End of the Road? Autonomous Vehicles and Displacement Risk

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Abstract

New technologies have renewed concerns about job displacement. In this paper, I link workers' subjective displacement expectations to their direct and social exposure to a disruptive technology: autonomous vehicles (AVs). I find that commercial driver licensing and employment in truck driving fall disproportionately in more AV-exposed areas. The remaining drivers extend their work hours and reduce participation in mortgage markets relative to less-exposed, neighboring drivers. Changes in household spending on alcohol and tobacco products are consistent with heightened automation-induced anxiety. The results indicate that perceived displacement risk affects households' labor supply, credit behavior, and health, all of which could inform welfare assessments and policy responses to automation.

Keywords: automation; displacement; autonomous vehicles; household finance; social networks

JEL Classification: O3, D8, J2, G5, R4

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The classic debate between technology doomsayers and optimists has regained relevance. While some commentators argue that artificial intelligence (AI) will broadly displace labor, others maintain that the current wave of innovation resembles earlier episodes of creative destruction, where job creation ultimately outpaced job loss.[1] Although much of this discussion centers on aggregate labor markets, less is known about how perceived displacement risk translates into changes in household behavior. Whether households update their beliefs about impending displacement and take precautionary measures remains unclear, particularly when myopic or wishful thinking might lead them to downplay emerging risks (Beshears et al., 2018; Engelmann et al., 2024) or when adaptive capacity is limited (Manning and Aguirre, 2025).

My paper analyzes how potentially adversely affected households, facing uncertainty about future displacements and the value of their human capital, respond to the threat of automation. The dynamics of automation-induced labor adjustment are not fully understood. The modern academic literature often employs a task-based framework to study how new technologies affect labor demand, focusing on task displacement, productivity, and reinstatement effects (Acemoglu and Restrepo, 2018, 2019; Feigenbaum and Gross, 2024; Hampole et al., 2025). By contrast, less attention has been paid to the labor supply side of this phenomenon. In principle, rational, forward-looking households may anticipate the looming obsolescence of an occupation and preemptively reduce their labor supply in response. While standard economic theory implies such an anticipatory effect, empirical demonstrations have been scarce and inconclusive.

I provide direct empirical evidence that households respond preemptively to automation threats, thereby highlighting a crucial labor supply channel that has been underexplored in the literature. Focusing on truck drivers—a group of workers for whom displacement risk has been highly salient—I demonstrate that there have already been initial labor market reallocations before actual displacements are realized, i.e., before the widespread deployment of self-driving cars and trucks.[2] The approximately two million heavy and tractor-trailer truck drivers in the United States, specifically those with long-distance driving jobs with few specialized tasks, are most at risk of displacement given that automation of highway driving is a central objective of many developers of autonomous vehicles (AVs) (Viscelli, 2018; Gittleman and Monaco, 2020; Mohan and Vaishnav, 2022).

I rely on two main data sources. First, I obtain the universe of driver licenses in California and

[1] Historically, the creative destruction wrought by the adoption of new technologies favored job creation over job destruction (Autor, 2015). Yet academic perspectives are shifting, with growing concern over the pace and scope of automation (Autor, 2022; Bond and Kremens, 2023; Jones, 2024; Korinek and Suh, 2024; Restrepo, 2025).

[2] Fredrick Kunkle, "From road cowboys to robots: Truckers are wary of autonomous rigs," *The Washington Post*, May 23, 2017.

New York State. The de-identified data allow me to distinguish commercial truck drivers, including heavy-duty truck operators, using the listed license classes. Second, I hand-collect a panel dataset on large-scale AV testing across zip codes in the United States. Using residential information from the licenses, I compute each driver's direct or indirect exposure to these areas, which uniquely had ubiquitous exposure to self-driving cars. Robotaxis, while not the same as autonomous trucks, are informative about the progress of self-driving technology since information about their deployment and effectiveness may shift truck drivers' perceptions of displacement risk.

As a first step, I document a sharp fall in commercial driver licensing in zip codes exposed to AV testing in California relative to other zip codes in the same county that did not have AV deployments. The point estimates correspond to a 0.6 to 1% decline in the commercial driver license (CDL) share following AV-exposure. I further show that zip codes that had a greater number of AV trips had disproportionately fewer commercial drivers by the end of the sample period. Next, given concerns about endogenous deployments of self-driving cars in specific locations in California and richer data in New York State, I study the role of social networks in influencing licensing behavior beyond AV's direct geographic footprint. Specifically, I link New York truck drivers using their license zip codes to Facebook's Social Connectedness Index, which captures the probability that Facebook users in a pair of locations are friends with each other (Bailey et al., 2018).

Leveraging the quasi-exogenous geographical rollout of AV testing, I relate changes in commercial driving to changes in friend exposure to AV, as self-driving cars were deployed in increasingly more areas. My primary result is that the CDL share falls disproportionately in zip codes that are more socially connected to areas with AV testing. Quantitatively, a one standard deviation higher friend exposure induces a reduction in the CDL share by 23 basis points, corresponding to 9% relative to the mean. Extrapolating the baseline estimate, I report that a one standard deviation increase in friend exposure to AV results in a fall of approximately 180,000 drivers nationally.

In addition, I report heterogeneous effects of friend exposure. I find larger point estimates among younger drivers, for whom the present value implications of displacement risk are greater. These workers are less likely to enter a 'risky' occupation, and conditional on entry, they are more likely to incur the switching costs to exit. I estimate that the CDL share among the young falls by 41 basis points following a one standard deviation increase in friend exposure to AV. This result suggests that observed declines in employment for young workers in occupations exposed to AI may have an important supply component (Brynjolfsson, Chandar and Chen, 2025). I also show that the results are specific to long-haul, heavy truck drivers, not finding similar results for local delivery and bus drivers, who have a lower share of their tasks exposed to AV technology.

I find evidence that labor market adjustments to disruptive technologies take place faster if information frictions are reduced. Comparing the response to AV testing in the metro Phoenix area, I find sharper effects in New York following AV testing in San Francisco. The results align with greater knowledge diffusion across more socially connected regions (Diemer and Regan, 2022). In placebo tests, I show that friend exposure to metropolitan areas without large-scale AV testing is not associated with statistically significant changes in the CDL share. I also find support for the baseline estimate in an out-of-sample analysis in that the share of employment in truck driving falls disproportionately in areas with higher social exposure to AV. Cumulatively, the evidence indicates that individuals with friends in early AV hot spots reduced their supply of labor to trucking more, relative to neighbors who had weaker ties to these locations.

Using the American Community Survey (ACS), I document complementary evidence on the intensive margin in terms of hours worked per driver and on real earnings, both of which are positively associated with exposure to AV testing. The results are consistent with a precautionary saving motive in that workers who revise their subjective displacement expectations upward work more to accumulate a buffer stock of savings (Deaton, 1991; Carroll, 1997; Low, Meghir and Pistaferri, 2010).[3] The latter is also consistent with workers demanding increased compensation for displacement risk.

I then show that increased displacement risk may have reduced drivers' willingness to take on a mortgage. Life cycle portfolio choice theory suggests that less wealth would be allocated to risky assets such as stocks and real estate when the value of human capital, a relatively safe asset, falls (Gomes, Jansson and Karabulut, 2024). In this context, drivers may perceive a diminishment in the value of their human capital, not from the normal course of aging, but rather due to heightened displacement risk from the rollout of autonomous vehicles and artificial intelligence more broadly. Alternatively, the result may reflect a shift in households' long-term liquidity management behavior, as they reduce exposure to a fixed payment schedule.

Finally, I document evidence for the proposed mechanism: drivers, receiving information about self-driving cars through their social networks, revise their beliefs about their susceptibility to automation. Higher displacement expectations may be accompanied by an increase in anticipatory anxiety. Using the NielsenIQ Consumer Panel, I show that relatively more exposed households—

[3] Jiang et al. (2025) also find evidence of increased working hours in AI-exposed occupations which they attribute to enhanced productivity and monitoring of workers.

those who have more friends in AV testing locations and where the head of household has a driving-related occupation—increased spending on alcohol and tobacco products, consumption of which has been linked to anxiety disorders and self-medication of anxiety symptoms (Kushner, Abrams and Borchardt, 2000; Dee, 2001; Morissette et al., 2007; Dávalos, Fang and French, 2012). These results are complementary to other studies that rely on different methods in indicating that many drivers have negative sentiment towards and concerns about automation (Shoag, Strain and Veuger, 2021; Orii et al., 2021; Van Fossen et al., 2023). While some workers may have engaged in wishful thinking, the licensing and employment results suggest that others acted upon their revised forecasts about their occupation's automatability. In other words, I find evidence of effects of social networks on both workers' beliefs and behavior.

My findings contribute to the growing literature on the economics of automation. Most closely related to my paper, Cavounidis et al. (2023) develop an overlapping generations model that shows that young workers receive an obsolescence rent for entering a risky occupation, where risk refers to facing a negative labor demand shock with an uncertain date. They document stylized facts consistent with their model for teamsters, dressmakers, and milliners in the early 20$^{\text{th}}$ century, finding mixed evidence regarding the current state of trucking employment.[4] Using a more empirical approach, I provide causal estimates for the anticipatory effects of automation on the supply of truckers in the modern era with heightened concerns about new technologies.

My focus on displacement risk is closely associated with a collection of financial economics papers on labor income risk. One branch of the literature studies wage premia in highly levered firms (Titman, 1984; Berk, Stanton and Zechner, 2010; Agrawal and Matsa, 2013; Graham et al., 2023; Dore and Zarutskie, 2023). In equilibrium, employees receive a compensating differential for unemployment risk associated with working for a financially distressed firm. A second branch links innovative activities to increased displacement risk and falls in workers' human capital (Gârleanu, Kogan and Panageas, 2012; Kogan et al., 2020, 2023). For firms, perceived displacement risk may affect capital structure decisions (Matsa, 2018). Building on induced innovation and technology adoption logic in which labor scarcity raises automation (Zeira, 1998; Acemoglu and Restrepo, 2019; Hémous et al., 2025), the subjective displacement beliefs highlighted here may also generate a novel self-fulfilling feedback loop: as households reduce labor supply to occupations they view as high risk, labor costs in those occupations rise, thereby intensifying firms' incentives to automate.

More broadly, my results add to a literature examining the role of social networks in shap-

[4] Castex, Chow and Dechter (2024) illustrate similar patterns for a broader set of occupations.

ing households' decision making. Researchers estimate network and peer effects in the context of social distancing during the pandemic (Bailey et al., 2024), mortgage refinancing (Maturana and Nickerson, 2019), job finding (Gee, Jones and Burke, 2017), stock market and saving participation (Cannon, Hirshleifer and Thornton, 2024), insurance take-up (Hu, 2022), and trading behavior (Hirshleifer, Peng and Wang, 2024).

The remainder of this paper is structured as follows: Section I outlines the conceptual framework; Section II discusses the institutional background; Section III presents the data; Section IV describes the direct effects of AV testing in California; Section V reports social spillovers in New York State; Section VI provides evidence on the underlying mechanism; and Section VII concludes.

I Conceptual Framework

In this section, I set up a stylized equation, illustrating the key trade-off underpinning the empirical analysis.

Suppose individuals are infinitely lived. Each worker computes the present value of her labor income stream from her current occupation i relative to that from an alternative occupation j. Workers remain in their current occupation if the following inequality holds:

$$\frac{w_i}{r+\tilde{\delta}} \geq \frac{w_j}{r} - c \quad \forall j \neq i. \tag{1}$$

Let r denote the risk-free rate. The wage term w can equivalently be thought of as the dividend or yield on human capital, a nontradable asset (Viceira, 2001). I assume that labor income is uninsurable, and I abstract away from a hedging demand given the low share of financial market participation among individuals in my sample (see Table 1).

Subjective displacement risk $\tilde{\delta}$ reduces the present value of each worker's current occupation relative to her outside option. The trade-off is starker for entrants because they face no switching costs, denoted by c. Displacement risk in an occupation reflects the uncertainty of an upcoming labor demand adjustment, in terms of capital substituting for labor which would induce a reduction in employment and wages in that occupation. The uncertainty could be in the form of whether or when such an adjustment will occur.

Equation 1 demonstrates that increased subjective displacement expectations can generate a leftward shift in labor supply in anticipation, in partial equilibrium. Although a new automation technology could shift displacement risk across several occupations at once, I focus on a single focal occupation for simplicity, treating risk in all other occupations as fixed. Equivalently, $\tilde{\delta}$ can represent relative or incremental displacement risk in the focal occupation.

II Institutional Background

This section provides a brief institutional background relevant for the research designs I implement. For a more comprehensive survey charting the history and technical research on self-driving cars, see Badue et al. (2021). See Viscelli (2016) and Levy (2023) for detailed descriptions of the modern trucking industry. For characteristics of the industry before and after the Carter deregulation specifically, refer to Zingales (1998).

II.1 Autonomous Vehicle Testing

For subjective displacement expectations to affect households' decision making, it is crucial that the new labor displacing technology is salient. Autonomous vehicles (AVs) are one such technology. Self-driving cars and trucks have received much commercial and media attention due to their large potential labor market impacts.[5] A National Academies report predicted that self-driving vehicles would have become widespread by now, with significant effects on the employment of long-haul truckers (National Academies of Sciences, Engineering, and Medicine, 2017). Hype surrounding the diffusion of AV has intensified and waned over the years; however, rapid occupation loss in the transportation sector remains a concern.

Although news and academic articles are sources of public signals that can shift displacement beliefs, I rely on a setting that produces cross-sectional variation in private signals and, subsequently, in displacement beliefs in order to estimate causal effects. While AV testing has a rich history, going back many decades, I focus on the large-scale testing and deployment of robotaxi services in Arizona and California. Waymo (formerly known as the Google Self-Driving Car Project) was the first to offer rides in autonomous vehicles to the general public. Waymo initiated public trials of autonomous ride-hailing in the metro Phoenix area via its Early Rider Program in 2017, launching a commercial service dubbed Waymo One in the following year. In 2021, Waymo launched a similar pilot program in San Francisco, with Cruise (a subsidiary of General Motors) following soon after.[6]

[5] Conor Dougherty, "Self-Driving Trucks May Be Closer Than They Appear," *New York Times*, November 13, 2017.

[6] The California Department of Motor Vehicles suspended Cruise's AV permits on Oct 24, 2023. In December 2024, General Motors shut down Cruise's robotaxi operations.

In 2024, Waymo began operations in Los Angeles, starting with a restricted number of testers before opening up its ride-hailing service to all residents.

II.2 The Trucking Industry

> *If you got it, a truck brought it to you! If you got your food, your clothing, your medicine; if you got fuel for your homes, fuel for your industries, a truck brought it to you. The day our trucks stop, America stops!*
>
> – Al Pacino as Jimmy Hoffa, former President of the Teamsters Union, in *The Irishman*

The trucking industry is large. Echoing the epigraph to this section, 63% of total freight (by value) was transported by truck in the United States in 2021, including 75% of domestic shipments.[7] The Department of Transportation (DOT) valued the trucking industry as a whole at $389.3 billion, corresponding to 1.7% of gross domestic product in 2021. The Bureau of Labor Statistics (BLS) estimated that there were upwards of 3.5 million individuals in the "driver/sales workers and truck drivers" occupation category in 2022, 86% of whom were truck drivers (BLS, Occupational Employment and Wage Statistics). Heavy and tractor-trailer truck drivers specifically composed almost two million workers, which may be an underestimate considering that a number of self-employed truckers are not counted in the BLS data (Viscelli, 2018). Not only is trucking a large source of employment, it is also geographically widespread, representing the most common occupation in 29 states.[8]

Trucking is sometimes characterized as a job of last resort, a recourse for workers desiring to maintain their standard of living after the loss of a previously held job. Phares and Balthrop (2022) document that the non-employed compose the largest category of workers who enter the trucking profession. The other top occupations contributing to inflows of new truckers include transportation and material moving workers as well as those in construction and extraction roles. The welfare impact of AVs could be sizable if fewer trucking jobs exist to cushion blue-collar workers against job losses and the accompanying large, persistent effects on earnings and mortality (Sullivan and von Wachter, 2009; Braxton and Taska, 2023; Fallick et al., 2025; Cockriel, 2025).[9]

To the extent that unions can promote job security, truckers' displacement risk due to AVs is

[7] See *Freight Facts and Figures*, developed by the Bureau of Transportation Statistics, part of the Department of Transportation.

[8] Quoctrung Bui, "Map: The Most Common Job In Every State," *NPR*, February 5, 2015.

[9] At the same time, self-driving technology could lead to a large reduction in the number of lives lost in motor vehicle accidents (Kalra and Groves, 2017).

mitigated. While membership data is scarce, it is apparent that rates have fallen dramatically from their heyday in the 1970s. Using the Current Population Survey, I show that the self-reported union share among driver/sales workers and truck drivers is less than 10% (see Appendix Figure A.1). Viscelli (2016, 2018) reports that union membership is concentrated among less-than-truckload firms and parcel companies and is rare among long-haul, full-truckload drivers. It is the latter group who are more likely to be among the first targets of automation, given that their jobs have essentially been reduced to the task of driving (Mohan and Vaishnav, 2022).

III Data

III.1 Waymo Introduction

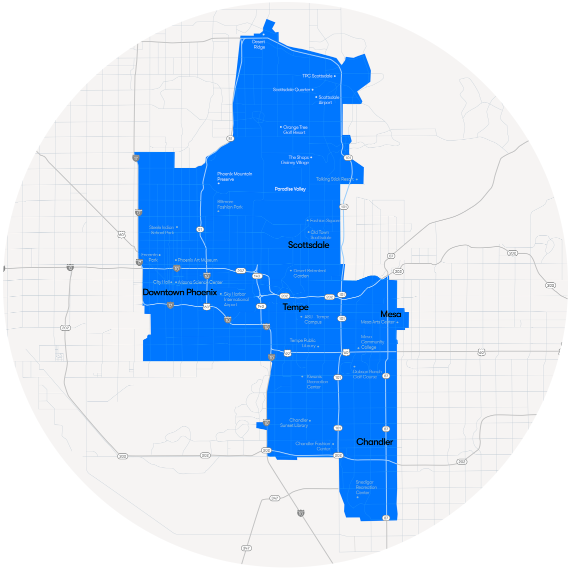
Using publicly available maps of Waymo's service areas, I manually identify all zip codes with autonomous ride-hailing accessible to the general public from 2017 to 2024. The data cover 136 zip codes in four metropolitan areas (Figure 1). In 2017, self-driving car coverage was limited to zip codes in Chandler, Tempe, and Mesa in the Phoenix metro area. In 2021, coverage expanded to San Francisco, and again in 2022, to downtown Phoenix. By 2024, Waymo's commercial operations had expanded further to Los Angeles and Austin.

Communities living within these service areas had ubiquitous exposure to self-driving cars, unlike virtually anywhere else. Indeed, an examination of Google Trends shows that even within metropolitan areas, normalized search volume for "Waymo" concentrates in exactly the places where self-driving cars were first deployed (Appendix Figure A.2).

III.2 Commercial Driver Licenses

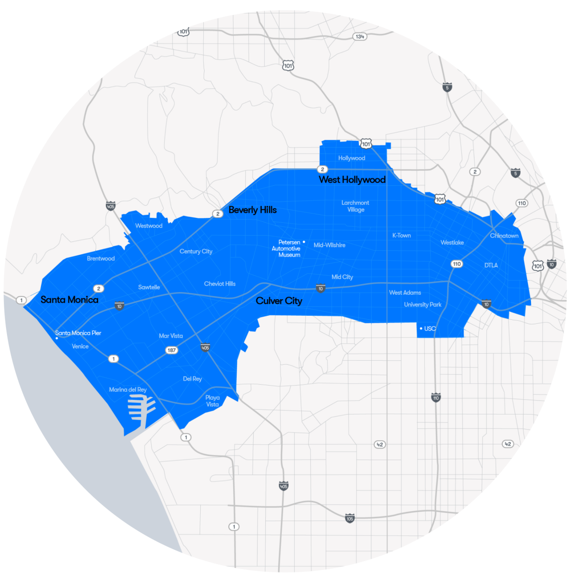
Given that there is no federal repository of commercial driver licenses (CDLs) in the United States, I obtain records from two state driver licensing agency systems. I rely on Waymo deployments in San Francisco and Los Angeles to estimate direct effects of AV-exposure in California, and deployments in suburban and downtown Phoenix and San Francisco to measure social spillovers in New York State. I omit Los Angeles and Austin from the latter tests due to limited data availability.

The California Department of Motor Vehicles maintains a card history record, consisting of salient details about each license or identification card issued to a given individual. Through a Freedom of Information Act (FOIA) request, I obtained annual counts of active driver licenses at



(a) Phoenix

(b) San Francisco



(c) Los Angeles

(d) Austin

Figure 1: Waymo Service Areas. The figures depict Waymo's service areas as of December 2024.

the zip code level from January 1, 2012 to June 9, 2025, with a breakdown by class and type.[10]

[10]Only one license is considered active for an individual at any given time. A license is considered to be 'active' from its issue date to the day prior to the next license's issue date or until it has been expired for 90 days, whichever comes first, and is counted as the active card for a given year if it was active as of December 31 of that year.

These data measure the stock of outstanding driver licenses in each zip code and year. As of 2024, I observe approximately 28 million driver licenses in California, of which approximately 550 thousand are Class A CDLs. Class A license holders are permitted to operate vehicles such as tractor-trailers with a gross combination weight rating (GCWR) of more than 26,000 pounds, where the towed vehicle's Gross Vehicle Weight Rating (GVWR) is over 10,000 pounds.

In contrast, the New York State data capture new driver license issuances, a flow measure. I acquired a snapshot provided by the New York Department of Motor Vehicles containing 16,406,138 de-identified records from all non-expired driver licenses, permits, or non-driver identification cards as of June 16, 2023.[11] The data include demographics such as the license holder's age, sex, and zip code, and details about the license including class, status, and expiration year. Since licenses are valid for 8 years in New York State, I can infer the year of issuance from the expiration year.

The sample is composed of 211,147 truckers who obtained a Class A CDL between 2015 and 2023. The data include all new issuances and do not allow classification of first-time CDL holders versus those who renewed their CDLs. Table 1a presents descriptive statistics for Class A CDL holders in New York State who tend to be middle-aged men on average.

In both datasets, I restrict subsequent analyses to zip-years that include at least 5 Class A CDL holders, and I omit zip codes that fail this criterion in any given year. Zip codes can be considered accurate to a point, based on the timeliness with which individuals reported their change of address after a move. I restrict the samples to California and New York State zip codes only. In New York, I omit licenses without full driving privileges, namely those that serve as identification cards only.

III.3 Population Survey

The American Community Survey (ACS) is representative of the U.S. population, and it is richer than the licensing data in terms of information collected. Respondents self-report their demographics, education, housing status, occupation, and earnings among other characteristics. I use the 1% samples from the 2012-2021 ACS 1-year files obtained from the Integrated Public Use Microdata Series (IPUMS) database.[12] The ACS microdata are only available at a coarser geography: public use microdata areas (PUMAs). I build a zip code to PUMA crosswalk using Census tracts.[13]

[11] See https://data.ny.gov/.

[12] Due to the effects of the COVID-19 pandemic on data collection, the Census Bureau advises against comparing the ACS 2020 microdata 1-year file to other ACS microdata sample years. I therefore exclude it from the analysis. After 2021, the ACS uses new PUMA definitions, rendering comparisons with earlier sample years highly imprecise.

[13] Census tracts are fully contained within PUMA boundaries and form the fundamental units of PUMA geography. Using the Census provided zip code to tract relationship file, I assign each tract to the zip code where the tract has the largest population share, winsorizing at the left tail at the 1% level. I then use the Census provided tract to

	Mean	SD	p10	p25	p50	p75	p90	N
Age	46.81	14.62	27.00	36.00	48.00	58.00	65.00	211,147
Female	0.02	0.14	0.00	0.00	0.00	0.00	0.00	211,147

(a) New York State

	Mean	SD	p10	p25	p50	p75	p90	N
Age	47.17	13.91	27.00	37.00	49.00	58.00	64.00	307,059
Female	0.06	0.24	0.00	0.00	0.00	0.00	0.00	307,059
Non-white	0.20	0.40	0.00	0.00	0.00	0.00	1.00	307,059
College	0.12	0.33	0.00	0.00	0.00	0.00	1.00	307,059
Hours worked	44.69	14.44	26.00	40.00	40.00	50.00	60.00	301,929
Real earnings (2010)	36.95	34.02	6.82	17.79	32.29	47.49	65.40	307,059
Mortgage	0.68	0.47	0.00	0.00	1.00	1.00	1.00	219,975
Investment income	0.07	0.25	0.00	0.00	0.00	0.00	0.00	307,059

(b) American Community Survey

	Mean	SD	p10	p25	p50	p75	p90	N
New York CDL share (%)	2.69	2.13	0.73	1.18	2.05	3.69	5.45	8,112
California CDL share (%)	2.81	2.27	0.46	1.12	2.33	3.90	5.72	28,295
ACS Driver share (%)	2.53	1.19	1.14	1.63	2.36	3.24	4.12	19,338

(c) Driver shares

Table 1: Summary Statistics. Panel (a) shows summary statistics for Class A commercial driver license holders in New York State. Panel (b) shows summary statistics for driver/sales workers and truck drivers in the ACS. Real earnings are reported in thousands of dollars using 2010 as the base year. Panel (c) shows summary statistics for Class A commercial license issuances in New York State as a share of total driver license issuances at the zip code level, active Class A commercial licenses in California as a share of total active licenses at the zip code level, and employment in the driver/sales workers and truck drivers category in the ACS as a share of the labor force at the PUMA level.

Table 1b presents descriptive statistics for driver/sales workers and truck drivers. Relative to heavy truck and tractor-trailer operators in New York State, there are more women represented in the ACS data. The vast majority of the workers in the latter dataset are employed as truck drivers (BLS, Occupational Employment and Wage Statistics). In addition, most of them are high school not college educated. A common misconception is that truckers are highly compensated. The ACS data indicate that this is not the case on average. However, hours worked, and hence earnings, may

PUMA relationship file to establish the crosswalk.

be higher than documented in Table 1 given that truckers have strong incentives to underreport them (Viscelli, 2016). Most of them have mortgages outstanding, and few report receiving any income in the form of an estate or trust, interest, dividends, royalties, and rents. It is unlikely that drivers hedge displacement risk by buying stocks negatively correlated with their income prospects, given the low share of those with investment income.

Despite differences in measurement of local trucking employment across datasets, Table 1c shows that driver shares range from 2-3% on average. Both the New York and California data measure Class A CDL employment at the zip code level, but the former tracks issuances and the latter captures the stock of active licenses. The ACS, in contrast, measures employment in truck driving as a share of the labor force at the PUMA level.

III.4 Social Networks

Since individuals' actual friendship networks are unobservable, I rely on an aggregated measure of social connectedness. Following Bailey et al. (2018), I use the Social Connectedness Index (SCI), computed as of October 2021:

$$\mathrm{SCI}_{i,j} = \frac{FB \text{ Connections}_{i,j}}{FB \text{ Users}_i * FB \text{ Users}_j}, \tag{2}$$

where FB Connections$_{i,j}$ is the total number of Facebook friendship links between Facebook users living in location i and Facebook users living in location j. Dividing by the product of Facebook users in each location, the SCI measures the probability that Facebook users in a pair of locations are friends with each other.[14] Previous research has shown that Facebook data are representative of the U.S. population and that they reflect real, offline friendships between people (Bailey et al., 2018). The network is relatively constant over time, capturing long-term, historic connections between people in different geographies (Bailey et al., 2024; Hirshleifer, Peng and Wang, 2024).

The heat maps in Appendix Figure A.3 plot the SCI for Maricopa County (Figure A.3a) and San Francisco County (Figure A.3b) with respect to other counties in the United States. Social connectedness is higher among geographically close counties with Maricopa County having stronger ties to counties in the Mountain states and similarly San Francisco to counties on the West Coast. At the same time, there are strong pockets of connections across the country, notably for San Francisco with counties in the Northeast. Importantly, there is substantial variation in social connectedness

[14]The publicly available measure of the SCI that I use here is scaled to have a maximum value of 1,000,000,000 and a minimum value of 1; therefore, it measures relative, not actual, probabilities.

in the two maps.

III.5 Spending

My final source of data is the NielsenIQ Consumer Panel.[15] This dataset tracks high-frequency household expenditures on nondurable goods such as groceries, cosmetics, and general merchandise. Households use in-home scanners to record all of their purchases intended for personal, in-home use.

The Consumer Panel also contains households' demographic information, including crucially zip code of residence and occupation categories. I focus on respondents where the head of household is in a driving-related occupation as of the 2021 panel year and data are non-missing for all months until December 2022. The occupation categories are coarse. The one capturing drivers also includes closely related blue-collar occupations, specifically factory/transportation workers and factory machine operators. However, approximately half of the workers within this occupation category are motor vehicle operators based on corresponding entries in the BLS Occupational Employment and Wage Statistics. I further limit the dataset to male respondents within this category to better match drivers in my main sample.

IV Direct Effects of AV on Licensing

I first document the direct effects of AV testing on driver-licensing behavior in California. I then turn to an analysis of the social transmission of displacement risk in New York State, where the data are richer and concerns about the endogenous entry of self-driving cars are mitigated. I begin by estimating difference-in-differences specifications of the form:

$$Y_{i,t+1} = \alpha_i + \sum_{t \neq -1} \beta_t \left(\text{AV}_i \times \text{Event Year}_t \right) + \gamma_t' X_{i,t} + \varepsilon_{i,t+1}. \tag{3}$$

where $Y_{i,t+1}$ is the number of active Class A CDLs as a share of total active licenses within zip code i as of year $t+1$. α_i represents zip code fixed effects. AV_i is an indicator equal to 1 if Waymo deployed self-driving cars in zip code i over the sample period, and Event Year_t is an indicator for the event year of the outcome. The coefficient for the year preceding an event is omitted for reference.

$X_{i,t}$ includes various covariates from the 5-year ACS (2017-2021) for zip code i at year t interacted with year fixed effects. These include the median age, female share, bachelor's degree share, non-

[15] The data is provided by the Kilts Center at the University of Chicago Booth School of Business.

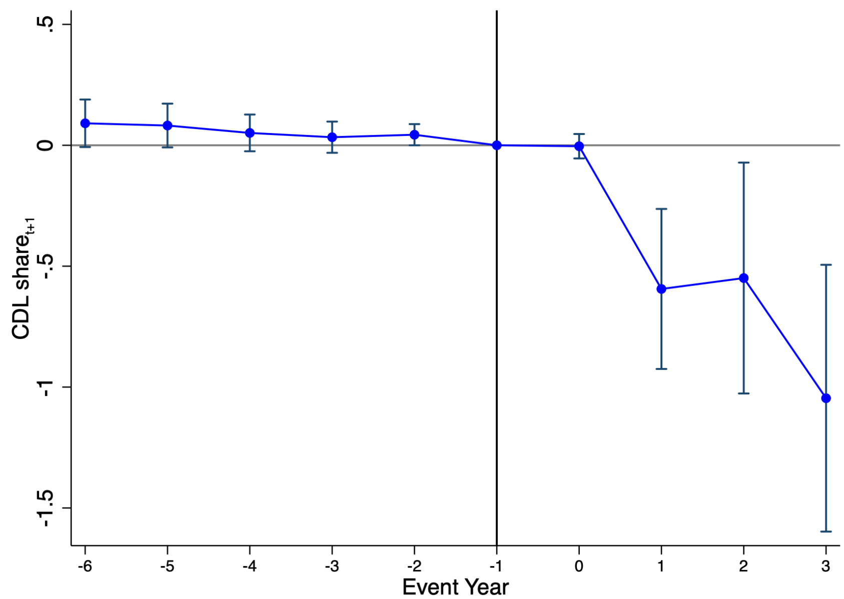


Figure 2: AV Testing in California. This figure plots coefficients estimated from a stacked difference-in-differences analysis based on whether AV testing took place within a zip code (treated) as of the sample period. The control units are the never-treated zip codes. The outcome variable is the share of Class A commercial driver licenses in a zip code. The specifications include zip code by stack and year by stack fixed effects and fixed effects for the following groups, interacted with dummies for each year: county, median age, female share, non-white share, bachelor's degree share, population density, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

white share, population density, median earnings, and friend-weighted density and earnings. The latter two measures are constructed in a similar fashion to equation 5 described below. In order to isolate an anticipatory labor supply channel, I also include county-year fixed effects, which absorb variation in local conditions, in particular demand for truck drivers. Effectively, with these fixed effects, I am comparing drivers living in the same county but in different zip codes which have varying levels of exposure to AV.

Given potential issues with staggered difference-in-differences designs when there is treatment effect heterogeneity, Figure 2 reports results from a stacked regression where treated zip codes are only compared to never-treated units (Baker, Larcker and Wang, 2022). Estimated treatment effects are near zero in the pre-period and they are negative and statistically significant following the launch of AV testing. The interpretation is that fewer people are renewing their Class A CDLs and that there are fewer entrants into this license class following AV exposure. The point estimates in the post-period correspond to a 0.6 to 1% decline in the CDL share, suggesting a strong reaction

	CDL share$_{2025}$	CDL share$_{2025}$	CDL share$_{2025}$	CDL share$_{2025}$
AV Trips$_{2022-2024}$	-0.20***	-0.16***	-0.16***	-0.11*
	(0.042)	(0.056)	(0.051)	(0.061)
County FE	NO	NO	YES	YES
Census Controls	NO	YES	NO	YES
Adj. R-squared	0.12	0.72	0.10	0.72
Observations	68	68	68	68

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: AV Trips. This table reports cross-sectional regressions at the zip code level of the share of Class A commercial driver licenses in 2025 on the number of Waymo self-driving car trips from 2022 to 2024. AV trips is a standardized measure of the total number of trips ending in each zip code. The controls include median age, female share, non-white share, college share, population density, and median earnings.

in zip codes that experienced a rollout of AV. The standard errors are larger in the post-period given the small number of zip codes in California that had AV deployments prior to 2024. I find that estimated dynamic effects are similar under alternative designs and with log outcomes (e.g, Appendix Figures A.4, A.5, and A.6).

In Table 2, I show evidence that the intensity of AV exposure is associated with larger effects. Using publicly available data from the California Public Utilities Commission (CPUC), I show that zip codes that had a greater number of AV trips in 2022-2024 had disproportionately lower CDL shares in 2025.[16] Column (1) reports that a 1 standard deviation increase in AV trips is associated with a 20 bp lower CDL share. The correlation persists within county and with additional controls.

Localized declines in Class A CDL uptake following large-scale AV deployments in California demonstrate that workers exposed directly to robotaxi testing adjust their licensing decisions. Yet in labor markets without active AV trials, workers may receive private signals about automation that can reshape their displacement expectations and, in turn, their occupational choices. Next, I turn to this broader, anticipatory channel. By exploiting variation in Facebook-based social connectedness to Phoenix and San Francisco (the first AV testbeds), I trace how news of autonomous vehicles propagates through networks to influence licensing behavior in New York State. This social-network-driven approach isolates the impact of subjective displacement risk, extending the analysis beyond AV's direct geographic footprint.

[16]The data can be obtained from https://www.cpuc.ca.gov/regulatory-services/licensing/transportation-licensing-and-analysis-branch/autonomous-vehicle-programs/quarterly-reporting.

V Effects of Friend Exposure to AV on Licensing

V.1 Empirical Strategy

The empirical analysis in this section aims to estimate the causal link between occupation and location-specific labor supply and the associated risk of automation-induced displacement.[17] Specifically, I relate the labor supply of truckers within a zip code Y_i to the level of subjective displacement risk in a given period $Disp\tilde{R}isk$:

$$Y_i = \alpha + \delta Disp\tilde{R}isk_i + \gamma' X_i + \epsilon_i. \tag{4}$$

Unfortunately, identifying δ from equation 4 is challenging for two reasons. First, directly eliciting displacement beliefs is difficult due to selection issues in who chooses to become or remain a truck driver. At any given time, one would need to survey a representative sample of all workers who have considered or dismissed truck driving as a viable occupation. Second, beliefs are typically equilibrium objects; thus, one cannot assume that they are uncorrelated with the levels of the outcome.

To overcome these challenges, an ideal experiment would involve having workers randomly update their displacement expectations (Golin and Rauh, 2022). As this is likely infeasible outside of a laboratory, I instead rely on the quasi-exogenous geographical rollout of AV testing, news of which diffuses differentially along social networks, to identify the impact of increased subjective displacement risk. I construct my social network-based exposure measure, as an instrument for subjective displacement expectations, as:

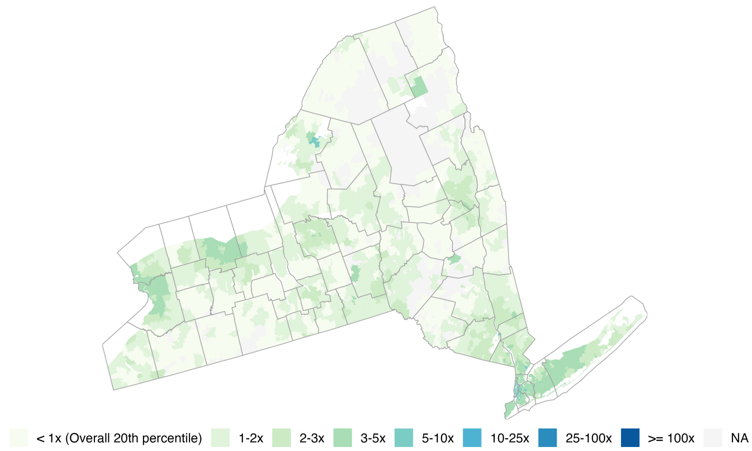
$$\text{Friend Exposure to AV}_{i,t} = \sum_j \frac{\text{SCl}_{i,j}}{\sum_h \text{SCl}_{i,h}} * \mathbb{1}\left\{\text{AV}_{j,t}\right\}. \tag{5}$$

For an individual living in zip code i, her friend exposure to AV at time t is the sum over all zip codes j in the U.S., with an indicator for whether AV testing is occurring, multiplied by her normalized social exposure to those zip codes.[18] The measure is a friend-weighted average of exposure to AV testing.

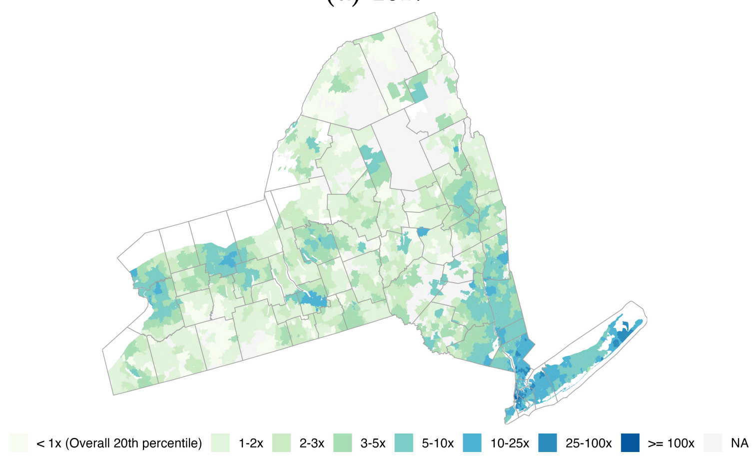
The heat maps in Figure 3 illustrate the changing geography of friend exposure in New York State, as increasingly more zip codes were exposed to AV testing via their social networks. In

[17] The exposition of my baseline empirical strategy is similar to Xu (2022).

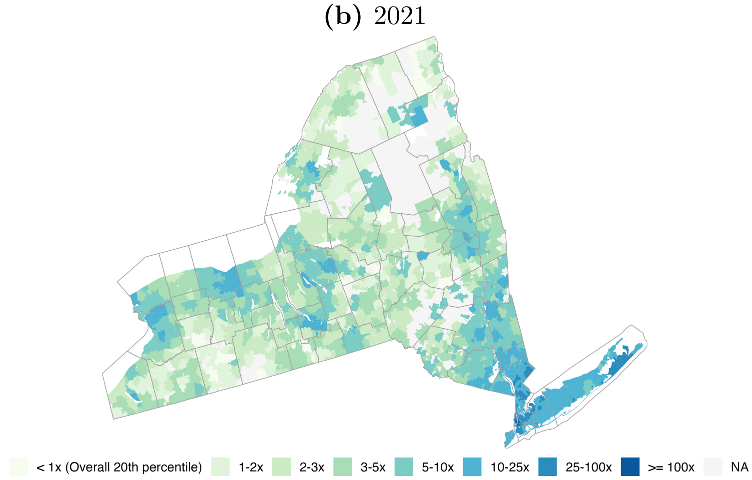
[18] While the SCI is defined at the ZIP Code Tabulation Areas (ZCTA) level, I refer to zip codes instead here and in all subsequent analyses for simplicity. I also standardize friend exposure for interpretability.



(a) 2017



(b) 2021



(c) 2022

Figure 3: Friend Exposure to Autonomous Vehicles. This figure plots zip code level friend exposure to autonomous vehicles (AVs) as defined in equation 5 for New York State. Panel (a) depicts friend exposure as of 2017. Panel (b) and (c) do so for 2021 and 2022 respectively. Darker colors correspond to higher friend exposure.

2017, early hot spots included New York City, Buffalo, Rochester, and Watertown. By 2021, communities in Long Island and Ithaca experienced the largest changes in friend exposure. In 2022, new hot spots included Syracuse and Albany. In aggregate, the largest growth in friend exposure occurred following AV testing in San Francisco and downtown Phoenix, reflecting the high social connectedness of urban areas.

Importantly, the sizable temporal and geographic variation in the maps indicates that different communities in New York State received news about AV from their friends at different times. In other words, in each year, different individuals happen to be most exposed to AV testing. Table A.1 shows the demographic correlates of changes in friend exposure. The magnitudes and the correlations are time-varying. For instance, in 2017, zip codes with higher median earnings had more exposure to AV testing; however, this relationship flipped in later years as testing expanded to San Francisco and downtown Phoenix.

V.2 Friend Exposure and Licensing Behavior

I study the relationship between friend exposure to AV and subsequent labor market adjustments by estimating the following reduced-form equation using comprehensive licensing data from New York State:

$$Y_{i,t+1} = \alpha_i + \beta \text{ Friend Exposure to AV}_{i,t} + \gamma_t' X_{i,t} + \epsilon_{i,t+1}. \tag{6}$$

I define $Y_{i,t+1}$ as Class A CDL issuances as a share of total license issuances within zip code i as of year $t+1$. α_i represents zip code fixed effects. $X_{i,t}$ captures a range of characteristics for zip code i at year t: time-varying ones such as the mean age and female share from the licensing data, and various covariates interacted with year fixed effects from the ACS. As before, I include county-year fixed effects which absorb variation in local demand conditions.

For β to receive causal interpretation, the identifying assumption is that the time-varying effects of unobservables are not systematically correlated with changes in friend exposure. Since AV deployment in Phoenix and San Francisco over time is likely exogenous with regard to workers' occupational decisions, particularly for those living in distant labor markets, the assumption is a plausible one.

Given the identifying assumption, Table 3 presents the results of the exposure research design. Column (1) shows that a 1 standard deviation increase in friend exposure leads to a 38 basis point

	CDL share_{t+1}	CDL share_{t+1}	CDL share_{t+1}	CDL share_{t+1}
Friend Exposure_t	-0.38***	-0.40**	-0.17**	-0.23**
	(0.14)	(0.16)	(0.070)	(0.089)
Zip Code FE	NO	NO	YES	YES
County-Year FE	YES	YES	YES	YES
License Controls	NO	YES	NO	YES
Census Controls-Year FE	NO	YES	NO	YES
Adj. R-squared	0.16	0.29	0.75	0.75
Observations	2160	2160	2160	2160

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Licensing in New York State. This table reports the results of regression 6. The outcome variable is the share of Class A commercial driver licenses in a zip code. Friend exposure is defined as in equation 5. The license controls include mean age and female share. The Census controls by year fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

(bp) decline in the CDL share. When including the full set of control variables in column (2), the point estimate remains approximately the same. Columns (3) and (4) incorporate the zip code specific fixed effects to account for unobservable time-invariant factors in the error term. These specifications are akin to two-way fixed effects (TWFE) regressions, where friend exposure captures the interaction of a post-treatment period indicator and a measure of treatment intensity. The final point estimate is -23 bps, which represents a 9% reduction relative to the mean CDL share. If one can extrapolate the baseline estimate to the entire U.S. labor market, a 1 standard deviation increase in friend exposure to AV results in a fall of approximately 180,000 drivers (9% of the 2 million heavy truck and tractor-trailer operators counted in the 2022 BLS Occupational Employment and Wage Statistics).

A reduction in trucking employment could result from either fewer new drivers entering the profession or more existing drivers leaving. In other words, people may be less likely to become truckers, or current drivers might switch to other occupations (or retire). Over a short time frame, changes in the CDL share—and thus coefficients in Table 3—are more likely to reflect new entries rather than exits, as commercial drivers typically would not cancel their licenses when leaving the profession, simply allowing them to expire instead. Although approximately 10,500 (5%) drivers voluntarily surrendered their CDLs over the sample period, the results remain robust to removing them (Appendix Table A.2). Additionally, concerns about measurement error in the form of inaccurate zip code information are minimized, since the Department of Motor Vehicles verifies addresses at the time of license issuance.

Importantly, I find that the impact of friend exposure to AV on the CDL share is stronger among younger workers. Specifically, the magnitudes of the estimated coefficients of friend exposure are almost twice as large for the sample of drivers below the median age in 2017 (Table 4).[19] Column (4) shows that the CDL share among the young falls by 0.41% following a one standard deviation increase in friend exposure to AV. This suggests that younger individuals are more sensitive to perceived displacement risk: they are less likely to enter an occupation when displacement risk rises, and those who do enter are more likely to incur the switching costs to exit. This result is consistent with the predictions of the overlapping generations model in Cavounidis et al. (2023) and may inform interpretations of reduced employment of young workers in AI-exposed occupations as in Brynjolfsson, Chandar and Chen (2025). Alternatively, since younger people are more likely to observe content about self-driving cars online, the coefficients may instead reflect higher effective exposure.

In addition, I show that the results are specific to Class A drivers. After controlling for zip code fixed effects, I do not find analogous results for Class B license and permit holders, who tend to work locally and operate buses or single-unit trucks rather than tractor-trailers (Appendix Table A.3). Within a task-based framework, these drivers spend a larger share of their time on activities such as customer service, vehicle inspection, and freight loading and unloading—tasks that are largely unaffected by AV technology and therefore less susceptible to automation. The attenuated point estimates in columns (3) and (4) suggest that Class B license holders responded less to news about AV, consistent with higher reported concerns for long-haul truckers (Viscelli, 2018; Gittleman and Monaco, 2020; Mohan and Vaishnav, 2022).

Instead of isolating particular zip codes where AV testing is occurring, an alternative approach uses a broader definition. It is reasonable to consider all zip codes within the Phoenix and San Francisco metropolitan areas as AV testing locations, given that all residents of these cities can potentially interact with self-driving cars. My results are strongly robust to incorporating this broader definition of AV testing in equation 5 (Appendix Table A.4). However, I maintain the more granular measure of friend exposure in my main tests because it has more temporal variation (expansion of AV testing in the Phoenix metro area from 2017 to 2022). There may also be a salience factor in that individuals who live within AV testing areas encounter and ride in the vehicles more

[19] The median age of 42 is computed in the unrestricted license dataset. I split the sample to focus on the share of young CLass A CDL holders relative to total young drivers which cannot be conveyed with interaction terms in Table 4.

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.58*	-0.84**	-0.29*	-0.41**
	(0.34)	(0.35)	(0.17)	(0.19)
Zip Code FE	NO	NO	YES	YES
County-Year FE	YES	YES	YES	YES
License Controls	NO	YES	NO	YES
Census Controls-Year FE	NO	YES	NO	YES
Adj. R-squared	0.10	0.22	0.80	0.80
Observations	1240	1240	1240	1240

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Young Drivers in New York State. This table reports the results of regression 6. The outcome variable is the share of Class A commercial driver licenses in a zip code among drivers 42 years old and younger. Friend exposure is defined as in equation 5. The license controls include mean age and female share. The Census controls by year fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

frequently, making them more likely to communicate news about AV to their social networks.

V.3 Dynamics of Licensing Behavior

To get a better sense of how average treatment effects evolve over time, I employ a difference-in-differences methodology within the following TWFE event study specification:

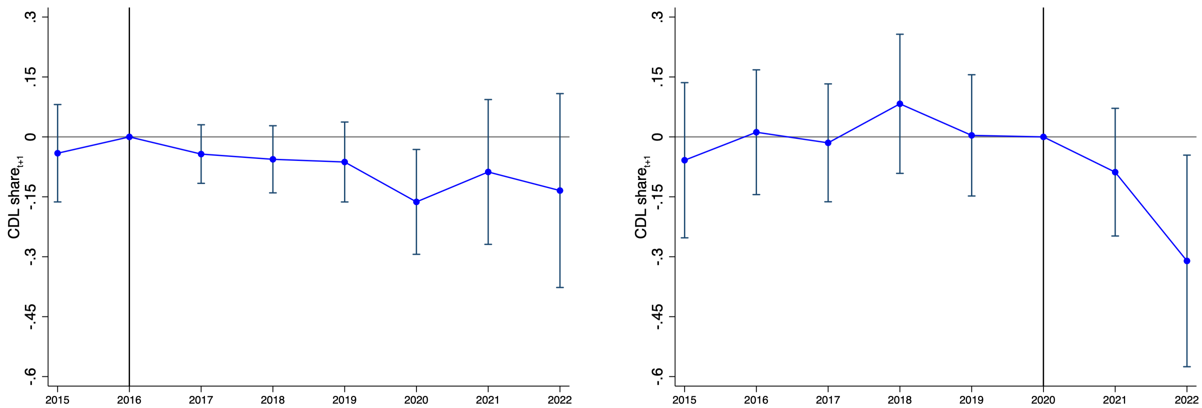
$$Y_{i,t+1} = \alpha_i + \sum_{t \neq -1} \beta_t \left(\text{HighExp}_i \times \text{Year}_t\right) + \gamma_t' X_{i,t} + \varepsilon_{i,t+1}. \tag{7}$$

$Y_{i,t+1}$, X_{it}, and α_i are defined as before. HighExp_i is an indicator equal to 1 if zip code i has friend exposure greater than the median friend exposure within its county as of 2017 or 2021, and Year_t is an indicator for the year of the outcome. The coefficient for the year preceding an event is omitted for reference.[20]

I isolate the response to AV testing in Chandler, Tempe, and Mesa in 2017 and in San Francisco in 2021, excluding the downtown Phoenix expansion which may have been anticipated. While estimated coefficients for treatment effects fall following AV testing in metro Phoenix (Figure 4a), the decline in estimated coefficients is sharper following AV testing in San Francisco (Figure 4b).[21]

[20] Appendix Figure A.7 documents average CDL shares over time by HighExp_i.

[21] Unlike equation 3, these tests do not suffer from potential issues related to staggered difference-in-differences designs because all units experience simultaneous shifts in social exposure to AV that differ only in magnitude not timing.



(a) Event: AV Testing in Phoenix Metro Area

(b) Event: AV Testing in San Francisco

Figure 4: Difference-in-Differences. The figures plot coefficients estimated from a difference-in-differences analysis based on whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2017 (Panel a) or 2021 (Panel b). The outcome variable is the share of Class A commercial driver licenses in a zip code. The specifications include age and gender controls, fixed effects for each zip code, and fixed effects for the following groups, interacted with dummies for each year: county, population density, bachelor's degree share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

This exercise illustrates that labor market adjustments to disruptive technologies can take place faster if information frictions are relaxed. On average, high exposure zip codes experience a relative fall in their CDL shares by approximately 30 bps after the launch of large-scale robotaxi services in San Francisco. The results in Figure 4 align with higher social connectedness—and hence faster information diffusion—between urban areas such as New York and San Francisco, compared to New York and suburban communities in Phoenix's East Valley (Diemer and Regan, 2022).

A concern with the previous tests is that the friend exposure measure captures general information gleaned from social networks, such as the state of the economy or advances in AI more broadly, that can affect licensing behavior, rather than specific news about AV deployments. To address this concern, I conduct placebo tests which compute friend exposure to counterfactual AV testing zip codes. I use nearest neighbor matching without replacement to assign each test location to another within the contiguous United States but outside of Maricopa and San Francisco counties. Appendix Figure A.8 shows that matched zip codes, which did not have large-scale AV testing, are highly similar on observables to zip codes in metro Phoenix and San Francisco which did have AV testing. Given the similarity (and in some cases proximity) of the matched zip codes to the true testing locations, indirect information transmission about AV testing could negatively bias the placebo estimates.

I repeat the difference-in-differences methodology specified in equation 7 using the alternative measure of friend exposure. Figure A.9 presents analogous estimates to those in Figure 4. The placebo analyses suggest that specific news about AV matters. Splitting zip codes into treatment and control units on the basis of friend exposure to a "synthetic" Phoenix or San Francisco does not yield statistically significant estimates, despite the potential of negative bias.

Another related concern is that social connectedness may be correlated with unobservable differences between individuals that independently affect licensing behavior following the rollout of AV. Political affiliation may be one example, insofar that it drives friendship links with Phoenix and San Francisco and differential time-varying expectations about the trucking industry (Mian, Sufi and Khoshkhou, 2023). Indeed, while high and low friend exposure zip codes are similar along a number of dimensions, they also differ in terms of the bachelor's degree share and median earnings (Appendix Table A.5). While the placebo tests partially address this concern, I perform further tests below. Following the approach in Bailey et al. (2024), I relate changes in friend exposure to changes in licensing behavior each year as AV testing expanded geographically:

$$\Delta Y_{i,t+1} = \sigma_0 + \sigma_1 \Delta \text{ Friend Exposure to AV}_{i,t} + \sigma_{2,t}' X_{i,t} + \epsilon_{i,t+1}. \tag{8}$$

For σ_1 to receive causal interpretation, the identifying assumption is the same as before: the time-varying effects of unobservables are not systematically correlated with changes in friend exposure. The first difference estimator encapsulates the weaker condition of contemporaneous exogeneity rather than strict exogeneity which underlies the previous TWFE specifications. Moreover, this dynamic formulation allows me to focus on the effects of changes in friend exposure, controlling for previous changes in friend exposure.

Column (1) of Table 5 shows that a 1 standard deviation increase in friend exposure to AV, induces a 10 bp fall in the CDL share. In columns (2-4), I split the sample to focus on pivotal years and include prior changes in friend exposure as controls. I find that reductions in the CDL share are driven by the most recent increase in friend exposure, primarily following AV testing expansion in San Francisco and downtown Phoenix. For these results to be explained by unobserved factors rather than reflecting a causal impact of friend exposure to AV on the CDL share, one would have to argue that, year after year, zip codes with social ties to regions where AV testing was introduced

	Δ CDL share$_{t+1}$	Δ CDL share$_{2018}$	Δ CDL share$_{2022}$	Δ CDL share$_{2023}$
Δ Friend Exposure$_t$	-0.10**			
	(0.047)			
Δ Friend Exposure$_{2017}$		-0.038	0.089	1.31*
		(0.19)	(0.48)	(0.75)
Δ Friend Exposure$_{2021}$			-0.071**	-0.066
			(0.033)	(0.041)
Δ Friend Exposure$_{2022}$				-0.88**
				(0.44)
County FE	YES x YEAR	YES	YES	YES
Census Controls FE	YES x YEAR	YES	YES	YES
Adj. R-squared	0.16	0.12	0.11	0.14
Observations	1890	270	270	270

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Changes in Licensing in New York State. This table reports the results of regression 8. The outcome variable is the yearly change in the share of Class A commercial driver licenses in a zip code. Friend exposure is defined as in equation 5. The Census controls fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

happened to cut back on their trucking workforce for reasons unrelated to social exposure to labor displacing technologies.

V.4 Out-of-Sample Analysis

I find support for the previous findings in an out-of-sample analysis using the American Community Survey (ACS). I first aggregate friend exposure to the PUMA level by summing across relevant zip codes j using the crosswalk described in Section III:

$$\text{Friend Exposure to AV}_{k,t} = \sum_{j \in k} \text{Friend Exposure to AV}_{j,t}. \tag{9}$$

This measure captures how much signal each PUMA k receives collectively about AV; however, my results are robust to taking averages instead. Next, I estimate equation 6 in the broader ACS sample, covering all states and the District of Columbia.[22]

As before, I include county-year fixed effects to absorb variation in local conditions and to allow

[22] I require each PUMA-year observation to include at least 5 drivers, and I exclude PUMAs that fail this criterion in any given year. All variables are weighted by the corresponding Census provided person and household survey weights.

	Driver share$_t$	Hours worked$_t$	Real earnings$_t$ (IHS)	Mortgage$_t$
Friend Exposure$_t$	-0.033***			-0.26*
	(0.011)			(0.15)
Friend Exposure$_{t-1}$		0.19***	0.026***	
		(0.031)	(0.0061)	
PUMA FE	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Controls-Year FE	YES	YES	YES	YES
Adj. R-squared	0.48	0.13	0.100	0.36
Observations	7200	6400	6400	7200

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Labor and Financial Outcomes of Drivers. This table reports the results of regression 6. The outcome variables are driver/sales workers and truck drivers as a share of the PUMA labor force, the usual hours worked per week in the preceding 12 months, the inverse hyperbolic sine (IHS) of the real earnings over the preceding 12 months, and the fraction of outstanding mortgages. Friend exposure is defined as in equation 5. The controls include mean age, female share, non-white share, and college share. The controls by year fixed effects include: population density, median earnings, and network-weighted density and earnings. Standard errors are clustered at the state level.

for a comparison between truck drivers living in nearby but different PUMAs with differential friend exposure.[23] Column (1) of Table 6 shows that employment in truck driving, as a share of the labor force, falls disproportionately in areas with higher social exposure to AV deployment in Phoenix and San Francisco. Quantitatively, a 1 standard deviation higher friend exposure is associated with a fall in the driver share by 3 bps, corresponding to 1.2% relative to the mean driver share in 2016.

Two important caveats about this analysis are that the sample ends in 2021, only one year into San Francisco's large-scale AV testing experiment, which motivated my choice of contemporaneous outcomes instead of leads, and secondly, drivers here belong to a larger occupational group. Although not entirely comparable, these two factors can explain the lower magnitude of the point estimate, relative to those in Table 3.

Leveraging the richness of the ACS, I analyze the relationship between friend exposure to AV and additional labor and financial outcomes. Specifically, column (2) of Table 6 documents a small increase in weekly work duration by 12 minutes associated with 1 standard deviation higher friend

[23] Geographically large PUMAs, mainly in rural, low-density areas, are omitted automatically because they are not contained within a county.

exposure. Column (3) shows a positive association between friend exposure and real earnings. Given that a large fraction of truck drivers are self-employed, I focus on real earnings as opposed to wages.[24] I use the lag of friend exposure given that drivers reported their usual hours worked and real earnings over the preceding 12 months.[25] Finally, column (4) illustrates a negative association between friend exposure and the fraction of drivers with outstanding mortgages.

In combination, the ACS results suggest that the labor supply of truckers responded negatively to the deployment of AV on the extensive margin but increased slightly on the intensive margin. The latter is consistent with a precautionary saving motive in that workers who revise their subjective displacement expectations upward work more to accumulate a buffer stock of savings (Deaton, 1991; Carroll, 1997; Low, Meghir and Pistaferri, 2010). While the real earnings result is also consistent with workers demanding increased compensation for displacement risk (Cavounidis et al., 2023).

Heightened expectations of displacement, as a form of background risk, may also induce a desire to rebalance one's exposure to risky assets (Gomes, Jansson and Karabulut, 2024). The mortgage share result indicates that drivers may have had reduced willingness to invest in real estate and carry a positive mortgage balance following the rollout of AV. At the same time, the result may indicate that households prefer to hold less debt following an increase in labor income risk for liquidity reasons.

VI Mechanism

Based on the conceptual framework in Section I, workers switch occupations when subjective displacement risk rises. The preceding analyses use friend exposure to automation technologies as an instrument, in the reduced-form, for such risk to show that workers adjust their labor market behavior in anticipation of future displacements. In this section, I provide support for the first-stage in that workers revise their displacement expectations when exposed to news about automation via their social networks.

Using the NielsenIQ Consumer Panel, I first compute monthly total spending for 2,365 households where the head of household had a driving-related occupation as of the 2021 panel year and data are non-missing for all months until December 2022 (the results are robust to this choice).

[24] Approximately 30% of workers in the trucking industry are self-employed while 88% of long-distance trucking businesses are nonemployers (Day and Hait, 2019). The Bureau of Transportation Statistics, using Federal Motor Carrier Safety Administration registration data, estimates owner-operators were 11.1% of all truck drivers as of November 2023.

[25] As a consequence, columns (2) and (3) only reflect the impact of friend exposure to AV testing in Phoenix.

I also compute spending on alcohol and tobacco products specifically, consumption of which has been linked to anxiety disorders and self-medication of anxiety symptoms (Kushner, Abrams and Borchardt, 2000; Dee, 2001; Morissette et al., 2007; Dávalos, Fang and French, 2012). Changes in substance use among exposed households following friend exposure to AV may reflect automation-induced anxiety and a revision in households' beliefs about their susceptibility to automation.

I estimate the following equation:

$$Y_{i,k,t+1} = \mu_i + \beta \left(\text{HighExp}_k^{2021} \times \text{Post}_t\right) + \gamma_t' \left(X_i \times \text{Month}_t\right) + \varepsilon_{i,k,t+1}, \tag{10}$$

where the outcome variable captures spending by household i located in zip code k in month $t+1$. HighExp_k is defined as before, an indicator equal to 1 if zip code k has friend exposure greater than the median friend exposure within its county as of August 2021. Unlike all the previous estimations which relied on geographical aggregates, I can include household-level fixed effects μ_i in this specification due to the longitudinal nature of the consumer data. X_i includes fixed effects for the county of residence, household size, household income, race, age, education, and network-weighted density and earnings. These are interacted with month fixed effects to absorb time-varying effects of location, household, and network characteristics.

Table 7 presents estimates of β, conveying whether high-exposure households have a differential spending response following the initiation of AV testing. Column (1) shows that the coefficient of interest is statistically indistinguishable from zero for total household expenditures on nondurable goods. However, column (2) shows a precisely estimated increase in spending on alcohol and tobacco products. Following the launch of AV testing in 2021, high-exposure households increase spending on these legal substances by \$2.6, which is 15% relative to the mean in July 2021.[26] Columns (3) and (4) show that this increase is driven by higher expenditure on both alcoholic beverages and tobacco products separately. The statistically significant, positive spending response is not present among workers in any other occupation category or in other broad spending categories (Appendix Figures A.10 and A.11).[27]

Complementary to other studies, these results suggest that friend exposure to automation induced an increase in anticipatory anxiety among households in driving-related occupations (Shoag,

[26] The majority of households do not report purchasing alcoholic beverages and tobacco products in a given month. The results are robust to dropping households that never report alcohol or tobacco consumption over the sample period.

[27] I omit occupation group 11 due to limited observations. I further omit occupation groups 7, 9, 10, and 12 which refer to members of the armed forces, farmers, students, and those outside the labor force respectively.

	Total Spending$_{t+1}$	Alcohol and Tobacco$_{t+1}$	Alcohol Only$_{t+1}$	Tobacco Only$_{t+1}$
High Exposure x Post	6.72	2.60***	1.45**	1.16**
	(14.3)	(0.94)	(0.73)	(0.52)
Household FE	YES	YES	YES	YES
County-Month FE	YES	YES	YES	YES
Controls-Month FE	YES	YES	YES	YES
Mean of Outcome	856.3	17.4	13.5	3.88
Adj. R-squared	0.66	0.64	0.58	0.74
Observations	42918	42918	42918	42918

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Spending response to displacement risk. This table reports the results of regression 10. The outcome variables are monthly total spending and monthly spending on alcohol and tobacco. High exposure indicates whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2021. The controls by month fixed effects include: household size, household income, race, age, education, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

Strain and Veuger, 2021; Orii et al., 2021; Van Fossen et al., 2023). Although some workers may have engaged in wishful thinking as described by Engelmann et al. (2024), the combination of the results in sections V and VI indicate that others acted upon their revised forecasts about their occupation's automatability.

VII Conclusion

The consequences of technological change hinge on how adversely affected households fare. My paper highlights that, far from being passive recipients of technology shocks, these households proactively adjust their labor supply, occupational choices, and financial behavior before jobs are automated. Social networks facilitate the diffusion of information about emerging risks, shaping the timing and magnitude of adjustments across places.

These anticipatory responses may themselves lead to a self-fulfilling prophecy. As households reduce labor supply to occupations they perceive as vulnerable, labor costs in those occupations rise, further strengthening firms' incentives to automate (Zeira, 1998; Acemoglu and Restrepo, 2019; Hémous et al., 2025). In this way, subjective displacement beliefs not only forecast but also accelerate the pace of innovation and adoption of automation technologies.

Although there are a number of advantages to my empirical approach, it is worth repeating certain limitations. First, individuals' actual friendship networks are unobservable, so I rely on an aggregated zip code level measure, namely the SCI. Second, my measure of friend exposure to AV lends itself to estimating the marginal effect of private signals about AV, not aggregate effects from public signals which may be quantitatively larger.

My results suggest that welfare assessments evaluating the impact of automation may be inaccurate if they fail to account for an anticipatory channel. Moreover, the findings may also have implications for the design and timing of retraining programs and information treatments to better enable households to adjust to automation. An important avenue for further research is to examine the effects of displacement risk on a broader range of occupations, especially those affected by recent advances in artificial intelligence and robotics.

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Appendix A

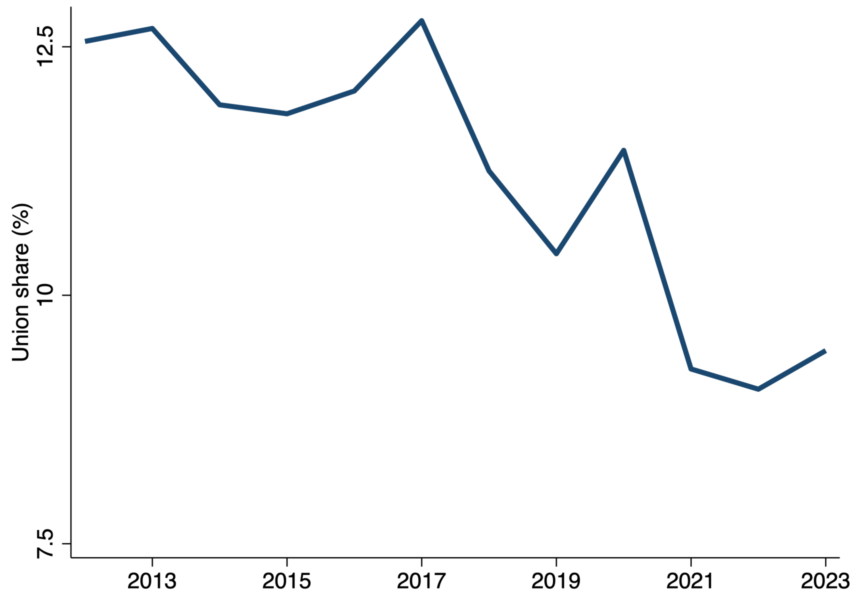
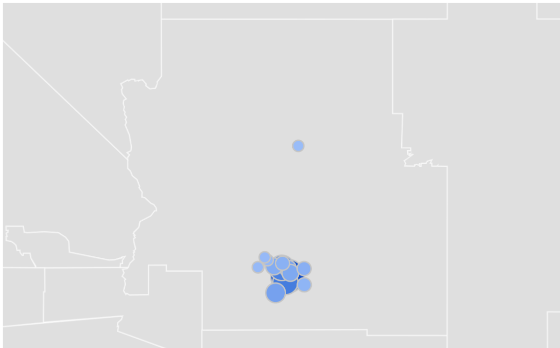
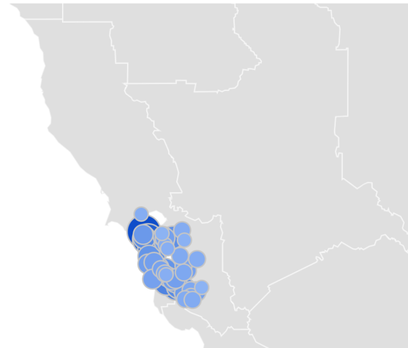


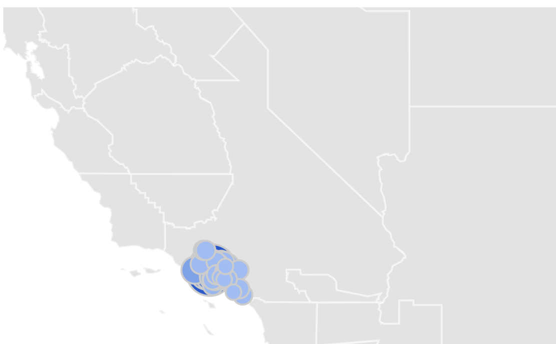
Figure A.1: Union Share. This figure reports the self-reported union share among driver/sales workers and truck drivers in the Current Population Survey.



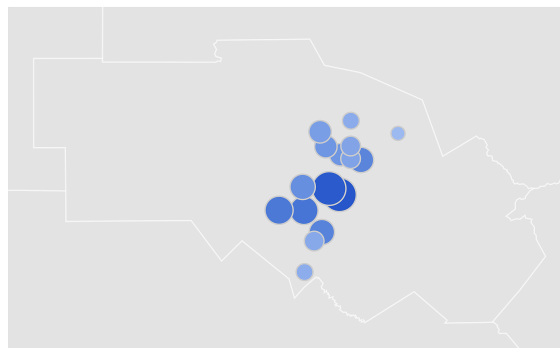
(a) Phoenix



(b) San Francisco

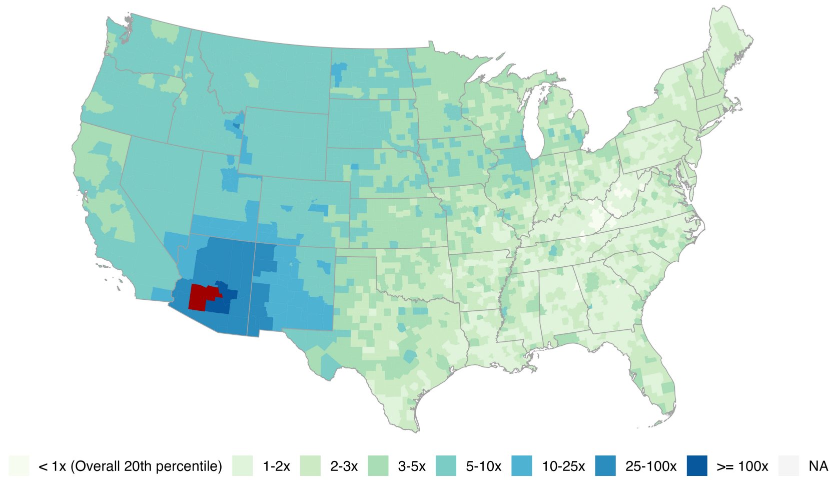


(c) Los Angeles

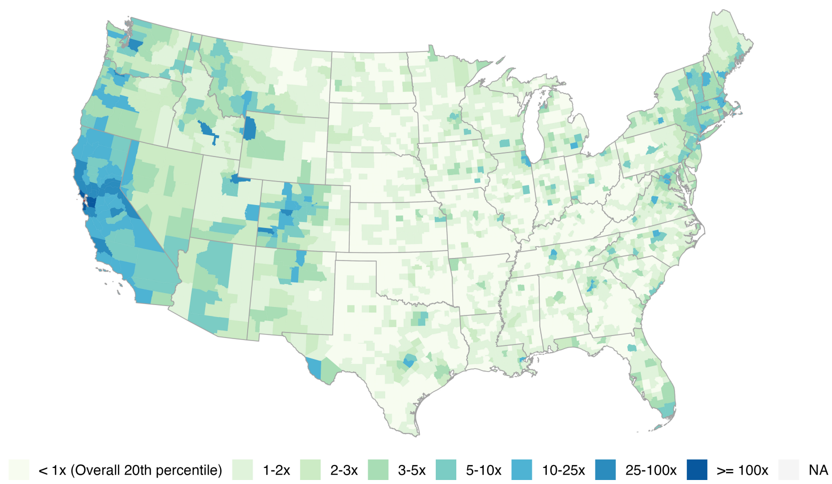


(d) Austin

Figure A.2: Google Trends. This figure plots aggregate Google searches for 'Waymo' in the Phoenix, San Francisco, Los Angeles, and Austin metro areas. The data cover the calendar years of 2017 (Panel a), 2021 (Panel b), and 2024 (Panels c & d). Darker colors correspond to higher normalized search intensity.



(a) Maricopa County, AZ



(b) San Francisco County, CA

Figure A.3: Social Connectedness Index. This figure plots the county-level social connectedness index (SCI) computed as of October 2021 as defined in equation 2. Panel (a) shows the SCI for Maricopa County, Arizona with respect to other counties in the United States. Panel (b) does so for San Francisco County, California. The focal county is represented in red. Darker colors correspond to higher social connectedness.

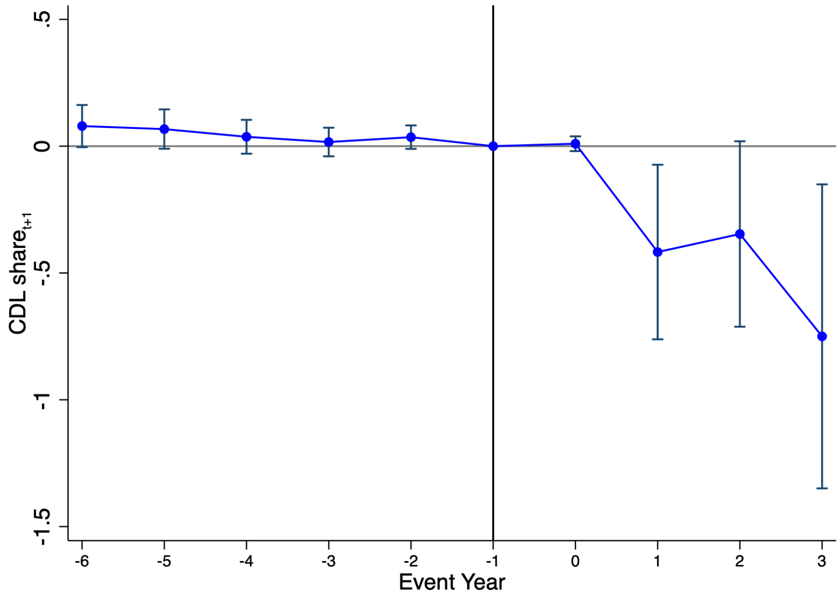


Figure A.4: Difference-in-Differences. This figure plots the results of regression 3. The outcome variable is the share of Class A commercial driver licenses in a zip code. The specifications include fixed effects for each zip code and fixed effects for the following groups, interacted with dummies for each year: county, median age, female share, non-white share, bachelor's degree share, population density, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

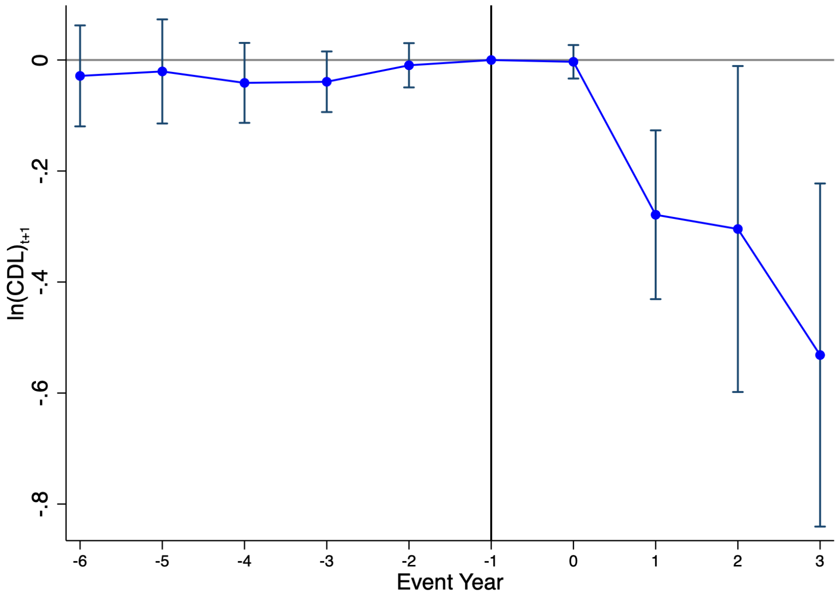


Figure A.5: Log Difference-in-Differences. This figure plots coefficients estimated from a stacked difference-in-differences analysis based on whether AV testing took place within a zip code (treated) as of the sample period. The control units are the never-treated zip codes. The outcome variable is the natural log of the number of Class A commercial driver licenses in a zip code. The specifications include zip code by stack and year by stack fixed effects and fixed effects for the following groups, interacted with dummies for each year: county, median age, female share, non-white share, bachelor's degree share, population density, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

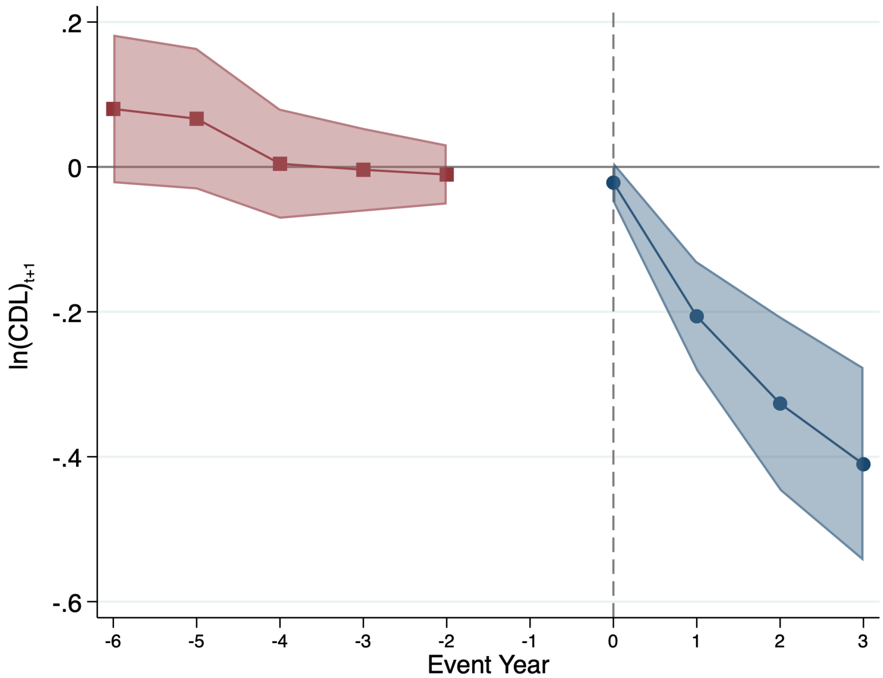
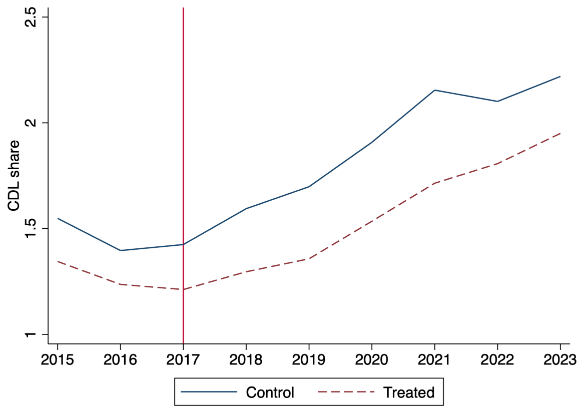
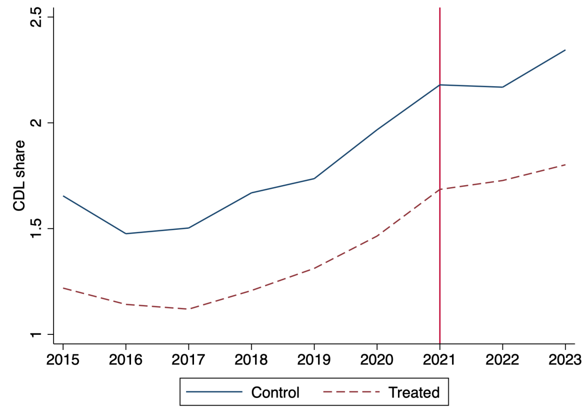


Figure A.6: Alternative Estimator. This figure plots the estimated coefficients and the associated 95% confidence intervals for dynamic treatment effects using the Sun and Abraham (2021) estimator. The treated units consist of zip codes which had AV testing during the sample period. The control units are the never-treated zip codes. The outcome variable is the natural log of the number of Class A commercial driver licenses in a zip code. The specifications include fixed effects for each zip code and fixed effects for the following groups, interacted with dummies for each year: county, median age, female share, non-white share, bachelor's degree share, population density, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.



(a) Event: AV Testing in Phoenix Metro Area



(b) Event: AV Testing in San Francisco

Figure A.7: Raw means. The figures plot time-series averages based on whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2017 (Panel a) or 2021 (Panel b). The y-axis shows the mean share of Class A commercial driver licenses.

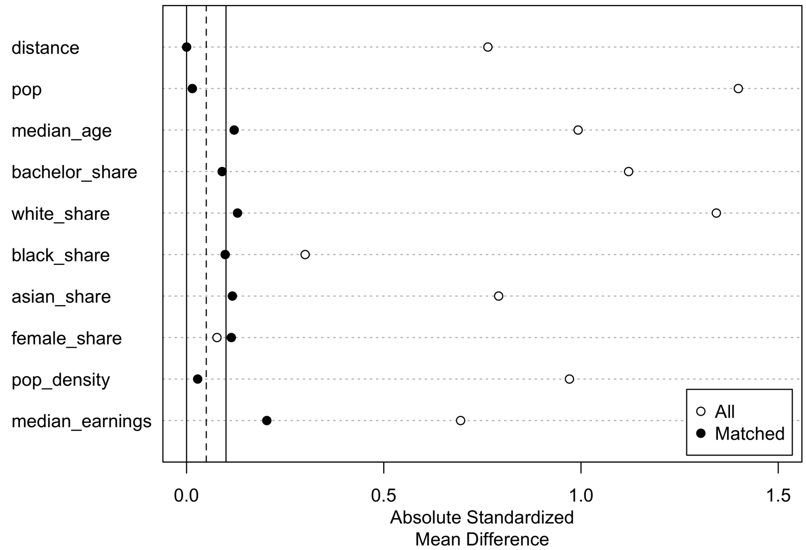
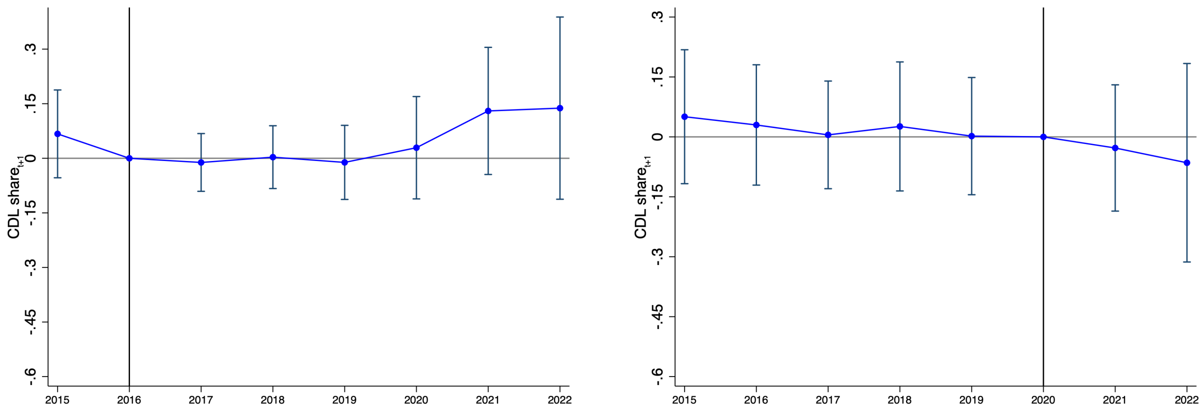


Figure A.8: Balance Plot. This figure reports absolute standardized mean differences in covariates between AV testing locations and matched zip codes as well as between AV testing locations and all zip codes. The matching pool includes all zip codes in the contiguous United States, excluding those in Maricopa and San Francisco counties. The covariates are total population, median age, bachelor share, white share, black share, Asian share, female share, population density, and median earnings. The matching algorithm was 1:1 nearest neighbor matching without replacement on the propensity score. Vertical lines indicate thresholds of 0, .05, and .1.



(a) Event: AV Testing in "Synthetic" Phoenix **(b)** Event: AV Testing in "Synthetic" San Francisco

Figure A.9: Placebo Tests. The figures plot coefficients estimated from a difference-in-differences analysis based on whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2017 (Panel a) or 2021 (Panel b). Friend exposure is calculated to propensity score matched zip codes relative to those with actual AV testing. The outcome variable is the share of Class A commercial driver licenses in a zip code. The specifications include age and gender controls, fixed effects for each zip code, and fixed effects for the following groups, interacted with dummies for each year: county, population density, bachelor's degree share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

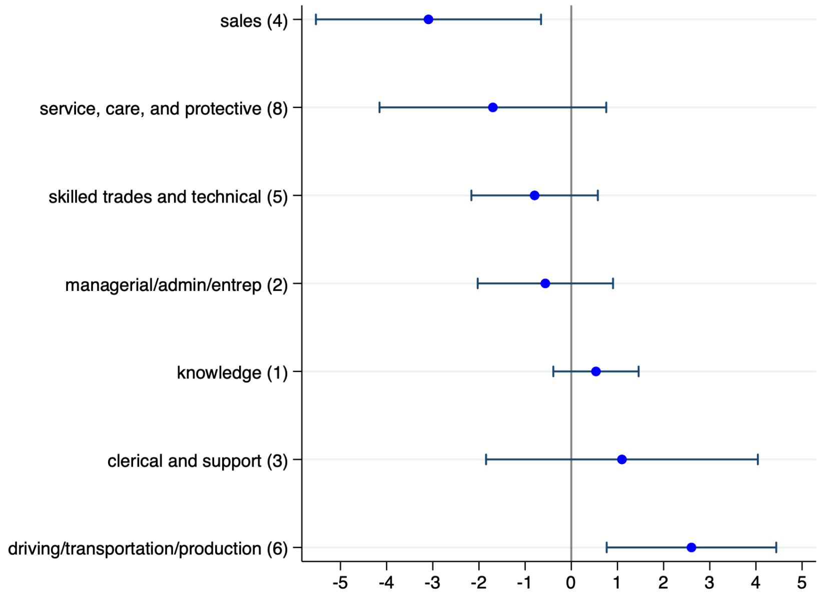


Figure A.10: Alcohol and Tobacco Spending. This table reports the results of regression 10 among households by male head occupation category. NielsenIQ Consumer Panel occupation codes are in parentheses. The outcome variable is the monthly total spending on alcohol and tobacco products. High exposure indicates whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2021. The controls by month fixed effects include: county, household size, household income, race, age, education, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

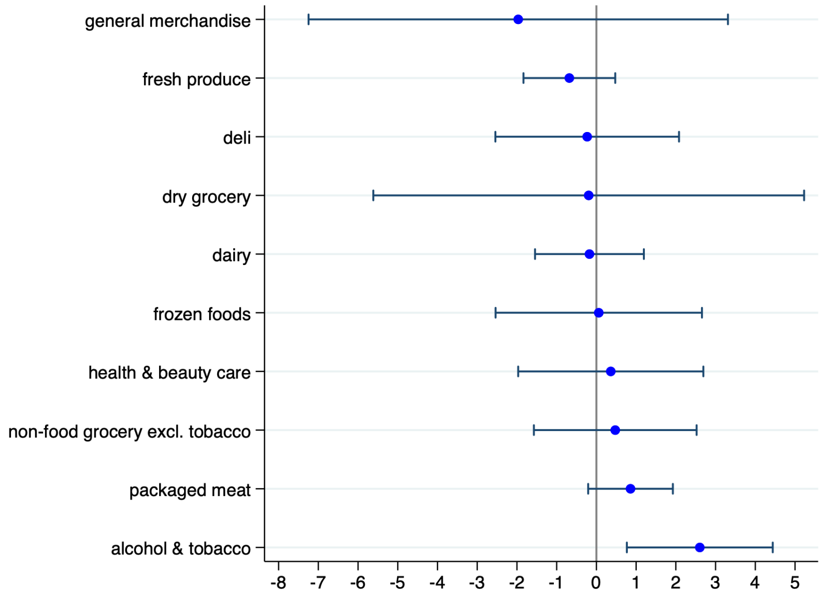


Figure A.11: Total Spending by Category. This table reports the results of regression 10. The outcome variable is monthly total spending. High exposure indicates whether a zip code was above (treated) or below (control) the median friend exposure to AV within its county as of 2021. The controls by month fixed effects include: county, household size, household income, race, age, education, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

	Δ Friend Exposure$_{2017}$	Δ Friend Exposure$_{2021}$	Δ Friend Exposure$_{2022}$
Mean Age	-0.0084***	-0.032***	-0.0093***
	(0.00090)	(0.0080)	(0.0023)
Female Share	-0.46*	3.98	0.16
	(0.26)	(6.38)	(0.43)
Density	0.0038***	0.056***	0.016***
	(0.00045)	(0.0098)	(0.0013)
College	1.57***	21.9***	4.14***
	(0.30)	(3.81)	(0.72)
Non-white	0.15***	-0.46	0.51***
	(0.034)	(0.40)	(0.087)
Real earnings (2021)	0.0045***	-0.027***	-0.0017
	(0.0014)	(0.011)	(0.0026)
Adj. R-squared	0.72	0.69	0.87
Observations	284	284	284

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.1: Determinants of Change in Friend Exposure. This table reports the demographic correlates of change in friend exposure. Friend exposure is defined as in equation 5. Standard errors are clustered at the zip code level.

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.38**	-0.36**	-0.17*	-0.19*
	(0.16)	(0.18)	(0.085)	(0.10)
Zip Code FE	NO	NO	YES	YES
County-Year FE	YES	YES	YES	YES
License Controls	NO	YES	NO	YES
Census Controls-Year FE	NO	YES	NO	YES
Adj. R-squared	0.18	0.30	0.74	0.75
Observations	1960	1960	1960	1960

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Licensing in New York State, excluding exits. This table reports the results of regression 6. The outcome variable is the share of Class A commercial driver licenses in a zip code. I exclude drivers who voluntarily surrender their CDLs during the sample period. Friend exposure is defined as in equation 5. The license controls include mean age and female share. The Census controls by year fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

	CDL share_{t+1}	CDL share_{t+1}	CDL share_{t+1}	CDL share_{t+1}
Friend Exposure_t	-0.34***	-0.15***	-0.033**	0.026
	(0.048)	(0.048)	(0.015)	(0.025)
Zip Code FE	NO	NO	YES	YES
County-Year FE	YES	YES	YES	YES
License Controls	NO	YES	NO	YES
Census Controls-Year FE	NO	YES	NO	YES
Adj. R-squared	0.37	0.63	0.81	0.84
Observations	2024	2024	2024	2024

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Class B Licensing in New York State. This table reports the results of regression 6. The outcome variable is the share of Class B commercial driver licenses in a zip code. Friend exposure is defined as in equation 5. The license controls include mean age and female share. The Census controls by year fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.49***	-0.57***	-0.19**	-0.27**
	(0.19)	(0.21)	(0.086)	(0.11)
Zip Code FE	NO	NO	YES	YES
County-Year FE	YES	YES	YES	YES
License Controls	NO	YES	NO	YES
Census Controls-Year FE	NO	YES	NO	YES
Adj. R-squared	0.16	0.30	0.74	0.75
Observations	2160	2160	2160	2160

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Licensing in New York State (broad AV exposure). This table reports the results of regression 6. The outcome variable is the share of Class A commercial driver licenses in a zip code. Friend exposure is defined as in equation 5. The license controls include mean age and female share. The Census controls by year fixed effects include: population density, bachelor share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

	Low Exposure			High Exposure			
	Mean	SD	Count	Mean	SD	Count	Diff
Mean Age	35.68	3.37	154	35.84	3.53	130	-0.16
Female Share	0.02	0.03	154	0.03	0.05	130	-0.01
College	0.12	0.04	154	0.15	0.04	130	-0.03
Non-white	0.43	0.31	154	0.42	0.26	130	0.00
Density	16241.45	23538.29	154	18516.83	23515.30	130	-2275.38
Real earnings (2021)	39833.75	9294.35	154	43377.83	8994.27	130	-3544.08
SCI weighted density	6637.42	5633.28	154	7100.82	4995.53	130	-463.40
SCI weighted earnings	43078.77	5540.23	154	44873.63	4870.30	130	-1794.87

(a) 2017

	Low Exposure			High Exposure			
	Mean	SD	Count	Mean	SD	Count	Diff
Mean Age	35.59	3.45	154	35.95	3.43	130	-0.35
Female Share	0.03	0.04	154	0.02	0.04	130	0.00
College	0.12	0.04	154	0.15	0.04	130	-0.03
Non-white	0.43	0.32	154	0.42	0.25	130	0.01
Density	15659.30	22517.95	154	19206.45	24589.81	130	-3547.14
Real earnings (2021)	39903.07	8880.68	154	43295.72	9507.27	130	-3392.64
SCI weighted density	6592.24	5630.58	154	7154.34	4993.61	130	-562.09
SCI weighted earnings	42929.99	5433.53	154	45049.88	4940.97	130	-2119.89

(b) 2021

Table A.5: Summary Statistics of Zip Codes with High and Low Friend-Exposure to AV in 2016. High exposure zip codes have friend exposure to AV greater than the median of their county of 2017 (Panel a) or 2021 (Panel b).