End of the Road? Autonomous Vehicles and Displacement Risk

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Abstract

New technologies have motivated renewed concerns about job displacement. In this paper, I link workers' subjective displacement expectations to their social exposure to a disruptive technology. I find that the share of commercial driver licenses and employment in truck driving fall disproportionately in areas that are more socially connected to Phoenix and San Francisco, cities with large-scale autonomous vehicle testing. The remaining drivers extend their work hours and decrease participation in mortgage markets relative to less connected, neighboring drivers. The results suggest that welfare or policy assessments evaluating the impact of automation should account for an anticipatory channel.

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

JEL Classification: J2, O3, G5, D8, E2, R0

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Researcher's own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

In recent years, the classic debate between technology doomsayers and optimists has become relevant again.[1] On one end of the spectrum, commentators argue that artificial intelligence (AI) will completely displace labor, whereas others think that the current era is no different from previous ones. Historically, the creative destruction wrought by the adoption of new technologies has favored job creation over job destruction (Autor, 2015). Traditionally on the more optimistic side, academic economists have grown more concerned about technological change (Autor, 2022; Bond and Kremens, 2023; Jones, 2024; Korinek and Suh, 2024). Rather than taking a stance on the public debate, this paper analyzes how workers, 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). By contrast, less attention has been paid to the labor supply side of this phenomenon. In principle, rational, forward-looking workers 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 (Roy, 1951; Becker, 1964), empirical demonstrations have been scarce and inconclusive. Moreover, whether individuals update their beliefs about impending displacement—particularly when anticipatory anxiety and wishful thinking might cause them to downplay emerging risks—remains unclear (Engelmann et al., 2024). In this paper, I provide direct empirical evidence that workers 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 realize 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 (AV) (Viscelli, 2018; Gittleman and Monaco, 2020; Mohan and Vaishnav, 2022).

I rely on two main data sources. First, I obtain the universe of non-expired driver licenses in

[1] Sarah Kessler, "The A.I. Revolution Will Change Work. Nobody Agrees How.," *New York Times*, June 10, 2023.

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

the state of New York. The de-identified data allow me to distinguish commercial truck drivers, including heavy-duty truck operators, using the listed license classes. Second, I link the 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). Manually identifying zip codes with large-scale AV testing in the metro Phoenix area and San Francisco, I instrument for subjective displacement expectations using social connectedness to these areas, which uniquely had ubiquitous exposure to self-driving cars.[3] Robotaxis, while not same as autonomous trucks, are informative about the progress of self-driving technology. As such, information about their deployment and effectiveness, transmitted via social networks, may shift truck drivers' perceptions of displacement risk.

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 commercial driver license (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 20 basis points, corresponding to 11% relative to the mean. Extrapolating the baseline estimate, I report that a 1% increase in friend exposure to AV results in a fall of approximately 220,000 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 36 basis points following a 1% increase in friend exposure to AV.

I find evidence that labor market adjustments to disruptive technologies can take place faster if information frictions are reduced. Comparing the response to AV testing in Chandler, Tempe, and Mesa in 2017 to that in San Francisco in 2021, I find sharper effects following that latter. The results align with higher social connectedness and faster information diffusion between urban areas. 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

[3]Ricardo Cano, "Robotaxis debuted in two U.S. cities. Only S.F. has a problem with it.," *San Francisco Chronicle*, October 17, 2023.

that individuals with friends in Phoenix and San Francisco, reduced their supply of labor to trucking more, relative to neighbors who had weaker ties to these locations.

Beyond shifting employment, increased displacement risk can affect related labor and financial outcomes. 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 savings motive in that workers who revise their subjective displacement expectations upwards work more to accumulate a buffer stock of savings (Beshears et al., 2018). 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.

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—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; Degenhardt, Hall and Lynskey, 2001; Morissette et al., 2007). 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). 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 automatibility. 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^{th} century, finding mixed evidence regarding the current state of trucking employment. 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 AI.

My focus on displacement risk is closely associated with a collection of economics and finance papers on labor income risk. Some papers in this literature utilize subjective job loss expectations elicited as part of surveys (Stephens, 2004; Hendren, 2017; Mueller and Spinnewijn, 2023). Others use a more structural approach, linking innovative activities to increased displacement risk and falls in workers' human capital (Gârleanu, Kogan and Panageas, 2012; Kogan et al., 2020). Kogan et al. (2023) measure workers' exposure to labor displacing and augmenting technologies using textual analysis of patents and job tasks which they then link to worker level outcomes. Causal inference in this literature has been challenging. An ideal but likely infeasible experiment, outside of a lab setting, would involve having households randomly update their displacement expectations (Golin and Rauh, 2022). In this paper, I rely on a quasi-experiment of AV deployment in Phoenix and California, news of which diffuses differentially along social networks, to identify the impact of increased displacement risk.

More broadly, my results add to a literature examining the role of social networks in shaping 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), and trading behavior (Hirshleifer, Peng and Wang, 2024).

The remainder of this paper is structured as follows: the next section outlines a brief conceptual framework, Section II discusses the institutional background, and Section III presents the data used in the analysis. Section IV describes the empirical strategy, Section V reports the main results, and Section VI provides evidence in support of the mechanism. Finally, 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 below).

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.

II Institutional Background

This section provides a brief institutional background relevant for the research designs I implement below. For a more comprehensive survey charting the history and technical research on self-driving cars, see Badue et al. (2021). See Viscelli (2016) for a detailed description and history of the trucking industry.[4]

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 (AV) 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

[4]For characteristics of the trucking industry before and after the Carter deregulation specifically, refer to Zingales (1998).

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

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 AVs has partially fallen in more recent 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 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 the metro Phoenix area and San Francisco. 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 Phoenix via its Early Rider Program in 2017, launching a commercial service dubbed as 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]

Using publicly available maps of Waymo's service areas, I manually identify zip codes with AV testing (see Appendix Figure A.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. Communities living within these service areas had ubiquitous exposure to self-driving cars, unlike virtually anywhere else.

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)

[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.

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

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 as of 2014.[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 from job losses and the accompanied large and persistent loss in earnings that follow (Braxton and Taska, 2023).

To the extent that union membership can protect individuals from job displacement, I am less likely to find effects of displacement risk on labor and financial outcomes. 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.2). 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 (Gittleman and Monaco, 2020; Mohan and Vaishnav, 2022).

III Data

This section describes the data used in this paper. I construct my main dataset by aggregating the universe of driver licenses in New York state to the zip code level and merging it with Facebook's Social Connectedness Index. Parts of the analysis also use the American Community Survey and the NielsenIQ Consumer Panel.

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

III.1 Commercial Driver Licenses

The Open NY initiative promotes transparency with regard to local government data.[9] I acquire a dataset, provided by the Department of Motor Vehicles on June 16, 2023, which contains de-identified information from all driver licenses, permits, or non-driver identification cards, excluding those which expired two years ago or earlier. 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.[10]

The initial dataset contains 16,406,138 records. I restrict the sample to New York state-issued licenses with full privileges. Importantly, I further limit the sample to commercial driver licenses (CDL), specifically Class A licenses and permits which identify tractor-trailer drivers. These license holders are permitted to operate vehicles with a gross combination weight rating (GCWR) of more than 26,000 pounds. The final sample is composed of 218,736 truckers who obtained a Class A CDL between 2015 and 2023.[11]

III.2 Social Networks

Since truckers' actual friendship networks are unobservable, I rely on an aggregated measure of social connectedness, assuming that truckers' friendship networks correlate with that of their neighbors.[12] Following Bailey et al. (2018), I use the Social Connectedness Index (SCI), computed as of October 2021:

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

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.[13] 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

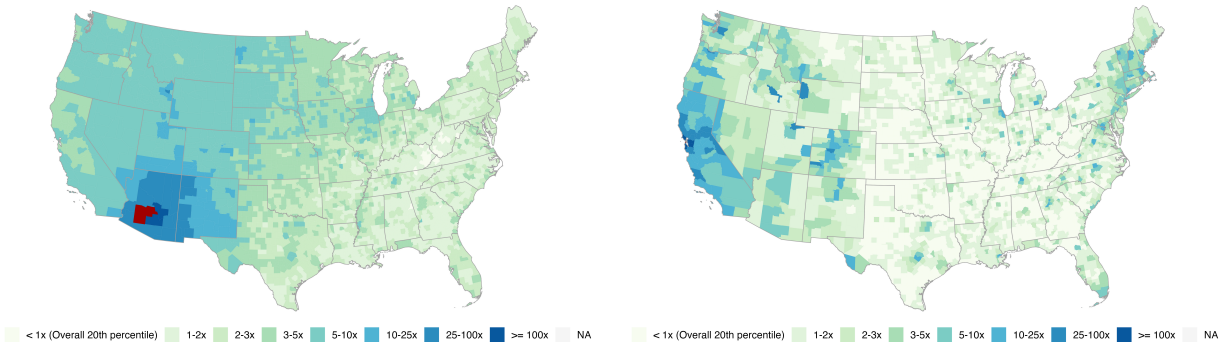
[9] See https://data.ny.gov/.

[10] I infer the year of issuance from the expiration year. CDLs are valid for 8 years in the state of New York

[11] For the zip code level specifications in section V, I require each zip-year observation to include at least 5 drivers. I omit zip codes that fail this criterion in any given year.

[12] An alternative framing is that truckers are exposed to information circulating in their neighborhoods.

[13] 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.



(a) Maricopa County, AZ **(b)** San Francisco County, CA

Figure 1: Social Connectedness Index. This figure plots the county-level social connectedness index (SCI) 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.

people in different geographies (Bailey et al., 2024; Hirshleifer, Peng and Wang, 2024).

The heat maps in Figure 1 plot the SCI for Maricopa County (Figure 1a) and San Francisco County (Figure 1b) 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 in the two maps.

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.[14] The ACS microdata are only available at a coarser geography: public use microdata areas (PUMAs). Since the SCI is not available at the PUMA-level, I build a zip code

[14]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.

	Mean	SD	p10	p25	p50	p75	p90	N
Age	46.20	14.86	26.00	34.00	47.00	58.00	65.00	218,736
Female	0.02	0.15	0.00	0.00	0.00	0.00	0.00	218,736

(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)	36,949.33	34,019.79	6,823.00	17,792.00	32,291.00	47,487.00	65,398.00	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

Table 1: Summary Statistics. Panel (a) shows summary statistics for Class A commercial driver license holders in New York state during 2015-2023. Panel (b) shows summary statistics for driver/sales workers and truck drivers in the American Community Survey from 2012-2021.

to PUMA crosswalk using Census tracts.[15]

Table 1 presents descriptive statistics for Class A CDL holders (Table 1a) and driver/sales workers and truck drivers (Table 1b). Heavy truck and tractor-trailer operators in New York state tend to be middle-aged men on average. In contrast, 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 indicates that is not the case on average. However, hours worked, and hence earnings, may 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.

[15]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 PUMA relationship file to establish the crosswalk.

III.4 Spending

My final source of data is the NielsenIQ Consumer Panel.[16] 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. The occupation categories are coarse. The one capturing drivers also includes closely related 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. The sample period is January 2021 to December 2022.

IV Empirical Strategy

My empirical analysis 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 $\widetilde{DispRisk}$:

$$Y_i = \alpha + \delta \widetilde{DispRisk}_i + \gamma' X_i + \epsilon_i. \tag{3}$$

Unfortunately, identifying δ from equation 3 is challenging because of 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.

I overcome these challenges by relying on the quasi-exogenous geographical rollout of AV testing in Phoenix and California, news of which diffuses differentially along social networks, to identify

[16] The data is provided by the Kilts Center at the University of Chicago Booth School of Business.
[17] The exposition of my baseline empirical strategy is similar to Xu (2022).

the impact of increased subjective displacement risk. I construct my social network-based exposure measure, as an instrument for subjective displacement expectations, as:

$$\text{Friend Exposure to AV}_{i,t} = \sum_j \frac{\text{SCI}_{i,j}}{\sum_h \text{SCI}_{i,h}} * \mathbb{1}\left\{\text{AV}_{j,t}\right\}. \tag{4}$$

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.

Using this measure, I study the relationship between friend exposure to AV and subsequent labor market adjustments by estimating the following reduced-form equation:

$$Y_{i,t+1} = \alpha_i + \beta \text{ Friend Exposure to AV}_{i,t} + \gamma_t' X_{i,t} + \epsilon_{i,t+1}. \tag{5}$$

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 regards to the occupational decisions of truckers, particularly those living in distant labor markets, the assumption is a plausible one.

V Results

V.1 Effects of Friend Exposure to AV on Licensing

In this section, I estimate equation 5 using comprehensive licensing data from New York state. I define $Y_{i,t+1}$ as Class A CDL issuances as a share of total license issuances within a zip code i as of year $t+1$.[19] α_i represents zip code fixed effects. I cluster standard errors at the zip code level.

$X_{i,t}$ 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 5-year ACS (2017-2021). These include the population density, bachelor degree share, non-white share, median earnings, and friend-weighted density and earnings. The

[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.

[19] Scaling by total licenses accounts for population differences in potential truck drivers between zip codes. Moreover, it accounts for mechanical differences in the observed levels of CDL over time due to license expirations and renewals.

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.39***	-0.39***	-0.16**	-0.20***
	(0.13)	(0.14)	(0.062)	(0.075)
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	0.19	0.30	0.75	0.76
Observations	2336	2336	2336	2336

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

Table 2: Licensing in New York State. This table reports the results of regression 5. The outcome variable is the share of Class A commercial driver licenses in a zip code. Friend exposure is defined as in equation 4. 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.

latter two measures are constructed in a similar fashion to equation 4.

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 social exposure to AV.

Given the identifying assumption in section IV, Table 2 presents the results of the exposure research design. Column (1) shows that a 1 standard deviation increase in friend exposure leads to a 39 basis point (bp) decline in the CDL share. When including the full set of control variables in column (2), the point estimate remains 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 -20 bps, which represents an 11% reduction relative to the mean CDL share in 2016. 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 220,000 drivers (11% 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

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.54*	-0.78**	-0.25*	-0.36**
	(0.32)	(0.33)	(0.15)	(0.17)
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	0.11	0.21	0.80	0.81
Observations	1376	1376	1376	1376

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

Table 3: Young Drivers in New York State. This table reports the results of regression 5. The outcome variable is the share of Class A commercial driver licenses in a zip code among drivers 48 years old and younger. Friend exposure is defined as in equation 4. 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.

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 2—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 (4.8%) drivers voluntarily surrendered their CDLs over the sample period, the results remain robust to removing them (Appendix Table A.1). Additionally, concerns about measurement error in the form of inaccurate zip code information due to people moving 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 larger for the sample of drivers below the median age in 2017 (Table 3).[20] Column (4) shows that the CDL share among the young falls by 0.36% following a 1% 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). Alternatively, since younger people tend to be more active online, the coefficients may instead reflect their higher overall exposure to videos of self-driving cars shared by their friends.

[20]The median age of 42 is computed in the unrestricted license dataset.

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 4 (Appendix Table A.2). 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 frequently, making them more likely to communicate news about AV to their social networks.

In addition, the results are qualitatively robust to a broader definition of the CDL share, which includes both Class A and Class B licenses and permits (Appendix Table A.3). The latter group of drivers tend to operate buses or single-unit trucks rather than tractor-trailers. The attenuated point estimate in column (4) suggests that Class B license holders responded less to news about AVs which is consistent with higher reported concerns for long-haul truckers.

V.2 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:

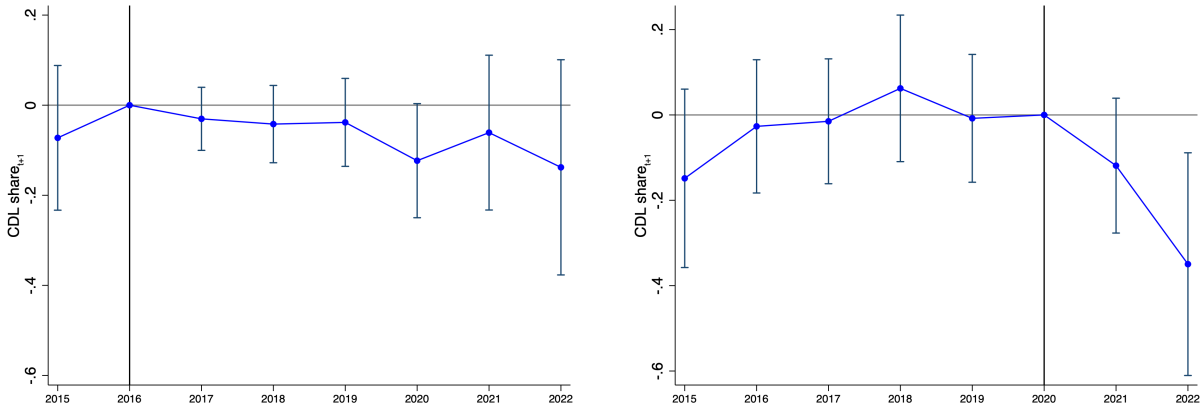
$$Y_{i,t+1} = \alpha_i + \sum_{t \neq -1} \beta_t \left(\text{HighExp}_i \times \text{Year}_t\right) + \gamma_t' X_{i,t} + \varepsilon_{i,t+1}. \tag{6}$$

$Y_{i,t+1}$, 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.[21]

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 only statistically significant at the 10% level, estimated coefficients for treatment effects fall following AV testing in metro Phoenix (Figure 2a). On the other hand, the decline in estimated coefficients is sharper and statistically significant following AV testing in San Francisco (Figure 2b).

This exercise illustrates that labor market adjustments to disruptive technologies can take place

[21] Appendix Figure A.3 documents average CDL shares over time by HighExp_i.

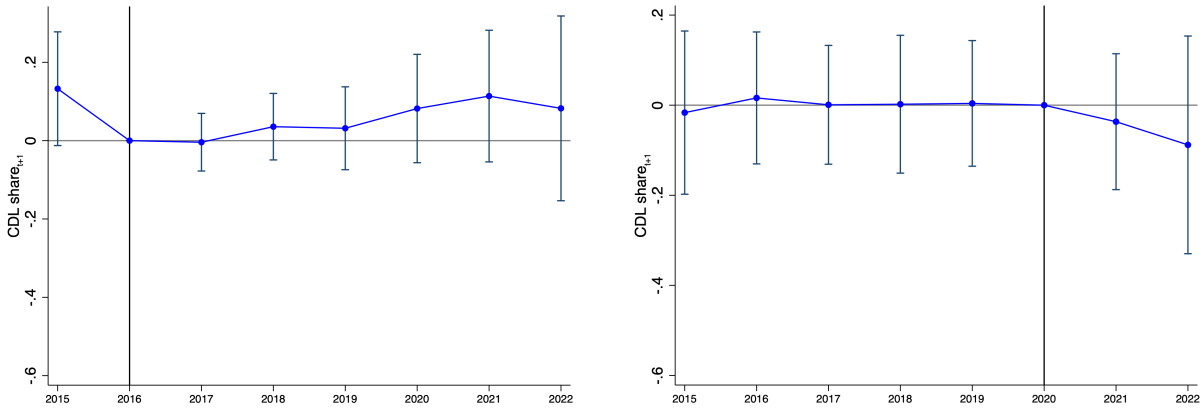


(a) Event: AV Testing in Phoenix Metro Area **(b)** Event: AV Testing in San Francisco

Figure 2: 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 degree share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

faster if information frictions are relaxed. On average, high exposure zip codes experience a relative fall in their CDL shares by almost 40 bps after the launch of large-scale robotaxi services in San Francisco. The results in Figure 2 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.

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, that can affect licensing behavior, rather than specific news about the deployment of AV. 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.4 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.



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

Figure 3: 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 degree share, non-white share, median earnings, and network-weighted density and earnings. Standard errors are clustered at the zip code level.

I repeat the difference-in-differences methodology specified in equation 6 using the alternative measure of friend exposure. Figure 3 presents analogous estimates to those in Figure 2. 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 exposure zip codes are similar along a number of dimensions, they also differ in terms of the bachelor degree share and median earnings (Appendix Table A.4). 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. The heat maps in Figure 4 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 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.

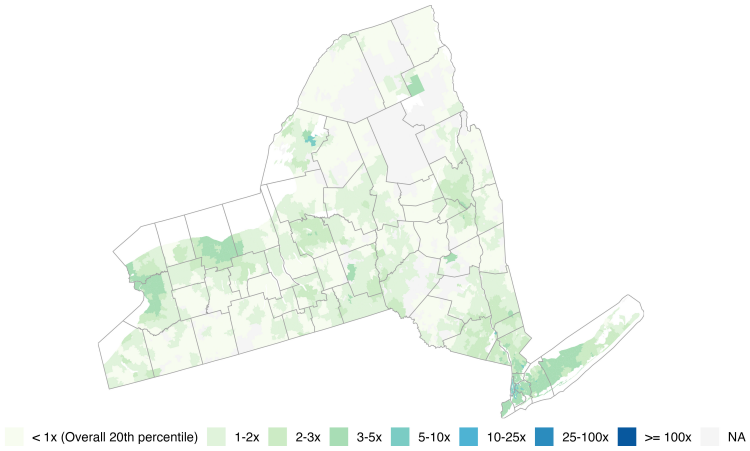
Importantly, the sizeable temporal and geographic variation in the maps indicates that different communities in New York state received news about AV from their friends at different times. In other words, in each year, different individuals happen to be most exposed to AV testing. Table A.5 shows the demographic correlates of changes in friend exposure. The magnitudes and the correlations are time-varying. For instance, in 2021, zip codes with a larger non-white population had lower exposure to AV testing; however, this relationship flipped in 2022 as testing expanded to downtown Phoenix.

Motivated by these dynamics, I estimate the following regression equation:

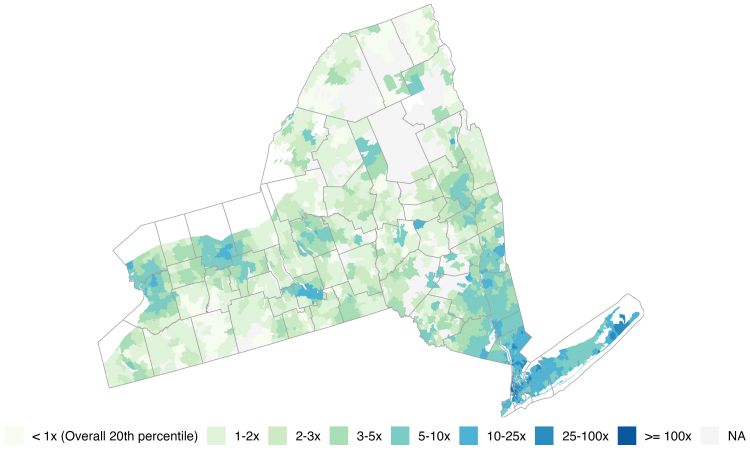
$$\Delta Y_{i,t+1} = \sigma_0 + \sigma_1 \Delta \text{ Friend Exposure to AV}_{i,t} + \sigma_{2,t}' X_{i,t} + \epsilon_{i,t+1}. \tag{7}$$

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.

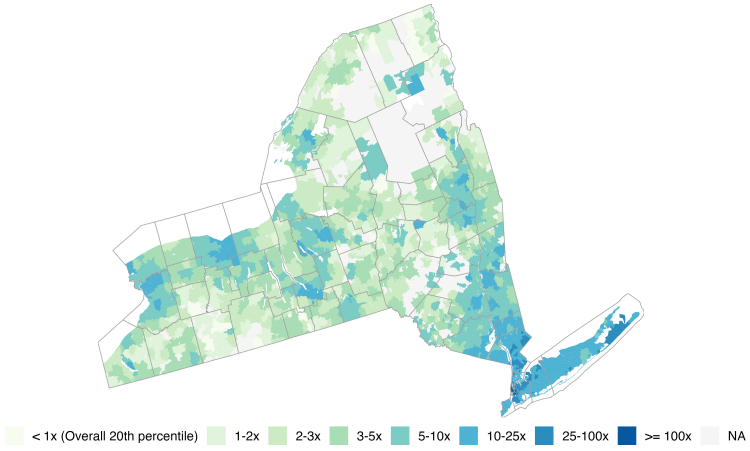
Column (1) of Table 4 shows that a 1 standard deviation increase in friend exposure to AV, induces a 9 bp fall in the CDL share. Column (2) incorporates zip code level fixed effects to absorb potential trends in licensing over time, raising the economic magnitude of the point estimate. In columns (3-5), 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 happened to cut back on their trucking workforce for reasons unrelated to social exposure to labor displacing technologies.



(a) 2017



(b) 2021



(c) 2022

Figure 4: Friend Exposure to Autonomous Vehicles. This figure plots zip code level friend exposure to autonomous vehicles (AV) as defined in equation 4 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.

	All	All	2018	2022	2023
Δ Friend Exposure$_t$	-0.094**	-0.11**	0.0098	-0.061**	-0.85**
	(0.042)	(0.050)	(0.17)	(0.029)	(0.37)
Δ Friend Exposure$_{2017}$				0.021	0.88
				(0.45)	(0.69)
Δ Friend Exposure$_{2021}$					-0.027
					(0.036)
Zip Code FE	NO	YES	NO	NO	NO
County FE	NO	NO	YES	YES	YES
County-Year FE	YES	YES	NO	NO	NO
License Controls	YES	YES	YES	YES	YES
Census Controls-Year FE	YES	YES	YES	YES	YES
Adj. R-squared	0.27	0.17	0.10	0.15	0.16
Observations	2044	2044	292	292	292

Standard errors in parentheses

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

Table 4: Changes in Licensing in New York State. This table reports the results of regression 7. 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 4. 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.

V.3 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:

$$\text{Friend Exposure to AV}_{k,t} = \sum_{j \in k} \text{Friend Exposure to AV}_{j,t}. \tag{8}$$

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 5 in the broader ACS sample, covering all states and the District of Columbia.[22]

[22] I require each PUMA-year observation to include at least 5 drivers, and I exclude PUMAs that fail this criterion

	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 5: Labor and Financial Outcomes of Drivers. This table reports the results of regression 5. 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 4. 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.

As before, I include county-year fixed effects to absorb variation in local conditions and to allow for a comparison between truck drivers living in nearby but different PUMAs with differential friend exposure.[23] Column (1) of Table 5 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 2.

Leveraging the richness of the ACS, I analyze the relationship between friend exposure to AV

in any given year. All variables are weighted by the corresponding Census provided person and household survey weights.

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

and additional labor and financial outcomes. Specifically, column (2) of Table 5 documents a small increase in weekly work duration by 12 minutes associated with 1 standard deviation higher friend 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 savings motive in that workers who revise their subjective displacement expectations upwards work more to accumulate a buffer stock of savings (Beshears et al., 2018). 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

[24] Approximately 30% of workers in the trucking industry are self-employed while 88% of long-haul drivers specifically are self-employed (Day and Hait, 2019).

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

data is non-missing for all months until December 2022 (the results are robust to this choice). 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; Degenhardt, Hall and Lynskey, 2001; Morissette et al., 2007). Changes in substance use among exposed households following friend exposure to AV may be reflective of automation-induced anxiety and a revision in households' beliefs about their susceptibility to automation.

I estimate the following equation:

$$Y_{i,k,t+1} = \mu_i + \beta \left(\text{HighExp}_k^{2021} \times \text{Post}_t\right) + \gamma_t' \left(X_i \times \text{Month}_t\right) + \varepsilon_{i,k,t+1}, \tag{9}$$

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 6 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 17% relative to the mean in January 2021.[26] Columns (3) and (4) show that the increase is driven relatively more from purchases of alcoholic beverages than tobacco products.

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, Strain and Veuger, 2021; Orii et al., 2021). 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 automatibility.

[26]The majority of households do not report purchasing alcoholic beverages and tobacco products in a given month.

	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
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 6: Spending response to displacement risk. This table reports the results of regression 9. 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.

VII Conclusion

Nearly 50 years ago, Thaler and Rosen (1976) described and estimated premia for "risky" occupations in labor markets. This paper presents similar evidence—not in terms of mortality and injury concerns, but rather displacement uncertainty—demonstrating how workers respond to such risks. Specifically, truckers are less likely to obtain or renew Class A CDLs upon receiving signals about AV testing via their social networks, relative to neighbors who are less socially connected to AV.

Although there are a number of advantages to my empirical approach, it is worth repeating certain limitations. First, truckers' actual friendship networks are unobservable, so I rely on a zip code level proxy using 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 or policy assessments evaluating the impact of automation may be inaccurate if they fail to account for an anticipatory channel. For instance, designing retraining programs requires estimates on the number of displaced households which could be lower than expected if some workers switch occupations preemptively. Moreover, a key takeaway from the analyses in this paper is that labor market adjustments to disruptive technologies can occur more rapidly if information frictions are reduced. 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.

Bibliography

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives*, 33(2): 3–30.

Autor, David. 2022. "The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty."

Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives*, 29(3): 3–30.

Badue, Claudine, Rânik Guidolini, Raphael Vivacqua Carneiro, Pedro Azevedo, Vinicius B. Cardoso, Avelino Forechi, Luan Jesus, Rodrigo Berriel, Thiago M. Paixão, Filipe Mutz, Lucas de Paula Veronese, Thiago Oliveira-Santos, and Alberto F. De Souza. 2021. "Self-driving cars: A survey." *Expert Systems with Applications*, 165: 113816.

Bailey, Michael, Drew Johnston, Martin Koenen, Theresa Kuchler, Dominic Russel, and Johannes Stroebel. 2024. "Social Networks Shape Beliefs and Behaviors: Evidence from Social Distancing during the COVID-19 Pandemic." *Journal of Political Economy Microeconomics*. Publisher: The University of Chicago Press.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong. 2018. "Social Connectedness: Measurement, Determinants, and Effects." *Journal of Economic Perspectives*, 32(3): 259–280.

Becker, Gary S. 1964. *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, First Edition.* NBER.

Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian. 2018. "Behavioral Household Finance." In *Handbook of Behavioral Economics: Applications and Foundations 1*. Vol. 1 of *Handbook of Behavioral Economics - Foundations and Applications 1*, , ed. B. Douglas Bernheim, Stefano DellaVigna and David Laibson, 177–276. North-Holland.

Bond, Philip, and Lukas Kremens. 2023. "Income and Inequality Under Asymptotically Full Automation."

Braxton, J. Carter, and Bledi Taska. 2023. "Technological Change and the Consequences of Job Loss." *American Economic Review*, 113(2): 279–316.

Cannon, Brad, David Hirshleifer, and Joshua Thornton. 2024. "Friends with Benefits: Social Capital and Household Financial Behavior."

Cavounidis, Costas, Qingyuan Chai, Kevin Lang, and Raghav Malhotra. 2023. "Obsolescence Rents: Teamsters, Truckers, and Impending Innovations."

Day, Jennifer, and Andrew Hait. 2019. "America Keeps on Truckin." *U.S. Census Bureau: America Counts*, Accessed: 2024-12-28.

Degenhardt, Louisa, Wayne Hall, and Michael Lynskey. 2001. "Alcohol, cannabis and tobacco use among Australians: a comparison of their associations with other drug use and use disorders, affective and anxiety disorders, and psychosis." *Addiction*, 96(11): 1603–1614. Publisher: John Wiley & Sons, Ltd.

Engelmann, Jan B., Maël Lebreton, Nahuel A. Salem-Garcia, Peter Schwardmann, and Joël J. van der Weele. 2024. "Anticipatory Anxiety and Wishful Thinking." *American Economic Review*, 114(4): 926–960.

Feigenbaum, James, and Daniel P Gross. 2024. "Answering the Call of Automation: How the Labor Market Adjusted to Mechanizing Telephone Operation." *The Quarterly Journal of Economics*.

Gârleanu, Nicolae, Leonid Kogan, and Stavros Panageas. 2012. "Displacement risk and asset returns." *Journal of Financial Economics*, 105(3): 491–510.

Gee, Laura K., Jason Jones, and Moira Burke. 2017. "Social Networks and Labor Markets: How Strong Ties Relate to Job Finding on Facebook's Social Network." *Journal of Labor Economics*, 35(2): 485–518. Publisher: The University of Chicago Press.

Gittleman, Maury, and Kristen Monaco. 2020. "Truck-Driving Jobs: Are They Headed for Rapid Elimination?" *ILR Review*, 73(1): 3–24. Publisher: SAGE Publications Inc.

Golin, M., and C. Rauh. 2022. "The Impact of Fear of Automation."

Gomes, Francisco, Thomas Jansson, and Yigitcan Karabulut. 2024. "Do Robots Increase Wealth Dispersion?" *The Review of Financial Studies*, 37(1): 119–160.

Hendren, Nathaniel. 2017. "Knowledge of Future Job Loss and Implications for Unemployment Insurance." *American Economic Review*, 107(7): 1778–1823.

Hirshleifer, David, Lin Peng, and Qiguang Wang. 2024. "News Diffusion in Social Networks and Stock Market Reactions." *The Review of Financial Studies*.

Jones, Charles I. 2024. "The AI Dilemma: Growth versus Existential Risk." *American Economic Review: Insights*, 6(4): 575–590.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence D. W. Schmidt, and Jae Song. 2020. "Technological Innovation and Labor Income Risk."

Kogan, Leonid, Dimitris Papanikolaou, Lawrence Schmidt, and Bryan Seegmiller. 2023. "Technology, Vintage-Specific Human Capital, and Labor Displacement: Evidence from Linking Patents with Occupations."

Korinek, Anton, and Donghyun Suh. 2024. "Scenarios for the Transition to AGI."

Kushner, Matt G, Kenneth Abrams, and Carrie Borchardt. 2000. "The relationship between anxiety disorders and alcohol use disorders: A review of major perspectives and findings." *Clinical Psychology Review*, 20(2): 149–171.

Maturana, Gonzalo, and Jordan Nickerson. 2019. "Teachers Teaching Teachers: The Role of Workplace Peer Effects in Financial Decisions." *The Review of Financial Studies*, 32(10): 3920–3957.

Mian, Atif, Amir Sufi, and Nasim Khoshkhou. 2023. "Partisan Bias, Economic Expectations, and Household Spending." *The Review of Economics and Statistics*, 105(3): 493–510.

Mohan, Aniruddh, and Parth Vaishnav. 2022. "Impact of automation on long haul trucking operator-hours in the United States." *Humanities and Social Sciences Communications*, 9(1): 1–10. Publisher: Palgrave.

Morissette, Sandra Baker, Matthew T. Tull, Suzy Bird Gulliver, Barbara Wolfsdorf Kamholz, and Rose T. Zimering. 2007. "Anxiety, anxiety disorders, tobacco use, and nicotine: A critical review of interrelationships." *Psychological Bulletin*, 133(2): 245–272. Place: US Publisher: American Psychological Association.

Mueller, Andreas I., and Johannes Spinnewijn. 2023. "Chapter 22 - Expectations data, labor market, and job search." In *Handbook of Economic Expectations.* , ed. Rüdiger Bachmann, Giorgio Topa and Wilbert van der Klaauw, 677–713. Academic Press.

National Academies of Sciences, Engineering, and Medicine. 2017. *Information Technology and the U.S. Workforce: Where Are We and Where Do We Go from Here?* Washington, D.C.:National Academies Press.

Orii, Lisa, Diana Tosca, Andrew L Kun, and Orit Shaer. 2021. "Perceptions on the Future of Automation in r/Truckers." *CHI EA '21*, 1–6. New York, NY, USA:Association for Computing Machinery.

Phares, Jonathan, and Andrew Balthrop. 2022. "Investigating the role of competing wage opportunities in truck driver occupational choice." *Journal of Business Logistics*, 43(2): 265–289. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jbl.12285.

Roy, A. D. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers*, 3(2): 135–146.

Shoag, Daniel, Michael R. Strain, and Stan Veuger. 2021. "How Do Workers Perceive the Risks from Automation and the Opportunities to Retrain? Evidence from a Survey of Truck Drivers."

Stephens, Jr., Melvin. 2004. "Job Loss Expectations, Realizations, and Household Consumption Behavior." *The Review of Economics and Statistics*, 86(1): 253–269.

Thaler, Richard, and Sherwin Rosen. 1976. "The Value of Saving a Life: Evidence from the Labor Market." In *Household Production and Consumption.* 265–302. NBER.

Viceira, Luis M. 2001. "Optimal Portfolio Choice for Long-Horizon Investors with Nontradable Labor Income." *The Journal of Finance*, 56(2): 433–470.

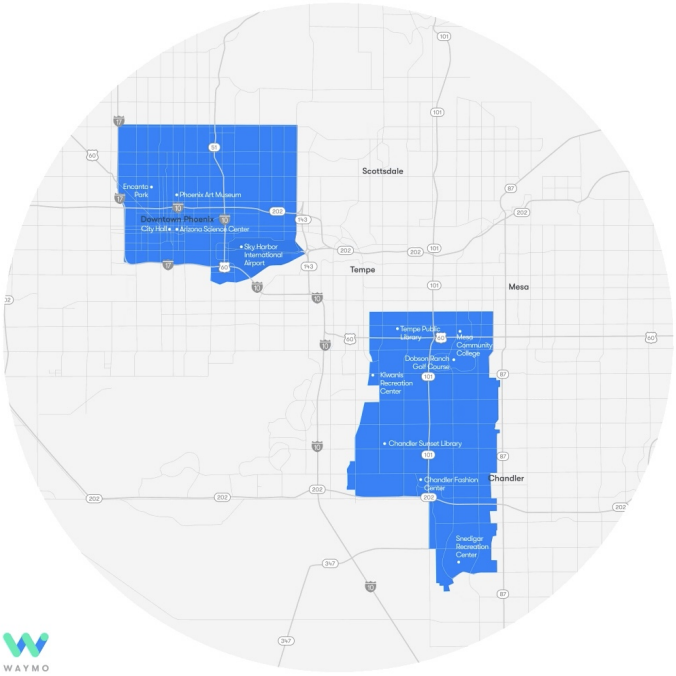
Viscelli, Steve. 2016. *The Big Rig: Trucking and the Decline of the American Dream.* Univ of California Press.

Viscelli, Steve. 2018. "Driverless? Autonomous Trucks and the Future of the American Trucker." Center for Labor Research and Education, University of California, Berkeley, and Working Partnerships USA.

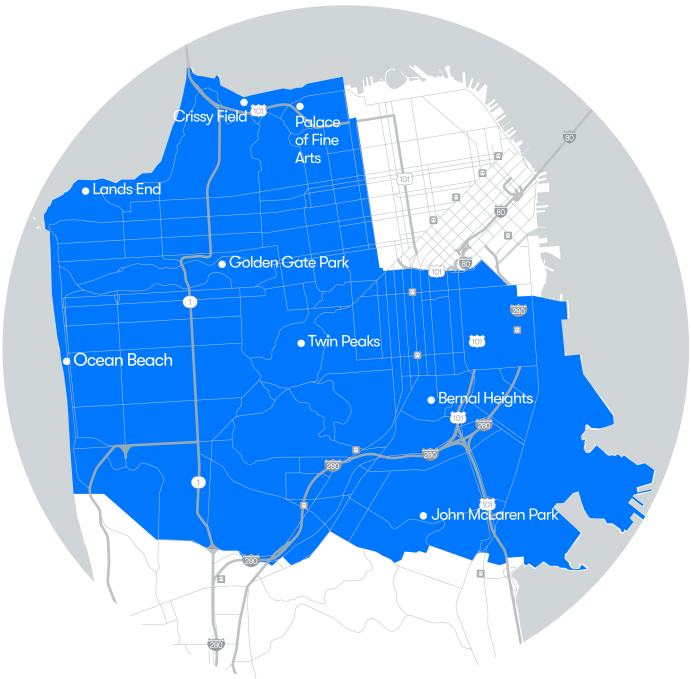
Xu, Chenzi. 2022. "Reshaping Global Trade: The Immediate and Long-Run Effects of Bank Failures*." *The Quarterly Journal of Economics*, 137(4): 2107–2161.

Zingales, Luigi. 1998. "Survival of the Fittest or the Fattest? Exit and Financing in the Trucking Industry." *The Journal of Finance*, 53(3): 905–938.

Appendix A



(a) Phoenix Metro Area



(b) San Francisco

Figure A.1: Waymo Service Areas. This figure shows Waymo's service areas as of February 2023.

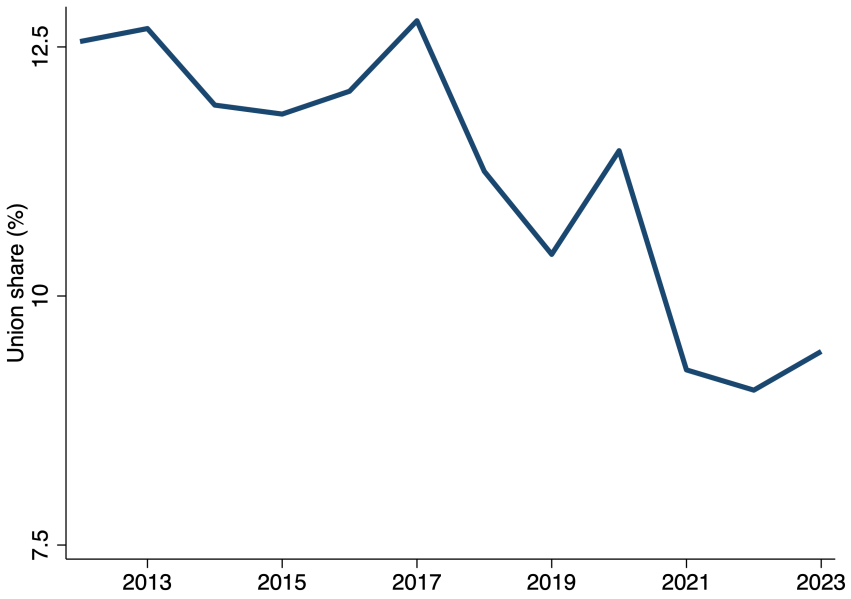
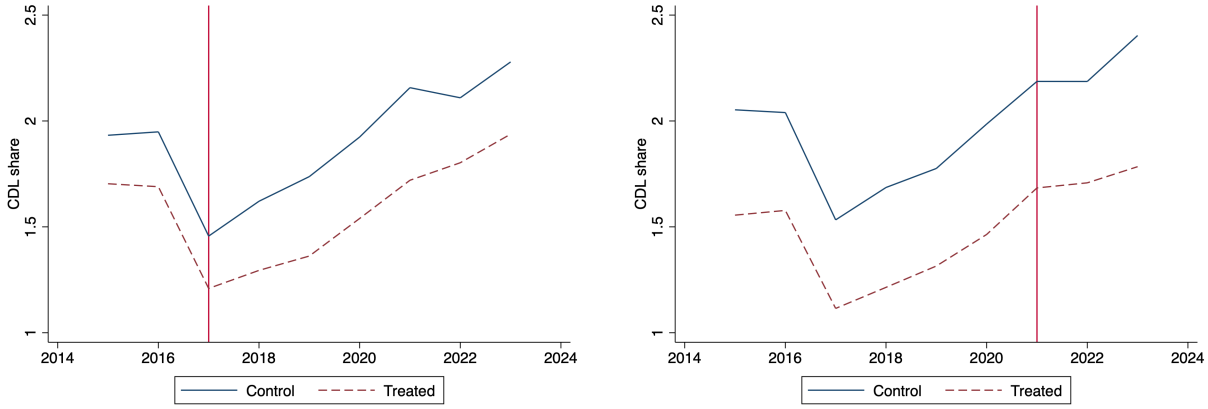


Figure A.2: Union Share. This figure reports the self-reported union share among driver/sales workers and truck drivers in the Current Population Survey.



(a) Event: AV Testing in Phoenix Metro Area

(b) Event: AV Testing in San Francisco

Figure A.3: 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.

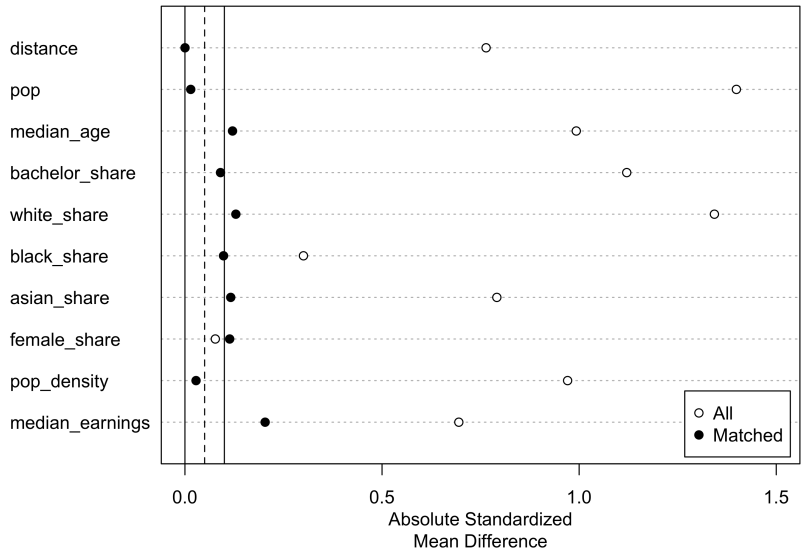


Figure A.4: Balance Plot. This figure reports absolute standardized mean differences in covariates between AV testing locations and matched zip codes as well as between AV testing locations and all zip codes. The matching pool includes all zip codes in the contiguous United States, excluding those in 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.

	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$	CDL share$_{t+1}$
Friend Exposure$_t$	-0.40***	-0.37**	-0.17**	-0.19**
	(0.13)	(0.14)	(0.068)	(0.078)
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	0.21	0.31	0.75	0.76
Observations	2256	2256	2256	2256

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

Table A.1: Licensing in New York State, excluding exits. This table reports the results of regression 5. The outcome variable is the share of Class A commercial driver licenses among zip codes in New York City. I exclude drivers who voluntarily surrender their CDLs during the sample period. Friend exposure is defined as in equation 4. 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$_t$	-0.51***	-0.54***	-0.16**	-0.21**
	(0.17)	(0.20)	(0.074)	(0.091)
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	0.19	0.30	0.75	0.76
Observations	2336	2336	2336	2336

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

Table A.2: Licensing in New York State (broad AV exposure). This table reports the results of regression 5. The outcome variable is the share of Class A commercial driver licenses in a zip code. Friend exposure is defined as in equation 4. 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$_t$	-0.74***	-0.39***	-0.18***	-0.089**
	(0.100)	(0.095)	(0.037)	(0.045)
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	0.36	0.50	0.82	0.83
Observations	4152	4152	4152	4152

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

Table A.3: Class A and B Licensing in New York State. This table reports the results of regression 5. The outcome variable is the share of Class A and Class B commercial driver licenses in a zip code. Friend exposure is defined as in equation 4. 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	33.75	2.90	170	34.02	2.88	138	-0.27
Female Share	0.04	0.04	170	0.04	0.04	138	0.00
College	0.12	0.04	170	0.15	0.04	138	-0.03
Non-white	0.41	0.31	170	0.41	0.26	138	-0.00
Density	15490.94	23096.31	170	17993.44	23950.87	138	-2502.50
Real earnings (2021)	40122.29	9676.04	170	43983.65	9334.04	138	-3861.36
SCI weighted density	6408.52	5542.99	170	6943.00	4905.70	138	-534.48
SCI weighted earnings	43179.83	5593.69	170	45127.79	4990.85	138	-1947.96

(a) 2017

	Low Exposure			High Exposure			
	Mean	SD	Count	Mean	SD	Count	Diff
Mean Age	33.56	2.93	170	34.25	2.79	138	-0.69
Female Share	0.04	0.04	170	0.03	0.03	138	0.01
College	0.12	0.04	170	0.15	0.05	138	-0.03
Non-white	0.42	0.32	170	0.40	0.25	138	0.02
Density	15124.86	22523.45	170	18444.41	24560.88	138	-3319.55
Real earnings (2021)	39980.83	9011.79	170	44157.91	10051.17	138	-4177.08
SCI weighted density	6388.15	5539.88	170	6968.10	4907.17	138	-579.96
SCI weighted earnings	42998.43	5415.22	170	45351.25	5134.60	138	-2352.83

(b) 2021

Table A.4: 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).

	Δ Friend Exposure$_{2017}$	Δ Friend Exposure$_{2021}$	Δ Friend Exposure$_{2022}$
Mean Age	-0.0081***	-0.033***	-0.0087***
	(0.00083)	(0.0072)	(0.0021)
Female Share	-0.36	5.28	-0.18
	(0.25)	(4.89)	(0.41)
Density	0.0036***	0.060***	0.016***
	(0.00040)	(0.0088)	(0.0012)
College	1.66***	20.5***	3.93***
	(0.29)	(3.68)	(0.67)
Non-white	0.17***	-0.70*	0.50***
	(0.032)	(0.36)	(0.080)
Real earnings (2021)	0.0036***	-0.021*	-0.0015
	(0.0013)	(0.012)	(0.0023)
Adj. R-squared	0.72	0.71	0.87
Observations	308	308	308

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

Table A.5: Determinants of Change in Friend Exposure. This table reports the demographic correlates of change in friend exposure. Friend exposure is defined as in equation 4. Standard errors are clustered at the zip code level.