Macroeconomic Impacts of Automated Driving Systems in Long-Haul Trucking

www.its.dot.gov/index.htm

Final Report – January 28, 2021
FWHA-JPO-21-847

U.S. Department of Transportation

Produced by IAA #693JJ318N300055, U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology

Notice

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA-JPO-21-847	(Delete and insert information here or leave blank)	(Delete and insert information here or leave blank)

4. Title and Subtitle	5. Report Date
Macroeconomic Impacts of Automated Driving Systems in Long-Haul Trucking	January 28, 2021
	6. Performing Organization Code
	(Delete and insert information here or leave blank)
7. Author(s)	8. Performing Organization Report No.
Robert Waschik ORCID 0000-0001-9306-1803 Catherine L. Taylor ORCID 0000-0003-0353-7666 Daniel Friedman ORCID 0000-0002-2773-4122 Jasmine Boatner ORCID 0000-0002-7341-6993	DOT-VNTSC-FHWA-20-16
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
Volpe National Transportation Systems Center: 55 Broadway, Cambridge, MA 02142 Centre of Policy Studies, Victoria University, PO Box 14428, Melbourne, Victoria, 8001, Australia	(Delete and insert information here or leave blank)
	11. Contract or Grant No.
	IAA #693JJ318N300055
12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
U.S. Department of Transportation Intelligent Transportation Systems Joint Program Office Office of the Assistant Secretary for Research and Technology	(Delete and insert information here or leave blank)
	14. Sponsoring Agency Code
	(Delete and insert information here or leave blank)

15. Supplementary Notes

(Delete and insert information here or leave blank)

16. Abstract

This report presents an analysis of the potential macroeconomic impacts resulting from the adoption of higher level automated driving systems (ADS) of the long-haul trucking industry in the United States. The analysis uses USAGE-Hwy, a computable general equilibrium (CGE) model of the U.S. economy that includes detail on transportation related industries including for-hire and in-house trucking. Three time profiles for the adoption of automation are explored. The results show that automation of the long-haul trucking industry is expected to bring welfare enhancing productivity enhancements to the economy. Assuming that occupational turnover rates remain as they are, these positive economic impacts would not be accompanied by forced-lay-offs under the slow and medium adoption scenarios. Only under the fast adoption scenario are there short-lived, small magnitude lay-offs.

17. Keywords	18. Distribution Statement
(Delete and insert information here or leave blank)	(Delete and insert information here or leave blank)

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
(Delete and insert information here or leave blank)	(Delete and insert information here or leave blank)	(Delete and insert information here or leave blank)	(Delete and insert information here or leave blank)

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Table of Contents

Executive Summary

This report leverages the modeling capabilities of the USAGE-Hwy model, a dynamic model of the U.S. economy, to simulate the macroeconomic impacts of automated driving systems (ADS) in long-haul trucking under a set of assumptions (described in Section 3, *Data and Methods)*. In this report, ADS refers to SAE Level 4 and Level 5 automation which does not require a human driver onboard the vehicle.[1] However, the timeline for adoption of ADS remains uncertain. Therefore, this analysis examines three scenarios: slow, medium, and fast adoption paths. The fast scenario is intentionally a very optimistic scenario in which 75 percent of new vehicle purchases involve ADS in 10 years of the technology becoming available. The medium and slow scenarios assume 48 percent and 19 percent of trucking firms will have begun adopting 10 years after the technology becomes available, respectively. Importantly, this research is the first that estimates not only the direct improvements to productivity in the trucking industry from ADS, but also the indirect impacts to other industries resulting from the central role transportation plays in the larger economy.

Our model indicates that the productivity enhancements from the adoption of ADS in the long-haul trucking sector will increase GDP, capital, employment, wages, and welfare that can be monetized into billions of dollars. Additionally, our model concludes that these economic benefits can likely be reaped without mass lay-offs of long-haul truck drivers. Assuming the occupational turnover remains near today's levels, employment levels in the long-haul trucking sector will necessarily fall due to automation, but will not force lay-offs in the slow and medium speed adoption scenarios. Only under the fast adoption scenario are lay-offs observed.

Specifically, this analysis finds that SAE Level 4 and Level 5 automation of the long-haul trucking industry would do the following:

- Produce welfare increases ranging from $35 per person in the U.S. per year under the slow adoption scenario to $69 per person per year under the fast adoption scenario.
- Raise annual earnings for all U.S. workers by $203 per worker per year under the slow scenario and $267 per worker per year under the fast scenario. These benefits accrue to all workers due to economy-wide productivity improvements.
- Increase total U.S. employment by 26,400 to 35,100 jobs per year on average during the analysis period, despite decreases in employment for long-haul truck drivers.
- The lower employment levels for long-haul truck drivers can largely be offset with natural occupational turnover. However, lay-offs for long-haul truck drivers are anticipated in the fast adoption scenario. Those lay-offs occur only during a period of 5 years and the maximum lay-offs in a single year is 11,000, just 1.7 percent of the long-haul driver workforce.
- Increase GDP by at least 0.3 percent by year 30 of the analysis period.

Chapter 1. Introduction

The Intelligent Transportation Systems Joint Program Office (ITS JPO) facilitates multimodal automation research and collaboration in safety, infrastructure interoperability, and policy analysis. In support of that role, ITS JPO has partnered with the USDOT John A. Volpe National Transportation Systems Center and the Center of Policy Studies at Victoria University in Melbourne, Australia to produce this report investigating the macroeconomic impacts from automated driving systems (ADS) in the long-haul trucking industry. The report is provided to the public for informational purposes only, and does not represent an official viewpoint or policy of the United States Department of Transportation.

Driving automation has the potential to significantly enhance the productivity of the trucking industry. Because of the central role trucking plays in the U.S. economy, such productivity enhancement would be expected to have ripple effects throughout the entire economy. The purpose of this research is to further our understanding of the possible magnitude of the economy-wide impacts from ADS in long-haul trucking.

This analysis examines the long-haul segment of the trucking industry. Unlike the short-haul segment, the long-haul segment involves long periods of uninterrupted highway driving (which is a less-complex environment than surface streets) and long-haul drivers have fewer non-driving responsibilities than short-haul drivers. As a consequence, several previous studies assert that long-haul trucking appears to be a likely early candidate for deployment of ADS.[2,3] Several companies, such as Embark, Kodiak, Plus.ai, TuSimple, and Waymo, are already using automated trucks to deliver goods to customers (albeit with safety drivers). Although the nascent industry has already seen turnover (Starsky Robotics, after failing to raise additional investment, announced in May 2020 that it had shut down all operations), competitors and industry analysts remain optimistic about automated trucking in general.[4,5] Note that while advanced driver assistance systems (SAE Level 1 and 2) are available today on production vehicles, these are out of scope of the present study, as they always require an engaged human driver behind the wheel.

This analysis incorporates estimates of expected capital cost savings, fuel cost savings, and safety improvements in addition to labor cost savings resultant from the removal of human drivers in the trucking industry.[i] These estimated cost savings are balanced against higher upfront costs for purchasing the technology.

The selection of this industry segment for analysis does not constitute an endorsement or a prediction of its adoption. Many practical issues remain to be resolved in order for ADS to be widely deployed in long-haul trucking, including technological maturation, negotiating the transition between human operators and the ADS (e.g., between long-haul segments and first-mile/last-mile segments of the trip), refueling

---

[i] Per the Federal Motor Carrier Safety Regulations (FMCSRs), a trained commercial driver must be behind the wheel at all times, regardless of any automated driving technologies available on the CMV, unless a petition for a waiver or exemption has been granted.

operations, securing loads, cybersecurity concerns related to software updates, and handling emergencies.

Chapter 2. Literature Review

Several studies discuss the benefits that ADS would bring to private consumers, producers, and to society at large. These benefits include productivity enhancements, improved access to labor markets and shopping opportunities, travel time savings, reductions in fuel use (which produces improvements in the balance of trade, energy security, and environmental quality), reduced congestion, and safety improvements.[6,7] Specific to commercial trucking, the ability to remove the driver from the truck represents a potential source of significant cost savings and a few studies note that improvements in productivity for the transportation system could have significant spill-over impacts to the rest of the economy.[6,8]

A prominent historical example of the connection between transportation industries and the larger economy is the observation that investments made in the highway system lead to higher economic growth. Nadiri and Mamuneas find that highway capital investment provides productivity enhancements and cost-reductions to almost all industries, thus impacting demand for labor, capital, and intermediate goods, and providing a rate of return up to 50 to 60 percent.[9,10] Similarly, Munnell and Cook estimate a production function that accounts for highway capital stock and find a 0.06 percentage point increase in GDP for each 1 percent increase in level of public highway capital stock, measured as the value of highway equipment and structures.[11]

Computable General Equilibrium (CGE) models are often used to analyze the interconnection among industries in an economy in order to understand the wider economic impacts from a proposed policy. For instance, CGE models have been used to analyze proposed environmental regulations that impose higher costs on certain industries and trace the impacts through to other industries and households.[12] In our case, adoption of ADS is voluntary and would result in cost savings rather than cost increases, but the mechanics of the model work in the same way: CGE models allow spillover effects from one industry to other sectors of the economy to be identified and evaluated. Outside of Constantini and Sforna who use a CGE model to analyze the impact of automation jointly with specification of population ageing and environmental tax reform, this research is the only example of using CGE models to analyze the impact of automation on the wider economy in terms gross domestic output (GDP), welfare, employment, wages, etc.[13]

Huang and Kockelman use a multi-region input-output model of the U.S. economy combined with a multinomial logit model of mode choice to estimate the impact of autonomous trucking on U.S. trade flows. Their research finds that the introduction of a lower cost transport option would increase U.S. domestic and international trade flows (as measured by ton-miles) by 3.1 percent.[14]

Despite the expected benefits from ADS, much attention has been given to the possibility of widespread job loss due to higher-level automation that replaces the human driver from the vehicle. One study finds that ADS could eliminate 1.3 to 2.3 million jobs over the next thirty years and raise unemployment rate by about 0.1 percentage points and lower labor force participation by about 0.1 percentage points for a number of years.[15] *Stick Shift: Autonomous Vehicles, Driving Jobs, and the Future of Work* by the Center for Global Policy Solutions, predicts at least 4 million jobs lost under a rapid transition to automated vehicles scenario, impacting driving occupations the hardest.[7]

Notably, the studies that identify very large job losses from ADS consider a wide focus on all driving jobs. Other studies carefully parse the potential for automation to handle all or most of responsibilities of the job, the nature of the driving required by the job, and other market conditions. In their report *Truck Driving Jobs: Are They Headed for Rapid Elimination,* Maury Gittleman and Kristen Monaco identify several reasons why other estimates of jobs impacted from automation are likely overstated, including the common conflation of truck driver counts resulting from ambiguous occupational classifications used in federal statistics, the variety of non-driving tasks for which truck drivers are generally responsible, and a regulatory environment rendering certain segments of the trucking industry more difficult to fully automate. As such, the authors argue that automation does not "necessarily imply the wholesale elimination of the truck driver labor market." Rather they identify long-haul trucking (particularly the for-hire segment) as the driving job most likely to feel the initial impacts of higher-level automation.[2]

In *Driverless? Autonomous Trucks and the Future of the American Trucker,* Steve Viscelli, a sociologist at the University of Pennsylvania, also argues that long-haul truck driving jobs (numbering 294,000) are most vulnerable to displacement from automation. He argues that in addition to the economic benefits mentioned in several prior reports, automating long-haul trucking will also create short-haul, local delivery jobs, leading to an uncertain net jobs impact. A key takeaway from this report is that there are only a few hundred thousand trucking jobs in danger of elimination initially, not millions.[3]

The timeline for technology development, deployment, and acceptance of SAE Level 4 and Level 5 ADS is uncertain, as are the resultant economic impacts. Many studies emphasize that the speed of adoption will impact the likelihood of significant job displacement, with faster adoption patterns witnessing more chance of significant job displacement.[15,16]

Just as the emergence of the internet and email has reduced the number of people employed as postal workers, certain technological advancements can be linked to lower levels of employment in *certain* occupations.[ii] However, the progress of technology advancements are not usually linked to observed higher levels of unemployment at the *macro* level. This is because prices and wages adjust to signal market changes, and as a consequence, people reskill and adapt to find new employment opportunities while the technology increases productivity and increases economic opportunity generally.[17] Often it enables completely new business models, products, and unanticipated consumer demands making the total impact of technology advancement difficult to predict.[18] Consider that while the number of postal workers has decreased, the number of package delivery workers has increased due to e-commerce.[19,20]

An area of anxiety present in the literature is that the driving jobs at risk from automation tend to be better paying than other jobs that do not require advanced degrees. There is concern that the new jobs that replace the lost driving jobs might be lower paying, or require skills or geographic locations that are not good matches for the individuals who are left without a driving job. These studies recommend supporting displaced workers financially and providing retraining opportunities.[7,15]

[ii] The number of postal workers employed by USPS has reduced by 38 percent since its peak in 1999. https://about.usps.com/who-we-are/postal-history/employees-since-1926.pdf

Chapter 3. Data and Methods

This effort to characterize potential macroeconomic impacts from ADS captures many (but not all) of the themes discussed in the literature. The analysis described below focuses on the impacts of automation on the long-haul trucking sector in isolation. While an analysis that incorporates automation occurring in multiple industries simultaneously might be of interest, we choose to focus on a single industry so that impacts can be isolated and examined with clearer focus than an analysis which contains multiple countervailing and confounding shocks and impacts.

This analysis focuses on the higher-level automation (SAE Level 4 and Level 5) that would remove the human driver from the vehicle. SAE Level 4 and 5 automation is not currently available, which is to say that an environment where a driver can be completely removed from the vehicle in most or all operating environments is not yet a technical reality. The limited number of pilot tests for long-haul trucking still use a test driver at the wheel and operate only under favorable conditions. The modeling in this analysis uses a notional abstraction of the impacts from this higher-level automation that assumes that the removal of the human driver would result in labor cost savings, the magnitude of which are estimated based on current wages to the current driving workforce. This analysis does not consider any countervailing increase in short-haul driving as suggested by Viscelli due lack of information on the magnitude of that potential relationship. As a result, this analysis may slightly overstate the productivity improvements of automation while at the same time offering a conservative approach when considering the potential for lay-offs due to automation.[3] Additional productivity impacts to the long-haul trucking sector take the form of capital cost savings, fuel cost savings and safety improvements. These positive impacts are balanced against higher upfront costs for purchasing the technology. The magnitudes of these impacts are estimated based on available information but are still highly uncertain.

Because the existing literature emphasizes that the timeline for adoption of ADS is uncertain but has a substantial influence on the expected economic impacts, this report analyzes three scenarios: slow, medium, and fast adoption paths.

This research is the first of its kind that estimates not only the direct improvements to productivity in the trucking industry from automation, but also the indirect impacts to other industries resulting from the central role transportation plays in the larger economy. This analysis uses a computable general equilibrium (CGE) model of the U.S. economy that has been adapted to give detailed representation of transportation-related industries, including trucking. This CGE model will produce expected macroeconomic impacts from productivity shocks to the trucking industry resulting from SAE Level 4 and Level 5 ADS in the long-haul trucking sector. The impacts the CGE model produces are presented in terms of changes in GDP, employment levels, average wages, and consumer welfare. One limitation of the model in its present form is that is considers a single uniform labor market and thus the potentially differing impacts of automation on low skill jobs versus high skill jobs remains an area for future research.

Model

USAGE-Hwy is a dynamic computable general equilibrium (CGE) model of the U.S. economy. In a CGE model, the supply and demand for each commodity is determined as the outcome of optimizing behavior of economic agents. Industries are assumed to choose labor, capital and land so as to minimize costs while operating in a competitive market, subject to technology constraints. Households purchase a particular bundle of goods in accordance with the household's preferences, relative prices and its amount of disposable income. Capital creators assemble, in a cost-minimizing manner, units of industry-specific capital for each industry. Investment is allocated across industries to maximize rates of returns to investors (households, firms). Governments operate within a fiscal federal framework. The behavior of foreign entities is summarized by export demand curves for domestically produced goods and by supply curves for international imports. Changes in exports and imports for goods and services impact the economy's trade or current account balance, with offsetting effects on its capital account. In each period or year for which the CGE model provides a solution, all economy-wide constraints must be satisfied: for each commodity the total quantity demanded by all economic agents will equal the quantity supplied; household spending is constrained to equal available income; and the economy-wide demand for factors of production (labor, capital, land, natural resources) is constrained by the economy's capacity to supply these factors. In this way, changes to supply or demand for one commodity ripple through the entire economy.

The interconnectedness of industries in CGE models sets them apart from input-output (IO) models that are typically used to estimate economic impacts from transportation projects that require substantial capital investment. IO models generally assume that there are no supply-side constraints on the economy. Labor and capital are assumed to be available with perfect elasticity of supply. There is no trade-balance constraint, nor any constraint on government borrowing. Without appropriate constraints, IO models often produce results that demonstrate unexpectedly large economic gains derived from what is referred to as "manna from heaven." Additional final demand is accommodated by increased domestic output, without any crowding-out of other elements of domestic demand. In the typical IO model, an increase in demand associated with a new project generates an increase in domestic output that is bigger than the direct increase in demand. It also generates a move towards surplus in the balance of trade; the increase in exports being only partially offset by increases in the demand for imports induced by the indirect expansion of domestic aggregate demand.

Realistically, the supply side of the economy is neither completely flexible nor absolutely fixed. Balance of payments and public sector borrowing pressures exert some influence on exchange rates and interest rates. In addition, price responses to higher activity in one part of the economy tend to induce adjustment to demand and supply more generally. In short, expansion in one part of the economy tends to "crowd out" activity elsewhere. By requiring that economy-wide constraints are always satisfied, CGE models capture these crowding-out effects, while IO models do not, ensuring that CGE models provide a much more balanced assessment of the true costs and benefits transportation investments.

The starting point for USAGE-Hwy was the USAGE model, developed since 2001 by the Centre of Policy Studies (now at Victoria University, Melbourne) in collaboration with the U.S. International Trade Commission. This analysis uses USAGE-Hwy v1.1, which represents an initial 2016 initial equilibrium, based on industry input-output data from the U.S. Bureau of Economic Analysis (BEA).[21] USAGE-Hwy v1.1 also includes as separate industries In-House Transport for Air, Rail, Water and Trucking which are based on the 2016 Transportation Satellite Accounts (TSA) published by Bureau of Transportation Statistics (BTS). While USAGE-Hwy shares the features common to all CGE models described earlier, it has been tailored to analyze the economy-wide effects of changes in highway-related industries by including:

- modeling of a separate industry for construction of highways and bridges and for street repairs. These two industries would typically be aggregated together as part of a single economy-wide construction industry
- representation of a separate private road transport industry that uses cars, household car repairs and gasoline as inputs
- separate commuter transport and vacation transport industries. Vacation transport uses inputs of private road transport, air transport, water transport and passenger transport (buses, taxis and trains) to provide transport services to facilitate vacation activities. Similarly, commuter transport uses these inputs to provide transport services to facilitate travel to work, shopping, etc. The

output of vacation transport is sold to the vacation industry whose output is in turn sold to households. The output of commuter transport is sold directly to households

- artificial taxes on sales to commuter transport and vacation transport that cover the cost of driver time
- variables that allow USAGE-Hwy to incorporate other non-traditional inputs related to analysis of highway investments such as:
    - fuel use per mile traveled in passenger cars and in trucks;
    - vehicle operating costs per mile traveled in passenger cars and in trucks;
    - safety costs;
    - road maintenance costs;
    - road fatalities; and
    - driving time per mile traveled in passenger cars and trucks.

Simulations with USAGE models consist of a baseline run representing a business-as-usual evolution of the economy; and policy runs which show the evolution of the economy with the addition of policy shocks to the baseline. Comparison of a policy run to the baseline shows the effects of that policy. The baseline reflects macro and energy forecasts informed by the Annual Energy Outlook published by the Energy Information Administration. To analyze the effects of automation in long-haul trucking, we construct shocks to reflect the expected impacts of automation in long-haul trucking. These shocks are applied in the policy simulations.

Results from these policy simulations are compared to a common baseline which is consistent with annual increases in real GDP of 2.4 percent, reflecting the following baseline behavior in USAGE-Hwy macroeconomic aggregates: [iii]

- 2.7 percent annual growth in aggregate real consumption
- 1.7 percent annual growth in aggregate real investment
- 1.7 percent annual growth in aggregate real government spending
- 5.2 percent annual growth in aggregate real exports
- 4.8 percent annual growth in aggregate real imports

The consumer price index is chosen as the numeraire, and the real exchange rate is set to devalue by -0.6 percent per year. We assume that the annual increase in the U.S. population is 0.936 percent and aggregate labor market behavior is characterized by:

- 1.085 percent annual increase in hours worked
- 1.1 percent annual increase in the aggregate real wage

For this analysis, USAGE-Hwy analyzes the macroeconomic effects of the introduction of automation in the long-haul trucking sectors in the United States by introducing productivity shocks to the trucking

[iii] These macroeconomic forecasts are derived from and consistent with assumptions underlying the reference case forecast scenario in the 2016 *Annual Energy Outlook* published by the U.S. Energy Information Administration (EIA), available at https://www.eia.gov/outlooks/archive/aeo16/.

sector from labor costs savings, fuel cost savings, capital cost savings, and safety improvements that are expected from automation. The simulations also take into account the upfront cost of acquiring the technology. The basis for estimating the magnitudes of those shocks are discussed below.

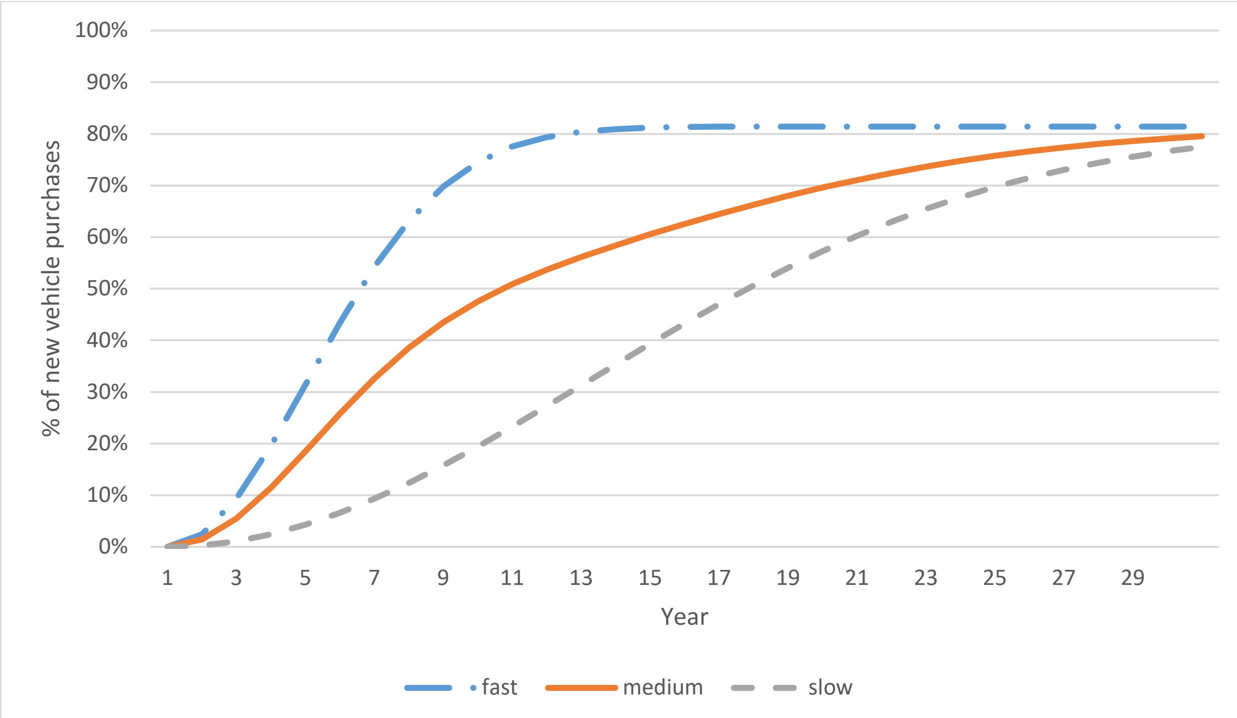
Technology Adoption

We suppose that the first firms in the trucking industry begin adopting automation in long-haul trucking starting in Year 1, and that Year 0 is an economy similar to the 2019 economy. This assumption allows us to explore the possible economic consequences of automation. The rate at which these firms adopt automation will be affected by a number of factors including anticipated labor and fuel cost savings, as well as the costs associated with the driving automation systems themselves. To reflect the uncertainty around these factors, we consider three separate time paths that dictate the share of the trucking industry that begins to adopt automation in long-haul trucking over a period of 30 years. These time paths are developed using three components:

- three technology adoption rates (fast, medium, and slow) for new vehicle purchases,
- a fleet turnover model which produces estimates of the number of new vehicles that are purchased each year, and
- a maximum adoption ceiling.

Three technology adoption rates for new vehicle purchases are explored in this analysis to highlight the significant level of uncertainty related to how fast SAE Level 4 and 5 ADS would be adopted in the long-haul trucking sector. These adoption rates for new vehicle purchases are presented in Figure 1 below. The fast scenario is intentionally a very optimistic scenario in which 75 percent of new vehicle purchases involve ADS in 10 years of the technology becoming available. The medium and slow scenarios assume 48 percent and 19 percent of trucking firms will have begun adopting 10 years after the technology becomes available, respectively. Note, these adoption rates are for new vehicle purchases only, adoption for the entire fleet depends on fleet turnover rates which are discussed below.

Figure 1: Technology adoption rates for new vehicle purchases



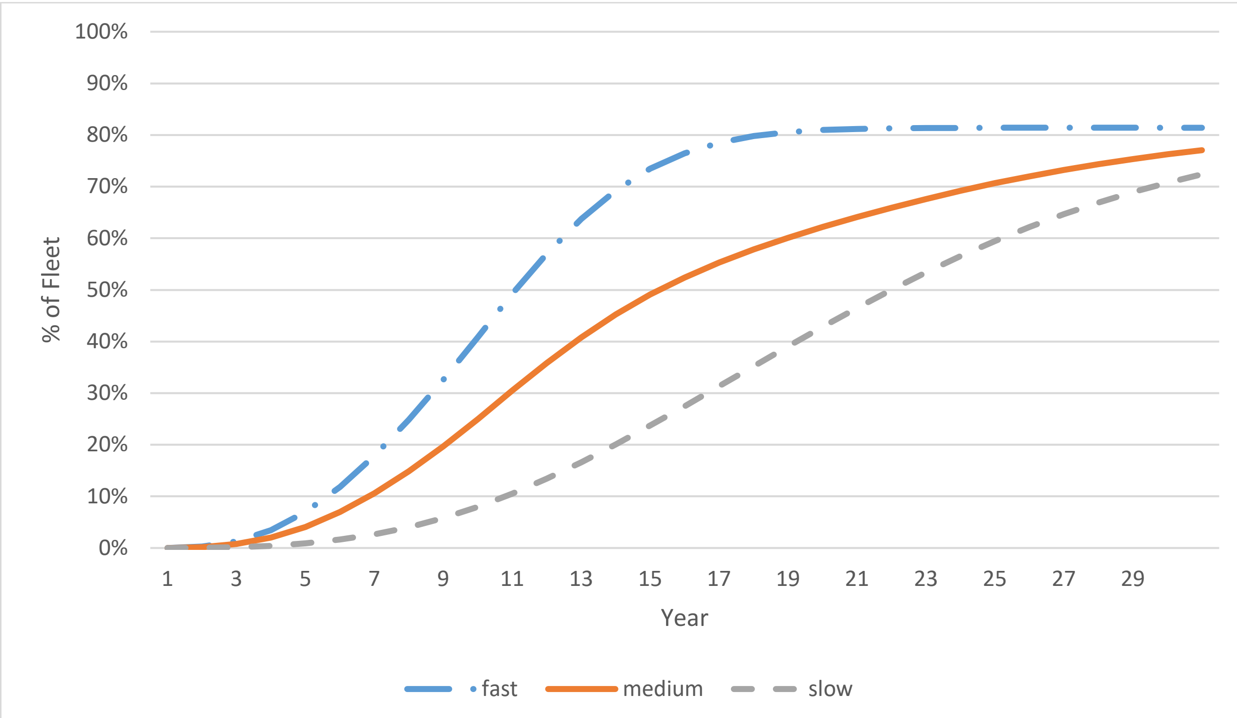
Based on analysis of truck registration data, the typical useful life of a Class 8 tractor is roughly one million miles or approximately 11 years, after which the mileage put on older tractors drops off dramatically.[iv] Because tractors in the long-haul segment are used more intensely, the typical useful life is likely a bit shorter than the average—approximately nine years. Tractors used in short-haul service may last longer, perhaps 15 years, before they reach one million miles.[22] Based on this information, we assume the existing fleet of long-haul trucks turns over every nine years. On average, in any given year, 1/9th of the fleet will be replaced with newly purchased vehicles, and those new vehicles will be equipped with ADS at the rate of the technology adoption for new vehicles show in Figure 1 above. This implies that the share in year t of the fleet of long-haul trucks in the trucking industry that will have been converted to accommodate automation will be given by the sum over the period [t-9 to t] of the share of adopting firms in Figure 1 multiplied by 1/9.

The development of those time-paths for adoption includes the expectation that even if the technology were widely available, not *all* human drivers in the long-haul sector could be replaced by automation. There are certain categories of shipments such as high-value goods, hazardous materials, or cross-border movements that would likely retain a human onboard regardless of technological advancement. However, the exact proportion of shipments that would always require a human onboard is not clear. For expediency, this analysis adopts the results from a study by the McKinsey Global Institute that found that

[iv] Class 8 trucks are those that have a gross vehicle weight rating (GVWR) of 33,000 pounds or more and include tractor-trailers.

the maximum technical automation potential was 81.4 percent for the occupation "Heavy and Tractor-Trailer Truck Drivers."[23] Note that the category of "Heavy and Tractor-Trailer Truck Drivers" includes both long-haul and short-haul driving but we apply the ceiling to solely long-haul in this analysis. Thus, the fleet adoption rates discussed above have a "ceiling" of 81.4 percent as shown in Figure 2 below.

Figure 2: Share of industry fleet with driverless tech



Labor-Saving Technical Change

Table 1 below summarizes the two-truck transport industries in USAGE-Hwy. USAGE-Hwy has always included NAICS industry 484 "For-hire truck transportation" as a separate activity. Earlier analysis with USAGE-Hwy involved the introduction of four in-house transport industries, one of which modeled industry 47OT.484 "In-house truck transportation." Activity in these industries in USAGE-Hwy was calibrated to be consistent with total demand for "For-hire truck transportation" in 2016 as reported in the BEA and for "In-house truck transportation" in 2016 as reported in the TSA. Also, the labor and capital inputs in these sectors were calibrated to match "Compensation of employees" and "Gross operating surplus" as reported in the 2016 TSA USE table for NAICS industries 484 and 47OT.484, respectively.

Table 1: Truck Transport industries in USAGE-Hwy ($m)

NAICS Industry	Intermediate inputs	Compensation of employees	Gross operating surplus	Taxes	Value of industry output	Value of commodity sales
484 For-Hire Truck transportation	156,224	90,051	52,920	8,040	307,235	320,016
47OT.484 In-House Truck Transportation	175,978	86,338	50,738	0	313,054	313,054

To model the impact that automation in long-haul trucking would have on labor-saving technological change, we need to isolate the component of total "Compensation of employees" listed above in Table 1 that would be impacted by the introduction of driverless trucks. We also need to estimate the number of truck drivers in both the For-Hire sector and the In-House Trucking sector, since we will be interested in how automation in long-haul trucking could lead to lay-offs in the trucking industry.

We begin with data from the BLS Occupational Employment Statistics which reports "total employment" and "mean annual wage" in 2017 for NAICS industry 484000 "Truck Transportation" as 1,476,970 and $46,340, respectively. Of these employees, 880,710 are employed in the Standard Occupational Classification 53-3032 "Heavy and Tractor-Trailer Truck Drivers", earning a mean annual wage of $46,230. As a result, we assume that 59.5 percent of the "Compensation of employees" in Table 1 represents compensation to "Heavy and Tractor-Trailer Drivers" in USAGE-Hwy's trucking industries.

The total number employed in Standard Occupational Classification 53-3032 "Heavy and Tractor-Trailer Truck Drivers" is 1,800,310. Presuming that all Heavy and Tractor-Trailer Drivers not in NAICS industry 484000 "Truck Transportation" are employed as In-House truck drivers results in an estimate of 919,600 Heavy Truck and Tractor-Trailer Operators employed in the "In-house Trucking" industry.

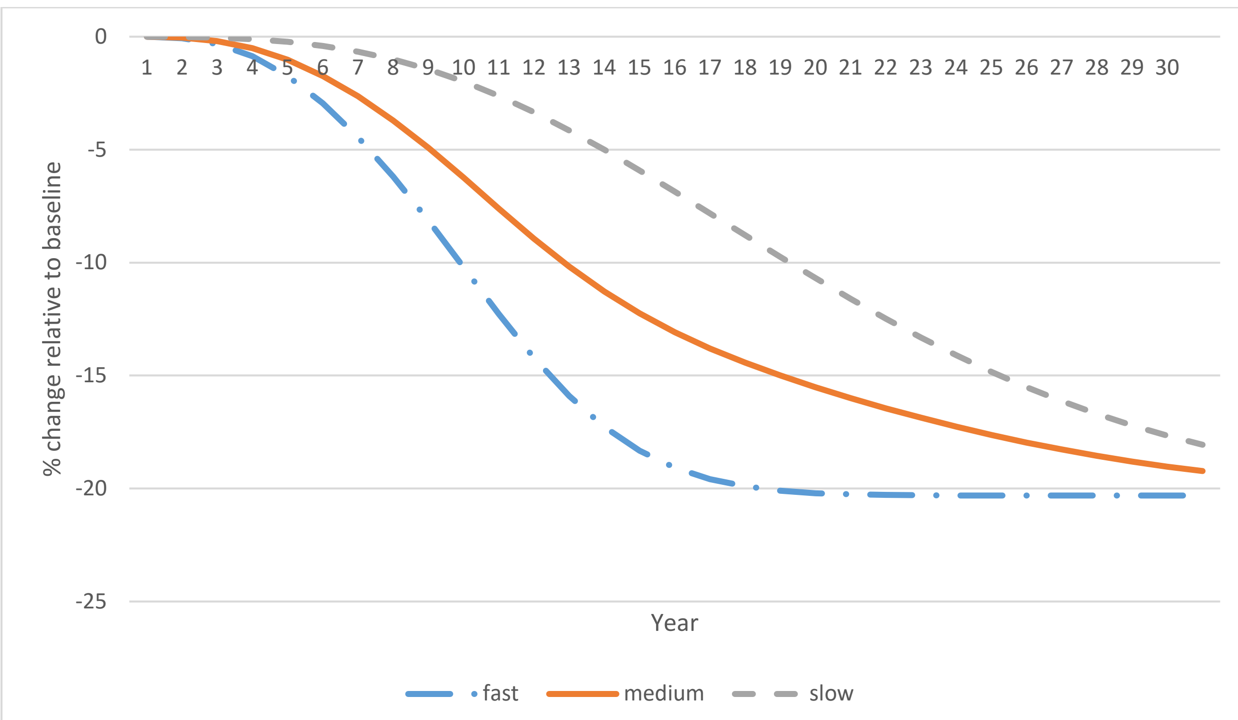
But not all "Heavy and Tractor-Trailer Drivers" would be affected by automation in long-haul trucking, since only some of these are long-haul truck drivers. We follow Gittleman and Monaco who employ data from the 2002 Vehicle Inventory and Use Survey (VIUS). They report the share of heavy trucks by sector and range of operations.[2] Since we are interested in long-haul trucking, we consider only those heavy trucks whose range of operations was more than 200 miles. As a result, we assume that of all "Heavy and Tractor Trailer Drivers" employed in the for-hire trucking and private trucking sectors, 51.52 percent and 8.13 percent were long-haul truck drivers, respectively, and that overall, 29.36 percent of all "Heavy and Tractor Trailer Drivers" are employed in the long-haul sector.

We conclude that in 2017, there were 453,773 and 74,718 Long Distance Tractor-trailer Drivers in the "Trucking Services" and "In-house Trucking" sectors, respectively. These are the number of driving jobs at risk of elimination due to adoption of automation in long-haul trucking.[v]

Similar to the upper–bound, on-fleet adoption, we assume 81.4 percent will be the maximum of the value of compensation of employees attributed to long-haul truck drivers that could be saved upon adoption of automation in long-haul trucking due to the understanding that not all long-haul trucking would be automated.

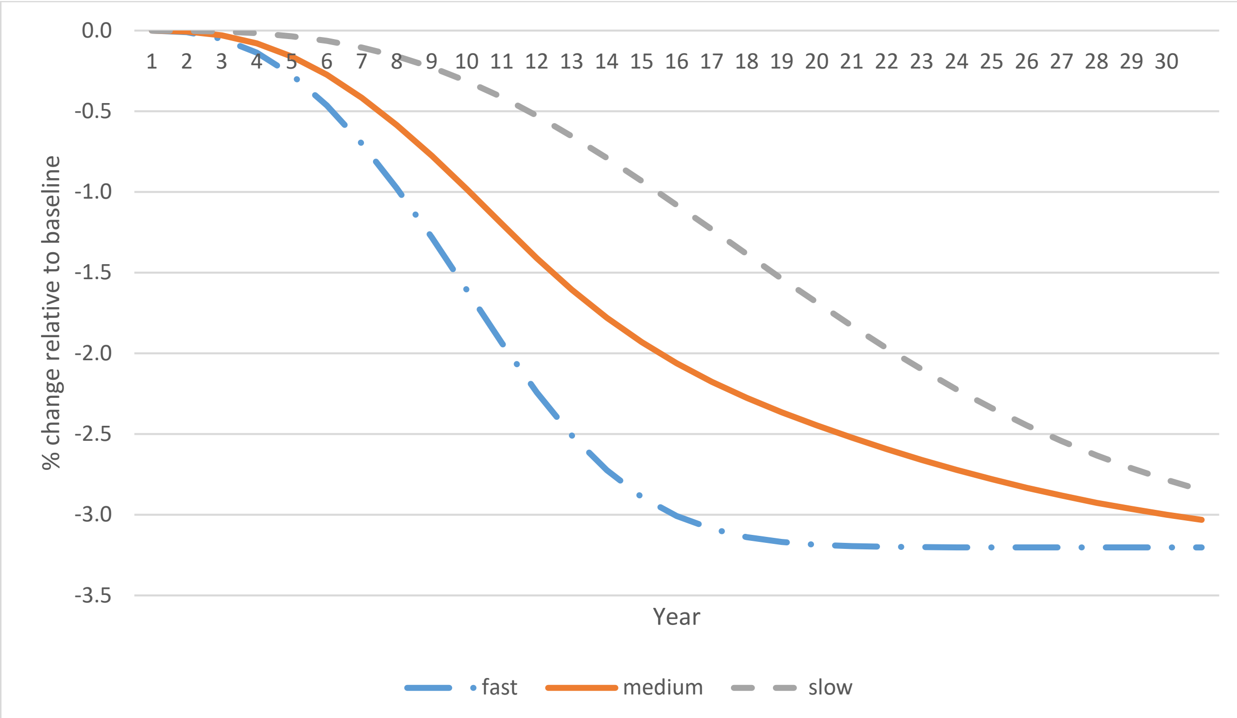
Figure 3 and Figure 4plot the shocks to labor-saving technical change under the different adoption paths in USAGE-Hwy's two trucking industries: For-Hire and In-House. Note that labor-saving technical change is measured here as the change in the amount of labor required to produce one unit of output holding other inputs constant. Thus, the productivity shocks are negative because *less* labor is required to produce the same level of output.

Figure 3: Labor saving technical change in For-Hire (relative to baseline)



[v] This analysis considers only the impacts on labor costs associated with employees. Significant numbers of self-employed drivers (known as owner-operators) also operate in the trucking industry. But due to the difficulty in identifying these entities in the underlying Industry Input-Output data from the BEA, this analysis implicitly assumes self-employed drivers are not impacted by automation.

Figure 4: Labor saving technical change in In-House (relative to baseline)



The two figures have the same shape, since they both reflect the same adoption paths in Figure 2. But in the In-House Trucking industry (Figure 4), the shocks to labor productivity are much smaller than those in the For-Hire Trucking industry (Figure 3). This reflects our observation that a much smaller share of truck drivers in In-House trucking (8.13 percent) are long-haul truck drivers than in the for-hire trucking industry (51.52 percent). For example, under the fast scenario, ten years from adoption, just over 41 percent of the industry fleet will be converted to accommodate automation in long-haul trucking. Ten years after adoption, the labor saving technical change shock in For-Hire and In-House is -12.53 percent and -1.98 percent, respectively. As noted above, the shock is negative, reflecting the fact that less labor is required to produce the same level of output, given the level of usage of other inputs. In the medium scenario, only 25 percent of the industry fleet will be converted ten years after adoption, so the labor saving technical change shock in the medium scenario ten years after adoption in For-Hire and In-House is -7.66 percent and -1.21 percent, respectively.

Cost of Adopting Automation

We estimate the cost of adopting automation in long-haul trucking by estimating the cost of replacing the current fleet of long-haul trucks with one where all trucks are fitted with the technology to allow for automated operation.

Chottani *et al*. report that trucks outfitted with lidar, sensors, and other technology to allow the vehicle to operate without human intervention cost can cost between $30,000 and $100,000.[vi,24] Baseline investment expenditures in the For-Hire and In-House industries in USAGE-Hwy reflect the expenditures needed to produce new capital (trucks) as those in the current fleet need to be replaced. To model the switch to trucks capable of automated operation, we assume that each new truck that is replaced will require an extra investment expenditure of $100,000 per truck. We assume that this per-truck cost for adopting automation technology falls over time with the inverse of the technology adoption rates (1 minus the adoption rate) in Figure 2, to a minimum of 50 percent. This reflects the idea that early adopters of new technology face higher adoption costs than late adopters, but places a lower bound on the cost that late adopters must incur.

There are of approximately 2.0 million tractor trailers in the U.S. fleet serving both short-haul and long-haul sectors.[23] This figure is consistent with our earlier discussion that the typical useful life of a long-haul truck is about nine years and figures reported by FleetOwner that approximately 200,000 new Class 8 (truck tractors) are sold each year.[vii]

Recall that overall (across both in-house and for-hire industries), 29.36 percent of all “Heavy and Tractor Trailer Drivers” are employed in the long-haul sector. We use this same share to estimate that the fleet of long-haul tractor trailers in the U.S. in 2016 was 587,111 trucks. Over the simulation period, we assume that the size of the fleet of long-haul trucks grows, following the expected growth in truck vehicle miles traveled over the same period as used the forthcoming 24th Edition of the FHWA Conditions and Performance (C&P) Report under the “sustain current spending scenario” – approximately 1.8% annually.[viii]

To calculate the shock to investment in USAGE-Hwy that reflects the cost of automation, we multiply the size of the fleet of long-haul tractor trailers by the extra investment expenditure per truck to allow for automated operation ($100,000), discounted by 1 minus the technology adoption rate in Figure 2, by the share of the industry fleet being converted to driverless technology in that year from Figure 2, as a share of baseline investment in the For-Hire and In-House industries. These shocks are reported in Figure 5 and Figure 6, reflecting the extra investment expenditure in these two industries at baseline prices. The shocks reflect two effects: the increased capital requirement per unit of output in the industry and the increased output (number of trucks) in the industry. Under the fast adoption scenario, this shock is highest in Year 7 when 8.62 percent of the fleet is converted to allow for automated operation, bringing the total share of the fleet converted by Year 7 to 30.51 percent (see Figure 2). By Year 7, the size of the long-haul trucking fleet has grown to 718,710 tractor-trailers. The share of this fleet in the For-Hire and In-House sectors is 86.4 percent and 13.6 percent, respectively.

[vi] LIDAR stands for *Light Detection and Ranging*, a remote sensing method that uses light in the form of a pulsed laser to measure ranges (variable distances) to the Earth. See https://oceanservice.noaa.gov/facts/lidar.html.

[vii] Data from the American Trucking Associations “Freight Transportation Forecast 2017-2028”, cited in https://www.fleetowner.com/truck-stats/trucking-by-the-numbers/media-gallery/21702887/trucking-by-the-numbers-2018-the-equipment-fleets-use/slideshow?slide=6.

[viii] We are assuming that the existing fleet is fully utilized, so to achieve a 5 percent increase in Truck vehicle miles traveled, it is necessary to have 5 percent more trucks and 5 percent more drivers.

Figure 5: Cost of adopting automation in For-Hire (% change relative to baseline)

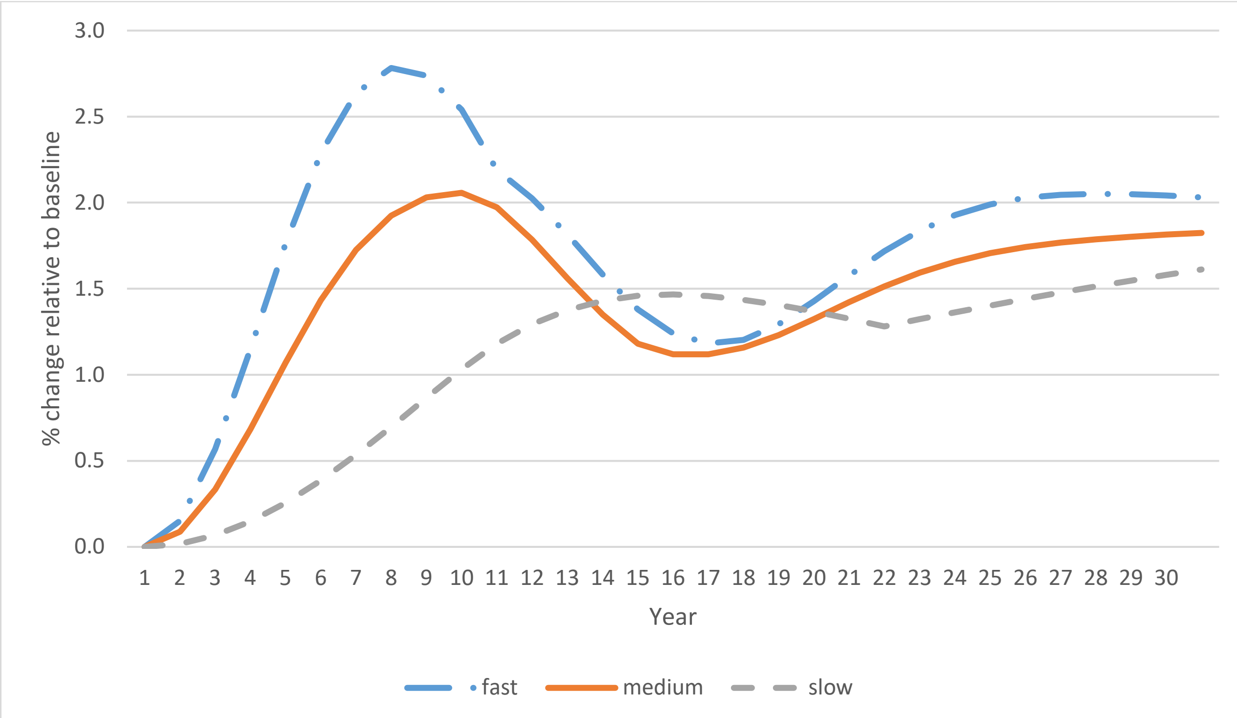
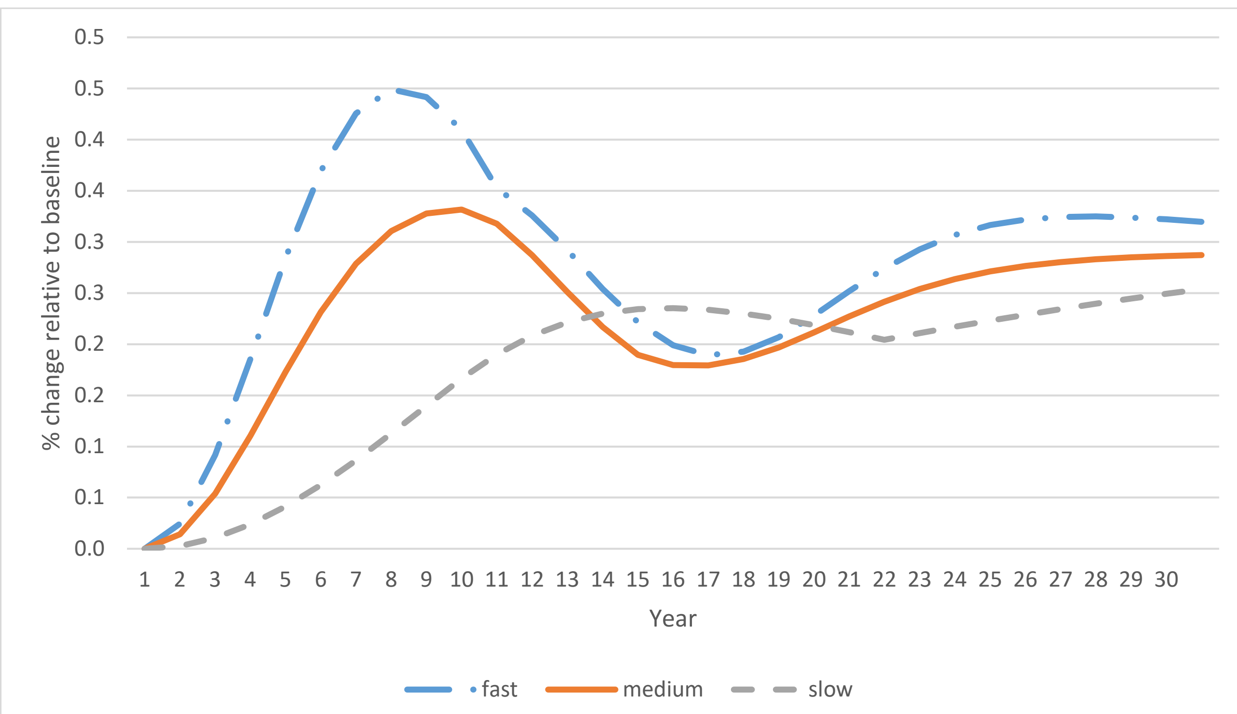


Figure 6: Cost of adopting automation in In-House (% relative to baseline)



After Year 9, the first trucks that were upgraded in Year 1 will be 9 years old and will need to be replaced. This explains why the curves in Figure 5 and Figure 6 never return to baseline. For example, under the fast adoption scenario, the baseline growth in vehicle miles traveled suggests that the number of long-haul trucks will have increased to just over one million by Year 30. In the policy scenario, these will now all be equipped with automation technology that costs $50,000 per truck. With baseline investment in the For-Hire industry projected to reach $203 billion by Year 30, the cost of adopting automation in the For-Hire sector reaches almost 2.5 percent above baseline by Year 30.

Again, Figure 5 and Figure 6 have the same shape, since they both reflect the same adoption paths in Figure 2, and they both presume the same replacement cost necessary for automating long-haul trucks. But while baseline investment in the For-Hire and In-House industries in USAGE-Hwy is quite similar (i.e., the denominator in the shocks in Figure 5 and Figure 6), the share of the "Heavy Truck and Tractor-Trailer Operators" that are "Long Distance Tractor-trailer Drivers" in the In-House industry (8.13 percent) was much smaller than that in the For-Hire industry (51.52 percent). This accounts for most of the difference between the scale on Figure 5 (where the largest investment shock in For-Hire under the fast adoption scenario in Year 7 is 3.16 percent) and the scale on Figure 6 (where the largest investment shock in In-House under the fast adoption scenario in Year 7 is 0.51 percent).

Fuel Cost Savings

There is evidence that automation of long-haul trucking could lead to reductions in fuel costs. Driving automation could decrease fuel costs by optimizing throttle and brake controls to minimize fuel burn. Other types of automation have also been shown to lead to fuel savings. For example, the practice of “truck platooning” involves the implementation of systems that allow communication and close following between multiple trucks traveling close together. When SAE Level 1 platooning was tested, Shladover *et al*. found that a three-truck platoon traveling at 65 mph could save between 5 and 6 percent of its fuel.[25] Fuel savings can also be experienced due to maintaining lower speeds than human drivers typically choose: a truck traveling at 65 mph instead of 75 mph will experience a 27 percent improvement in fuel use.[26] The United States is currently pursuing several policy options to improve fuel economy in large trucks (for example, speed regulators and improved fuel economy standards) so it is difficult to estimate the incremental impact that automation will have. For the purposes of this analysis, we adopt a central case value for the reduction in fuel use by long-haul trucks due to automation of 5.22 percent. This value is derived from the estimated fuel savings of 5 to 5.5 percent expected from mandated speed controls.[27] It is also consistent with the fuel savings due to truck platooning cited above in Shladover *et al*. and the 15 percent realized fuel savings claimed by TuSimple.[25,28]

Figure 7 and Figure 8 present the percentage reductions in fuel use per unit of output that are anticipated upon adoption of automation in long-haul trucking. Given the evidence summarized above, we assume that fuel costs fall by 5.22 percent for those firms that adopt automation in long-haul trucking. As a result, the shocks in the For-Hire and In-House industries in USAGE-Hwy reflect the adoption rates in Figure 2 and the fact that a much smaller share of drivers in private or in-house trucking engage in long-haul trucking than those in for-hire trucking. For example, under the fast adoption scenario, after Year 20 when maximum percent of the fleet has been converted to accommodate automation in long-haul trucking, the fuel-saving shock is -2.18 percent in the For-Hire industry and -0.34 percent in the In-House industry, reflecting the share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum fleet adoption rate 81.4 percent. As was the case for the labor-saving technical change shocks, these shock are negative, reflecting the fact that less fuel is required to produce the same level of output, given the level of usage of other inputs.

Figure 7: Fuel saving in For-Hire (% relative to baseline)

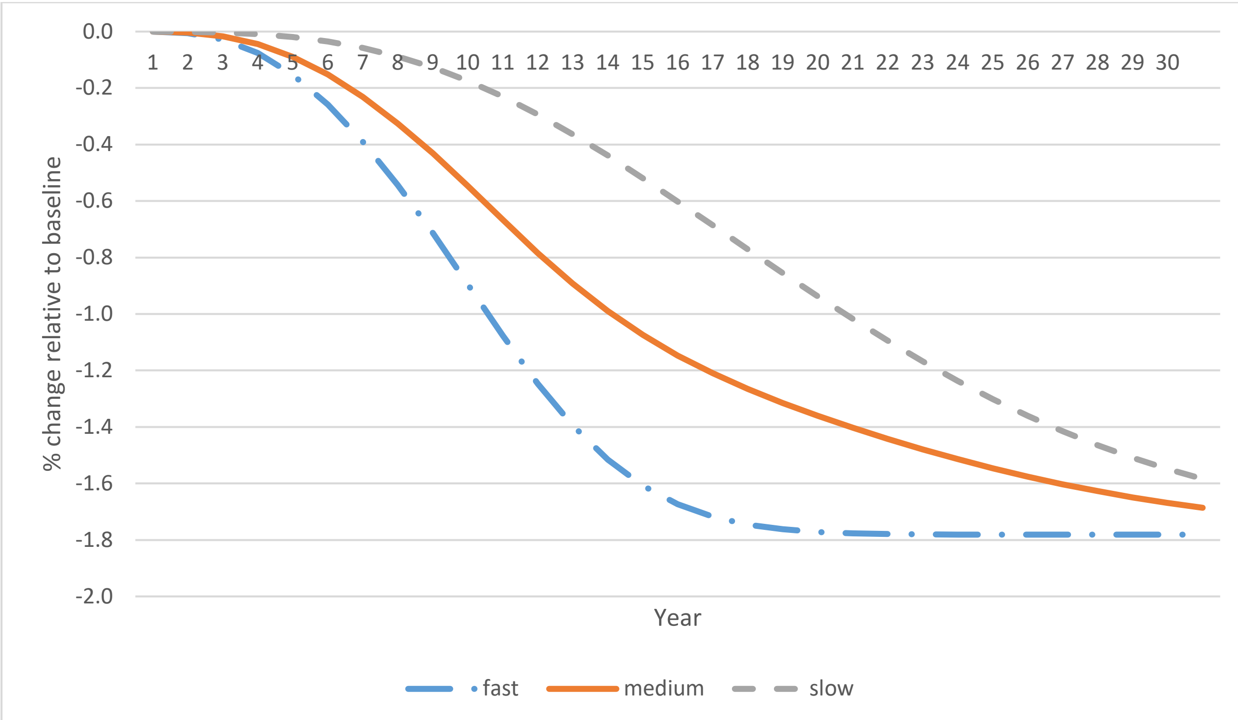
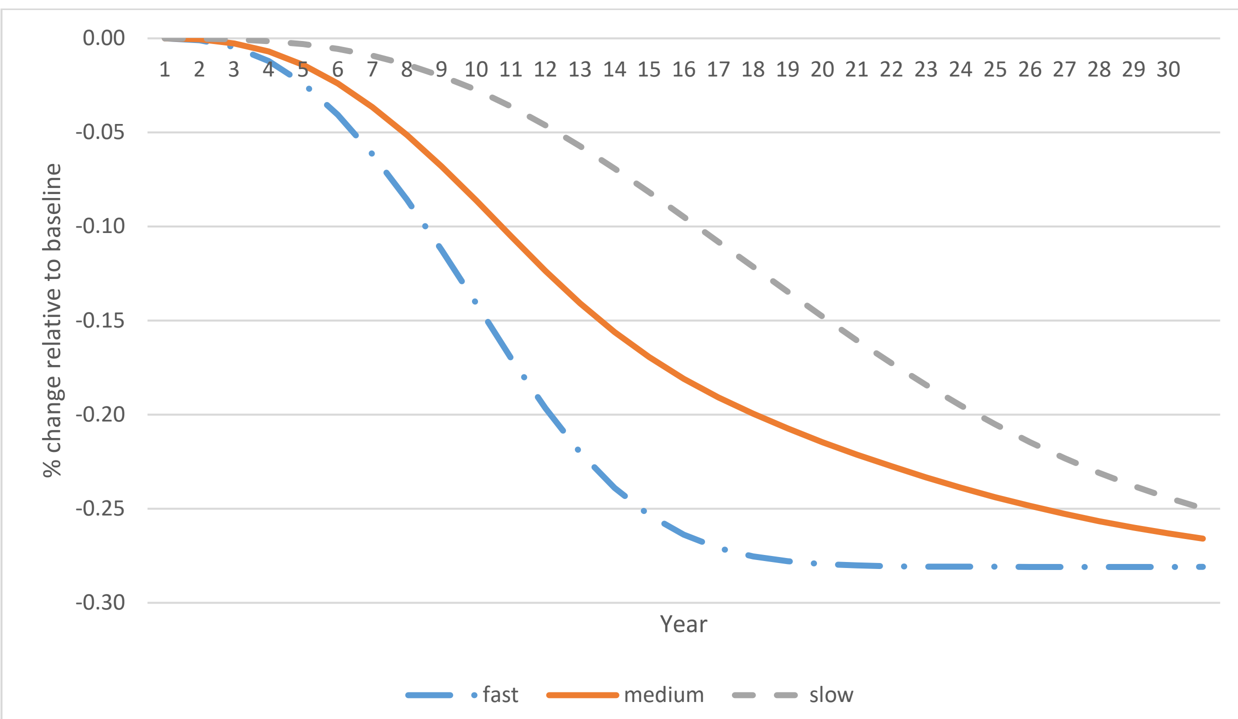


Figure 8: Fuel saving in In-House (% relative to baseline)



Capital Cost Savings

Automation is expected to lead to capital cost savings due to improved fleet utilization. Automation could allow trucks to potentially run nearly nonstop, without the need for human drivers to rest, which would reduce the capital costs associated with the trucks themselves. Of course, while a truck could be run more hours per day, we must also account for the fact that the truck will wear out sooner. A McKinsey report estimates that SAE Level 4 and 5 automation could reduce the total cost of ownership (TCO) by 45 percent.[29]

Figure 9 and Figure 10 present the anticipated improvements in the productivity of capital in trucking industries per unit of output upon adoption of automation in long-haul trucking. As was the case for previous shocks, those in the For-Hire and In-House industries in USAGE-Hwy reflect the shares of the industry fleet that have adopted automation in Figure 2 and the fact that a much smaller share of in-house trucking employees engage in long-haul trucking that those in for-hire trucking. Once the entire fleet has adopted the technology needed for driverless trucks (after Year 20 in the fast scenario), the capital improvement is reflected in a shock of -18.8 percent and -3.0 percent in For-Hire and In-House, respectively, reflecting the share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum fleet adoption rate of 81.4 percent. Like the labor-saving technical change shocks, these capital-saving technical change shocks reflect the fact that upon adoption of automation in long-haul trucking, less capital is required to produce the same level of output, given the level of usage of other inputs, so these shocks are negative.

Figure 9: Capital-saving technical change in For-Hire (% relative to baseline)

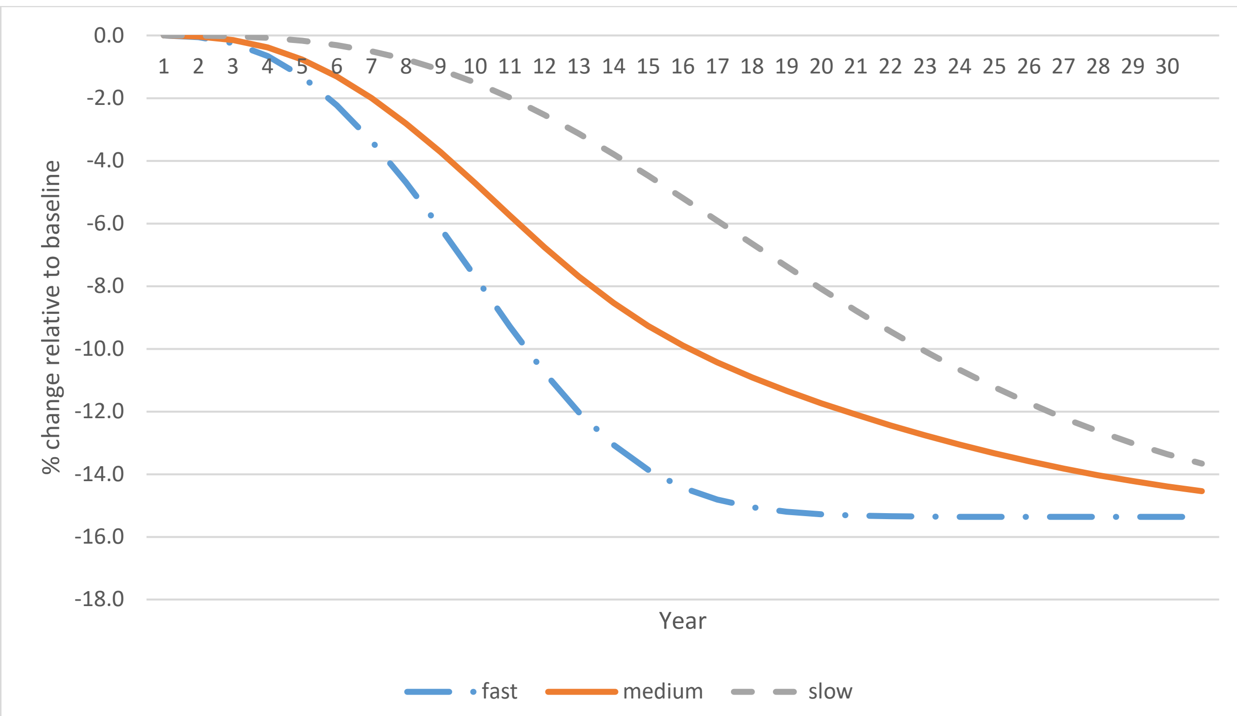
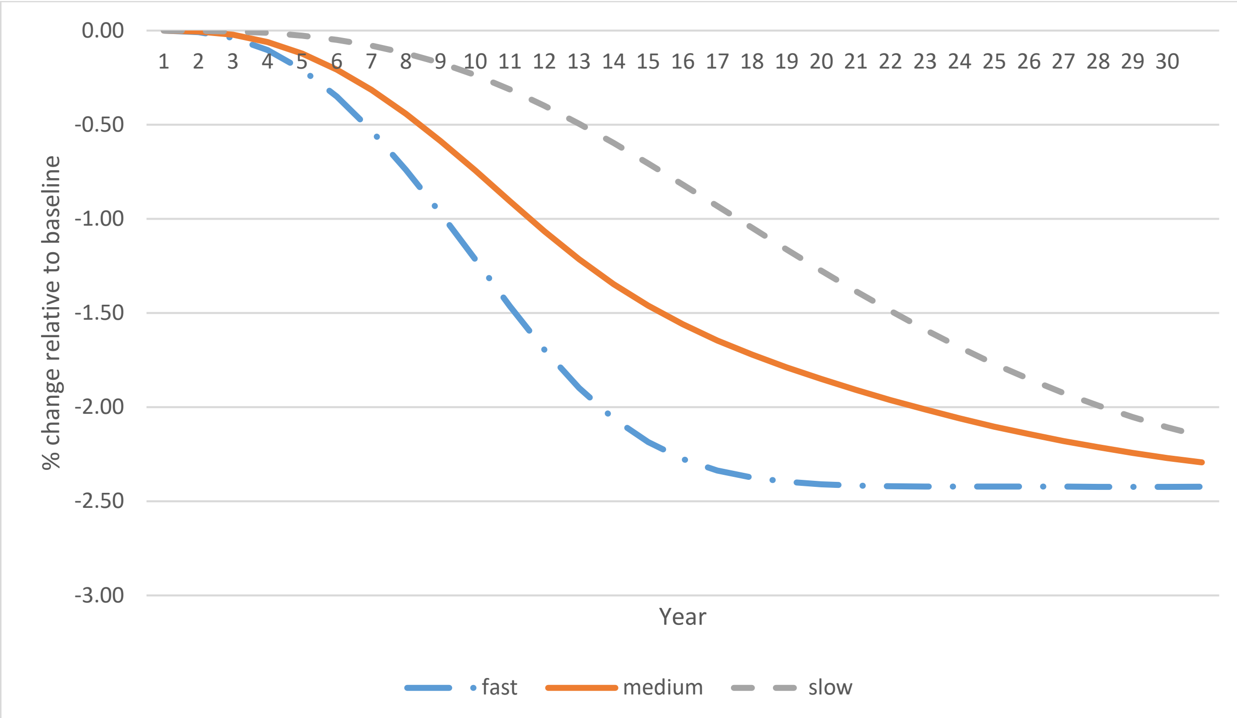


Figure 10: Capital-saving technical change in In-House (% relative to baseline)



Fatalities and Safety Costs

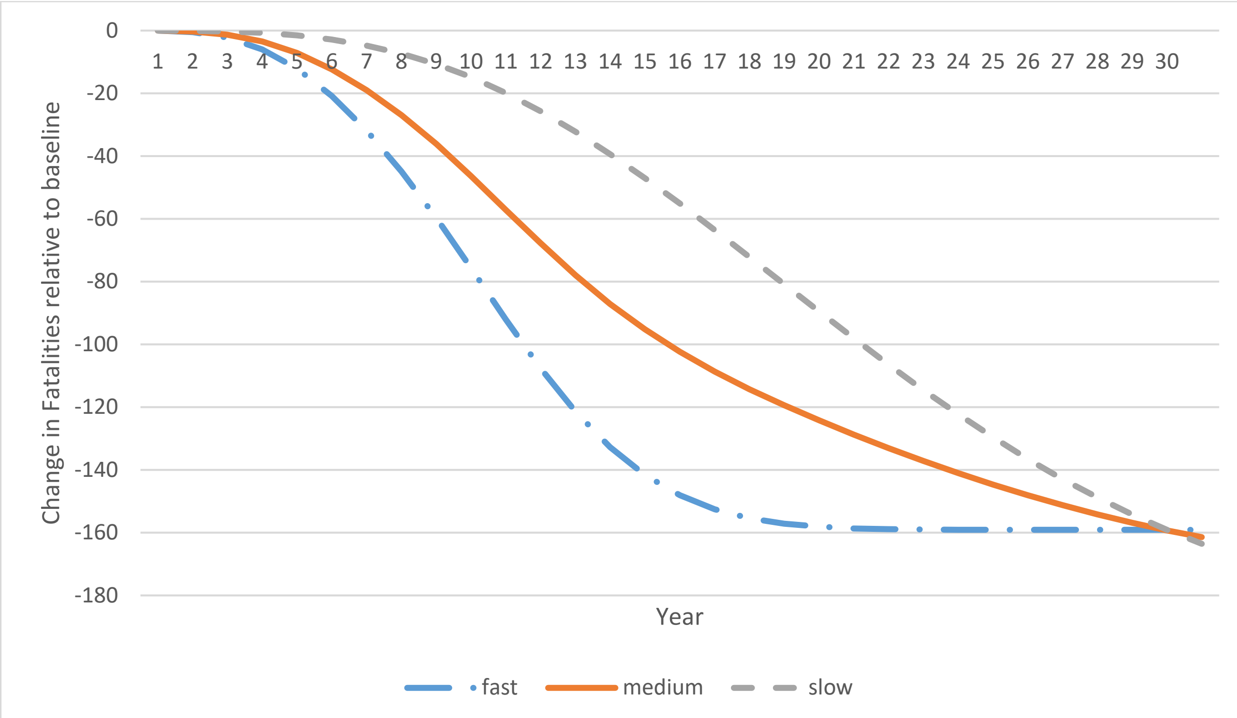
Many studies are optimistic about the potential for automation to improve highway safety. Therefore this study incorporates an estimate of safety benefits as an exploratory premise. We focus on the set of currently observed crashes that involve only a single large truck (as opposed to multi-vehicle crashes) presuming that these crashes are likely to be the fault of the truck or truck driver. Since some multi-vehicle crashes will also be the fault of the truck driver (the others being the fault of the other vehicle or its driver), our estimates represent a lower-bound on the fatalities and safety costs impacted by the adoption of automation in long-haul trucking. In 2017, there were 4,237 fatal crashes involving large trucks. Of these, 2,910 involved combination trucks, the type used in long-haul trucking. Crashes involving just a single large truck killed 885 people (often the driver of the truck but sometimes pedestrians and bicyclists) and injured approximately 17,000 additional people.[30] Of these single truck fatalities, we estimate that 29.36 percent involved long-haul trucks, matching the overall percent of truck drivers employed in the long-haul sector. Craft found that for 87 percent of large truck crashes, the critical factor was related to the driver (lack of sleep, inattentiveness, speeding or aggressive driving, etc.).[31] Based on this information, and assuming that automation could eliminate all of the single-vehicle crashes where the critical factor is related to driver performance, we estimate that approximately 155 fatalities involving large trucks in 2017 would be avoided if the entire long-haul fleet was automated. To derive an estimate of safety costs that could be saved due to automation, we use the observation that the cost per injury crash involving a truck tractor with one trailer in 2005 dollars was $22,934.[32] We update these 2005 costs to

2017 using a factor of 1.43 based on the U.S. health care inflation rate.[ix] As a result, we assume that total automation of the long-haul trucking sector would save $97.8 million in annual medical costs from injury-only crashes (measured in 2017 dollars). Note that this is an optimistic assumption that does not account for the possibility that automation might introduce new types of crashes. Therefore on net, not all crashes would be eliminated. On the other hand, one could reasonably expect that some portion of multi-vehicle crashes might also be avoided due to automation, and this source of possible safety benefits is not included in this analysis. While the estimated pool of possible safety benefits is highly uncertain, the impact of this category of benefits is small, accounting for roughly 5 percent of welfare impacts.

The final shocks reflect the assumption that the adoption of automation in long-haul trucking would eliminate crashes that involve a single large truck where the crash is due to at least one truck-driver-related factor such as non-performance, inattention, speeding or overcompensation while driving. We assume that if these crashes were eliminated, any fatalities or injuries that would have resulted from these crashes would also be eliminated. Note that although these avoided crashes are credited to the SAE Level 4 and Level 5 automation that is the focus of this report, SAE Level 1 and Level 2 technologies, such as advanced driver-assistance systems (ADAS), may also prevent some subset of these crashes as well. We begin with our estimates that there were 155 fatalities and $97.8 million in costs associated with injuries that could have been avoided in 2017 had automation in long-haul trucking been adopted. We suppose that the number of crashes involving long-haul trucks over the simulation period would follow the increase in truck vehicle miles traveled over the same period. Together with the shares of the industry fleet that has adopted automation in Figure 2, these statistics suggest a reduction in fatalities per unit of output under either fast, medium or slow adoption of automation in long-haul trucking as presented in Figure 11. As in previous work with USAGE-Hwy, each extra fatality is valued at $9.6 million in 2016 dollars, following USDOT guidance on Value of Statistical Life.

[ix] This U.S. health care inflation rate is compounded over 2005-2017 using data from https://ycharts.com/indicators/us_health_care_inflation_rate.

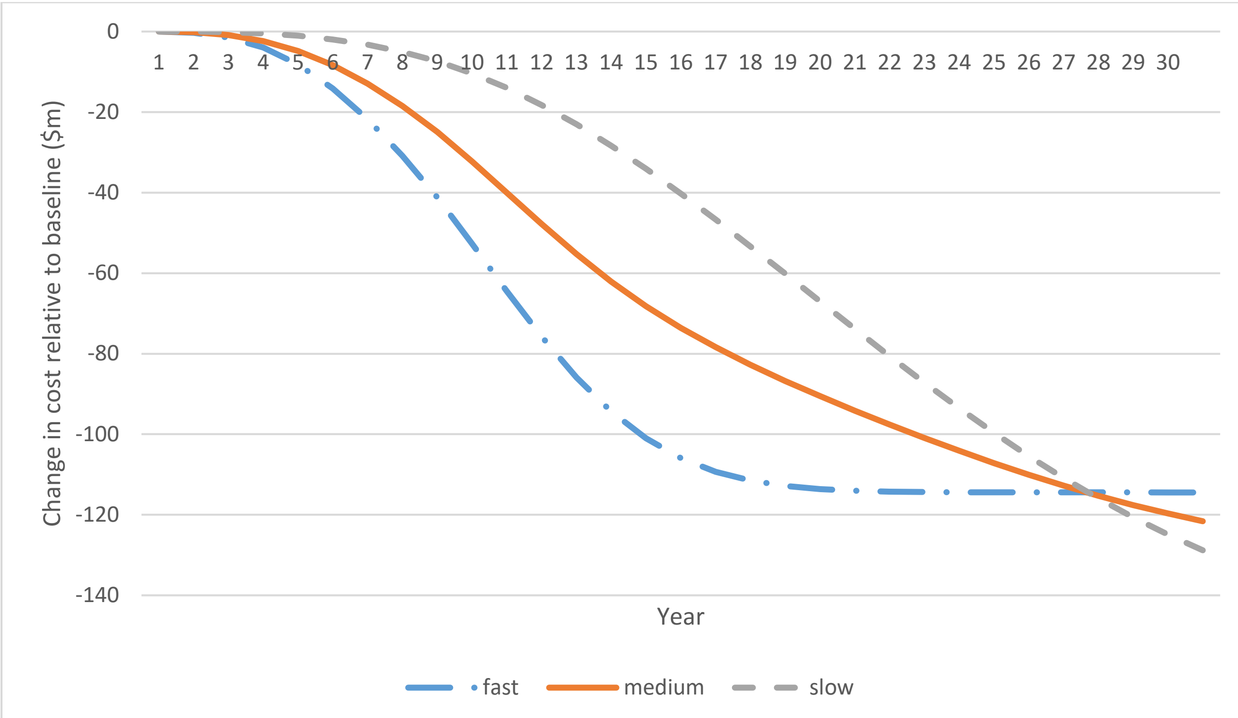
Figure 11: Change in fatalities (# relative to baseline)



The reduction in safety costs (in $millions) per unit of output due to the reduction in truck crashes and associated injuries upon adoption of automation in long-haul trucking as presented in Figure 12 under either fast, medium or slow adoption rates. The shape of these curves is similar to those in Figure 11 since both are based upon the same adoption rates in Figure 2.[x] In simulations, we introduced this information as reduced purchases of medical services by the household sector. Since we excluded medical expenditures when measuring welfare-relevant household consumption, reduced medical expenditures imposed on households are welfare-improving: they improve the ability of households to consume welfare-enhancing products. Both fatalities and safety-cost shocks are negative, reflecting the fact that fatalities and safety costs per unit of output are expected to fall upon adoption of automation in long-haul trucking.

[x] Figure 13 shows the reduction in safety costs for the medium and slow scenarios exceeding the reduction in the fast scenario towards the end of the analysis period. This happens because under medium and slow adoption, fleet conversion rates have only reached 77 percent and 72 percent compared to a maximum of 81.4 percent in the fast scenario. As time goes on, the value of the safety cost for a single crash increases, so saving that extra crash later under medium and slow scenarios results in slightly larger savings.

Figure 12: Reduction in safety costs ($m relative to baseline)



Chapter 4. Results

To begin our analysis of the impact of these shocks that represent the adoption of automation in long-haul trucking, we look at the direct consequences of the increase in investment spending in the For-Hire and In-House Trucking industries. Over the simulation period, under the fast adoption scenario, replacing the long-haul trucking fleet with vehicles that are equipped for automated operation results in an extra $111 billion of aggregate investment spending in the U.S. economy relative to baseline. As illustrated in Figure 13, this increased investment translates into an increase in aggregate capital that reaches almost 0.4 percent above baseline by Year 30. Under the medium and slow adoption scenarios, this increase in capital reaches 0.35 and 0.30 percent above baseline by Year 30 (under the medium and slow scenarios the fleet does not reach the maximum adoption ceiling by Year 30).

Figure 13: Aggregate capital (% deviations from baseline)

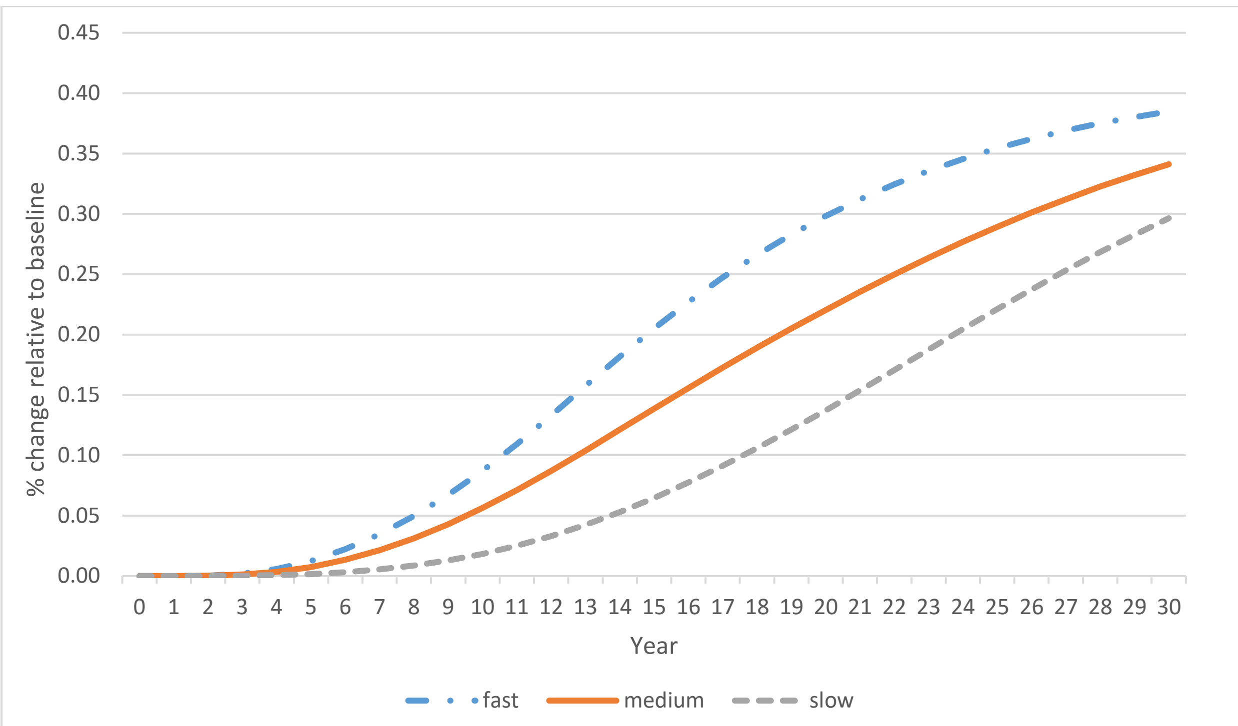
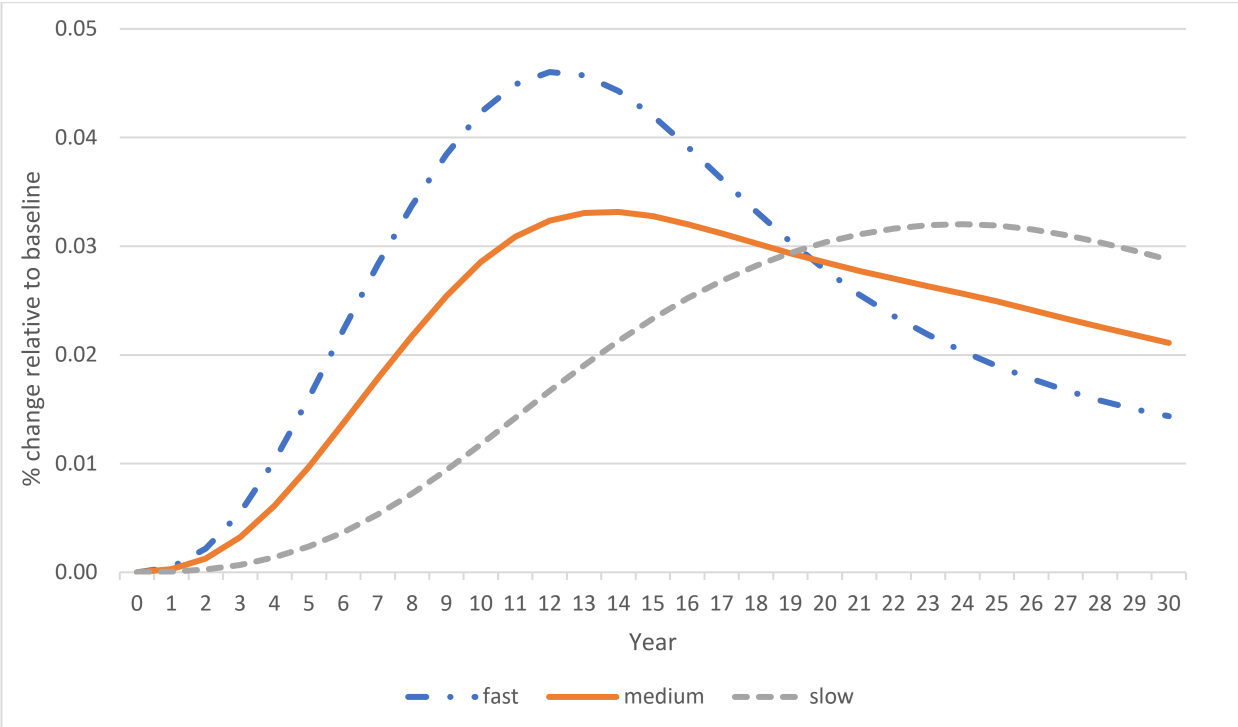


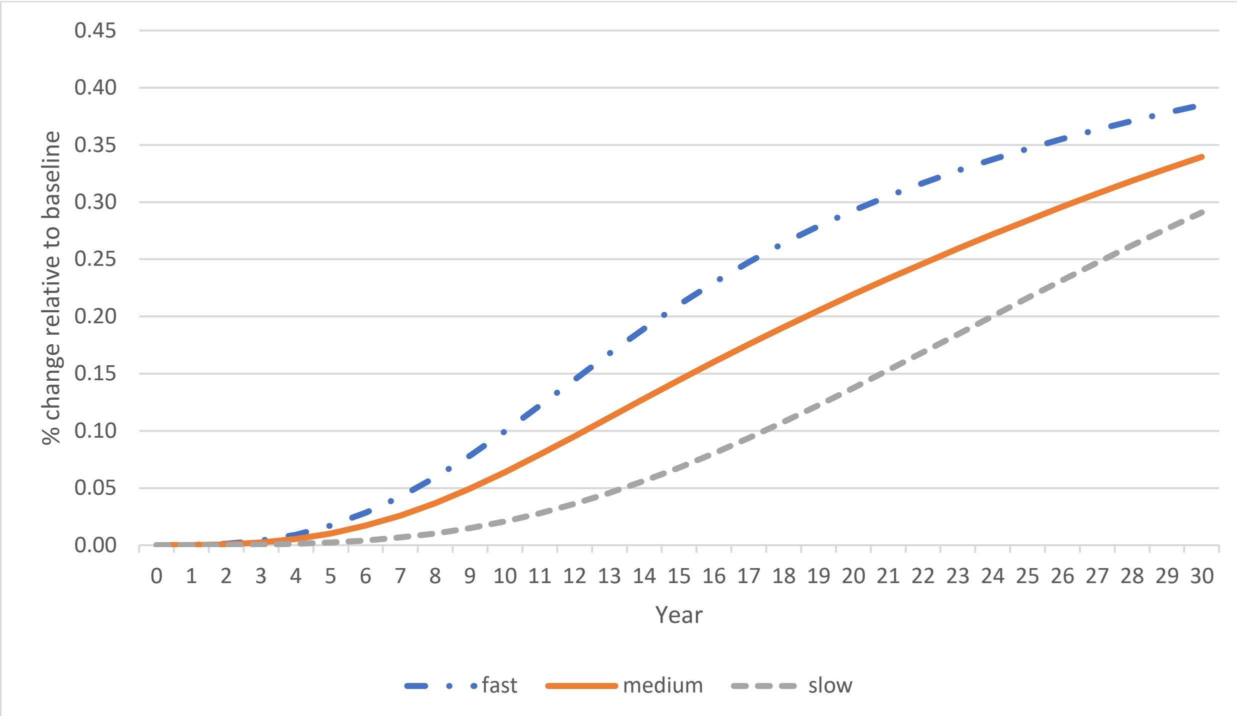
Figure 14: Aggregate employment (% deviations from baseline)



If the same amount of labor in the economy can now be combined with more capital, then labor productivity will increase. This effect is distinct from, and additional to, the direct impact that automation has on labor productivity in the trucking sectors: the increase in aggregate capital will make the average unit of labor across the whole economy more productive. At a given real wage, this increases the demand for labor. Figure 14 illustrates this increase in labor demand or employment over the simulation period while capital is increasing. Employment (labor demand) increases as capital increases, reaching a peak around Year 12 under the fast scenario. In USAGE-Hwy, labor supply is exogenous, determined by changes in population and participation rates that come from outside the model. Hence, the investment in the adoption of automation in long-haul trucking stimulates labor demand, causing an excess demand for labor. This results in the increase in the real wage illustrated in Figure 15. As long as employment remains above labor supply, the real wage will increase, to eliminate the excess demand for labor. This process continues throughout the simulation period as long as capital is increasing relative to baseline. The change in capital occurs at different rates under the different adoption scenarios. Under the fast adoption scenario, capital rises more sharply earlier in the simulation period, and as a result, labor demand increases more and earlier, reaching almost 0.05 percent above baseline in Year 12. Thereafter, employment drifts back to baseline. But since investment remains above baseline throughout the simulation period, employment never quite returns to baseline, even by 2050 by which point the entire long-haul trucking fleet has been converted to accommodate automation. Relative to U.S. employment in 2019, the average annual gain in employment over the simulation period is equivalent to almost 35,100 jobs; the gain in average wages is $267 on average per year. These additional jobs are created throughout the economy, not limited to transportation industries.

Under the slow adoption scenario (see Figure 13 above), the rate of growth of capital is not as rapid, and by Year 30, capital is still growing, while it has flattened by Year 30 under the fast scenario. As a result, under the slow scenario, labor demand is more elevated (0.033 above baseline) than under the fast scenario. The average annual gain in employment over the simulation period is 26,400 jobs; the gain in average wages is $203 on average per year.

Figure 15: Real wage (% deviations from baseline)



How do these changes in capital and labor translate into changes in real GDP and welfare? Figure 16 and Figure 17 below show how real GDP and welfare change as automation in long-haul trucking is adopted under the three different scenarios.

Figure 16: Real GDP (% deviations from baseline)

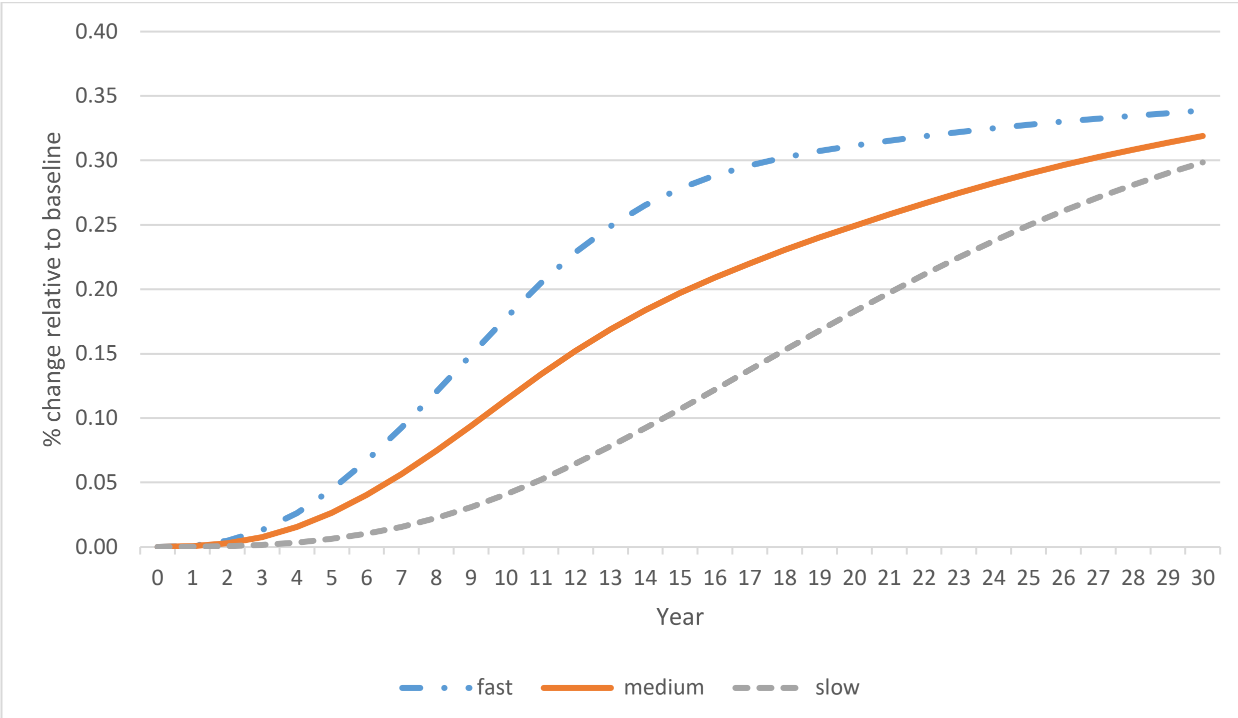
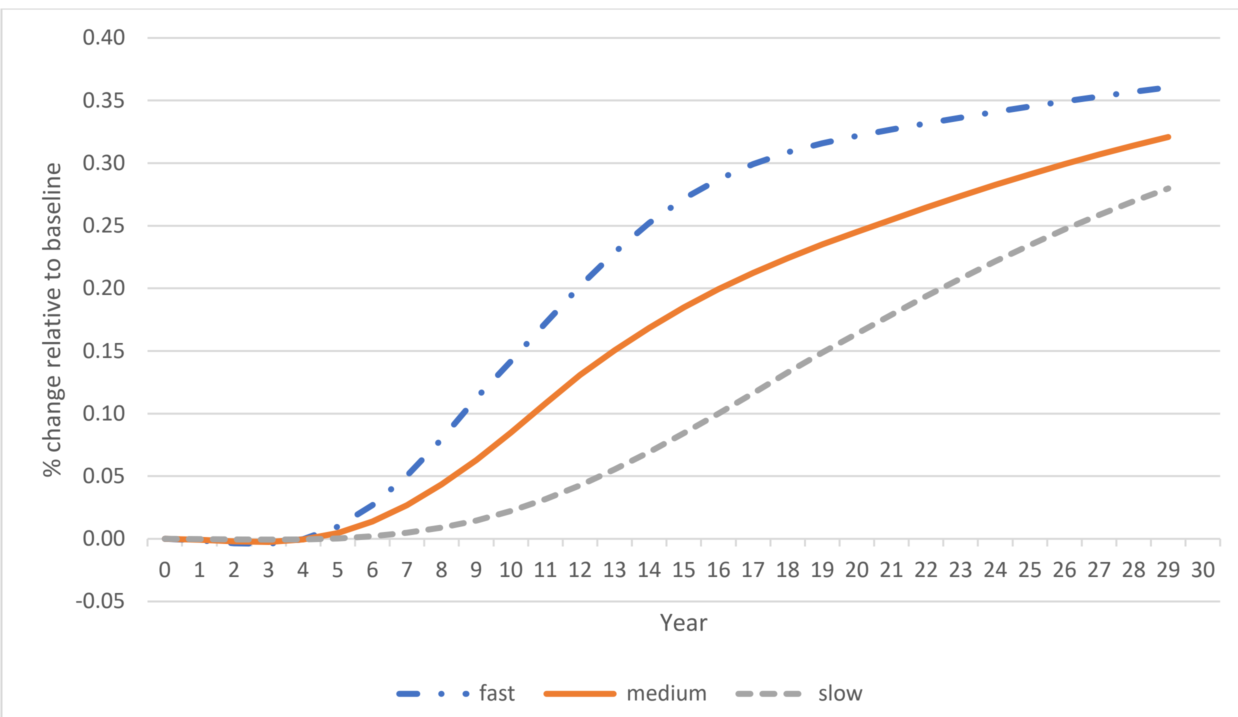


Figure 17: Welfare (% deviations from baseline)



By Year 30, under the fast adoption scenario, GDP reaches almost 0.34 percent above baseline, equivalent to just over $68 billion relative to 2019 GDP. By Year 30, labor has almost returned to baseline, so the contribution of labor to this real GDP gain is negligible. But at 0.38 percent above baseline, capital growth contributes just one-third of overall GDP gain (just over 0.12 percent points of the total 0.38 percentage point gain in real GDP). The largest share of real GDP gain is accounted for by technical change. Labor-saving, capital-saving, and fuel-saving technical change associated with the adoption of automation in long-haul trucking contribute over half of overall GDP gain (0.20 percentage points of the total 0.38 percentage point gain in real GDP).[xi] The dynamics of the modeled changes in rates of technical change are discussed in Chapter 3. The small remainder is accounted for by the impact of changes in revenue from indirect taxes. By comparison, the impact on real GDP of the medium and slow adoption scenarios mimics the impact on capital, with real GDP rising more slowly but steadily throughout the simulation period under the slow adoption scenario.

Figure 17 reports the effects of automation in long-haul trucking on aggregate welfare. This measure of welfare incorporates the impact of automation on private consumption net of medical expenses and road fatalities. As noted in the discussion around Figure 11 and Figure 12, our measure of welfare accommodates these impacts since medical expenditures are excluded when measuring welfare-relevant consumption, and extra fatalities are deducted from welfare. The adoption of automation in long-haul trucking leads to an increase in aggregate welfare relative to baseline that is initially smaller than the increase in real GDP, but ultimately ends up larger than the increase in real GDP. For example, in the fast adoption scenario, the welfare gains are smaller than the real GDP gains until about Year 17. This occurs because, over that part of the simulation period, the higher investment expenditures needed to convert to driverless trucks cause the real GDP gains to be higher than the welfare gains. After Year 17 the welfare gains are slightly greater than the real GDP gains because welfare incorporates the positive impact that automation has on reduced medical costs and fatalities, while these measures are not part of GDP. The increase in welfare reaches just over 0.36 percent by Year 30 under the fast adoption scenario, equivalent to about $40 billion in 2019 prices. The average yearly welfare increase is just over 0.20 percent, equivalent to about $22.8 billion in 2019 prices or $69 per person. Under the slow scenario, the corresponding figures are 0.28 percent by the end of the simulation period, equivalent to about $31 billion in 2019 prices. The average yearly welfare increase is 0.10 percent, equivalent to about $11.4 billion in 2019 prices or $35 per person. Thus, the fast scenario produces the largest increase in total welfare over the analysis period.

Next, we consider the impact of automation in long-haul trucking on some of the industries that are most impacted by these shocks. We begin with the For-Hire Trucking Services and In-House Trucking sectors. The For-Hire Trucking Services industry sees larger technological improvements due to the adoption of automation than the In-house Trucking sector, since there are many more long-haul truck drivers in the For-Hire Trucking Services industry. As a result, Figure 19 shows that the adoption of automation in long-haul trucking leads to an increase in output of the For-Hire Trucking Services sector that reaches about 4

[xi] By Year 30, labor and capital in the For-Hire sectors each account for about 0.56 and 0.29 percent of GDP, while in In-House Trucking, they account for 0.53 and 0.31 percent of GDP, respectively. From Figure 3 and Figure 4, as well as Figure 9 and Figure 10, labor- and capital-saving technical change is 25 percent and 19 percent in the For-Hire sector, and 4 and 3 percent in the In-House Trucking sector, respectively. The overall contribution of technical change to real GDP is 0.20 percent.

percent above baseline by Year 30. Figure 19 shows that the increase in output for the In-House Trucking sector only reaches 0.5 percent above baseline by Year 30.

Figure 18: For-Hire Trucking Services Output (% deviations from baseline)

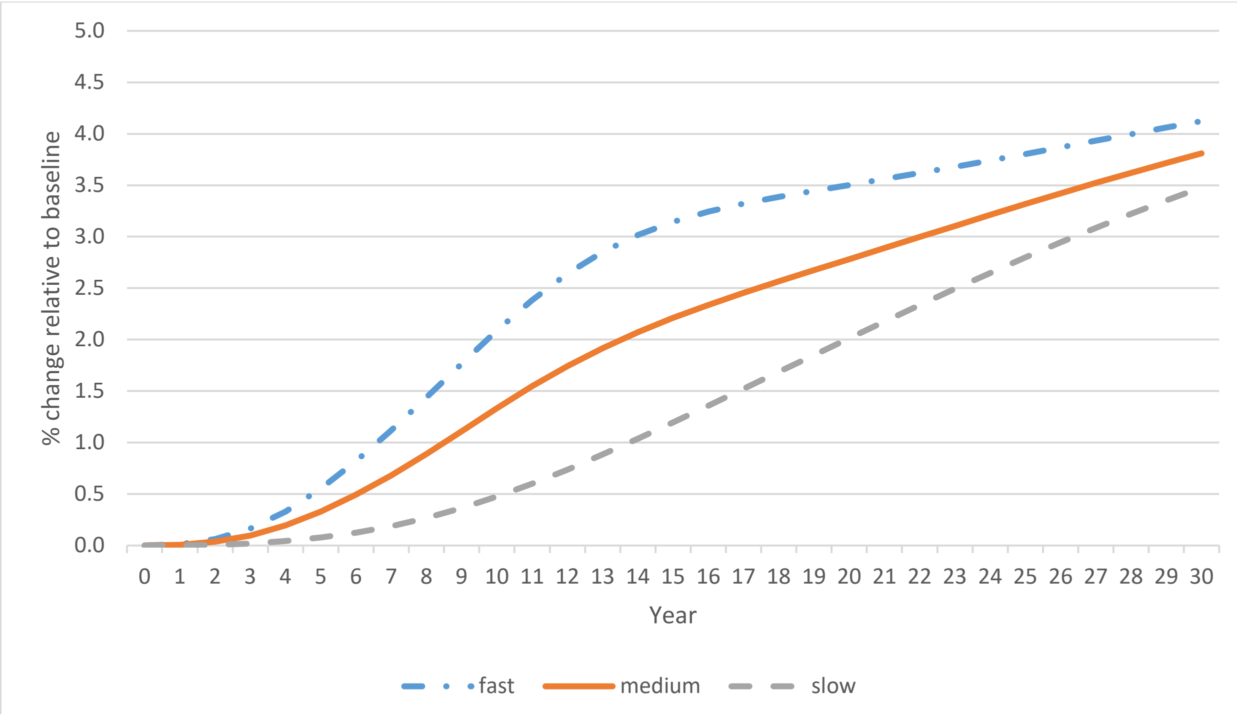


Figure 19: In-House Trucking Output (% deviations from baseline)

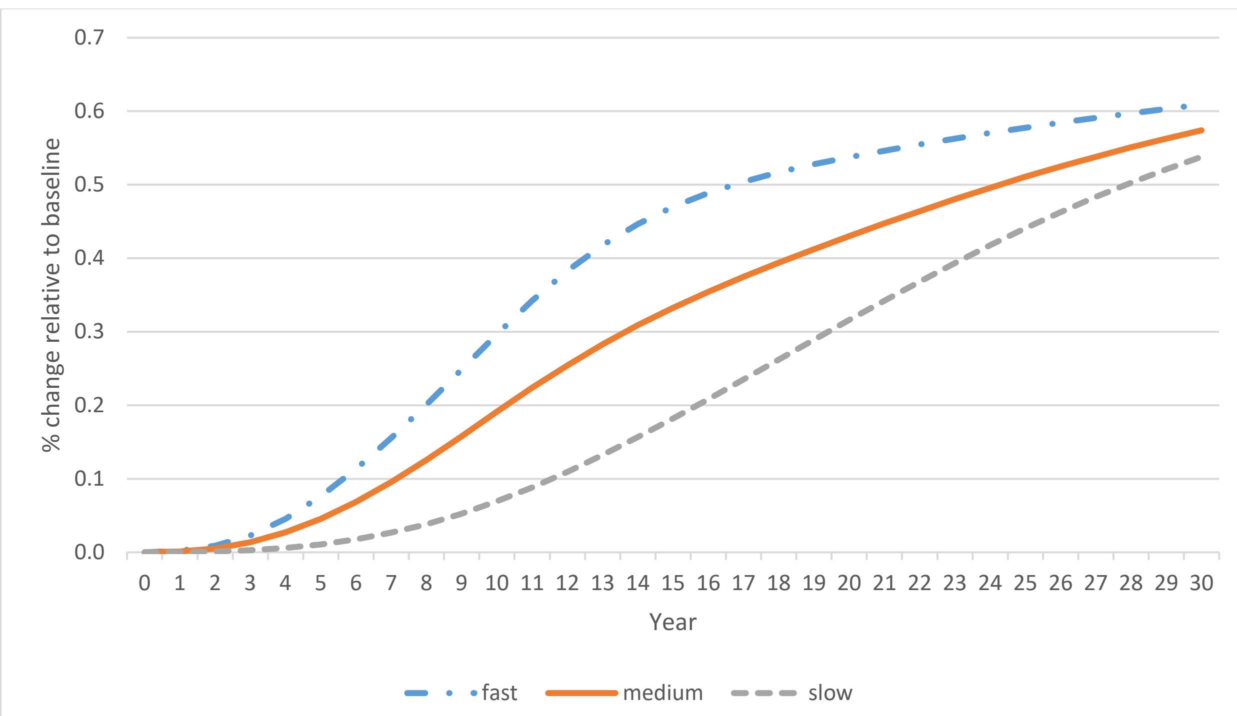


Figure 20: For-Hire Trucking Services Employment (% deviations from baseline)

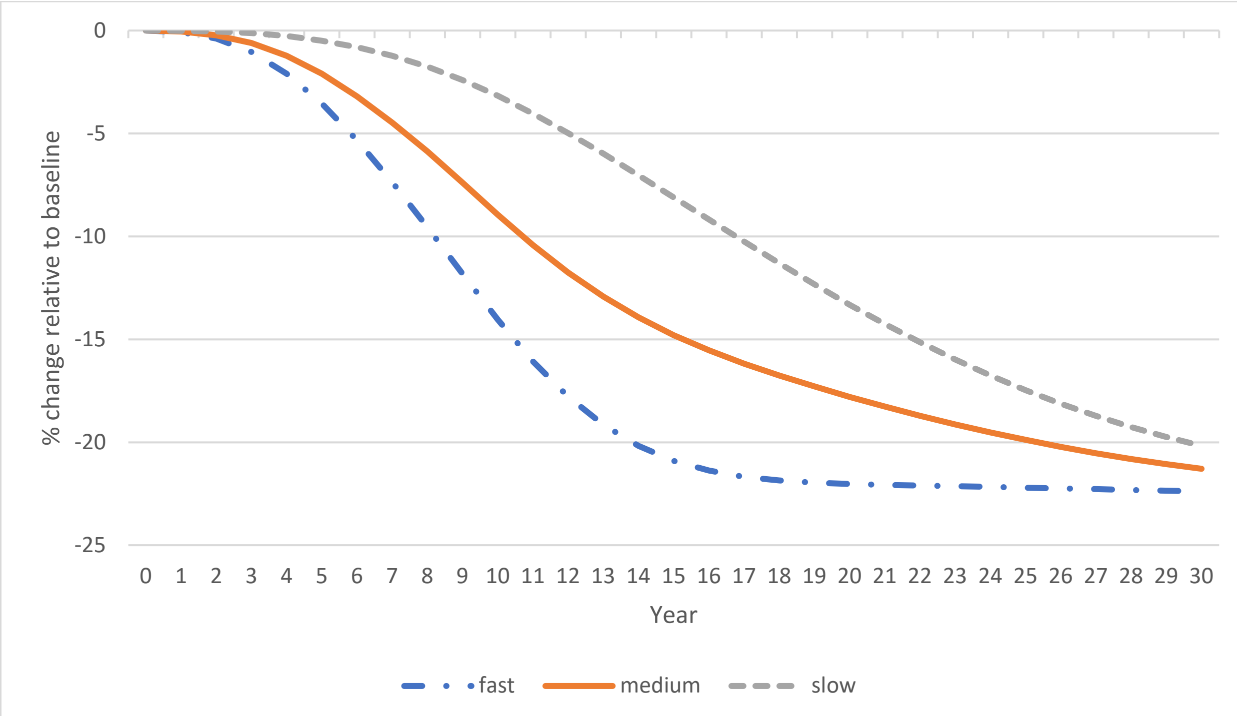
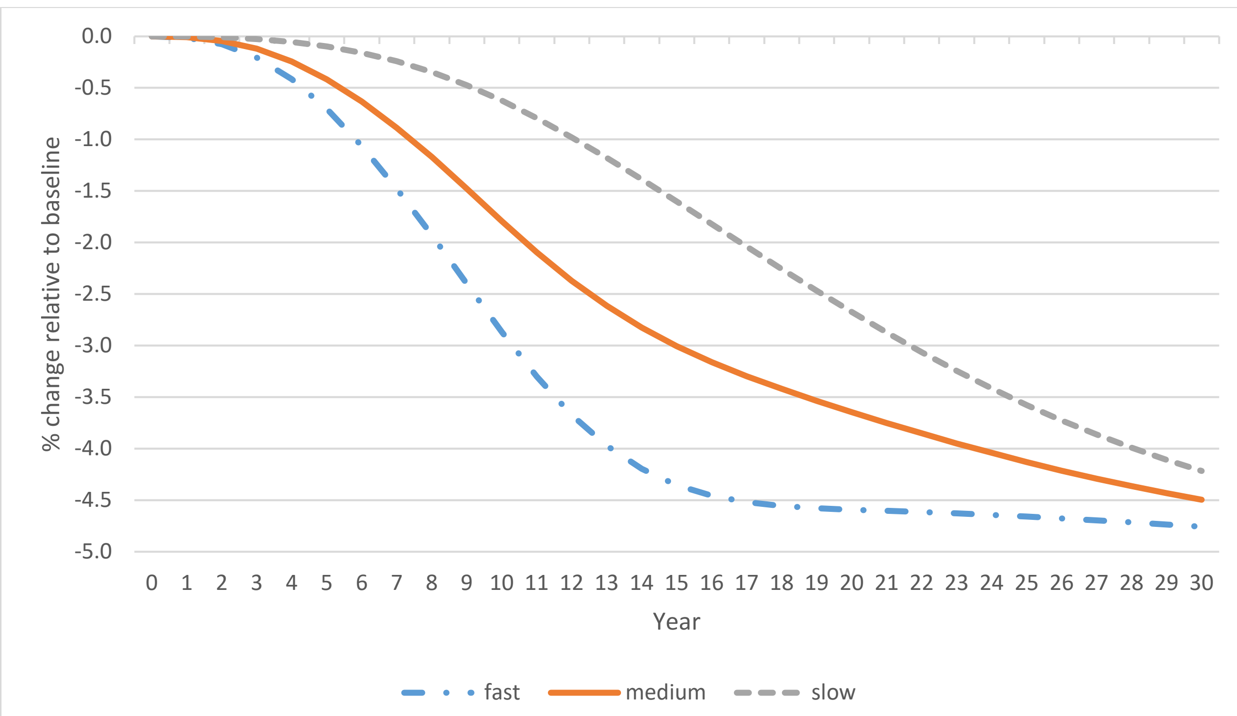


Figure 21: In-House Trucking Employment (% deviations from baseline)



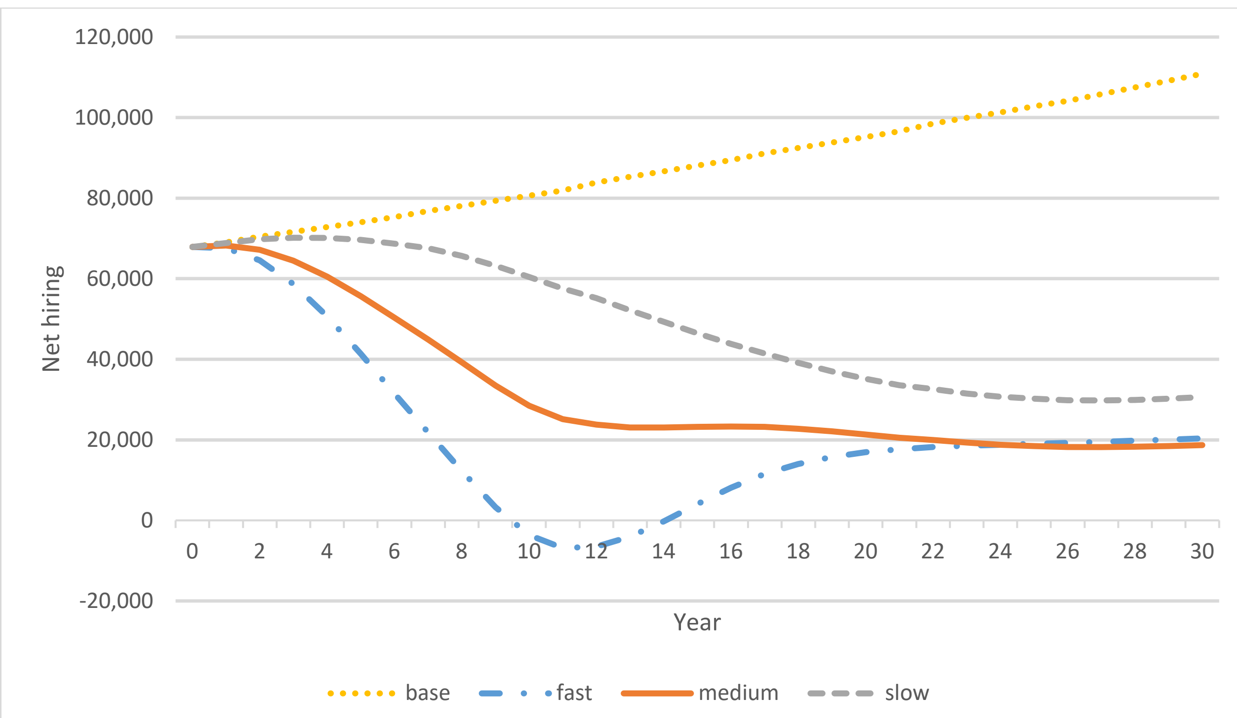
Along with the increase in output in the For-Hire and In-House sectors, Figure 20 and Figure 21 also report a large decrease in employment in these industries. These are consistent with the labor-saving technical change shocks reported in Figure 3 and Figure 4. As firms in these sectors adopt automation technologies, by Year 30, employment in the For-Hire and In-House sectors falls by 20-25 percent and 4-5 percent, respectively. However, recall that overall employment in the economy rises slightly. These sector-specific decreases in employment are not accompanied by decreases in overall employment as the productivity improvements cause employment growth in other sectors.

Finally, we consider the impact of the adoption of automation in long-haul trucking on job security of the drivers of long-haul trucks. There is concern that the adoption of automation in the long-haul trucking industry will lead to large lay-offs of drivers of long-haul trucks. Figure 22 below reports the new hiring of drivers of long-haul trucks in the baseline scenario, and under the fast, medium and slow adoption scenarios. New hiring is defined as the difference between employment in year t and employment in the previous year, plus employment in the previous year multiplied by the turnover rate:

$$\textit{New hiring} = \textit{employment (t)} - \textit{employment (t-1)} + \textit{employment (t-1)} \cdot \textit{turnover rate}.$$

That is, new hiring is the difference between demand for long-haul truck drivers from one year to the next, plus the replacement of drivers in the previous year who leave the occupation either through retirement or job change. Groshen *et al.* cite BLS occupational turnover projections to argue for use of an annual occupational turnover rate of 10.5 percent for long-haul truck drivers.[15]

Figure 22: Net hiring of Long-haul Truckers



In Year 0, the USAGE-Hwy baseline suggests employment of 559,027 long-haul truck drivers (479,993 in For-Hire and 79,035 in In-House Trucking),[xii] increasing to 569,370 in Year 1. As a result, Figure 22 reports baseline new hiring of long-haul truck drivers in Year 1 of 69,041, rising to over 110,000 by Year 30.

The impact of the adoption of automation on the hiring of long-haul truckers is illustrated in Figure 22. There are no lay-offs under the medium and slow adoption scenarios, since net hiring is always positive. But under the fast adoption scenario, after Year 9 (by which point just over 50 percent of the fleet will have been converted to accommodate automation), net hiring of long-haul truckers turns negative for five years, implying that there will be lay-offs of long-haul truckers. The number of lay-offs reaches a maximum of about 11,000 in Year 11, roughly 1.7 percent of baseline employment of long-haul truckers in Year 11. But by the time the whole fleet has been converted to accommodate automation, net hiring ultimately trends to approximately +20,000. This long-term net hiring by Year 30 reflects our assumption that the maximum technology adoption in the long-haul trucking industry is 81.4 percent, so of the 110,000 net hires of long-haul truckers under the baseline by Year 30, around 20,000 are still required to manage shipments such as high-value goods, hazardous materials, or cross-border movements. It is also important to recall that long-haul truckers represent only a fraction of the “Heavy and Tractor-Trailer Drivers” employed in BLS Occupation 53-3032. We noted earlier that the BLS reported that there were 1,800,310 “Heavy and Tractor-Trailer Drivers” in 2017, of whom 453,773 and 74,718 were Long Distance Tractor-trailer Drivers in the For-Hire and In-House Trucking sectors, respectively. Using the same annual occupational turnover rate of 10.5 percent for all truck drivers, this suggests an annual turnover of 133,541 short-haul truck drivers in 2017. This turnover is an order of magnitude greater than the largest lay-offs of long-haul truck drivers. As a result, we conclude that long-haul truck drivers should be able to find employment as short-haul truck drivers, so properly managed, the issue of lay-offs should not be a significant concern when considering the adoption of automation in long-haul trucking.

Before concluding, we consider a simple sensitivity test by re-running all simulations against a baseline where the assumed annual growth rate in real GDP is halved from 2.4 percent to 1.2 percent. This implies that the investment shocks need to be re-calibrated against a baseline where the growth in investment in the For-Hire and In-House Trucking sectors is lower. At the same time, we halve the growth rate in truck vehicle miles traveled reported in the forthcoming 24th Edition of the FHWA Conditions and Performance (C&P) Report, and re-calibrate baseline employment in the For-Hire and In-House Trucking sectors accordingly. Since truck vehicle miles traveled is growing more slowly, associated fatalities and medical costs will also grow more slowly; shocks to fatalities and medical costs are re-calibrated accordingly. All other shocks remain the same. For the purposes of this sensitivity analysis, we use the fast adoption scenario to contrast the “central case” results against the “sensitivity” results where the annual growth rate in real GDP is halved.

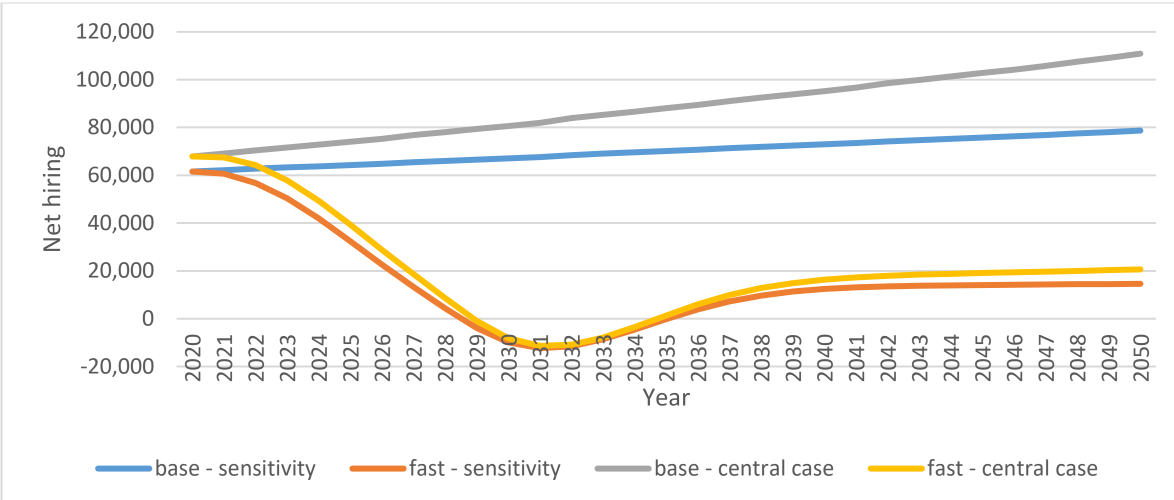
In the “central case” scenario, baseline employment in the For-Hire and In-House Trucking sectors was assumed to follow the change in truck vehicle miles traveled as reported in the forthcoming 24th Edition of the FHWA Conditions and Performance (C&P) Report, an annual growth rate of about 1.8 per cent. In the “sensitivity” scenario, this growth rate is halved. As a result, Figure 23 shows that net hiring of long-haul truck drivers in the baseline is considerably lower under the “sensitivity” scenario compared to the “central

---

[xii] Using BLS Occupational Employment Statistics and evidence from Gittleman and Monaco, we argued earlier that there were 453,773 and 74,718 Long Distance Tractor-trailer Drivers in the “Trucking Services” and “In-house Trucking” sectors, respectively in 2017 (See Endnote 4).

case" scenario. By Year 30, net hiring of long-haul truck drivers is just under 79,000 under the "sensitivity" scenario, compared to just under 111,000 under the "central case" scenario.

Figure 23: Net hiring of Long-haul Truckers (#)



As a result, after the adoption of automation under the fast scenario, net hiring of long-haul truck drivers is also lower under the "sensitivity" scenario than under the "central case" scenario. By Year 30, net hiring is about 20,600 under the "sensitivity" scenario, compared to about 22,800 under the central case scenario. Since baseline hiring is weaker, there is a slight increase in the largest number of lay-offs under the "sensitivity" scenario, where net hiring falls to about -12,300 in Year 11, compared to about -11,300 under the "central case" scenario. But these differences are relatively small, and as we argued earlier under the "central case" scenario, any laid-off long-haul truck drivers should always be able to find employment as short-haul truck drivers. This result echoes the available literature that finds that the speed of technology adoption would impact the expect job displacement in the trucking sector.[15,16]

Chapter 5. Conclusions

Our model indicates that the adoption of driving automation will bring direct productivity enhancements to the long-haul trucking sector and (due to transportation's central role in the economy) produce secondary productivity enhancements to the larger macroeconomy. These productivity enhancements will increase GDP, capital, employment, wages, and welfare that can be monetized into billions of dollars. Additionally, our model concluded that these economic benefits can likely be reaped without mass lay-offs of long-haul truck drivers. Assuming the occupational turnover remains near today's levels, employment levels in the long-haul trucking sector will necessarily fall due to automation but will not force lay-offs in the slow and medium speed adoption scenarios. Only under the fast adoption scenario are lay-offs observed, but they are at most 1.7 percent of the long-haul workforce in a single year and the layoffs only occur during a five-year period. As a result, we conclude that long-haul truck drivers should be able to find employment as short-haul truck drivers, so the issue of lay-offs should not be a significant concern when considering the adoption of automation in long-haul trucking.

Specifically, this analysis finds that SAE Level 4 and Level 5 automation of the long-haul trucking industry would be accompanied by welfare increases ranging from $35 per person (for the whole population) on average over the 30-year period under the slow scenario to $69 per person under the fast scenario. Workers would see annual earnings rise by $203 per worker per year under the slow scenario and $267 per worker per year under the fast scenario.

References

1. SAE International. J3016. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles [Internet]. SAE International; 2018 Jun. Available from: https://www.sae.org/standards/content/j3016_201806
2. Gittleman M, Monaco K. Truck-Driving Jobs: Are They Headed for Rapid Elimination? ILR Rev. 2019;73(1):3–24.
3. Viscelli S. Driverless? Autonomous Trucks and the Future of the American Trucker. Cent Labor Res Educ Univ Calif Berkeley Work Partnersh USA. 2018 Sep;73.
4. Seltz-Axmacher S. The End of Starsky Robotics. Medium [Internet]. 2020 Mar 19; Available from: https://medium.com/starsky-robotics-blog/the-end-of-starsky-robotics-acb8a6a8a5f5
5. Bishop R. Starsky Robotics Failed. Does That Mean Automated Trucking is Dead? Forbes [Internet]. 2020 Mar 24; Available from: https://www.forbes.com/sites/richardbishop1/2020/03/24/starsky-robotics-failed-does-that-mean-automated-trucking-is-dead/#38a4e80940c8
6. Montgomery D W. Public and Private Benefits of Autonomous Vehicles [Internet]. Securing America's Future Energy; 2018 Jun. Available from: https://avworkforce.secureenergy.org/wp-content/uploads/2018/06/W.-David-Montgomery-Report-June-2018.pdf
7. Center for Global Policy Solutions. Stick Shift: Autonomous Vehicles, Driving Jobs and the Future of Work [Internet]. Washington, DC: Center for Global Policy Solutions; 2017 [cited 2020 Aug 18]. Available from: http://globalpolicysolutions.org/report/stick-shift-autonomous-vehicles-driving-jobs-and-the-future-of-work/
8. Securing America's Future Energy. America's Workforce and the Self-Driving Future [Internet]. 2018 Jun [cited 2020 Jan 13]. Available from: https://avworkforce.secureenergy.org/wp-content/uploads/2018/06/Americas-Workforce-and-the-Self-Driving-Future_Realizing-Productivity-Gains-and-Spurring-Economic-Growth.pdf
9. Nadiri I, Mamuneas T. Contribution of Highway Capital to Industry and National Productivity Growth. Federal Highway Administration; 1996 Sep.
10. Nadiri I, Mamuneas T. Contributions of Highway Capital to Output and Productivity Growth in the U.S. Economy and Industries. 1998 Aug.
11. Cook LM, Munnell AH. How Does Public Infrastructure Affect Regional Economic Performance? N Engl Econ Rev. 1990;(Sep):11–33.
12. Environmental Protection Agency Science Advisory Board. SAB Advice on the Use of Economy-Wide Models in Evaluating the Social Costs, Benefits, and Economic Impacts of Air Regulations. Washington D.C.: US Environmental Protection Agency; 2017 Sep. Report No.: EPA-SAB-17-012.
13. Costantini V, Sforna G. A dynamic CGE model for jointly accounting ageing population, automation and environmental tax reform. European Union as a case study. Econ Model. 2020 May 1;87:280–306.
14. Huang Y, Kockelman KM. What Will Autonomous Trucking Do To U.S. Trade Flows? Application Of The Random-Utility-Based Multi-Regional Input-Output Model. In 2019 [cited 2020 Jul 13]. Available from: https://trid.trb.org/view/1572578
15. Groshen EL, Helper S, MacDuffie JP, Carson C. Preparing U.S. Workers and Employers for an Autonomous Vehicle Future [Internet]. W.E. Upjohn Institute; 2018. Available from: https://doi.org/10.17848/tr19-036
16. International Transport Forum. Managing the Transition to Driverless Road Freight Transport [Internet]. Paris: International Transport Forum; 2017 May [cited 2020 Aug 18]. Available from: https://www.itf-oecd.org/managing-transition-driverless-road-freight-transport
17. Shiller R. Narratives about Technology-Induced Job Degradations Then and Now [Internet]. Cambridge, MA: National Bureau of Economic Research; 2019 Feb [cited 2020 Aug 18] p.

w25536. (NBER Working Paper Series). Report No.: w25536. Available from: http://www.nber.org/papers/w25536.pdf

18. Autor DH. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. J Econ Perspect. 2015 Sep;29(3):3–30.
19. Bureau of Labor Statistics. Postal Service Workers [Internet]. U.S. Department of Labor; 2020 Apr. (Occupational Outlook Handbook). Available from: https://www.bls.gov/ooh/office-and-administrative-support/postal-service-workers.htm
20. Bureau of Labor Statistics. Delivery Truck Drivers and Driver/Sales Workers [Internet]. U.S. Department of Labor; 2020 Apr. (Occupational Outlook Handbook). Available from: https://www.bls.gov/ooh/transportation-and-material-moving/delivery-truck-drivers-and-driver-sales-workers.htm
21. Dixon PB, Rimmer MT, Waschik R. Linking CGE and specialist models: Deriving the implications of highway policy using USAGE-Hwy. Econ Model. 2017;66:1–18.
22. USDOT. Driving Automation Systems in Long-Haul Trucking and Bus Transit: Preliminary Analysis of Potential Workforce Impacts. Department of Transportation; 2021 Jan.
23. McKinsey Global Institute. A Future that Works: Automation, Employment, and Productivity [Internet]. McKinsey & Company; 2017 Jan. Available from: https://www.mckinsey.com/~/media/mckinsey/featured%20insights/Digital%20Disruption/Harnessing%20automation%20for%20a%20future%20that%20works/MGI-A-future-that-works-Full-report.ashx
24. Chottani A, Murnane J, Neuhaus F. Distraction or Disruption? Autonomous trucks disrupt US logistics. McKinsey & Company: Travel, Logistics & Transport Infrastructure [Internet]. 2018 Dec 10 [cited 2020 Aug 18]; Available from: https://www.mckinsey.com/industries/travel-logistics-and-transport-infrastructure/our-insights/distraction-or-disruption-autonomous-trucks-gain-ground-in-us-logistics#
25. Shladover S, Lu X-Y, Yang S, Ramezani H, Spring J, Nowakowski C, et al. Cooperative Adaptive Cruise Control (CACC) [Internet]. For Partially Automated Truck Platooning:Final Report; 2018. Available from: https://escholarship.org/uc/item/260060w4
26. Garthwaite J. Smarter Trucking Saves Fuel Over the Long Haul. National Geographic [Internet]. 2011 Sep 24 [cited 2020 Aug 18]; Available from: https://www.nationalgeographic.com/news/energy/2011/09/110923-fuel-economy-for-trucks/
27. National Highway Traffic Safety Administration. Speed Limiting Devices [Internet]. U.S. Department of Transportation; 2016 Aug. Report No.: FMVSS No. 140. Available from: https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/speed-limiter-pria-082016.pdf
28. Wiggers K. TuSimple raises $120 million to expand its fleet of driverless delivery trucks [Internet]. VentureBeat. 2019 [cited 2020 Aug 24]. Available from: https://venturebeat.com/2019/09/17/tusimple-raises-120-million-to-expand-its-fleet-of-driverless-delivery-trucks/
29. McKinsey. Route 2030: The fast track to the future of the commercial vehicle industry | McKinsey [Internet]. McKinsey & Company; 2018 Sep [cited 2020 Aug 18]. Available from: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/route-2030-the-fast-track-to-the-future-of-the-commercial-vehicle-industry
30. Federal Motor Carrier Safety Administration. Large Truck and Bus Crash Facts 2017 [Internet]. U.S. Department of Transportation; 2019 May. Report No.: FMCSA-RRA-18-018. Available from: https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/safety/data-and-statistics/461861/ltcbf-2017-final-5-6-2019.pdf
31. Craft R. Why Trucks and Cars Collide. 2008 Jul 31; Federal Motor Carrier Safety Administration.
32. Federal Motor Carrier Safety Administration. Unit Costs of Medium and Heavy Truck Crashes [Internet]. U.S. Department of Transportation; 2007 Mar. Report No.: FMCSA-RRA-07-034. Available from: https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/UnitCostsTruck%20Crashes2007.pdf

U.S. Department of Transportation
ITS Joint Program Office – HOIT
1200 New Jersey Avenue, SE
Washington, DC 20590

Toll-Free "Help Line" 866-367-7487

www.its.dot.gov

FHWA-JPO-21-847

U.S. Department of Transportation