability in peer groups: the number of peers who are at the three-year leasing renewal contract, and whose contract is therefore likely up for renewal. Section H.3 presents the the regression-based analysis of peer effects for general cars. The underlying peer effect dynamics are illustrated thereafter in Section H.4.

H.1 Peer Effect Specification

To estimate the size of the peer effects for new cars in the Swedish market for vehicles, the equation of interest (or second stage) (27) is given by a regression of whether individual i adopts a new car in quarter q on the number of new cars in the previous quarter q_{-1} in peer group p, conditional on all individual and peer group characteristics:

$$V_{i,q} \ = \ \alpha + \ \theta V_{p_{-i},q_{-1}} + \ \gamma \overline{X}_{p_{-i},q} \ + \ \delta X_{i,q} \ + \phi_q \ + \ \varepsilon_{i,q}, \tag{27}$$

where the dependent variable, $V_{i,q}$, is an indicator of whether individual i acquires a new car in quarter q. The peer influence variable equals the sum of all new car registrations per peer group in the previous quarter q_{-1} excluding individual i: $V_{p_{-i},q_{-1}} = \sum_{j\epsilon N, j\neq i} V_{j,q_{-1}}$. The peer-influence coefficient (θ) measures the effect of the number of new cars in the peer group in the previous quarter ($V_{p_{-i},q_{-1}}$) on whether the person adopts a new car in the current quarter ($V_{i,q}$).

H.2 Contract Renewal Instrument

1. *First Stage and Reduced Regression.* To overcome the aforementioned identification threats, I implement an instrumental variable (IV) approach using the timing of the contract renewal as exogenous variation to car adoption of peers. The peer group level first stage (28) and reduced form equation (29) can be implemented by the following two-equation system:

$$V_{p_{-i},q_{-1}} \ = \ \alpha \sum_{j\epsilon N} V^{3y}_{j,q_{-1}} \ + \ \delta X_{i,q} \ + \ \gamma \overline{X}_{p_{-i},q} \ + \ \phi_q \ + \ e_{i,q_{-1}} \tag{28}$$

$$V^{e}_{i,q} \ = \ \beta \sum_{j\epsilon N} V^{3y}_{j,q_{-1}} \ + \ \delta X_{i,q} \ + \ \gamma \overline{X}_{p_{-i},q} \ + \ \phi_q \ + \ e_{i,q}, \tag{29}$$

where $V^{3y}_{i,q_{-1}}$ equals 1 if individual j is at the three-year contract renewal in quarter q_{-1}. The first stage estimate of equation (28) measures the first stage relationship between the instrument, the number of leasing contract renewals in a given quarter, and the number of new cars in that peer group. The reduced form estimate of equation (29) measures how the number of peers at the three-year car-renewal threshold in a given quarter affects the individual's car acquisition. The second stage estimate θ then corresponds to the total car adoption in quarter q that were induced by the instrument (β) scaled by the first stage estimate (α) of how many new peer cars happened at the contract renewal. Since individuals who have a higher share of peers that regularly replace their cars every third year are plausibly different from individuals with friends who have older cars on average, I directly control for the quarterly average share of friends whose car are 12 quarters old over the entire time horizon. The associated identifying assumption is that the number of peers with a three-year old leased car in a given quarter is conditionally random after accounting for a set of control variables.

2. *First Stage Results.* To provide some evidence for the validity of the contract renewal instrument, I begin with a graphical depiction of the first stage. Figure H1 displays the point estimates and 95%-confidence intervals of the first stage equation (28) for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Both measures have been residualized on the full set of baseline controls and peer-fixed effects. The y-axis plots peer group car adoption within bins of peers at the car contract renewal. The slope of the regression line is equivalent to the coefficient α from equation (28). The figure portrays that each additional peer at the contract renewal is associated with an approximately .4 increase in the adoption of new cars in that peer group. The F-statistics for workplaces (3128.07), families (12423.3), and neighborhoods (1379.73) exceed critical values for instrument validity and strengthen the relevance assumption.

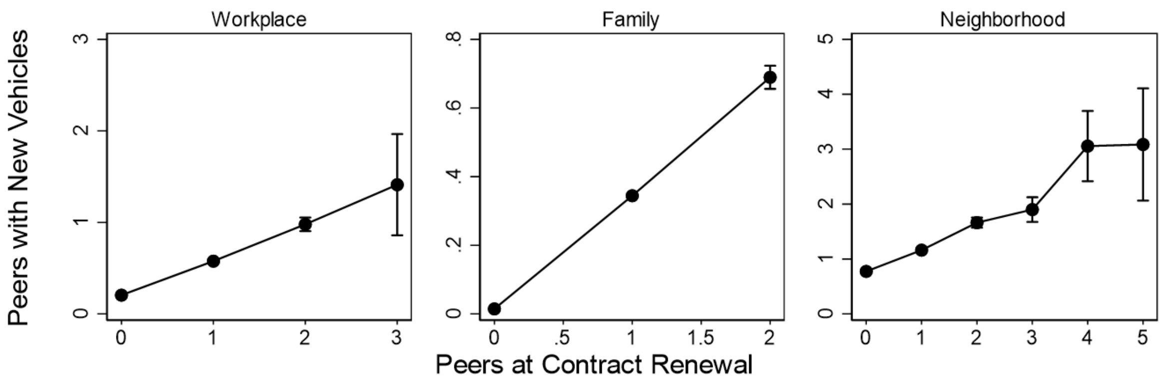


Figure H1: First Stage Coefficient Plots

Notes: The figures present point estimates in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C) of the first stage equation (28) using the contract renewal as instrument. The y-axis plots peer group car adoption within bins of peers at the car-leasing contract renewal. Both relationships are residual of the control variables: individual-demographic variables, peer group characteristics, chargings infrastructure, past car choices, and quarter-fixed effects. 95%-confidence intervals are indicated through the error bars.

3. *Event-Study Design.* To estimate the effect of the leasing contract renewal on car adoption, I perform an event-study analysis, taking a person who leases a car for exactly 12 quarters as event and who is therefore likely up for renewal. In this context, the event-study specification relative to the three-year contract renewal threshold for quarters $\tau = -8, ..., 8$, controlling for quarterly- and peer group fixed effects, is given by:

$$V_{i,q} \; = \sum_{\tau=-8}^{8} \beta_\tau V_{i,q-\tau} \; + \; \phi_q \; + \; \phi_p + \; \varepsilon_{i,q} \tag{30}$$

The β_τ coefficient quantifies how the probability of adopting a new car changes in the quarters preceding ($\tau < 0$) and after the three-year leasing contract renewal ($\tau \geq 0$). Figure H2 plots the β_τ coefficients for the contract renewal within the 8 quarters time window. There is a significant jump in the car adoption exactly 12 quarters after leasing the previous car, which provides further evidence that a considerable part of individuals tend to adopt a new vehicle at the three-year renewal threshold.

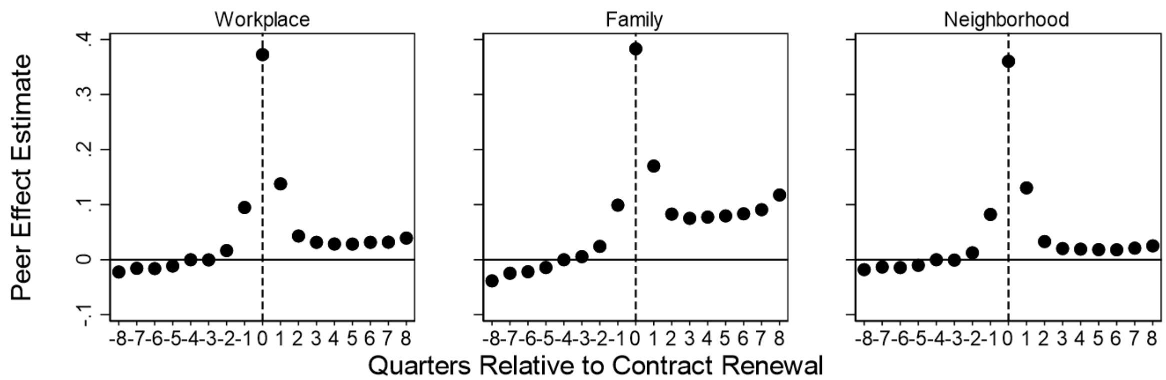


Figure H2: Event-Study of New car Adoption at Contract Renewal

Notes: The figures present the coefficients of the event-study for workplaces (Panel A), families (Panel B), and neighborhoods (Panel C) in equation (30). All coefficients are relative to the reference category in quarter q=-4.

H.3 Regression Results

Analogous to the electric car specification in the main Section (IV), Table H1 reports OLS, first stage, and 2SLS estimates of peer effects for new cars in the workplace (Panel A), family (Panel B) and neighborhood (Panel C). The peer coefficients in columns (1) and (3) indicate how the adoption of one new car influences the total number of new cars in the peer group in the next quarter. In column (4), the peer coefficient implies how one new peer car affects the car adoption of one co-worker, relative, or neighbor in the following quarter.

The OLS results in column (1) display peer effects for new car. Particularly, a new car by a co-worker, relative, and neighbor is associated with .034, .01, and .035 additional new cars through peer effects in the next quarter. To address the identification challenges, I employ an instrumental variable approach using the leasing contract renewal as exogenous shock the peer car adoption for the remainder of the Table H1.

The first stage estimate in column (2) corresponding to Figure H1 corroborate that the timing of the leasing renewal is a strong predictor of new car take-up in peer groups. The underlying coefficient implies that one additional person at the renewal threshold adds .37 new cars in the workplace, .33 in the family, and .41 in the neighborhood. Put differently, every second to third person at the leasing renewal threshold adopts a new car in the same quarter. This aligns with the fact that around 40% of individuals lease a new vehicle at the three-year threshold (Figure II).

The 2SLS estimates indicate strong evidence for peer effects adopting new cars in families and neighborhoods, while no effects are found in the workplaces. The peer effect can be interpreted as follows: One additional new car in the peer group induced by the leasing contract renewal leads to an additional .009 new cars in the family and .033 in the neighborhood through peer effects in the next quarter. This translates into a 40.1% effect in the family and 3.1 effect in the neighborhood relative to the average quarterly adoption probability of a new car. The absence of peer effects in workplaces may be driven by stricter renewal policies in firms relative to families and neighborhoods.

Similar to the empirical findings for electric cars, the peer effects are most substantial in the neighborhood, but on a per capita basis, peer effects are largest in the family, as shown in column (4).

Table H1: Peer Effects for New Cars

	OLS	First Stage	Second Stage	
	(1)	(2)	Total(3)	Per Capita(4)
A.Workplace Network				
Peer Coefficient	.0336***	.3682***	-.0011	-.0000
	(.0021)	(.0080)	(.0076)	(.0002)
%-Effect	15.91	174.44	-.53	-.53
Mean Dep. Variable	.211	.211	.211	.005
B.Family Network				
Peer Coefficient	.0103***	.3297***	.0086***	.0017***
	(.0002)	(.0010)	(.0022)	(.0004)
%-Effect	47.97	1537.2	40.13	40.13
Mean Dep. Variable	.021	.021	.021	.004
C.Neighborhood Network				
Peer Coefficient	.0348***	.4104***	.0334***	.0001***
	(.0015)	(.0111)	(.0099)	(.0000)
%-Effect	3.25	38.35	3.12	3.12
Mean Dep. Variable	1.07	1.07	1.07	.004

Notes: This table presents the regression estimates of peer effects for all new cars in workplaces (Panel A), families (Panel B), and neighborhoods (Panel C). Column (1) presents OLS estimates from the regression in equation (27), column (2) equals the first stage estimation of equation (28), and columns (3) and (4) reflect the second state estimation. The dependent variable in columns (1), (2), and (3) indicates the number of new cars in the peer group in a given quarter. The dependent variable in column (4) indicates whether the individual adopts a new car. All regressions include individual demographic, past car attributes, peer group demographic control variables, and quarter-fixed effects. The %-effect and the mean dependent variable are reported below the coefficients. The unit of observation is individual×quarter. The time period reaches from 2012 until 2020. Robust standard errors, clustered by plants in Panel A, family in Panel B, and neighborhoods in Panel C, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

H.4 Peer Effect Dynamics

In addition to investigating the immediate response of a person's car purchasing behavior immediately following a new car in a peer group, I also explore whether these peer effects generate additional demand or pull forward already-planned future purchases. This Section therefore analyzes for how long does the adoption of a new car by a peer influence a person's own car decision. To tackle this question, I expand the horizon over which peer effects are measured to include four quarters prior and up to eight quarters following the new peer car. To capture the exact timing of the peer effect, I construct dependent variables of the form $V_{i,\tau}$ for $\tau = -4, ..., 8$.

Figure H3 displays the total peer effect coefficients (θ_τ) using the specified horizon across the three peer groups. The dashed line refers to the peer car adoption period, which resembles the first stage regression corresponding to equation (28). The dynamics reveal that the peer effects of electric cars affect the car choice for the first four quarters in the family, and two quarters in the neighborhood. While the aggregate effect converges towards zero in the family, there is a reduced demand for cars in the neighborhood. This implies that neighbors pull forward future planned car purchases instead of generating demand for new additional cars.

Notably, there is no significant social influence in the quarters prior to the contract renewal timing of peers. This provides further support for the validity of the exclusion restriction, which requires that individuals with and without an exogenously-induced peers at the leasing contract renewal would behave conditionally similarly in the absence of the peer adoption.

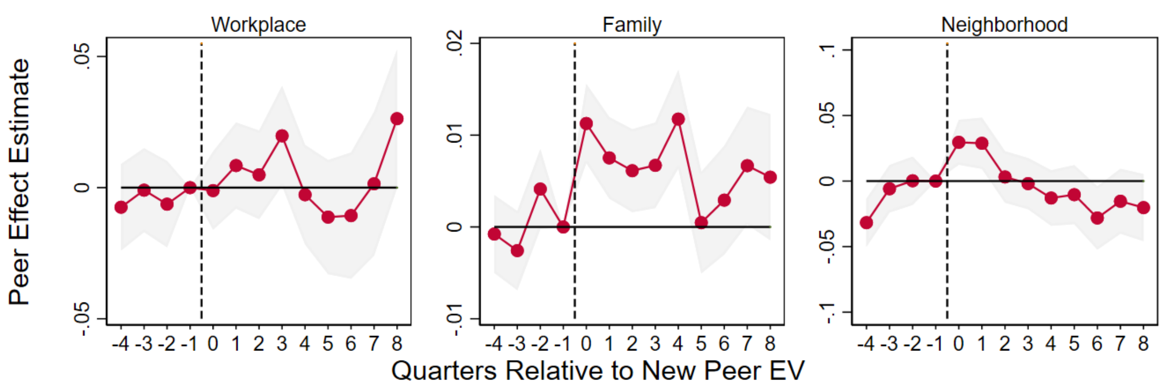


Figure H3: Peer Effects Dynamics

Notes: The figure displays regression estimates of peer effects at various horizons in the workplace (Panel A), family (Panel B), and neighborhood (Panel C). The dependent variable indicates the number of new cars in the peer group in a given quarter. The dashed line between period -1 and 0 refers to the peer car adoption period. The IV coefficients capture the total effect of peer car adoption induced by the leasing contract renewal in quarter q=-1. 95%-confidence intervals are indicated through the error bars.

I Policy Implication

1. *Proof of Proposition 1.* This Section derives the optimal Pigouvian subsidy $\tau^{*}(\theta^e)$ in the presence of peer effects as stated in Proposition 1. Suppose a policymaker sets an upfront subsidy τ for electric cars that equals the net present value of externalities e ($\tau = e$). The total value of externalities for electric cars equals the difference between each externality that arises from adopting the electric car $e_j(V^e)$ and the externality from the counterfactual car $e_j(V^c)$ according to equation (9). In the presence of peer effects θ^e, the total externality scales with the size of the peer effect and equals $[e_j(V^e) - e_j(V^c)](1+\theta^e)$ for each externality e_j. The optimal Pigouvian subsidy that accounts for peer effects $\tau^{*}(\theta^e)$ relative to a standard Pigouvian subsidy is given by the ratio of externalities with and without peer effects:

$$
\begin{aligned}
\frac{\tau^{*}(\theta^e)}{\tau} &= \frac{e(\theta^e)}{e} \\
\frac{\tau^{*}(\theta^e)}{\tau} &= \frac{\sum_{j=1}^{J}[e_j(V^e) - e_j(V^c)] \cdot (1+\theta^e)}{\sum_{j=1}^{J}[e_j(V^e) - e_j(V^c)]} \\
\tau^{*}(\theta^e) &= \tau \cdot (1+\theta^e) \\
\tau^{*}(\theta^e) &= e \cdot (1+\theta^e)
\end{aligned}
\tag{31}
$$

The optimal Pigouvian subsidy equals the total value of externalities for electric cars scaled by the size of the peer effect.

Assumption 1. The empirical evidence of Section IV.B indicates that the estimated peer effects do not solely increase the subsequent adoption of electric cars in peer groups, but also reduce the adoption of new petrol and diesel cars (Figure VI). This implies that peer effects crowd out follow-on purchases of fossil fuel cars (θ^c), such that the externality reduces by the peer effect on fossil fuel cars $\theta^c(e_j(V^e) - e_j(V^m))$. If we incorporate the peer effect of electric cars on the adoption of fossil fuel cars θ^c, the optimal Pigouvian subsidy becomes:

$$
\begin{aligned}
\frac{\tau^{*}(\theta^e)}{\tau^{*}} &= \frac{\sum_{j=1}^{J}[e_j(V^e) - e_j(V^c)] \cdot (1+\theta^e-\theta^c)}{\sum_{j=1}^{J}[e_j(V^e) - e_j(V^c)]} \\
\tau^{*}(\theta^e) &= \tau^{*} \cdot (1+\theta^e-\theta^c) \\
\tau^{*}(\theta^e) &= e \cdot (1+\theta^e-\theta^c)
\end{aligned}
\tag{32}
$$

The optimal Pigouvian subsidy that accounts for peer effects on electric and fossil fuel cars scales the externality by the peer effect on electric cars, but subtracts the substitution towards fossil fuel cars. Intuitively, if there is crowding out of fossil fuel cars through the adoption of new electric cars (i.e.,$\theta^c < 0$), then the optimal Pigouvian subsidy for electric cars increases even further relative to the standard Pigouvian subsidy.

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