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Daniel W. Shoag
Case Western Reserve University

Michael R. Strain
American Enterprise Institute and IZA

Stan A. Veuger
American Enterprise Institute

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

How Do Workers Perceive the Risks from Automation and the Opportunities to Retrain? Evidence from a Survey of Truck Drivers*

How do truck drivers perceive the risk they face from automation and their opportunities to retrain for employment in a different occupation? Autonomous vehicle (AV) technology has made rapid progress in recent years, so these questions are likely salient to truckers. Based on surveys of the new RAND American Truck Driver Panel, we find that those drivers who are most concerned about automation are, counterintuitively, also most likely to say they intend to re-invest in driving by seeking additional endorsements or purchasing their own truck. This zero-sum "arms race" for remaining positions is socially inefficient, and it may be driven by incorrect information about outside options. Specifically, the effect disappears among those drivers who are most familiar with the generally low costs of community college. We show that this is consistent with a simple model in which idiosyncratic noise in the perceived cost of retraining can lead to inefficient outcomes. This mechanism suggests that effective information provision can have large positive externalities and welfare consequences. However, a calibration of labor market prospects suggests that information provision about the true costs of retraining may not be adequate to induce occupational switching if truckers believe wages for survivors will continue to grow. This points to another important role for perceptions about the future, and for a policy of information interventions.

JEL Classification: J23, J24, J62, J68, O33

Keywords: automation, autonomous vehicles, retraining

Corresponding author:
Michael R. Strain
American Enterprise Institute
1789 Massachusetts Avenue NW
Washington, DC 20036
USA

E-mail: michael.strain@aei.org

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Section I: Introduction

What are the economic prospects for workers who will be displaced by automation? How can policy help their transition to new occupations or industries? To answer these questions, economists and policymakers need a better understanding of how workers perceive both the risk of displacement they face from automation and the costs of and opportunities for retraining.

Workers' perceptions of the risk they face will shape their willingness to consider leaving their occupation. And their perceptions of the difficulty of retraining and transitioning to a new occupation will shape their willingness to do so. Knowing workers' perceptions about these two issues is of first-order importance in understanding the labor market effects of technological change and the optimal policy response to it.

In this paper, we present evidence on those perceptions. We present the results of a survey of truck drivers that we designed and commissioned. We find evidence that misperceptions about the cost of retraining may be leading truck drivers to double down on their current occupation, even if they are concerned about being displaced by technology.

We study truck drivers because they are in an occupation at high risk from automation (e.g., Chottani et al., 2018). We find that truck drivers themselves are split about the threat they face. Around 44 percent of respondents are very or somewhat worried about the development of driverless vehicles, and 56 percent believe that autonomous vehicles will become the dominant vehicles on the road within the next few decades.

According to our survey results, truck drivers overestimate the costs associated with retraining. Fifty percent believe that one course at a community college would cost more than $600. In reality, the average cost of a community college course is likely near or even below zero.[1]

More respondents mentioned that they would save if they discovered they were forced to leave trucking within one year (28 percent) than mentioned retraining via additional schooling (22

[1] Net annual tuition after aid has been estimated be as low as -$430 (CollegeBoard, 2019), though pricing is not particularly transparent (Dynarski and Scott-Clayton, 2017).

percent). The correlation between the perceived cost of community college and the likelihood of saying they would return to school if forced to leave trucking within one year is strong.

We present a counterintuitive finding: Those drivers who are most concerned about automation are also most likely to say they intend to invest in truck driving as an occupation by seeking additional endorsements or purchasing their own truck. To build intuition to explain this survey result, we present a model in which industry contraction entices workers to try to outcompete other works for the remaining jobs. This congestion equilibrium is socially inefficient.

Moreover, we find evidence that this counterintuitive finding is driven by misperceptions about the cost of retraining. This effect disappears among those drivers who are most familiar with the generally low costs of community college.

This suggests that information interventions could be a particularly helpful, low-cost policy to address the effects of automation, in line with the findings of Dynarski et al. (2018) in the context of college applications by low-income high school seniors.

But information may not be sufficient. To further probe our empirical result that the decision to invest in trucking is driven by misperceptions about the cost of retraining, we calibrate a simple model to real-world data to capture the choices facing younger and older workers: to stay in trucking and make investments in it (for example, by acquiring new certifications), to stay in trucking without investing, or to leave trucking and gain additional education and skills at a community college.

This exercise suggests that the choice facing truckers is not straightforward because the remuneration for remaining a truck driver is large. In our calibrated model, even if half the jobs in trucking were to disappear, both older and younger (risk-neutral) drivers would prefer to gamble on a 50-50 chance of staying in trucking rather than attend a community college, even after accounting for the cost of investing in trucking as an occupation (which we parameterize at $5,000) and, importantly, even if they know the true cost of attending community college.

However, in our model, we find that if drivers anticipate stagnant wages in the trucking industry, then younger drivers would be more easily induced to leave trucking and retrain, especially if they knew the true cost of community college. An industry with declining labor demand would not be expected to feature strong wage growth. This suggests another potential avenue for information interventions.

This paper is organized as follows. Section II provides motivation for and background to our research questions. Section III presents a simple game-theoretic model that helps us understand the strategic interactions between different workers in an industry with declining labor demand. Section IV provides an overview of the design of the RAND American Truck Driver Panel. Survey results from the panel are presented in Section V and analyzed in Section VI. In Section VII we calibrate the environment in which truckers make their decision in order to contextualize our survey results. In Section VIII we conclude.

Section II: Motivation and Background

Though many in the policy community are concerned about the effect automation will have on the labor market in the future, technological change has already altered the job market — and American society as a whole — in fundamental ways. Technological change is a driving force, for example, behind the shift in employment away from middle-skill, middle-wage occupations and towards both high- and low-wage occupations (Autor, 2019). It has been an important factor in changing the geography of where workers of different educational background are most likely to find high-paying jobs (Hoxie, Shoag, and Veuger, 2020). These changes have affected advanced economies beyond the U.S. (Goos, Manning, and Salomons, 2014).

In addition to fundamentally altering the labor market, technological change is also a key factor behind the increase in income inequality (Autor, Goldin, and Katz, 2020). New technology has increased labor market competition for higher-skilled workers, driving up their wage and increasing inequality.

Much like technological change in recent decades, automation is likely to have positive effects on the U.S. economy as a whole, but the effects on different industries and occupations, and on workers with different skills, will vary widely. Capturing the aggregate gains automation promises while addressing the potentially rapid decline in employment opportunities and wages for workers in at-risk industries or occupations will be a major policy challenge.

Understanding how workers whose jobs are at risk of being automated perceive that risk is of first-order importance to designing optimal policy, as is learning how workers perceive the costs of and opportunities for acquiring additional education and training. Understanding these perceptions is also critical to understanding how the labor market responds to technological change.

Unfortunately, existing job training programs have a limited record of success in helping workers transition to new occupations and industries (Card, Kluve, and Weber, 2018; Greenberg, Michalopoulos, and Robbins, 2003). Studies exploring the returns of community college paint a more positive picture. In one of the first papers to explore the issue in administrative data, Jacobson, Lalonde, and Sullivan (2005) found significant wage gains for attendees using within-person comparisons. This is especially true for more technical fields of study. This finding has been replicated several times (e.g., Backes, Holzer, and Velez, 2015; Jepsen, Troske, and Coomes, 2015; and Liu, Belfield, and Trimble, 2015). A recent review by Bailey and Belfield (2011) summarizes 17 studies and concludes that gains averaged 13-21% (or $4,500-$7,150 per year). We use these findings to motivate an information experiment.

Autonomous vehicle (AV) technology has made rapid progress in recent years. Economists studying the matter forecast that their increasing adoption will displace millions of jobs in the relatively near term (Groshen et al., 2019). While there is obviously uncertainty regarding these forecasts, the possibility of rapid displacement is a reason for serious concern in terms of its potential impact on the labor market.

Long distance trucking is the among the ten most common occupations in fifteen US states and employs roughly 1.9 million people (BLS, 2020a). Roughly, two thirds of drivers have not been educated beyond the high school. The median age of drivers is 46.2 and over 90 percent are male. The median annual wage ($46,850) significantly exceeds the median wage for this education and age bracket (BLS, 2020b). Truck driving requires training, expensive licensing, and many drivers make a significant financial investment by purchasing their own truck. Moreover, many drivers have strong preferences for the non-traditional work environment offered by driving. Displacement, which is associated with significant lifetime earning losses even in typical environments, could generate even greater losses were it to occur rapidly in this group.

Most studies of rapid technological displacement focus on its aftermath (Chin et al., 2005; Horton and Tambe, 2019). Fewer papers investigate decision making in the specter of automation. There is still considerable uncertainty in the literature as to how drivers view the risk of automation and their adjustment options and what, if any, interventions might help this group.

Section III: Staying, Leaving, or Doubling-Down on an Occupation at Risk of Automation: A Simple Model

To guide intuition for how individual workers and the trucking occupation as a whole might respond to the threat of automation, we present a simple model with the following underlying logic. If an occupation is (at risk of) going through a process of gradual decline, workers in the occupation face a choice between (1) attempting to stay in the occupation and investing in occupation-specific human capital, (2) attempting to stay in the occupation and not investing in occupation-specific human capital, and (3) leaving the occupation.

Staying in the occupation will, roughly speaking, be attractive in two situations: If the risk of decline does not materialize, or if it does and some workers are nevertheless able to outcompete other workers in retaining a job in the occupation. The latter is more likely after additional investment in occupation-specific human capital. Leaving the occupation, on the other hand, is attractive if the occupation does indeed decline, in particular if the workers can find a good outside option.

Formalizing this, we can model this situation as a game between the workers. Consider two workers, players A and B. Let us think of player A as a younger worker and player B as an older worker. While this game is being played, the industry in which the workers work is not in decline.

They face the following game depicted in matrix form in Figure 1, where we can think of the left and top strategies as making an investment in skills to remain in the occupation and the right and bottom strategies as leaving and going to community college, while the middle strategies reflect a decision to stay without additional investment. The perceived payoffs shown below are for a situation where the occupation does not decline.

Figure 1: Modeling Interactions Between Older and Younger Workers

		B		
		Invest	Stay	College
A	Invest	2,2	2,3	2,-2
	Stay	3,2	3,3	3,-2
	College	0,2	0,3	0,-2

If both workers make investments to stay in the occupation, their expected payoff is two: the payoff (3) of working in the good economy, minus the cost of investment (1). Staying without paying the investment cost produces a payoff of 3, while heading for college is perceived[2] to cost 3 without generating additional pay for the young worker and is seen as reducing the old worker's pay when he returns to the labor force.

In this situation, the unique equilibrium is for both workers to say and receive a payout of 3: there is no point to investing in the profession as all can be employed anyway, and trucking pays as well as any other job available after additional formal education.

Now decline sets in, and payoffs are cut by half if both workers choose to invest or both choose to stay. If only one of them invests and the other stays, the worker who invested gets the job (and a payoff of 3 minus 1) and the worker who did not receives nothing. If one of the workers goes to community college, payoffs for the other worker are as before. The new unique equilibrium is that of an arms race, with both workers investing to secure the remaining surplus and receiving a meager 0.5 payoff.

This is bleak, but let us now assume that workers have so far overestimated the cost of community college, and that we can provide them with correct information. The new game features perceived payoffs associated with leaving the industry that are 3 units greater than before. All other payoffs remain the same.

[2] This is an overestimate, a fact that will become important shortly.

Figure 2: Modeling Interactions Between Older and Younger Workers in Response to Automation with Incorrect Information Regarding Outside Options

		B: Invest	B: Stay	B: College
A	Invest	0.5,0.5	2,0	2,-2
A	Stay	0,2	1.5,1.5	3,-2
A	College	0,2	0,3	0,-2

Figure 3: Modeling Interactions Between Older and Younger Workers in Response to Automation if Workers Learns True Cost of Outside Option

		B: Invest	B: Stay	B: College
A	Invest	1,1	2,0	2,1
A	Stay	0,2	1.5,1.5	3,1
A	College	3,2	3,3	3,1

This game has a unique pure-strategy equilibrium point: player A stays, player B leaves and retrains. The payoffs attained correspond to the "good" equilibrium from the original game.

With this intuition in mind, we turn to our survey, beginning with a discussion of the survey design.

Section IV: Survey Design

We developed the RAND American Truck Driver Panel with the goal of understanding how truckers assess the risks they face. This development process consists of three steps: (1) identification of intercept recruitment sites, (2) in-person intercepts to recruit our panel, and (3) an online enrollment survey to carry out the survey.

Identification of Recruitment Sites

We targeted the West-South-Central region for recruitment. The sample frame from which sites were selected was comprised of private truck stops, travel plazas and commercial stops in Census Region 3, Division 7 and includes the states of Arkansas, Louisiana, Oklahoma and Texas. We selected a total of 3 sites for conducting data collection during this project. The methodology used to select these sites relied publicly available data through the Department of Transportation's Highway Performance Monitoring System, which provides count station coordinates and annual average daily traffic counts at the national level. Details are in Appendix A.

In-Person Recruitment

To recruit participants in the study, our vendor's field staff approached truckers in a systematic way to ensure random selection is used to invite potential survey participants. Surveyors were initially asked to approach every 5th trucker encountered during field period. However, this was reduced due to lower than anticipated driver volume and adjusted as needed based on staffing and driver volume. After completing the tablet survey, the surveyor provided an information packet to the truck driver, along with a promotional item branded with the logo of the RAND American Truck Driver Panel. Following completion, the driver was sent a $10 gift card via email.

Intercept survey data collection took place from Monday, June 23rd to Thursday, August 16th at Oklahoma City East Travel Center (June 23rd – 26th), Lafayette Travel Center (June 30th – August 2nd), and Petro Beaumont (August 6th – 8th & August 13th – 16th). Surveying originally began at approximately 11:00 a.m., but was changed to 9 a.m. and 8 a.m. due to a heavier traffic flow of drivers in the earlier hours. Table 1 provides the number of long-haul vehicles arriving at each of the three data collection sites. During data collection, 1,237 long-haul vehicle drivers were intercepted and asked to participate. Table 2 summarizes the number of intercepted long-haul drivers by site. Table 3 provides a summary of final survey disposition by site. The data show an overall response rate of 41 percent and an overall refusal rate of 47 percent. When analyzed at the site level, Oklahoma City East had the highest response rate and the lowest refusal rates. Conversely, Petro Beaumont had the lowest response rate and the highest refusal rate.

Gathering Baseline Information

RAND received 506 intercept-recruited truck drivers with a valid email address from NuStats. These drivers were invited to complete an online enrollment survey via email and offered a $15 Amazon gift code for completing the online survey.

Working with RAND, we drafted an online enrollment survey that would collect baseline information about truckers. The survey was designed for administration to drivers who had completed the intercept screener survey and provided a valid email address as part of that process. The enrollment survey included questions about the following:

- Truck driving experience
- Endorsements/efforts to improve marketability
- Driver and vehicle monitoring
- Self-perceived driver quality/skill
- Perceptions of driverless vehicles
- Political views
- Driver demographics
- Facility and opportunities for retraining
- Work experience in other industries

Following the initial launch of the survey, RAND sent 6 email reminders on a near-weekly basis (see Table 4 for the enrollment survey fielding timeline). The email reminders were sent to all drivers who had not fully completed the enrollment survey. The subject header and email content varied for each reminder message. In addition to email reminders, RAND delivered a hardcopy letter and a text reminder. The hardcopy letter was mailed to 414 drivers who had not completed the enrollment survey as of the mailing date (October 8). Mailing addresses were collected during the in-person intercept recruitment. And while addresses were collected, they were not validated and we had a high rate of returns (27%; 112 returns out of 414 sent).

The text message was sent on Oct. 25 to 69 drivers who had been recruited in the intercept, but not yet responded to the enrollment survey email invitations. Overall, we collected about 100 mobile telephone numbers during the enrollment survey. Of those, nearly 30 drivers had completed the enrollment survey by Oct. 25, leaving 69 drivers eligible to text. The text included a very short message to complete the American Truck Driver Panel enrollment survey and a link directly to the survey.

After sending the sixth email reminder on November 3 and receiving no additional completed enrollment surveys, the enrollment survey was closed on November 12. The final number of enrollment surveys included 123 (24.3%), with 96 (19.0%) fully-completed enrollment surveys and 27 partially-completed surveys.

Section V: Survey Results

In this section we present summary statistics describing our sample and our respondents' views on the future of trucking and the costs associated with community college.

About two thirds of our 123 respondents report working 47 or more weeks per year, as shown in Table 5. More than 36% of the sample report no work experience in any industry other than trucking. Small numbers report prior experience in industries such as business, law, computers, architecture, social services, sciences, health care, personal care, and office work. Most respondents point toward reduced earnings when asked about leaving trucking. Non-monetary aspects of trucking are important to a meaningful subgroup. 15% of respondents say they would not like working in the presence of a boss or co-workers, relative to 67% who report being concerned about making less money.

We asked several questions about drivers' views on autonomous vehicles. When asked, "how enthusiastic are you, if at all, about the development of driverless vehicles?", only 5% report being very or somewhat enthusiastic. By contrast, 95% of respondents report being not enthusiastic, for perhaps obvious reasons.

When asked "how worried are you, if at all, about the development of driverless vehicles?", more than 44% respond that they are very or somewhat worried. Drivers are similarly divided about how long it would take for AVs to become the dominant vehicles on the road. Only 56%

believe it will happen within the next 50 years.[3] Roughly 24% of respondents believe there would be “a lot fewer” trucking jobs over the next 10 years.

For parsimony, we collapse these measures into a single “very concerned” indicator. This indicator is set equal to one for those responding that they are “very worried” about driverless vehicles, feel driverless vehicles will outnumber human drivers within 10 years or that the number of trucking jobs will contract significantly within the next 10 years. All told, 29% are very concerned by this measure. Our “very concerned” measure is equal to one if the respondent reports being very worried about trucking, chooses the shortest window for projecting when AVs will outnumber human drivers, or believes the number of jobs in trucking in the next ten years will decline sharply.

Focusing more on respondents’ future plans, we first ask about additional endorsements, which are extra permissions added to a commercial driver’s license and can be seen as a way of committing to driving. Roughly 21% of respondent are seeking additional endorsements, with 49% saying no, and 30% being unsure.

If truckers were instead to switch industries, the returns to community college become of central interest. As discussed above, there is significant research that small changes in the cost of community college can have a large impact on attendance. For example, Jepsen (2009) finds that distance is an important determinant.

We asked respondents how far they thought they lived from the nearest community college. Roughly a quarter think they live more than 20 miles from one. Similarly, 50% of respondents believe that one course at a community college would cost more than $600.[4] These numbers

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[3] How <u>enthusiastic</u> are you, if at all, about the development of driverless vehicles? Responses: Very enthusiastic: 2%; Somewhat enthusiastic: 4%; Not too enthusiastic: 35%; Not at all enthusiastic: 60%.

How <u>worried</u> are you, if at all, about the development of driverless vehicles? Responses: Very worried: 15%; Somewhat worried: 29%; Not too worried: 27%; Not at all worried: 29%.

[4] How far do you think you live from the nearest community college? Responses: Less than 10 miles: 42%; 11 to 20 miles: 31%; 21 to 50 miles: 21%; More than 40 miles: 5%.

How much do you think one course would cost at a community college? Responses: $100 to 199: 5%; $200 to 299: 8%; $300 to 399: 15%; $400 to 499: 7%; $500 to 599: 14%; $600 to 699: 7%; $700 to 799: 4%; $800 to 899: 4%; $900 to 999: 3%; $1000 or more: 32%.

might explain concerning responses to a scenario we asked drivers to consider. Specifically, we asked what course of action drivers would pursue if forced to leave trucking in a year. Only 22% mention retraining via school. By contrast, 28% mention saving in advance of such a shock, 9% mention moving, and 32% would do nothing to prepare.

Section VI: Analysis of Survey Results

Turning now to analysis of the responses, we find a strong connection between the perceived cost of community college and the likelihood of a respondent saying she would return to school in this scenario. We discuss our regression models and estimates in this section. See Appendix B for robustness checks of our main findings.

We estimate an equation of the following form:

$$CheapCC_i = \alpha + \beta * CCReturn_i + \varepsilon_i,$$

where $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the reverse. $CCReturn_i$ is a dummy variable taking a value of 1 if the respondent would "go back to school" if they decide to exit trucking and a value of 0 if they would not choose to return to school.

Column 1 of Table 6 reports the results. Respondents who reported that they would go back to school upon leaving trucking are 40 percent more likely to think that community college is relatively cheap relative to those who respond that they would not go back to school upon leaving trucking.

One concern is that our measure of the "perceived cost of community college" is merely a proxy for differences in a less mutable characteristic. To test this hypothesis, we regress our measure of community college costs on a host of characteristics.

Specifically, we switch $CCReturn_i$ with one of eight explanatory variables used to explain possible correlates with $CheapCC_i$: age, years of experience in truck driving, a dummy variable for whether or not the driver owns their own truck, dummy variables for routes driven (over the road, regional, and local), a self-reported measure of experience, dummies for black and

Hispanic drivers, 2017 income, and the summary dummy measure indicating if the driver is worried about AV.

The summary worried about AV dummy takes a value of 1 if the respondent reported being very worried about trucking, chose the shortest time for AV to outnumber human drivers, or believes the number of trucking jobs will decline sharply in the next ten years. The baseline rate is represented as α.

Columns 2 through 9 of Table 6 report the results from these eight regressions. We find no correlation between knowledge of these costs and a host of characteristics. This is reassuring that our estimate may reflect the causal effect of this knowledge rather than simply a correlation with other measures.

We investigate why truckers who are worried about AV choose to invest more in trucking. Motivated by our model, we test whether this seemingly inconsistent set of responses is driven by misinformation about the cost of outside options—specifically, of attending community college.

We estimate the following equation:

$$Endorsements_i = \alpha + \beta * ConcernAV_i + \gamma * CheapCC_i + \delta(ConcernAV * CheapCC)_i + \varepsilon_i,$$

where $Endorsements_i$ is a dummy variable taking a value of 1 if the respondent is seeking additional endorsements and a value of 0 if they are not seeking additional endorsements. $ConcernAV_i$ is a dummy that takes a value of 1 if the driver reports being very worried about trucking, chooses the shortest window for projecting when AVs will outnumber human drivers, or believes the number of jobs in trucing in the next ten years will decline sharply. $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the opposite.

These two dummy variables are then multiplied together in an interaction term that takes a value of 1 for drivers that are both very concerned about AV and perceive community college to be relatively cheap.

We report the results in column 1 of Table 7, and find that respondents who are both very concerned about AV and correctly perceive community college to be inexpensive are 39.8 percent less likely to invest more in their trucking career by seeking additional endorsements.

In column 2 of Table 7, we replace $Endorsements_i$ as the dependent variable with $StayInTrucking_i$, a dummy variable that takes a value of 1 if the driver responds that they plan to stay in trucking over the next five years (and 0 otherwise). Our results are very similar. At baseline, concern among respondents about AV is positively (but statistically insignificantly) associated with planning to stay in trucking for the coming five years, while the coefficient on the interaction term between concern and perceiving community college to be relatively cheap is large and negative.

This finding aligns with the qualitative responses as well. For example, a driver reporting concern over AV who believed community college cost $900+ a course reported, "[o]n one hand I feel like my job is in jeopardy; I have a family to provide for and this is how I make my living. I hope that these fancy owners have a heart and keep truckers around." This driver reported seeking additional endorsement, such as an endorsement to carry hazardous material. A similar driver who was concerned about AV but also believed community college to cost $100-$200 a course after aid reported, instead, he was "[p]lanning to go to school to learn some other profession."

Section VII: Staying, Leaving, or Doubling-Down on an Occupation at Risk of Automation: Calibration

In this section, we contextualize the empirical findings in the previous section by calibrating the simple model presented in Section 3. The question we try to get it is whether information regarding the cost of community college might be sufficient, quantitatively, to shift worker behavior. This calibration is intended to be illustrative, not definitive, and to explore whether misperceptions could reasonably be a significant factor in truckers' decisions about their careers.

Based on data from the Bureau of Labor Statistics, we calibrate annual earnings for younger (age 35) high school graduates as $24,609 and $31,083 for older (age 55) high school graduate workers. Workers with an associate's degree or some college education earn corresponding median wages of $31,729 and $41,823.

Calibrating annual wage growth to match these moments and using a representative 5 percent discount rate yields significant premia associated with an associate's degree, in present value terms, for both younger ($580,800 vs $461,700) and older ($301,500 vs. $363,300) workers. These premia remain large even after accounting for misperceptions of the cost of community college and are obviously larger for the younger worker.

To calibrate earnings for truckers, we use data from the BLS. This returns annual earnings of $52,565 for older truckers and $33,361 for younger drivers. Given these calibrated earnings, wage growth, and discount rates, the present value of future earnings for younger and older drivers is $718,700 and $509,000, respectively.

The large premium associated with trucking is such that, even if half the jobs in trucking were to disappear, both younger and older risk-neutral drivers would prefer to gamble on a 50-50 chance of the non-college/trucking outcome rather than attend community college. The preference is strong enough to induce them to make inefficient investments (such as earning additional endorsements of around $5,000 in value) that would enable them to have this option.

That is, our calibration produces the inefficient equilibrium represented in Figure 2, in which we used a simple game to model interactions between older and younger workers in the face of automation risk and with incorrect information about outside options. This equilibrium obtains regardless of whether truckers incorrectly anticipate community college to be costly (which we parameterize as $10,000 per year) or free.

Alternatively, if drivers anticipate not only job loss but also no wage growth in the trucking industry, then younger drivers would no longer find it worthwhile to invest in remaining in the trucking industry. With zero wage growth in the trucking industry, younger drivers (but not older ones) have a higher present discounted value of lifetime earnings when attending community college. This produces the equilibrium in Figure 3, in which we alter our game and allow the older and younger workers to learn the true cost of retraining.

Which situation is reasonable? Do workers in automating industries consider the cost of retraining when deciding to re-invest in their industry? How do they think about future wages?

The empirical analysis of our survey results — presented in the previous section — sheds some light on these questions.

Those results, taken together with this calibration exercise, suggest that workers may not expect trucking wages to stagnate even if they are concerned that the number of jobs in trucking will decline, and that their own job may be at risk. In a textbook labor market model, this would be rational if they expect demand for truckers to fall by less than the supply of truckers. So investing in trucking may be individually rational. But it strikes us as more likely that in the trucking industry, labor demand would decline faster than labor supply. This suggests that perceptions about the future path of wages in an at-risk industry are an important factor for economists and policymakers to understand.

Our survey confirms this. We find that respondents who expected to see earning grow were 51 percentage points more likely to say they intended to continue as truck drivers for more than 5 years. Similarly, those who expected the industry to contract rapidly in terms of total employment were 41 percentage points less likely to say they intended to remain in the profession.

Furthermore, our estimates suggest that truckers likely do consider the cost of retraining when thinking about their futures — but that they are misinformed about those costs.

Section VIII: Discussion and Conclusion

The policy debate about the labor market effects of automation largely focuses on how to mitigate its harmful effects for displaced workers. This paper suggests, instead, that policymakers may want to focus on the decisions of workers in at-risk occupations before risks fully materialize. By better understanding workers' perceptions of the risk they face and of their opportunities for retraining for a new occupation, economists and policymakers can better understand the way automation affects the labor market, and how best to offer opportunities to workers who will be affected by technological change.

To further our understanding of these questions, we present the results of a new survey of truck drivers. We find that truckers have mixed views on the risk they face, with around half (44 percent) very or somewhat worried about driverless trucks, and around half (56 percent) not.

Apart from personal risk, 56 percent believe that autonomous vehicles will be the dominant vehicles on U.S. roads in the coming decades.

The respondents to our survey who are most concerned about automation are also the most likely to report intentions to invest in trucking as an occupation. This finding is counterintuitive but can be reconciled in a model in which industry contraction entices workers to try to outcompete other works for the remaining jobs. This inefficient congestion equilibrium creates a motive for welfare improving government intervention.

Moreover, we find that this counterintuitive finding is driven in part by misperceptions about the costs associated with switching occupations. In our survey, half of truckers believe that one course at a community college costs more than $600. In reality, the average cost of a community college course is close to zero.

Still, even if truckers knew the correct costs of retraining, their situation is complicated by the large existing wage premia for trucking. We calibrate a model of occupational switching to real-world data, and find that even if half the jobs in trucking were to disappear, both older and younger (risk-neutral) drivers would prefer to gamble on a 50-50 chance of staying in trucking rather than attend a community college.

However, this finding is contingent on perceptions of the future path of trucking wages. Truckers who anticipate relatively slow or stagnant wage growth are significantly more likely to leave trucking and retain, when they understand the true costs of retraining. In an industry with declining labor demand, wages are unlikely to grow robustly.

Overall, our findings suggest two information interventions for policymakers to consider. Information provision on the costs of community college may be more welfare enhancing than simply correcting individual decision making. We find evidence that incorrect perceptions about the costs of retraining are keeping truckers in trucking, and may even be leading some truckers to invest in that occupation. In addition, information about the outlook for the industry — including the outlook for wage growth — may help truckers to make better informed decisions about the future course of their careers.

The scale of disruption from automation and the low cost of information provision suggests that the net social benefit from providing better information to American workers could be quite large.

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Tables and Figures

Table 1: Number of Long-haul Vehicles at Sites During Hours of Data Collection

Hour of Day	Oklahoma City East Travel Center	Lafayette Travel Center	Petro Beaumont
08:00	NA	NA	5
09:00	29	137	49
10:00	25	129	56
11:00	71	105	49
12:00	66	80	77
13:00	30	83	60
14:00	69	58	53
15:00	62	48	58
16:00	80	28	45
17:00	61	27	25
18:00	28	18	20
19:00	23	NA	NA

Note: This table shows the number of long-haul vehicles that arrived at the three sites during hours of observation by time of day. Data were collected from three locations: first, from Oklahoma City East Travel Center from Monday, June 23rd, 2019 to Thursday, June 26th, 2019; second, from Lafayette Travel Center from Monday, June 30th, 2019 to Thursday, August 2nd, 2019; and third, from Petro Beaumont from Monday, August 6th, 2019 to Wednesday, August 8th, and then again from Petro Beaumont from Monday, August 13th to Thursday, August 16th. These numbers were added together by hour of observation across all the days at a given observation site. The first two days of observation at the Oklahoma City East Travel Center began at 11 AM. The third day of observations, and subsequent days at the other centers began, at 9 AM. One day of observation, only at Petro Beaumont, began at 8 AM.

Table 2: Number of Long-haul Vehicles at Sites During Hours of Data Collection

Oklahoma City East Travel Center	Lafayette Travel Center	Petro Beaumont	Total
380	312	545	1,237

Note: This table shows the number of long-haul vehicles that arrived at the three sites during hours of observation by time of day. Data were collected from three locations: first, from Oklahoma City East Travel Center from Monday, June 23rd, 2019 to Thursday, June 26th, 2019; second, from Lafayette Travel Center from Monday, June 30th, 2019 to Thursday, August 2nd, 2019; and third, from Petro Beaumont from Monday, August 6th, 2019 to Wednesday, August 8th, and then again from Petro Beaumont from Monday, August 13th to Thursday, August 16th. These numbers were added together by hour of observation across all the days at a given observation site. The first two days of observation at the Oklahoma City East Travel Center began at 11 AM. The third day of observations, and subsequent days at the other centers began, at 9 AM. One day of observation, only at Petro Beaumont, began at 8 AM.

Table 3: Number of Long-haul Vehicles at Sites During Hours of Data Collection

Survey Disposition	Oklahoma City East Travel Center	Lafayette Travel Center	Petro Beaumont	Total
Completed Interview	185 / 49%	132 / 42%	189 / 35%	506 / 41%
Partial Complete	48 / 12%	3 / 1%	31 / 6%	82 / 7%
Ineligible	11 / 3%	17 / 6%	34 / 6%	62 / 5%
Refusal	136 / 36%	160 / 51%	291 / 53%	587 / 47%
Total	380 / 100%	312 / 100%	545 / 100%	1,237 / 100%

Note: This table shows the total number of long-haul vehicles drivers that agreed to participate in the survey and the degree to which they completed it. Each column shows counts and percentages for each of the three collection sites and a fourth column shows the total counts and percentages for all three sites. Data were collected from three locations: first, from Oklahoma City East Travel Center from Monday, June 23rd, 2019 to Thursday, June 26th, 2019; second, from Lafayette Travel Center from Monday, June 30th, 2019 to Thursday, August 2nd, 2019; and third, from Petro Beaumont from Monday, August 6th, 2019 to Wednesday, August 8th, and then again from Petro Beaumont from Monday, August 13th to Thursday, August 16th. The first two days of observation at the Oklahoma City East Travel Center began at 11 AM. The third day of observations, and subsequent days at the other centers began, at 9 AM. One day of observation only at Petro Beaumont began at 8 AM. observations, and subsequent days at the other centers began, at 9 AM. One day of observation, only at Petro Beaumont, began at 8 AM.

High temperatures had an impact on one surveyor during data collection at the Lafayette Travel Center location. This surveyor was thanked for their time and work and by mutual agreement, was removed from data collection due to the extreme heat for the remainder of data collection at this location. At the Beaumont location, twice as many drivers were recruited as necessary due to two interviewers falsifying data. We discovered this thanks to data anomalies and once confronted, these surveyors admitted the data falsification and were dismissed. This explains the relatively larger number of interviews at Beaumont. Several surveyors ceased collection at Lafayette during the initial period for personal reasons, and our field coordinator went back into the field, the week of August 13th – 16th to collect additional respondents. Data collection concluded at all locations between 6:00 p.m. and 7:00 p.m., depending on site-specific activity.

Table 4: Number of Long-haul Vehicles at Sites During Hours of Data Collection

Date	Activity
Sept. 6 (Thurs)	50P6 email invitations sent
Sept. 12 (Wed)	First email reminder sent
Sept. 19 (Wed)	Second email reminder sent
Sept. 28 (Fri)	Third email reminder sent
Oct. 6 (Sat)	Fourth email reminder sent
Oct. 8 (Mon)	Hardcopy reminder letter mailed to 414 drivers
Oct. 17 (Wed)	Fifth email reminder sent
Oct. 25 (Thurs)	Text messages sent to 69 mobile numbers collected
Nov. 3 (Sat)	Sixth email reminder sent (final)
Nov. 12 (Mon)	Enrollment survey closed

Note: This table shows the timeline used by RAND to contact the 506 respondents to the initial contact survey that provided a valid email address.

Table 5: Summary Statistics for Survey Respondents

Variable	Mean (SD)	Variable	Mean
Age (years)	44.8 (12)	Fraction with Experience In:	
Male	88%	*Construction*	32%
High School or Less	51%	*Food Prep*	22%
Associates Degree or More	24%	*Management*	21%
White	58%	*Sales*	20%
Black	16%	*Building*	14%
Hispanic	10%	*Farm*	16%
Income in 2017	$67,809 ($48,668)	*Production*	13%
Years Spent Driving	16.45 (12.4)	Share with Additional Endorsements:	
Local Route	15%	*Double Trailer*	40%
Regional Route	15%	*Tank Vehicle*	46%
OTR	70%	*Hazardous Material*	26%
Truck Owner	32%	*Combo Tank and Hazardous Material*	32%
Own a Computer	73%	*TWIC Card*	33%
Voted for Trump	44%		
Voted for Clinton	15%		
Weekly Hours	56.9 (20.4)		

Note: This table reports the share of long-haul vehicle drivers that have received additional endorsements in various classes above their baseline qualifications. The sample of 123 long-haul vehicle drivers were first contacted at one of three survey sites and are a subset of 506 drivers who provided a valid email address on the initial contact survey at those sites.

Table 6: Correlations Between Perceived Costs of Community College and Factors Influencing the Perceived Threat of Automation

	(1) Would Return to School if Leaving Trucking	(2) Age	(3) Years Driving	(4) Ownership Dummies	(5) Route Type Dummies	(6) Self Assessed Rank	(7) Black Hispanic Dummies	(8) Income 2017	(9) Worried about AV
Perceived CC<$600	0.400***	-0.004	-0.004	-0.110	-0.125	0.003	0.035	-1.12e-06	0.127
	(0.116)	(0.005)	(0.004)	(0.106)	(0.178)	(0.003)	(0.131)	(1.05e-06)	(0.096)
				-0.207	-0.138		-0.302*		
				(0.199)	(0.139)		(0.161)		
Baseline Rate	0.267***	0.689***	0.511***	0.492***	0.562***	0.246	0.402***	0.556***	0.345***
	(0.051)	(0.246)	(0.079)	(0.062)	(0.126)	(0.235)	(0.049)	(0.088)	(0.052)
Observations	96	82	107	106	105	104	123	98	123
R-squared	0.120	0.009	0.012	0.017	0.010	0.008	0.030	0.012	0.014

Note: This table reports estimates of equations of the following form:

$$CheapCC_i = \alpha + \beta * ExpVariable_i + \varepsilon_i$$

Where $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the reverse. $ExpVariable_i$ is one of nine explanatory variables used to explain possible correlates with $CheapCC_i$, these include: a dummy for whether or not the driver would return to school if they decide to leave trucking, age, years of experience in truck driving, a dummy for whether or not the driver owns their own truck, dummies for routes driven (over the road, regional, and local), a self-reported measure of experience, dummies for black and Hispanic drivers, 2017 income, and the summary dummy measure indicating if the driver is worried about AV. The summary worried about AV dummy takes a value of 1 if the respondent reported being very worried about trucking, chose the shortest time for AV to outnumber human drivers, or believes the number of trucking jobs will decline sharply in the next ten years. The baseline rate is represented as α. The sample consists of 123 long-haul vehicle drivers; the sample varies across columns due to data availability issues. Details for sample selection are presented in the text. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of Information Regarding AV on Decisions to Invest in Trucking

VARIABLES	(1) Seeking More Endorsements	(2) Plan to Stay in Trucking 5 More Years
Very Concerned About AV	0.316**	0.140
	(0.122)	(0.131)
Community College <$600 a course	0.0947	0.342***
	(0.0850)	(0.0965)
Interaction	-0.398**	-0.327*
	(0.164)	(0.189)
Constant	0.105**	0.491***
	(0.0413)	(0.0673)
Observations	123	123
R-squared	0.083	0.080

Note: This table reports estimates of equations of the following form:

$$Endorsements_i = \alpha + \beta * ConcernAV_i + \gamma * CheapCC_i + \delta(ConcernAV * CheapCC)_i + \varepsilon_i$$

Where $Endorsements_i$ is a dummy variable taking a value of 1 if the respondent is seeking additional endorsements and a value of 0 if they are not seeking additional endorsements. $ConcernAV_i$ is a dummy that takes a value of 1 if the driver reports being very worried about trucking, chooses the shortest window for projecting when AVs will outnumber human drivers, or believes the number of jobs in trucing in the next ten years will decline sharply. $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the reverse. These two dummy variables are then multiplied together in an interaction term that takes a value of 1 for drivers that are both very concerned about AV and perceive community college to be relatively cheap. In Column two $Endorsements_i$ is replaced with $StayInTrucking_i$, which is a dummy variable that takes a value of 1 if the driver responds that they plan to stay in trucking over the next five years. The sample consists of 123 long-haul vehicle drivers. Details for sample selection are presented in the text. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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APPENDIX A: DETAILS ON SITE SELECTION

For the study, we targeted the West-South-Central region for recruitment. The sample frame from which sites were selected was comprised of private truck stops, travel plazas and commercial stops in Census Region 3, Division 7 and includes the states of Arkansas, Louisiana, Oklahoma and Texas. We required a total of 3 sites for conducting data collection during this project. The methodology used to select these sites required careful review of publicly available data through the Department of Transportation's Highway Performance Monitoring System, which provides count station coordinates and annual average daily traffic counts (AADT) at the national level.

Annual average daily traffic (AADT) is a measure used in transportation planning and transportation engineering. The process of identifying the AADT is the total volume of vehicle traffic of a highway in a year divided by the total number of days in a year. This translates into how busy the highway is at each highway and road segment reported by the traffic counting station. The higher the AADT, the higher the volume of traffic. For the purposes of this project our site selection work focused on the total volume of truck traffic on a highway segment for one year or AADTT (annual average daily truck traffic).

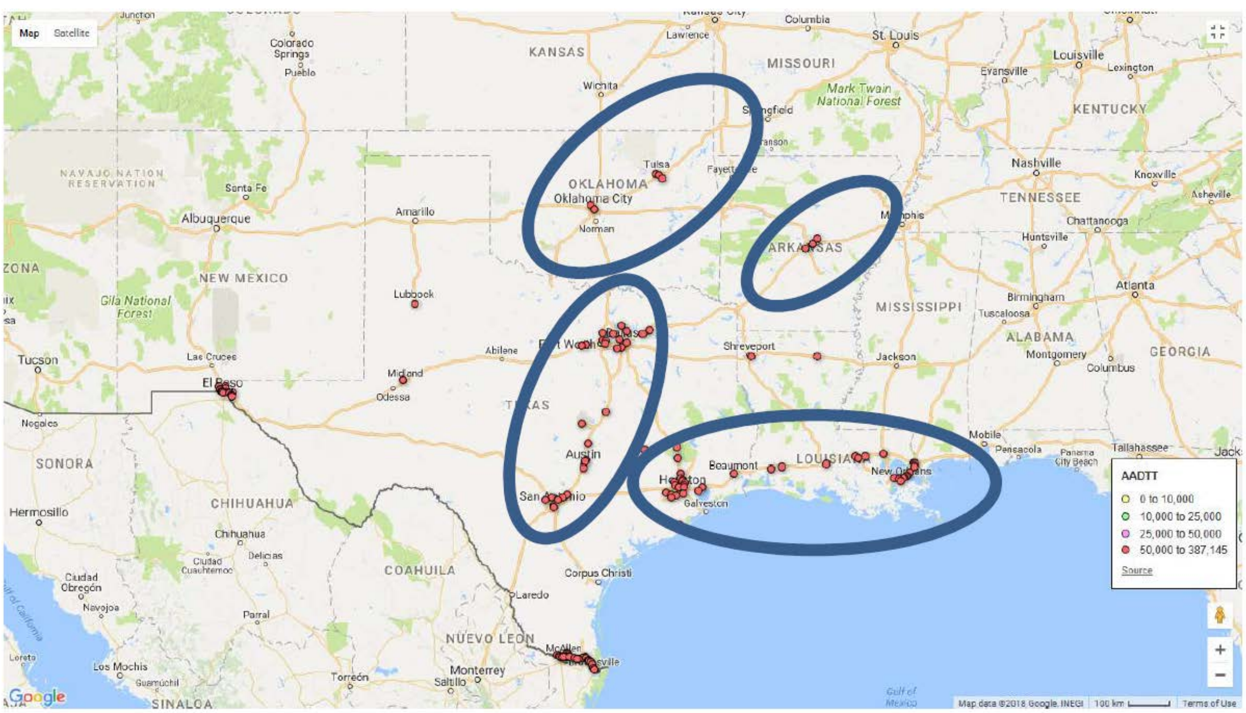
The agency responsible for calculating and reporting daily traffic volumes is the Department of Transportation (DOT) of each state. For this report, AADTT values were generated from public databases of the respective DOTs of the states of Arkansas, Louisiana, Oklahoma and Texas. There are a total of 63,525 counting stations where AADTT data is collected along these four states: 12,773 in Arkansas, 5,143 in Louisiana, 14,169 in Oklahoma and 31,440 in Texas.

To select 3 sites to conduct intercept data collection for this, our vendor NuStats used a systematic process that included the selection of 10 to 15 sites to conduct site visits. NuStats conducted in-person visits to confirm data about each selected site and to ensure the site meets optimum conditions for conducting the survey, to understand the logistics of getting surveyors to the site, and to obtain the necessary permissions for conducting intercept data collection at each site. The process for selecting sites for inspection is described below.

Site Selection

The first step in site selection was to identify the count stations along the target area. These data points were plotted on a map to better visualize the concentration of truck traffic volume used as the basis for selecting the transport corridors most suitable for data collection. The selection of transport corridors was done based on actual volume of truck traffic (AADTT) which is a subset of the AADT data; and the identification of actual count stations near potential sites (private truck stops, travel plazas and commercial stops). This process uncovered two main corridors, (1) the Oklahoma and Arkansas corridor and (2) the Texas and Louisiana corridor. Within these corridors four main high-volume truck traffic clusters were identified. Figure A1 displays these four main areas. In the Oklahoma and Arkansas corridor two high volume areas were identified, the first one along Oklahoma City and Tulsa, and the second one along Fayetteville and Fort Smith in Arkansas. The Little Rock area in Arkansas was also identified as a high truck volume area but is considered a back-up corridor. In the Texas and Louisiana corridor two high truck traffic volume areas were identified, the first one along the San Antonio, Fort Worth, and Dallas corridor in Texas and the second one along the Gulf Coast area between Houston, Texas and New Orleans, Louisiana (see Figure A1).

Figure A1. High Truck Traffic Volume Clusters



Next, we ranked counties by AADTT using public data from the state departments of transportation for Arkansas, Oklahoma, Louisiana, and Texas. This information was used to further aid in the selection of traffic clusters best suited for intercept data collection. Table A1 shows AADTT counts by county for the top five counties with the highest AADTT for each state. These tables support the selection of data collection sites along Interstate 10 in the Houston, Texas (Harris County) and New Orleans, Louisiana (Orleans Parish) corridor and along Interstate 44 in Oklahoma and Interstate 49 in Arkansas, specifically along the counties of Cleveland, Oklahoma, and Tulsa counties in Oklahoma and Pulaski County in Arkansas.

Third, to obtain a representative sample of long-haul truck drivers and make the project efficient both in terms of cost and timeline it was necessary to consider the proximity between each site in the final selection of a transport corridor. Sites that are reasonably close that offer the proper conditions for interviewing can provide cost savings, allowing NuStats to train fewer interviewers that are able to travel between sites. Fewer interviewers working more hours in the project allows the team to become experts in the logistics and procedures used in data collection which makes the entire process more effective. In addition, selecting sites which are reasonably close allows utilization of back up sites should a change in plans be necessary during the scheduled data collection day, for example, if the selected truck stop is closed or access is not allowed due to an unexpected situation.

Using this “convenience” factor, we selected the Oklahoma City/Tulsa- Fayetteville/Fort Smith corridor along Oklahoma and Arkansas (Figure A2) and the Houston-New Orleans corridor along Texas and Louisiana (Figure A3). The next step was to identify count stations with an AADTT of 50,000 trucks per year or higher and plot the sites (private truck stops, travel plazas and commercial stops) near these count stations; these are displayed in Figures A2 and A3.

Fourth, we selected stations for further consideration collection based on their proximity to count stations with an AADTT volume of 80,000 trucks per year or higher and high-capacity parking as revealed by aerial images of each station. We reviewed aerial data for all locations identified. Figure A4 shows an example for an aerial image of Petro Stopping Center in Beaumont, Texas.

Table A1: Annual Average Daily Truck Traffic (AADTT): High-Volume Clusters

State	County	AADTT
Oklahoma	Cleveland	97,331
	Oklahoma	96,154
	Tulsa	77,832
	Rogers	74,600
	Canadian	73,800
Arkansas	Pulaski	91,079
	St. Francis	85,640
	Benton	70,448
	Washington	69,756
	Lonoke	65,230
Texas	Harris	145,988
	Dallas	141,240
	Collin	133,617
	Comal	130,133
	Hays	128,084
Louisiana	Orleans	110,908
	Jefferson	107,380
	East Baton Rouge	99,960
	Ascension	79,559
	Ouachita	76,837

Note: This table shows the annual average daily truck traffic for select high volume clusters from the states of Oklahoma, Arkansas, Texas, and Louisiana. The data are from the state departments of transportation for Oklahoma, Arkansas, Texas, and Louisiana.

Figure A2. High AADTT and Truck Stops for Arkansas and Louisiana

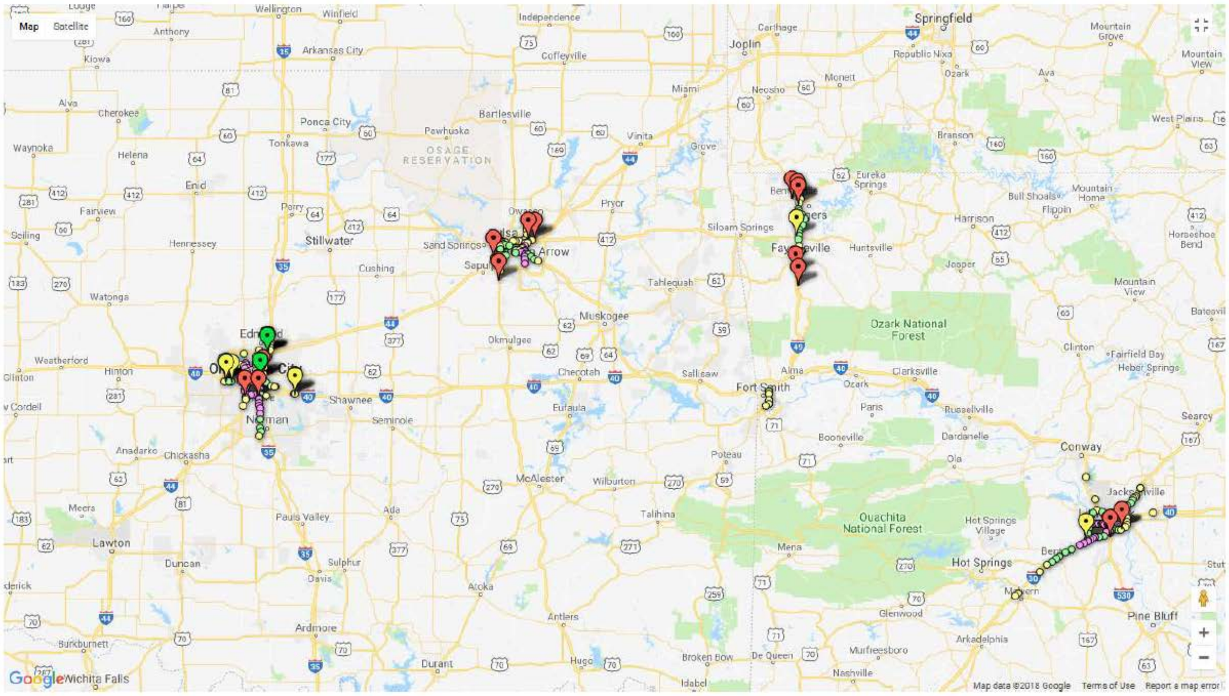
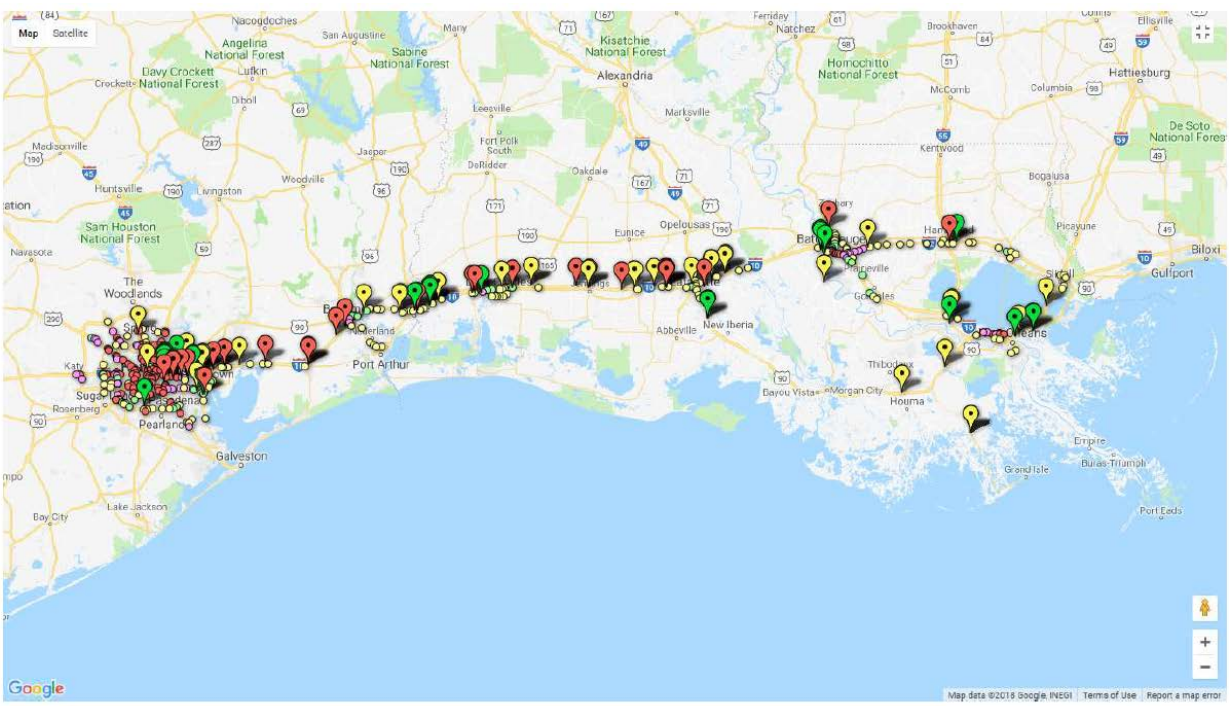


Figure A3. High AADTT and Truck Stops for Louisiana and Texas



Based on the process outlined in this section, we selected 17 locations in the Arkansas-Oklahoma corridor and 27 in the Texas-Louisiana corridor. We contacted each of these locations to confirm daily truck volume at each location as well as the amenities offered. We selected the 10 locations with the highest daily volume to receive in-person site visits. The site visits are necessary to confirm all information available for each location and to make final site selections for intercept data collection.

Figure A4. Aerial Image of Petro Stopping Center in Beaumont, Texas

Site Visits

Personnel from our vendor NuStats visited each primary site to conduct a thorough site evaluation. NuStats visited 10 different sites prior to making the final decision of where to conduct intercept data collection. The site visits provided an opportunity to:

- Identify/confirm location data, such as truck traffic levels, that were key to selecting the location and obtaining the desired number of completed recruits per day
- Collect/confirm site-specific data, such as available amenities, number of parking spaces, parking restrictions, etc.
- Select potential locations at each site where interviewers might have the greatest propensity to intercept commercial vehicle operators
- Meet the owner/operator/manager from whom permission is to be obtained
- Identify the logistics of getting interviewers to the site

Site evaluations were conducted in May and June 2018. Table A2 summarizes the data collected during site evaluations. These data allowed NuStats to rank each site and select the top five for data collection. Two sites served as back up sites in the event data collection at the main site is not possible when scheduled. Back up sites will be located reasonably close to main sites.

Table A2: Site Evaluation Indicators

Variable Name	Definition	Values
SiteName	Facility name	
SiteID	Facility ID	
SiteType	Site type	
Phase	Phase	1=Pilot ;2=Full Study
County	County in which facility is located	
Route	Route on which facility is located	

Milepost/Reference Marker	Milepost or reference marker in closest proximity to facility	
EvalDate	Date of site evaluation	
EvalTime	Time of site evaluation	
Muni	Municipality in closest proximity to facility	
Exit	Exit in closest proximity to facility	
XCOORD	Longitude of facility	
YCOORD	Latitude of facility	
OccTruck	Total number of occupied commercial vehicle parking spaces	
TotTruck	Total number of commercial vehicles parked at facility	
Fee	Presence of parking fee at facility	0=Not present;1=Present
FeeAmt	Parking fee amount at facility	
Limit	Presence of parking time limit at facility	0=Not present;1=Present
MaxTime	Presence of maximum park time at facility	0=Not present;1=Present

Attndnt	Presence of parking attendant at facility	0=Not present;1=Present
Surveyor	Names of surveyors conducting site evaluation	
RestRooms	Presence of rest rooms at facility	0=Not present;1=Present
TIC	Presence of Traffic Information Center at facility	0=Not present;1=Present
Gas	Presence of gasoline fuel for sale at facility	0=Not present;1=Present
Diesel	Presence of diesel fuel for sale at facility	0=Not present;1=Present
AltFuel	Presence of alternative fuels for sale at facility	0=Not present;1=Present
Shower	Presence of showers at facility	0=Not present;1=Present
ELECT	Presence of charging stations for electronics	0=Not present;1=Present
Convene	Presence of convenience type store at facility	0=Not present;1=Present
FastFood	Presence of fast food restaurant at facility	0=Not present;1=Present
SitDown	Presence of sit down restaurant at facility	0=Not present;1=Present
Motel	Presence of motel at facility	0=Not present;1=Present
Scales	Presence of certified scales at facility	0=Not present;1=Present

HardWireInt	Presence of hard wire Internet at facility	0=Not present;1=Present
WiFi	Presence of wireless Internet connection at facility	0=Not present;1=Present
Wash	Presence of truck wash at facility	0=Not present;1=Present
ATM	Presence of Automated Teller Machine at facility	0=Not present;1=Present
WestUn	Presence of Western Union services at facility	0=Not present;1=Present
MO	Presence of money order service at facility	0=Not present;1=Present
NATSO	Presence of NATSO check line at facility	0=Not present;1=Present
Games	Presence of game room at facility	0=Not present;1=Present
Variable Name	Definition	Values
Vend	Presence of vending machine at facility	0=Not present;1=Present
Tires	Presence of tire sales at facility	0=Not present;1=Present
Repair	Presence of truck repair services at facility	0=Not present;1=Present
Laundry	Presence of washer/dryer or laundry service at facility	0=Not present;1=Present
IntLoc	Best spot to position interviewers for surveying	

Communication with Local Law Enforcement

Potentially affected law enforcement agencies are defined as those that are within a close enough proximity to the intercept sites that concerned citizens or commercial vehicle drivers may contact them with inquiries about the surveys being conducted. We contacted all identified law enforcement agencies and communicated details about the survey effort and provided approval documentation as needed, including the dates and times when the survey was scheduled.

APPENDIX B: ROBUSTNESS CHECKS

To address potential sample size concerns, we also calculate confidence intervals for the core result, which relates investment to the interaction of perceived college costs and AV concerns, using a wild bootstrap with 1,000 iterations and Rademacher weights, as recommended by Cameron et al. (2008). Using this procedure, we recover a 95% confidence set of [-.7226, -.08112], which excludes zero. Thus, it does not appear that asymptotically derived confidence intervals are artificially implying statistical significance.

We explore further robustness tests in Table B1. In column 1, we add controls for factors like race, income, and hours worked to our main result. The interaction of interest (between concerns over AV and knowledge of community college costs) is essentially unchanged by adding these variables to the model. In unreported results, we also explore whether any of these demographics interact with concern over AV. When added to the model, the interaction between concern and race, income, and hours are statistically and economically insignificant and do not change the coefficient of interest or its statistical significance.

Additionally, we perform a sanity test in columns 2 and 3. Intuitively, the cost of community college should not impact the investment decision of those who have already earned an associate's degree or higher. It should still interact with concern over AVs for those without a 2-year degree. Columns 2 and 3 demonstrate, as expected, that community college costs only moderates worry for the group without an existing degree. The dependent variable, seeking additional endorsements, is binary. Running our results using probit and logistic interactions produces quantitatively similar results as well.

Finally, in Table B2, we explore the result using a split sample nearest-neighbor matching procedure. For both the population worried about automation (column 2) and the population that does not report being worried (column 1), we investigate whether perceiving community college as cheap impacted investment plans. We match individuals based on age, race, income, and years of experience driving.

Again, as evident in Table B2, we robustly find an interaction between worry and the perceived cost community college. Individuals worried about AV who are matched on age, race, income, and years of experience have different plans based on whether they misperceive the cost of community college. For those unconcerned about AV, the cost of outside options is – unsurprisingly – irrelevant to future plans. For those anticipating or concerned about AV disruption, these perceived costs are significant.

Table B1: Effect of Information Regarding AV on Decisions to Invest in Trucking Including Demographic Controls

VARIABLES	(1) Seeking More Endorsements	(2) Seeking More Endorsements	(3) Seeking More Endorsements
Very Concerned About AV	0.233*	0.332**	0.167
	(0.140)	(0.135)	(0.422)
Community College <$600 a course	0.0406	0.170	-0.233
	(0.0990)	(0.114)	(0.200)
Interaction	-0.339*	-0.505***	-0.017
	(0.175)	(0.184)	(0.494)
White	0.0462		
	(0.0999)		
Black	0.202		
	(0.150)		
Income in 2017	-1.49e-06*		
	(7.79e-07)		
Weekly Hours	0.00131		
	(0.00173)		
Sample	All	Without Associates Degree	With Associates Degree
Observations	98	74	24
R-squared	0.107	0.114	0.089

Note: This table reports estimates of equations of the following form:

$$Endorsements_i = \alpha + \beta * ConcernAV_i + \gamma * CheapCC_i + \delta(ConcernAV * CheapCC)_i + \vec{\boldsymbol{D}}_i\theta + \varepsilon_i$$

Where $Endorsements_i$ is a dummy variable taking a value of 1 if the respondent is seeking additional endorsements and a value of 0 if they are not seeking additional endorsements. $ConcernAV_i$is a dummy that takes a value of 1 if the driver reported being very worried about trucking, chooses the shortest window for projecting when AVs will outnumber human drivers, or believes the number of jobs in trucking in the next ten years will decline sharply. $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the reverse. These two dummy variables are then multiplied together in an interaction term that takes a value of 1 for drivers that are both very concerned about AV and perceive community college to be relatively cheap. $\vec{\boldsymbol{D}}_i$ represents a vector of individual control variables including race dummies, 2017 income, and weekly hours. Columns two and three split the sample into drivers without an Associate's degree and driers with an Associate's degree but both do not include the vector of individual controls. The sample consists of 123 long-haul vehicle drivers. Details for sample selection are presented in the text. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Information Regarding AV on Decisions to Invest in Trucking

	(1)	(2)
VARIABLES	Seeking More Endorsements	Seeking More Endorsements
Community College <$600 a course	0.041	-0.323***
	(0.127)	(0.156)
Worried about AV	No	Yes
Observations	49	31
Nearest Neighbor Matching	X	X
(Age, Race, Income, Years Driving)		

Note: This table reports estimates of equations of the following form:

$$Endorsements_i = \alpha + \beta * CheapCC_i + \varepsilon_i$$

Where $Endorsements_i$ is a dummy variable taking a value of 1 if the respondent is seeking additional endorsements and a value of 0 if they are not seeking additional endorsements. $CheapCC_i$ is a dummy variable that takes a value of 1 if the respondent perceives the cost of community college to be lower than $600 per course (nominal 2019 USD) or a value of 0 for the reverse. The sample consists of 123 long-haul vehicle drivers that are matched into one of two groups: not worried about AV and worried about AV. These groups are determined using a K-nearest neighbors matching method on driver age, race, income, and years of driving experience. Column one reports estimates for drivers that are not concerned about AV and Column two presents estimates for drivers that are concerned about AV. Details for sample selection are presented in the text. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.