Evaluating the Impact of Automation in Long-Haul Trucking Using USAGE-Hwy

CoPS Working Paper No. G-326, April 2022

Catherine Taylor
Volpe National Transportation Systems Center,
Boston

And

Robert Waschik
Centre of Policy Studies,
Victoria University

ISSN 1 921654 02 3 ISBN 978-1-921654-34-3

The Centre of Policy Studies (CoPS), incorporating the IMPACT project, is a research centre at Victoria University devoted to quantitative analysis of issues relevant to economic policy. Address: Centre of Policy Studies, Victoria University, PO Box 14428, Melbourne, Victoria, 8001 home page: www.vu.edu.au/CoPS/ email: copsinfo@vu.edu.au Telephone +61 3 9919 1877

About us

Researchers at the Centre of Policy Studies have a 45-year history of continuous achievement in the development, application and dissemination of large-scale economic models. Our models and software are used around the world to analyse a diverse range of economic issues. CoPS' funders include: Australian federal and state government departments; private firms and universities in many parts of the world; central government agencies such as finance and trade ministries in many countries; and international development organisations. The Centre's GEMPACK software, used for solving large economic models, is used at more than 700 sites in over 95 countries.

Citation

Taylor, C. and R. Waschik (2022), "Evaluating the impact of automation in long-haul trucking using USAGE-Hwy", Centre of Policy Studies Working Paper No. G-326, Victoria University, April 2022.

Evaluating the impact of automation in long-haul trucking using USAGE-Hwy

Catherine Taylor[a] and Robert Waschik[b]

[a]Volpe National Transportation Systems Center, Boston
[b]Centre of Policy Studies, Victoria University, Melbourne

April 2022

Abstract

We evaluate the macroeconomic effects of the introduction of automation in the long-haul trucking sectors in the United States, along with the output and employment impacts in the long-haul trucking sector itself, using the purpose-built computable general equilibrium (CGE) USAGE-Hwy model.[1] We simulate the automation of long-haul trucking in the US by assuming that the fleet of long-haul trucks is converted for automation technology over the period 2021-2050 following a "fast", "medium" or "slow" adoption path. After accounting for the cost of converting the fleet for automation, the efficiency and safety improvements contribute to an increase in real GDP and welfare in the US in 2050 of between 0.35-0.40 per cent. Despite the fact that automation technology obviates the need for most long-haul truck drivers, hiring of long-haul truck drivers remains positive throughout the simulation period in all scenarios, except for a five-year period under the "fast" adoption of automation. Over this five-year period, at most 10,000 long-haul truck drivers per year are laid off. Given an annual occupational turnover rate for truck drivers of 10.5 per cent, the annual turnover of short-haul truck drivers in 2018 was almost 138,000, implying that the issue of layoffs of long-haul truck drivers should not be a significant concern when considering the adoption of automation in long-haul trucking.

Keywords: autonomous vehicles, driverless trucks, computable general equilibrium

JEL classifications: O18, O33, C68

---

[1] This paper is based on previous work published by the US Department of Transportation Intelligent Transportation Systems Joint Program Office (see Waschik *et al*., Jan. 2021). The views expressed in this paper do not represent the opinions of the U.S. Department of Transportation and do not constitute an endorsement, recommendation, or specification by the U.S. Department of Transportation.

Contents

1. Introduction and relevant literature

There has long been concern about the impact of technological change on the economy in general and employment and labor markets in particular. Does automation lead to increases in aggregate demand that are sufficient to lead to increases in employment, or does automation merely replace human labor with machines? Autor (2015) provides an excellent review of the relationship between automation and employment, with examples spanning the 19th century Luddite movement to current examples of technologies that substitute for human labor. He argues that "technological change is not necessarily employment-increasing or Pareto-improving", but that it depends upon the labor supply elasticity, the output and income elasticities of demand, and the extent to which workers supply tasks that are either complemented or substituted by automation. Acemoglu and Restrepo (2017) found that between 1990 and 2007, both employment and wages declined in 19 industries exposed to an increase in robot usage, and did "not find positive and offsetting employment gains in any occupation or education groups" (Acemoglu and Restrepo; 2017:5). Bessen (2019) argues that much of the recent literature on the impacts of automation on employment consider single sector economies, so that they could not capture the impact of inter-sectoral differences in demand elasticities. He argues that an industry-level analysis is more appropriate when looking at the impacts of automation on employment, and uses long data series to provide examples where automation in high-demand-elasticity sectors let to growth in employment. Vermeulen *et al*. (2018) use the assessments of occupational experts of the Bureau of Labor Statistics regarding technology-driven employment shifts to forecast the displacement of employment by technology for different occupations and across sectors over the next ten years, and find that we are facing "the usual structural change" rather than the "end of work".

The objective of this paper is to contribute to this literature by modelling a specific example of the potential impact of automation that is expected to replace a large share of the employment of labor in a specific industry: the impact of automation in long-haul trucking. Vermeulen *et al*. (2018) rank the Transportation and Material Moving occupation among the major occupation groups with the highest "automatability score" (see Vermeulen *et al*. (2018:12), Table 3). The long-haul segment of the trucking industry should be the first to be impacted by automation (compared to other segments like short-haul heavy truck and tractor-trailer driving) in part because:

1. Current driving automation system development focuses on limited access highways because they are a less-complex environment than surface streets;
2. Unlike the short-haul segment, the long-haul segment involves long periods of uninterrupted highway driving; and
3. Long-haul drivers have fewer non-driving responsibilities than short-haul drivers.

Of course, there are different degrees of automation that could be implemented in long-haul trucking. For example, in a Level 4 application where a human driver remains onboard, the human driver may not need to remain in the driver's seat at all times, and theoretically could ride in the sleeper cab when the automated driving system (ADS) is engaged and the vehicle is within its operational design domain (ODD). The driver could potentially receive their Federal Motor Carrier Safety Administration (FMCSA)-mandated rest or engage in other non-driving tasks while riding in the cab during the automated portion of the trip, increasing overall worker productivity. Alternatively, we could "… envision an environment when the longer, line-haul portion of truck freight movements are completed by autonomous trucks and local pick-up and delivery routes are completed by drivers" (Costello 2017:12). For our purposes, we presume that the adoption of automation in long-haul trucking allows for the operation of activities in the trucking industry without the need for long-haul truck drivers in those vehicles that have been fitted with automation technology.

While a number of recent studies have considered the impact of the introduction of autonomous vehicles, much of this literature focuses on passenger vehicles, including private transport, public transport and taxis, as well as truck transport. At the same time, these studies have to evaluate the suitability of automation for different driving domains, ranging from inner-city urban areas to limited access highways. Raj *et al*. (2020) identify a number of barriers to and benefits from the introduction of autonomous vehicles, including concerns with customer acceptance, inadequate infrastructure and issues with standards, as well as reduced traffic and parking congestion and enhanced mobility for elderly and disabled passengers. Clements and Kockelman (2017) estimated the economic impacts of the adoption of automation of heavy trucks as well as personal vehicles, taxis, buses and other forms of group travel at \$1.2 trillion, nearly 8% of the entire U.S. gross domestic product. Fagnant and Kockelman (2015) find that savings from the introduction of automated vehicles may eventually approach nearly \$4000 per AV. But in all of these studies, savings are derived from the introduction of all road vehicles, including short-haul and long-haul trucks as well as passenger vehicles. At the same time, these studies do not present a clear estimate of the economic costs that would be involved in upgrading all vehicles to enable autonomous operation. For example, Clements and Kockelman (2017) note that "autonomous features … may eventually represent 40% of the car value" (Clements and Kockelman 2017:108), but in their Table 1 that summarizes the economic effects of autonomous vehicles, they seem to only include gains from improved productivity and safety.

The focus of our study is narrower, considering only the adoption of automation in long-haul trucking. A few recent studies focus specifically on the impacts of automation in trucking. Fagnant and Kockelman (2015) include a subsection on freight transportation where they recognize fuel savings and a decrease in the need for truck drivers. Engholm *et al*. (2020) estimated that truck acquisition costs could increase by 25% on a baseline cost of 60ton truck of \$295,877, or about \$75,000. Wadud (2017) estimated the cost savings for a driverless truck in the UK to be between 15%-19.5%. These and other estimates are integrated into our shocks which are constructed to simulate the impact of automation in long-haul trucking.

A few studies provide estimates of the impact of automation in long-haul trucking on some economic variables. After accounting for turnover, Groshen *et al*. (2018) forecast job reductions over 2018-2051 of almost 1.8 million workers. Engholm *et al*. (2021) found that the adoption of driverless trucks could lead to an increase in road tonne-kilometers of 11%. But we found no study that solves for the economic impacts of automation in long-haul trucking in a general equilibrium economic model. Indeed, Engholm *et al*. (2021) allude to the potential benefits of a general equilibrium modelling approach to the problem of autonomous trucks when they suggest "using models that include demand-related feedback mechanisms to achieve a more complete understanding of the effects on transport demand" (Engholm *et al*. 2021:249).

We simulate the automation of long-haul trucking in the US using a computable general equilibrium (CGE) model, by assuming that the fleet of long-haul trucks is converted for automation technology over the period 2021-2050 following a "fast", "medium" or "slow" adoption path. After accounting for the cost of converting the fleet for automation, the efficiency and safety improvements contribute to an annual increase in real GDP and welfare in the US by 2050 of between 0.35-0.40 per cent relative to baseline, equivalent to \$72b-\$84b of 2018 GDP. Aggregate annual labor demand relative to baseline rises by a maximum of almost 0.05 per cent after 12 years under the "fast" adoption scenario, with an average annual gain in employment over the simulation period equivalent to about 36k-48k jobs. By 2050, output of the "For-hire" trucking industry rises by about 8 per cent relative to baseline, with transport users substituting away from rail transport, where output falls by about 10 per cent.

But what is the impact of automation in long-haul trucking on the number of long-haul truck drivers? Results suggest that under the "medium" and "slow" adoption scenarios, hiring of long-haul truck drivers remains positive throughout the simulation period, due in part to an occupational turnover rate of 10.5 per cent. Under the "fast" adoption scenario, USAGE-Hwy simulations forecast a 5-year period starting in 2032 where layoffs of long-haul truck drivers are positive, reaching almost 10,000 truck drivers per year in 2033 and 2034. But a 10.5 per cent turnover of short-haul truck drivers implies net positive hiring of short-haul truckers of at least 140k per year. We conclude that the issue of layoffs of long-haul truck drivers should not be a significant concern when considering the adoption of automation in long-haul trucking.

The paper proceeds as follows. In Section 2, we give a brief description of USAGE-Hwy, the CGE model that we use to simulate the impacts of the adoption of automation in long-haul trucking, and a detailed description of the shocks that are used to inform the simulations and represent the impacts of automation in long-haul trucking. Section 3 presents macroeconomic results due to automation for the US economy, including the impacts of automation on real GDP, welfare and employment, as well as industry results for the transportation industries in the US and the impacts on employment of long-haul truck drivers. Section 4 concludes and discusses some avenues for future research in this area.

2. Simulating automation in long-haul trucking

We simulate the impacts of the adoption of automation in long-haul trucking in the US using USAGE-Hwy, a computable general equilibrium (CGE) model. In a CGE model, the supply and demand for each commodity is determined as the outcome of optimising behaviour of economic agents. Industries are assumed to choose inputs (labour, capital, intermediates) so as to minimize costs while operating in a competitive market, subject to technology constraints, while households purchase a particular bundle of goods in accordance with their preferences, relative prices and disposable income. CGE models are distinct from input-output (IO) models. Both IO and CGE models are typically based on the best available and most recent economic data from national statistical agencies, including detailed industry data. But IO models generally assume that there are no supply-side constraints on the economy: Labour and capital are assumed to be available with perfect elasticity of supply. 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. In each 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 primary factors of production (labour, capital, land, natural resources) is constrained by the economy's capacity to supply these factors.

USAGE-Hwy is a dynamic CGE model of the U.S. economy adapted from the USAGE model, itself developed since 2001 by the Centre of Policy Studies in collaboration with the U.S. International Trade Commission. USAGE-Hwy is tailor-made for analysing the economy-wide effects of investment in highway infrastructure. In creating USAGE-Hwy separate industries were made for: Highway and bridge construction; Street repairs; Private road transport; Vacation transport; Commuter transport; and Household car repairs. More recent work introduced four new industries to account for In-House Transport by Air, Rail, Water and Truck. For more detail on USAGE-Hwy, see Dixon *et al*. (2017). All USAGE-Hwy model simulations are set up and solved using the Centre of Policy Studies' purpose-built GEMPACK software, documented in Horridge *et al*. (2018).

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. The baseline reflects macroeconomic forecasts informed by the Annual Energy Outlook published by the Energy Information Administration and population and labor market forecasts using information from the IMF and World Bank. The initial period in USAGE-Hwy is 2018, so all macroeconomic and industry output data reflect US data for the year 2018 from sources including the Bureau of Economic Analysis (BEA), the Transport Satellite Accounts (TSA) and the Bureau of Labor Statistics (BLS).

To analyze the effects of automation in long-haul trucking, we compare the baseline simulation to a policy simulation that incorporates a series of shocks to reflect the expected impacts of automation in long-haul trucking in each year on the productivity of labor and capital used in the USAGE-Hwy long-haul trucking industries, as well as impacts on fuel use, safety costs, fatalities, and of course, the cost of upgrading trucks to be able to operate autonomously. These shocks are described in Sections 2.2-2.6. We simulate the introduction of automation in long-haul trucking over the period 2021-2050 – this process is detailed in Section 2.1. This enables us to evaluate the impacts of automation in long-haul trucking by comparing results from the policy simulation to results from the baseline simulation.

2.1 Automation and the truck transport industries in USAGE-Hwy

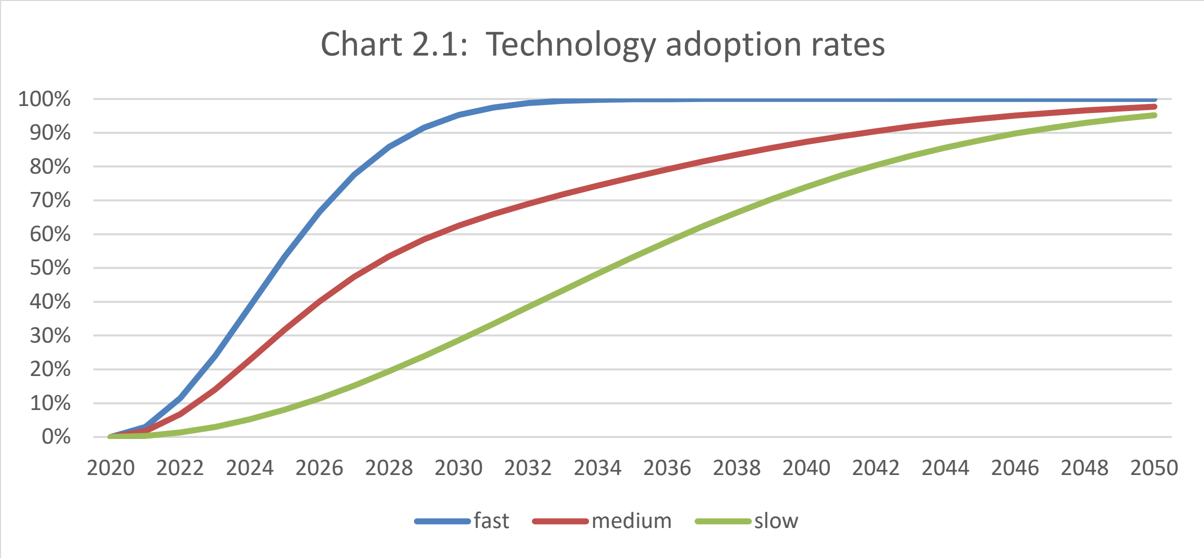
USAGE-Hwy includes two truck transport industries: NAICS industry 484 "For-hire truck transportation" (dominated by UPS Inc. and FedEx Corp.) and industry 47OT.484 "In-house truck transportation" (where firms provide their own truck transport services) are modelled as separate activities in USAGE-Hwy. Given the focus of this study, we ensured that activity in these industries in USAGE-Hwy was calibrated to be consistent with total demand for "For-hire truck transportation" in 2018 as reported in the BEA and for "In-house truck transportation" in 2018 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 2018 TSA USE table for NAICS industries 484 and 47OT.484, respectively. Table 2.1 below summarizes these two truck transport industries in USAGE-Hwy.

Table 2.1: Truck Transport industries in USAGE-Hwy (2018 $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	265,895	99,266	57,957	9,226	432,339	372,061
47OT.484 In-house truck transportation	255,702	116,837	68,216	0	440,755	440,754

We suppose that the first firms in the trucking industry begin adopting automation in long-haul trucking starting in 2021. This assumption allows us to explore the possible economic consequences of automation. In truth, Level 4 automation is not currently generally available: An environment where a driver can be completely removed from the vehicle is not a technical reality. The limited number of pilot tests for automated long-haul trucking still use a test driver at the wheel and operate only under favourable conditions. 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. Simpson *et al.* (2019) use a modified Bass model to estimate the future adoption of autonomous trucks by freight transportation organizations within the case study region of Shelby County, Tennessee. Their analyses suggest that the market penetration rate of autonomous trucks within 25 years varies from more than 95% to 20% or less. They find that adoption rates would depend upon improvements in autonomous technology over time, changes in public opinion on autonomous technology and external factors such as price and marketing.

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 are presented in Chart 2.1 below.



Under the “fast” adoption path, all firms in the for-hire and private trucking sectors will have begun adopting automation in long-haul trucking within 10-15 years, so that after 10-15 years over 90% of new investment in trucks will be on trucks with driverless capability. Under the “medium” and “slow” adoption paths, it takes much longer for all firms to begin to adopt this automation technology. As a result, after 10 years from when the technology becomes available and is taken up by the first adopters, about 95%, 60% and 30% of trucking firms will have begun adopting automation in long-haul trucking under the “fast”, “medium” and “slow” scenarios, respectively.

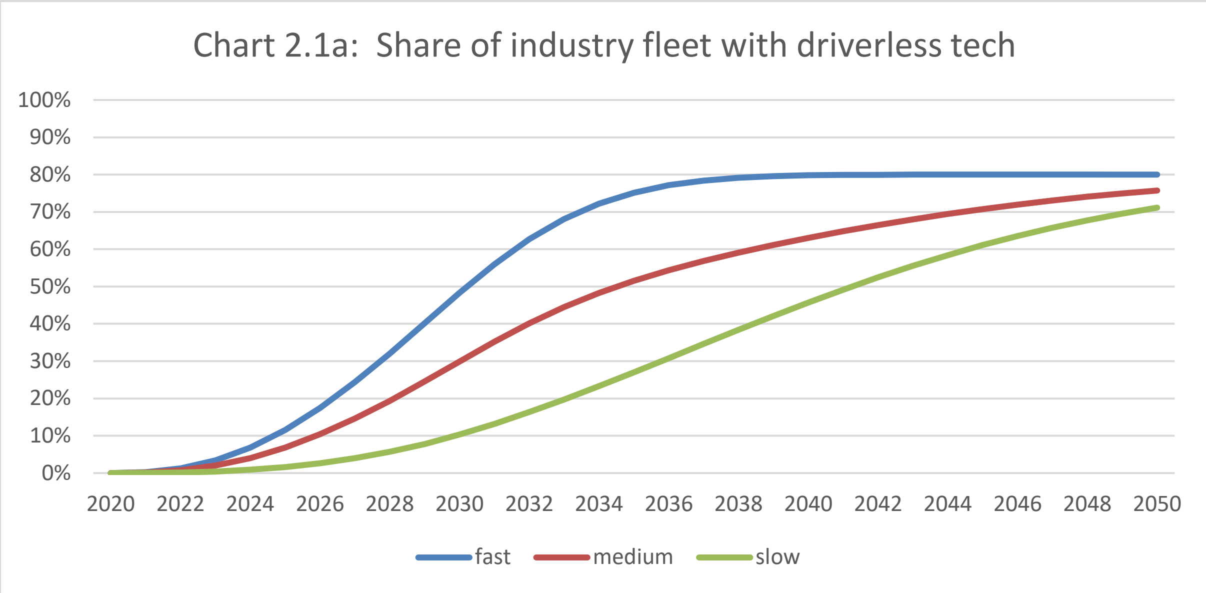
Based on analysis of truck registration data, the typical useful life of a Class 8 tractor[2] is roughly one million miles or approximately 11 years, after which the mileage put on older tractors drops off dramatically. Because tractors in the long-haul segment are used more intensely, the typical useful 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.[3] Based on this information, we assume the lifespan of the existing fleet of long-haul trucks to be nine years. On average, in any given year, any firm that has begun adopting automation technology will convert 1/9th of its fleet. 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,t] of the share of adopting firms in Chart 2.1 multiplied by 1/9.

Finally we use the results from a 2015 study by the McKinsey Global Institute that “analyzed the detailed work activities for over 750 occupations in the US to estimate the percentage of time that could be automated by adapting currently demonstrated technology”. For the occupation “Heavy and Tractor-Trailer Truck Drivers”, this study found that the maximum technical potential for automation was 81.4 per cent, noting that some long-haul truck drivers will still be required to manage shipments such as high-value goods, hazardous materials, or cross-border movements. Frey and Osborne (2017) examined the extent to which jobs were susceptible to automation by means of computer-controlled equipment. In ranking occupations according to their probability of computerisation, they assigned a probability of

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

[3] Kenny Veith (president, ACT Research) in conversation by phone with the U.S. DOT, June 3, 2019.

79 per cent to the occupation "Heavy and Tractor-Trailer drivers". Given results from these two studies, we adopt a value of 80 per cent for the maximum automation potential for long-haul truck drivers that could be saved upon adoption of automation in long-haul trucking. To find the share of the industry fleet that has been converted to accommodate automation, we combine the information on the useful life of long-haul trucks and this assumed maximum automation potential with the technology adoption rates in Chart 2.1. These shares are plotted in Chart 2.1a, and serve as fundamental inputs into the calculation of the shocks that are used to simulate the impacts of automation in long-haul trucking in the rest of this Section.



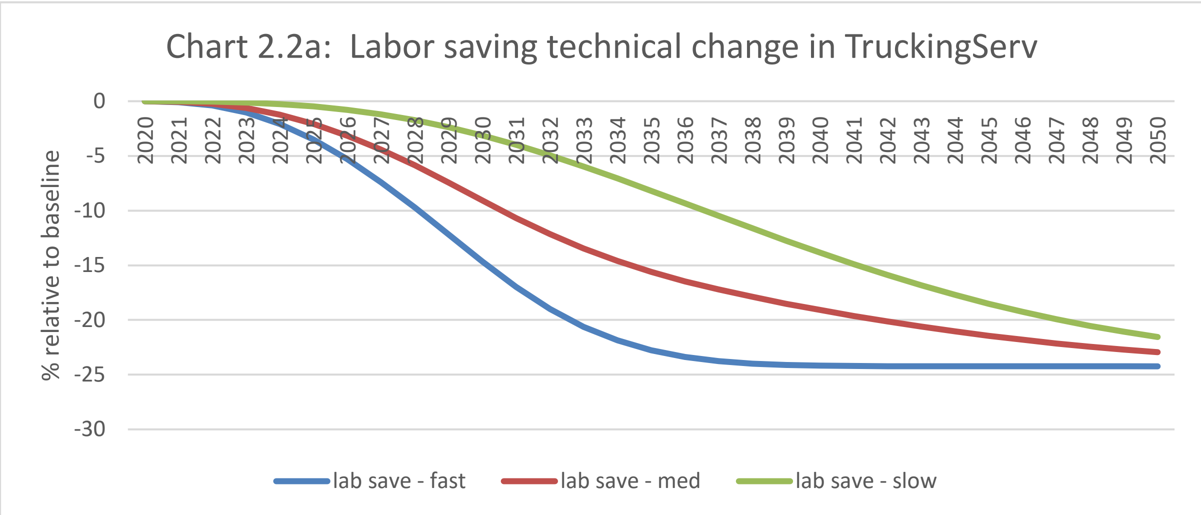
2.2 Labor saving technical change

The most obvious impact of automation in long-haul trucking is the savings by the for-hire and in-house truck transportation industries on the cost of labor. "Compensation of employees" in Table 2.1 will fall as trucking firms replace long-haul drivers with automation technology. For example, under the fast adoption scenario, by 2040, 80% of the US's fleet of long-haul trucks will be fitted with automation technology and will no longer require drivers. But "compensation of employees" includes compensation to long-haul truck drivers as well as short-haul truck drivers, employees who work in human resources, business and financial operations, sales, office and administrative support and all other employees in the for-hire and in-house truck transportation industries. 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" in Table 2.1 above that would be impacted by the introduction of driverless trucks.

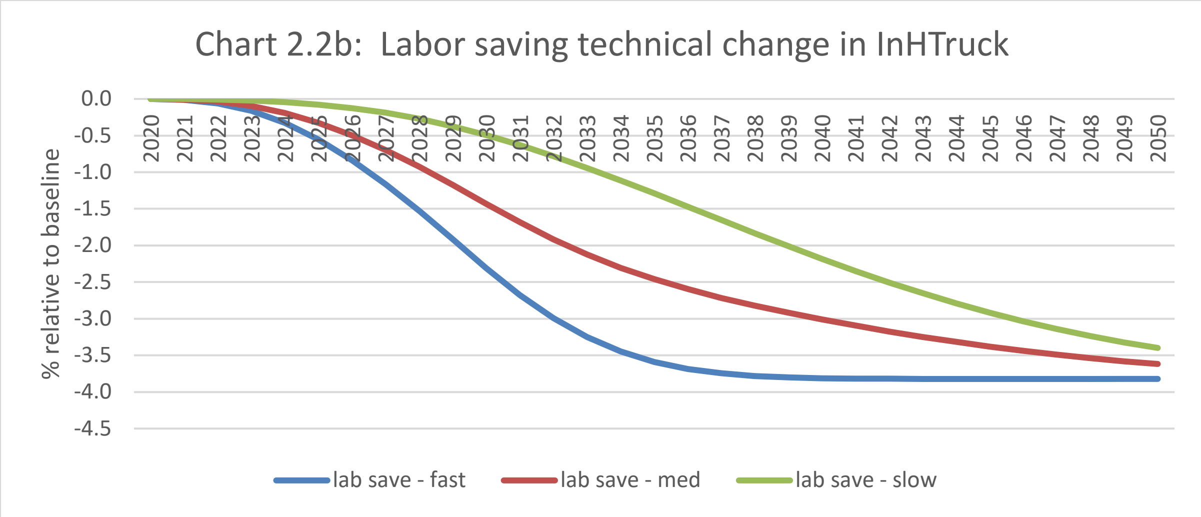
We begin with data from the BLS Occupational Employment Statistics which reports "total employment" and "mean annual wage" for NAICS industry 484000 "Truck Transportation" as 1,521,590 and $47,450 respectively (see line 18390 in the file "nat3d_M2019_dl.xlsx", available from https://www.bls.gov/oes/). Of these employees, 895,670 are employed in the Standard Occupational Classification 53-3032 "Heavy and Tractor-Trailer Truck Drivers", earning a mean annual wage of $47,400 (see line 18732 in the above-named file). These data let us conclude that 58.8% [= (47400·895670) / (47450·1521590)] of the "Compensation of employees" listed in Table 2.1 above represents compensation to "Heavy and Tractor-Trailer Drivers" in USAGE-Hwy's trucking industries.

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 (2020:16-18) who employ data from the 2002 Vehicle Inventory and Use Survey. Their Table 4 reports the share of heavy trucks by sector and range of operations. 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 in-house trucking sectors (ie: USAGE-Hwy industries TruckingServices and InHouse Trucking), 51.52% [= (6.1+12.5) / (33.1+3.0)] and 8.13% [= (3.5+1.7) / (41.3+22.7)][4] were long-haul truck drivers, respectively.

Charts 2.2a and 2.2b plot the shocks to labor-saving technical change under the different adoption paths in USAGE-Hwy's two trucking industries: TruckingServ (the For-hire Truck Transport industry) and InHTruck (the InHouse or Private Truck transport industry). Note that the labor-saving technical change shocks are negative. This reflects the fact that in USAGE-Hwy, a labor productivity **improvement** is represented by a **negative** value for labor-saving technical change: Less labor is required to produce the same level of output while holding other inputs constant.



[4] See Table 4 of Gittleman and Monaco (2020:18). We include for-hire and private tractor-trailer truck types but do not include straight truck types. We presume the majority of straight trucks would be owner-operated and would not be converted using automation technology.



The two charts have the same shape, since they both reflect the same adoption paths in Chart 2.1a. But in the InHouse Trucking industry (Chart 2.2b), the shocks to labor productivity are much smaller than those in the For-hire Trucking industry (Chart 2.2a). This reflects our observation from Gittleman and Monaco (2020) that a much smaller share of truck drivers in private (in-house) trucking (8.13%) are long-haul truck drivers than in the for-hire trucking industry (51.52%). The shocks in Charts 2.2 are derived by multiplying the number of long-haul truck drivers as a share of baseline employment in the relevant USAGE-Hwy trucking industry by the share of the industry fleet that has adopted automation from Chart 2.1a.[5] To illustrate, under the "fast" scenario, by 2030, just over 48% of the industry fleet will be converted to accommodate automation in long-haul trucking. In 2030, the labor saving technical change shock in TruckingServ and InHTruck is -14.7% [= -100 · 48.37% · 59.49% · 51.52%] and -2.31% [= -100 · 48.37% · 59.49% · 8.13%], 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 30% of the industry fleet will be converted by 2030, so the labor saving technical change shock in the "medium" scenario in 2030 in TruckingServ and InHTruck is -9.07% [= -100 · 29.95% · 59.49% · 51.52%] and -1.43% [= -100 · 29.95% · 59.49% · 8.13%], respectively.

Before finishing this subsection, we derive an estimate of the number of long-haul truck drivers in both the For Hire or TruckingServ sector and the Private or InHouse Trucking sector, since we will be interested in whether automation in long-haul trucking could lead to layoffs of labor in the trucking industry. We noted earlier that BLS Occupational Employment Statistics reported that of the 1,521,590 employed in NAICS industry 48400 "Truck Transportation", 895,670 were Heavy Truck and Tractor-Trailer Operators. Since the BLS does not report employment statistics in the "In-house Trucking" industry, we estimate employment there by subtracting the number of Heavy Truck and Tractor-Trailer Operators in NAICS industry 484000 "Truck Transportation" (895,670) from the total number employed in Occupation 53-3032 "Heavy and Tractor-Trailer Drivers" (1,852,450), presuming that all Heavy and Tractor-Trailer Drivers not in NAICS industry 484000 are employed as In-House truck drivers. So 956,780 [= 1,852,450 - 895,670) Heavy Truck and Tractor-Trailer Operators were employed in the "In-house Trucking" industry. To estimate the number of these truck drivers who were long-haul truck drivers, we follow Gittleman and Monaco

[5] Recall that the maximum automation potential of 80% was already incorporated in the shares in Chart 2.1a.

(2020:16-18) who argued that 51.52% and 8.13% of these were Long Distance Tractor-trailer Drivers in the "Trucking Services" and "In-house Trucking" sectors, respectively. We conclude that there were 461,481 [= 895,670 · 0.5152] and 77,738 [= 956,780 · 0.0813] Long Distance Tractor-trailer Drivers in the "Trucking Services" and "In-house Trucking" sectors, respectively. These are the driving jobs at risk of elimination due to the adoption of automation in long-haul trucking.

2.3 Cost of adopting automation

The next obvious feature of automation in long-haul trucking is that it will be costly. 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 autonomous operation. "There are approximately two million tractor-trailers in the United States" (McKinsey Global Institute 2017:79), though only a share of these are tractor-trailers used for long-haul trucking. 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.[6] "Already, companies have made fully autonomous beer deliveries and struck alliances to operate ATs jointly. The rigs these companies are using are typically new medium- and heavy-duty trucks, outfitted with lidars,[7] sensors, and other technology to allow the vehicle to operate without human intervention. Basic versions of the kit cost as little as $30,000; high-end packages might cost $100,000." (Chottani *et al*. 2018:4). Engholm *et al.* (2020) identify the acquisition cost of a 60-ton truck at $295,877 (see row 5 of their Table 1 on p.513), and estimate the cost of adding driving automation technology on top of conventional truck designs at 25% of the baseline acquisition cost, suggesting a cost of adopting automation of about $75,000. Baseline investment expenditures in the TruckingServ and InHTruck 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 autonomous operation, we assume that each old truck that is retired and 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 (ie: 1 minus) of the technology adoption rates in Chart 2.1a, to a minimum of $50,000. 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.

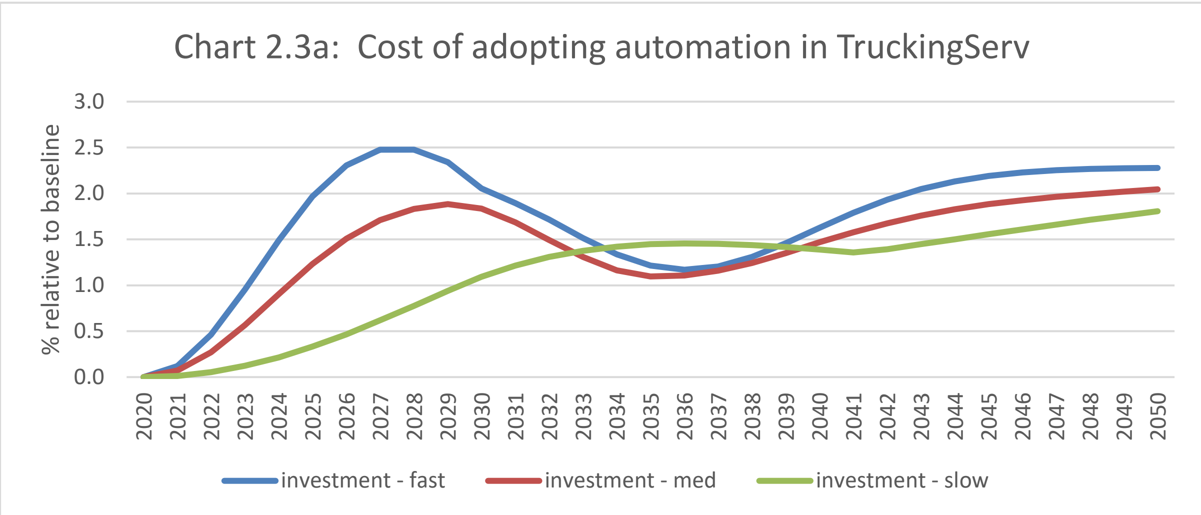
To proceed, we need to estimate the share of the two million tractor-trailers in the United States that are used for long-haul trucking. We use our results from the end of the previous subsection where we argued that total national employment of Heavy and Tractor-Trailer Truck Drivers was 1,852,450, of which 461,481 were Long Distance Tractor-trailer Drivers in the "Trucking Services" sector and 77,738 were Long Distance Tractor-trailer Drivers in the "In-house Trucking" sector. So in the US, 29.11 per cent [= (461481+77738) / 1852450] of "Heavy truck and tractor-trailer operators" were "Long distance tractor-trailer operators. We use this same share to conclude that the fleet of long-haul tractor trailers in the US in 2018 was 582,169 trucks [= 2,000,000 · 0.2911]. Over the simulation period, we assume that the

[6] 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.

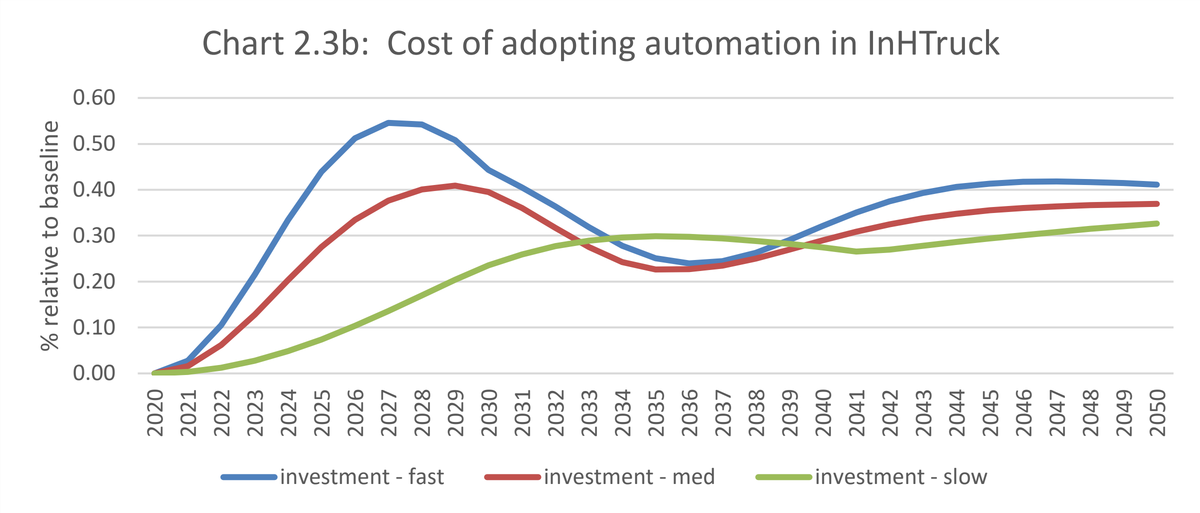
[7] LIDAR stands for *Light Detection and Ranging*, a remote sensing method that uses light in the form of a pulsed laser to measure ranges (variable distances). See https://oceanservice.noaa.gov/facts/lidar.html.

rate of growth of the fleet of long-haul trucks follows the increase in Truck vehicle-miles-travelled over the same period as reported by the US Department of Transportation.[8]

Now we can calculate the shock to investment in USAGE-Hwy that reflects the cost of automation. In each year, we multiply the size of the fleet of long-haul tractor trailers by the extra investment expenditure per truck to allow for autonomous operation ($100,000), discounted by 1 minus the technology adoption rate in that year from Chart 2.1a (to a minimum discount of 50%), by the share of the industry fleet being converted to driverless technology in that year from Chart 2.1a. This gives us the extra investment expenditure needed in each year for automation, which is expressed as a share of baseline investment in the TruckingServ and InHTruck industries. These shocks are reported in Charts 2.3a and 2.3b, reflecting the extra investment expenditure in the two trucking industries as a percentage of baseline investment. The shocks reflect two effects: the increased capital requirement per unit of output in the industry and the increased baseline number of trucks in the industry. Under the "fast" adoption scenario, this shock is highest in 2027 when 6.89 per cent of the fleet is converted to allow for autonomous operation, bringing the total share of the fleet converted by 2027 to 24.41 per cent (see Chart 2.1a). By 2027, the size of the long-haul trucking fleet has grown to 691,959 tractor-trailers. The share of this fleet in the TruckingServ and InHTruck sectors is 86.4 per cent [= 0.5152 / (0.5152+0.0813)] and 13.6 per cent [= 0.0813 / (0.5152+0.0813)], respectively. In USAGE-Hwy, baseline investment in 2027 is $125,779m and $89,995m for the TruckingServ and InHTruck industries, respectively. So in 2027, the investment shock is 2.48 per cent [= 100 · 691959 · 0.0689 · 0.1 · (1-0.2441) · 0.864 / 125779] in the Trucking Serv sector and 0.55 per cent [= 100 · 691959 · 0.0689 · 0.1 · (1-0.2441) · 0.136 / 89995] in the InHTruck sector. This equates to an additional $3,114m in the Trucking Serv sector and $491m in the InHTruck sector of investment spending for the 6.89 per cent of the fleet being converted in 2027 to allow for autonomous operation in 2027.



[8] Data on truck vehicle-miles-travelled was retrieved from Highway Economic Requirements System (HERS) spreadsheets supplied by the U.S. Department of Transportation and the Volpe National Transportation Center (Volpe Center) for the latest update to our project evaluating the Socioeconomic Impacts of Highway Investment. We are assuming that the existing fleet is fully utilized, so achieving a 5 per cent increase in Truck vehicle-miles-travelled would require a 5 per cent increase in trucks and a 5 per cent increase in drivers.



After 2029, the first trucks that were upgraded in 2020 will be 9 years old and will need to be replaced. This explains why the curves in Charts 2.3a and 2.3b never return to baseline. For example, under the "fast" adoption scenario, the baseline growth in vehicle miles travelled suggests that the number of long-haul trucks will have increased to just over one million by 2050. In the policy scenario, these will now all be equipped with automation technology that costs $50,000 per truck. With baseline investment in the Trucking Services industry projected to reach $172b by 2050, the cost of adopting automation in the Trucking Services sector reaches about 2.3 per cent [= (1/9) · number of trucks (1,020,751) · maximum automation potential (0.8) · TruckServ share (0.86) · $50k per truck / baseline investment in TruckServ ($172b)] above baseline by 2050.

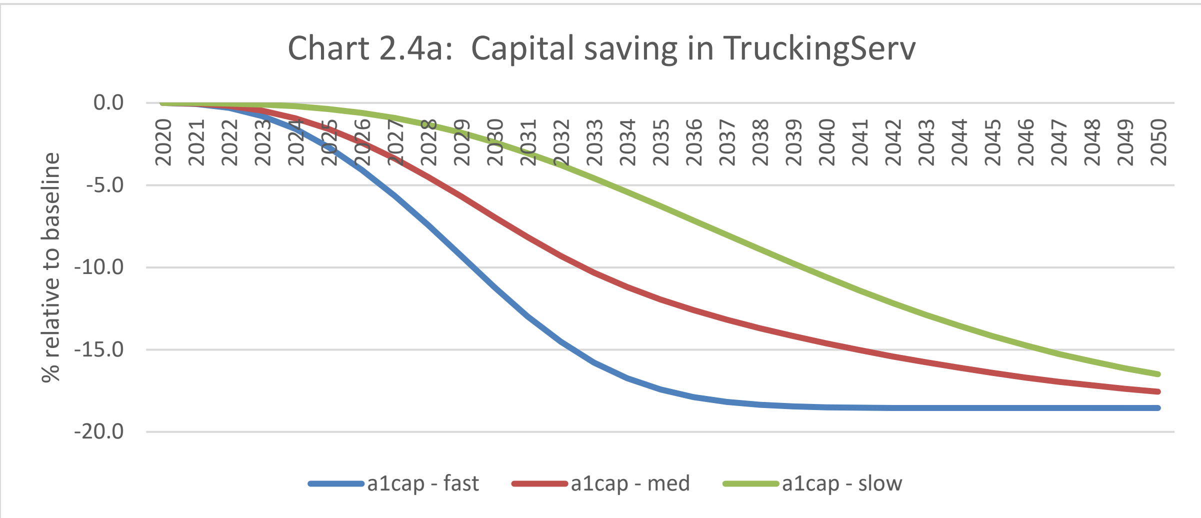
Again Charts 2.3a and 2.3b have the same shape, since they both reflect the same adoption paths in Chart 2.1a, and they both presume the same cost that needs to be incurred to replace a long-haul truck with one that is fitted to allow for autonomous operation. So what accounts for the large difference in the scale of the vertical axis between Charts 2.3a and 2.3b? First, baseline investment in the TruckingServ industry (ie: the denominator in the shocks in Charts 2.3a and 2.3b) is about $126b in 2027, about 40% greater than the $89b in the InHTruck industry in USAGE-Hwy. Second, the share of the "Heavy Truck and Tractor-Trailer Operators" that are "Long Distance Tractor-trailer Drivers" in the InHTruck industry [= 8.13 per cent] was much smaller than that in the TruckingServ industry [= 51.52 per cent]. These two ratios account for most of the difference between the scale on Chart 2.3a (where the largest investment shock in TruckingServ under the "fast" adoption scenario in 2027 is 2.48 per cent) and the scale on Chart 2.3b (where the largest investment shock in InHTruck under the "fast" adoption scenario in 2027 is 0.55 per cent ≈ 2.48 · (125779 / 89995 · (0.0813 / 0.5152)).

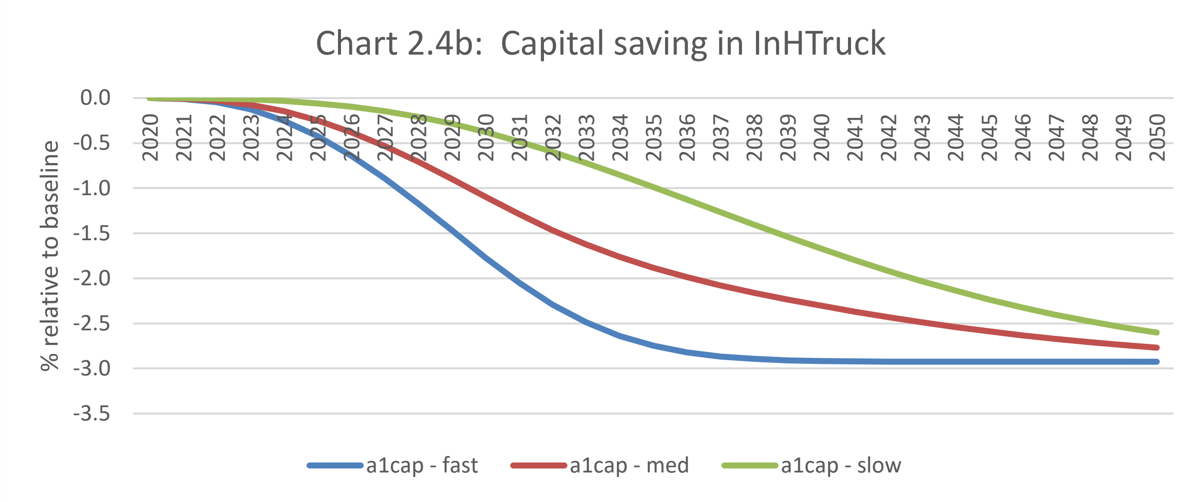
2.4 Capital-saving technological change

We expect that automation in long haul trucking should lead to a reduction in labor costs. But we should also expect automation to lead to capital-saving technological change, due to improved fleet utilization from the ability of trucks to potentially run nearly nonstop, without the need for human drivers to rest. 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. An estimate of capital cost savings due to the adoption of automation of long-haul trucking is in McKinsey

(2018:19) who estimate that full driver autonomy could reduce the total cost of ownership (TCO) by 45 per cent.

Charts 2.4a and 2.4b 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 noted in Section 1, this reflects the expectation that driverless trucks can be operated for longer hours than trucks with drivers who need mandated rest periods and can only work for a mandated number of hours without interruption. Following McKinsey (2018:19), we assume capital-saving technological change of 45% upon adoption of automation in long-haul trucking. As was the case for previous shocks, those in Charts 2.4a and 2.4b for the TruckingServ and InHTruck industries in USAGE-Hwy reflect the shares of the industry fleet that has adopted automation in Chart 2.1a and the fact that a much smaller share of employees in private or in-house trucking engage in long-haul trucking that those in for-hire trucking. Once the entire fleet has adopted the technology needed for driverless trucks (ie: after 2040 in the "fast" scenario), the capital improvement is reflected in a shock of -18.5 per cent [= -100 · 0.45 · 0.80 · 0.5152] and -2.9 per cent [= -100 · 0.45 · 0.80 · 0.0813] in TruckingServ and InHTrucking, respectively, reflecting our assumed share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum Technical Automation Potential of 80% for "Heavy and Tractor-trailer Truck Drivers". Like the labor-saving technical change shocks in Section 2.1, 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.





2.5 Fuel cost savings

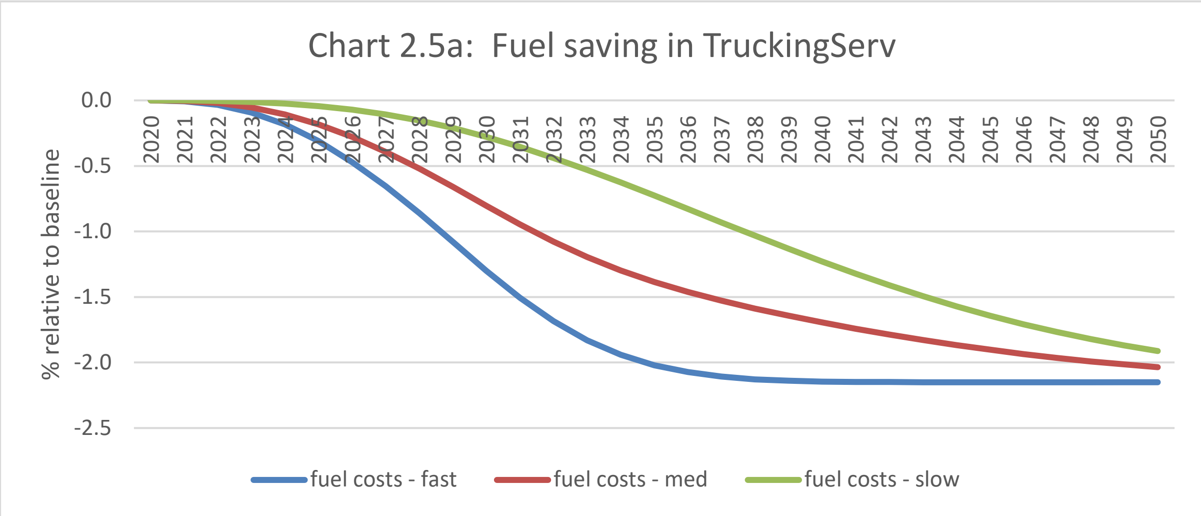
There is evidence that automation of long-haul trucking could lead to reductions in fuel costs. Driving automation could decrease fuel costs by optimizing throttle and brake controls to minimize fuel burn. Other types of automation have also been shown to lead to fuel savings. For example, the practice of "truck platooning" involves the implementation of systems that allow communication and close following between a number of trucks travelling close together. When Level 1 platooning was tested, Shladover *et al*. (2018:31) found that a three-truck platoon traveling at 65 mph could save between 5 and 6 percent of its fuel. 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% improvement in fuel use.[9] The US is currently pursuing several policy options to improve fuel economy in large trucks (speed regulators, 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%. This value is derived from the estimated fuel savings using a 65mph limiting device on combination trucks (see USDoT (2016) Table 72 on p.130) and consistent with the fuel savings due to truck platooning cited above in Shladover *et al*. (2018), the 4-7% reduction in diesel fuel bills referenced by Huang and Kockelman (2020), the 5 to 5.5% fuel savings expected from mandated speed controls[10] and the 15% realized fuel savings claimed by TuSimple.[11]

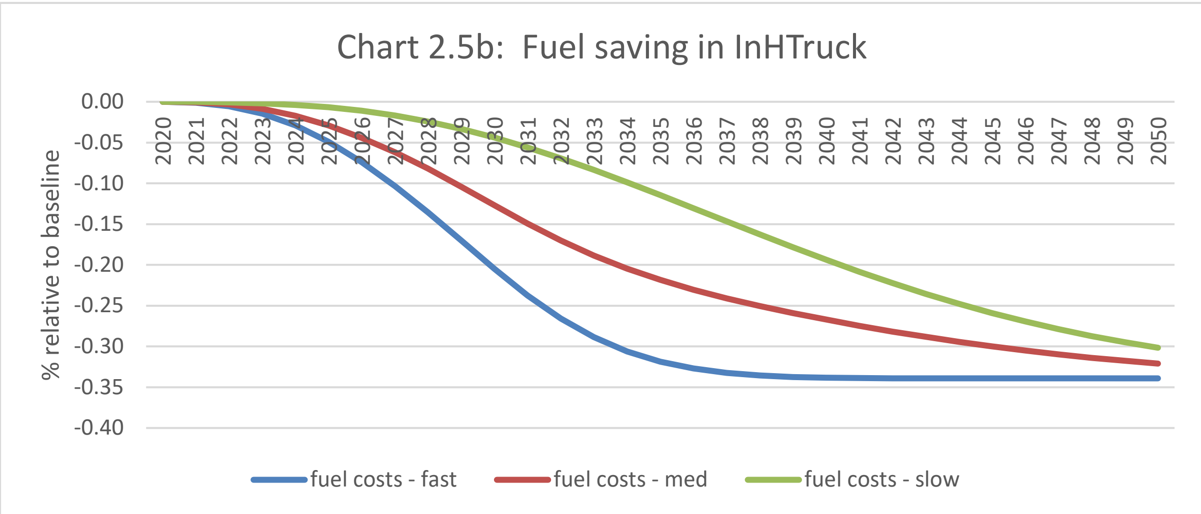
Charts 2.5a and 2.5b present the percentage reductions in fuel use per unit of output that are anticipated upon adoption of automation in long-haul trucking. The shocks in Charts 2.5a and 2.5b for the TruckingServ and InHTruck industries reflect our assumed central case value for the reduction in fuel use of 5.22%, the adoption rates in Chart 2.1a 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 2040 when 100% of the fleet has been converted to accommodate automation in long-haul trucking, the fuel-saving shock is -2.15% [= $-100 \cdot 0.0522 \cdot 0.5152 \cdot 0.80$] in the TruckingServ industry and -0.34% [= $-100 \cdot 0.0522 \cdot 0.0813 \cdot 0.80$] in the InHTruck industry,

---

[9] 'https://www.nationalgeographic.com/news/energy/2011/09/110923-fuel-economy-for-trucks/
[10] https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/speed-limiter-pria-082016.pdf
[11] https://venturebeat.com/2019/09/17/tusimple-raises-120-million-to-expand-its-fleet-of-driverless-delivery-trucks/

reflecting the share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum Technical Automation Potential of 80% for "Heavy and Tractor-trailer Truck Drivers". As was the case for the labor-saving technical change shocks described in Section 2.1, 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.





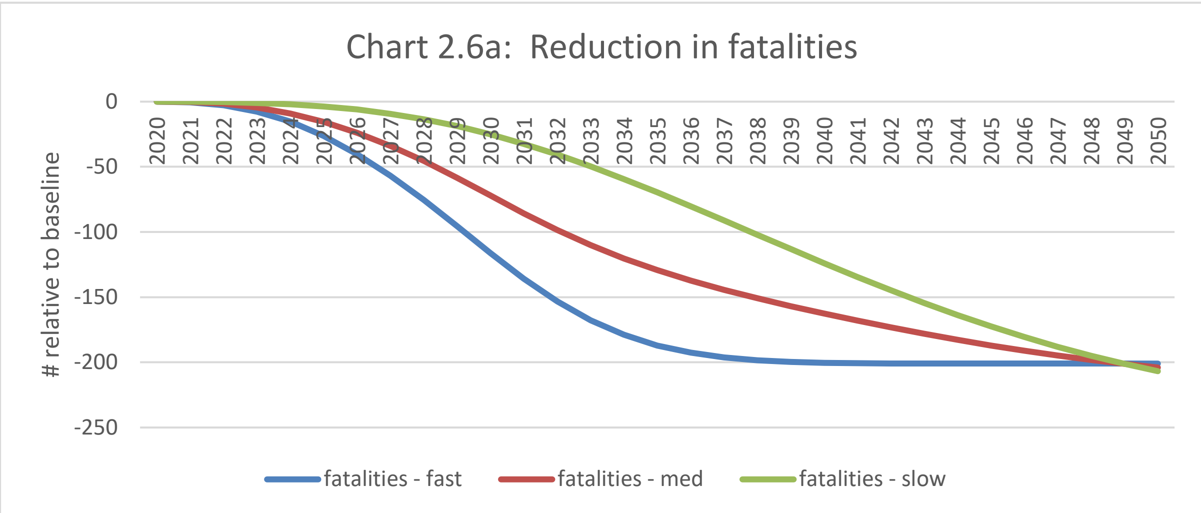
2.6 Fatalities and safety costs

In 2018, there were 4,415 fatal crashes involving large trucks: Of these 2,897 involved combination trucks, the type used in long-haul trucking (see US Department of Transportation (Sept. 2020) Trends Tables 4 and 16). Crashes involving just a single large truck killed 970 people (often the driver of the truck but sometimes pedestrians and bicyclists) and injured approximately 17,000 other people (US Department of Transportation (Sept. 2020) People Table 14).[12] Of these single large truck fatalities, we estimate that

[12] We focus on crashes involving only a single large truck (as opposed to multi-vehicle crashes). These crashes must be the fault of the truck or truck driver. Since some multi-vehicle crashes will also be the fault of the truck driver, our estimates represent a lower-bound on the fatalities and safety costs impacted by the adoption of automation in long-haul trucking.

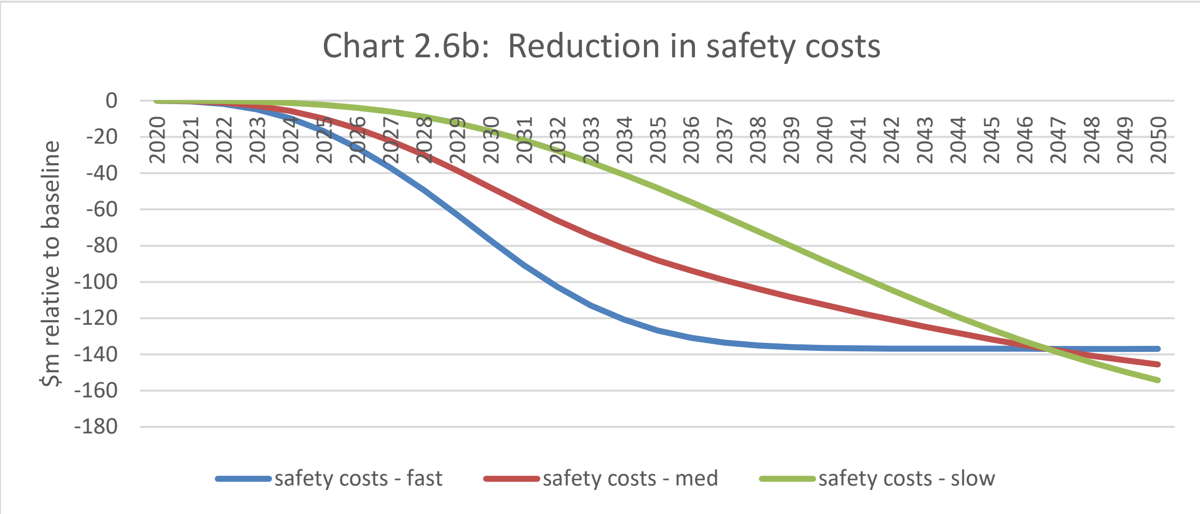
29.11% involved long-haul trucks.[13] Craft (2008) found that the critical factor was related to the driver (lack of sleep, inattentiveness, speeding or aggressive driving, etc.) for 87% of large truck crashes. Based on this information, and assuming that automation could eliminate all of the single vehicle crashes where the critical factor is related to driver performance, we estimate that approximately 161 fatalities [= 970 · (2897/4415) · 0.87 · 0.2911] of fatalities involving large trucks in 2018 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 1 trailer in 2005 dollars was $22,934 (USDoT 2007:10 Table 4). We update these 2005 costs to 2018 using the US health care inflation rate of 1.5.[14] As a result, we assume that automation would save $97.2 million [= 17000 · (2897/4415) · 0.87 · 0.2911 · 22934 · 1.5] in annual (2018) medical costs.

The final shocks reflect the expectation that the adoption of automation in long-haul trucking will eliminate crashes that involve large trucks 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 when these crashes are eliminated, any fatalities or injuries that would have resulted from these crashes are also eliminated. Using the information detailed above, we assume that there were 161 fatalities and $97.2m in costs associated with injuries that could have been avoided in 2018 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-travelled over the same period as reported by the US Department of Transportation (see subsection 2.3). Together with the shares of the industry fleet that has adopted automation in Chart 2.1a, 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 Chart 2.6a. We value each extra fatality at $10.5m.[15]



[13] This share was derived in subsection 2.3.
[14] This US health care inflation rate is compounded over 2005-2018 using data from https://ycharts.com/indicators/us_health_care_inflation_rate.
[15] See the US Department of Transportation Guidance on Valuation of a Statistical Life in Economic Analysis at https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis.

The reduction in safety costs (in $m) per unit of output due to the reduction in truck crashes and associated injuries upon adoption of automation in long-haul trucking are presented in Chart 2.6b under either fast, medium or slow adoption rates. The shape of these curves is similar to those in Chart 2.6a since both are based upon the same adoption rates in Chart 2.1a. In USAGE-Hwy simulations, we introduced this information on safety costs as reduced purchases of medical services by the household sector, and excluded medical expenditures when measuring welfare-relevant household consumption. In this way, reduced medical expenditures experienced by 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.



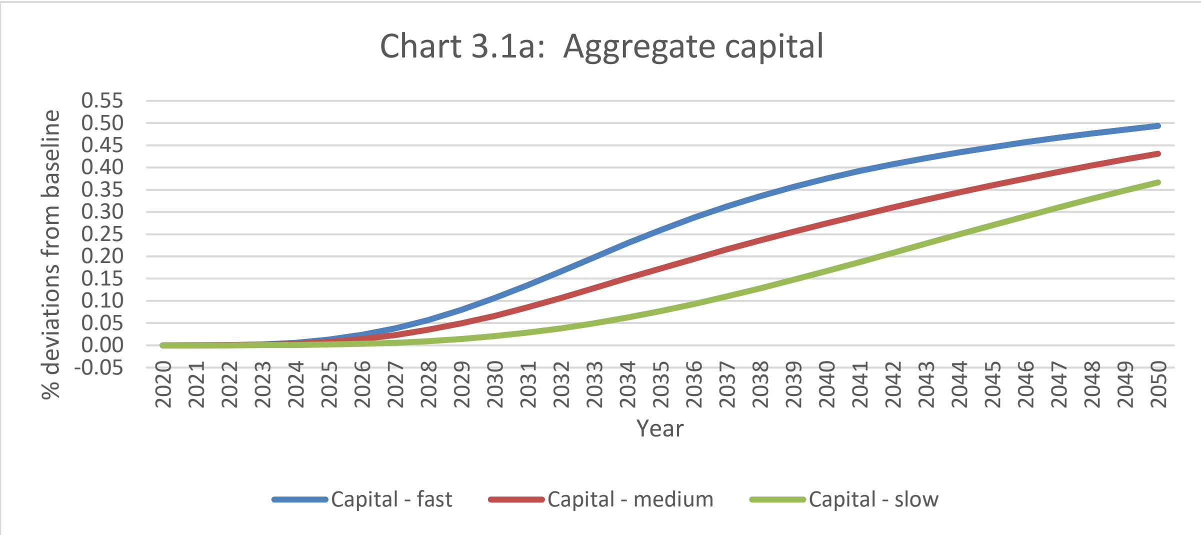
3. Effects of automation in long-haul trucking

We begin our presentation of the economic impacts of automation in long-haul trucking with an analysis of the economy-wide macroeconomic effects. Then in Section 3.2 we look at the impacts of automation at the industry level, including the effect of automation on employment in the USAGE-Hwy trucking industries.

3.1 Macroeconomic results

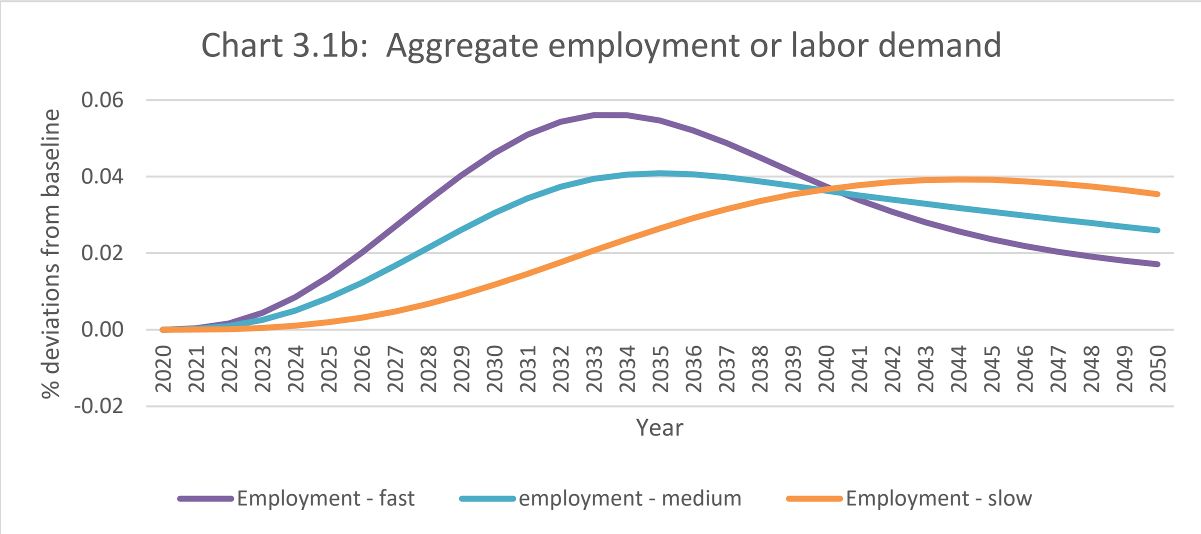
It helps to motivate our discussion of the macroeconomic impacts of automation by considering a stylized macro-level production function for the US economy: $Y = A \cdot f(K,L)$, where Y is real US GDP, K and L are the aggregate levels of usage of capital and labor in the US economy, respectively, and A represents productivity. Our discussion in the previous section detailed the anticipated impacts of automation on productivity. These productivity shocks will result in changes in aggregate labor and capital, all of which will impact national output or real GDP.

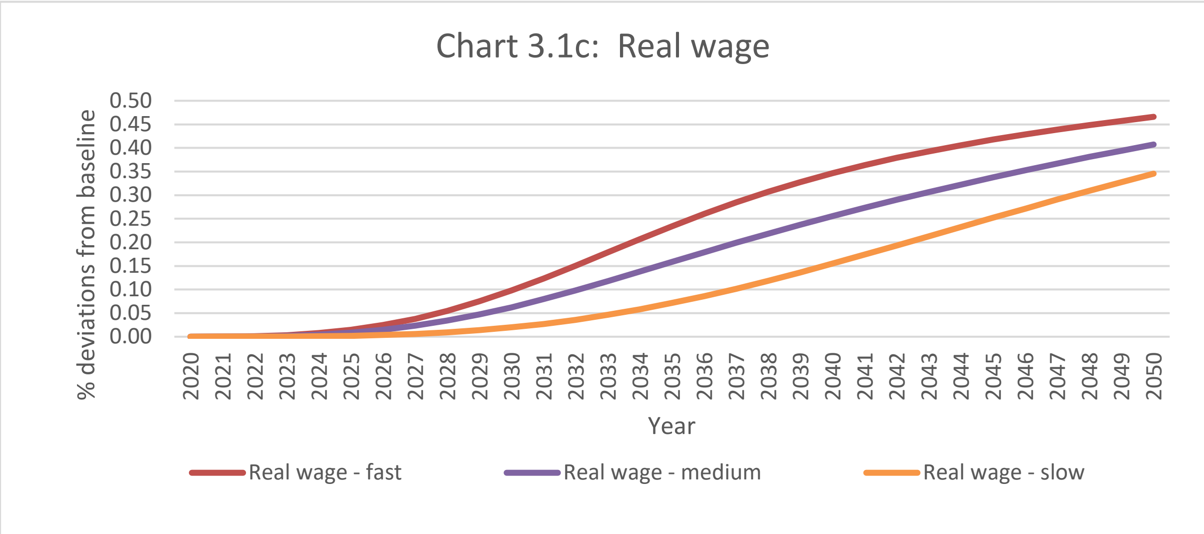
First off, we look at the direct consequences of the increase in investment spending in the TruckingServ and In-House Trucking industries, which will contribute to an increase in capital. Over the simulation period, under the "fast" adoption scenario, replacing the long-haul trucking fleet with stock that is equipped for automated operation results in an extra $88b of aggregate investment spending in the US economy relative to baseline. As illustrated in Chart 3.1a, this increased investment translates into an increase in aggregate capital that reaches almost 0.5 per cent above baseline by 2050. Under the "medium" and "slow" adoption scenarios, this increase in capital reaches 0.43 and 0.37 per cent above baseline by 2050. These increases in capital are smaller since a smaller share of the fleet is converted for the adoption of automation by 2050 under the "medium" and "slow" scenarios.



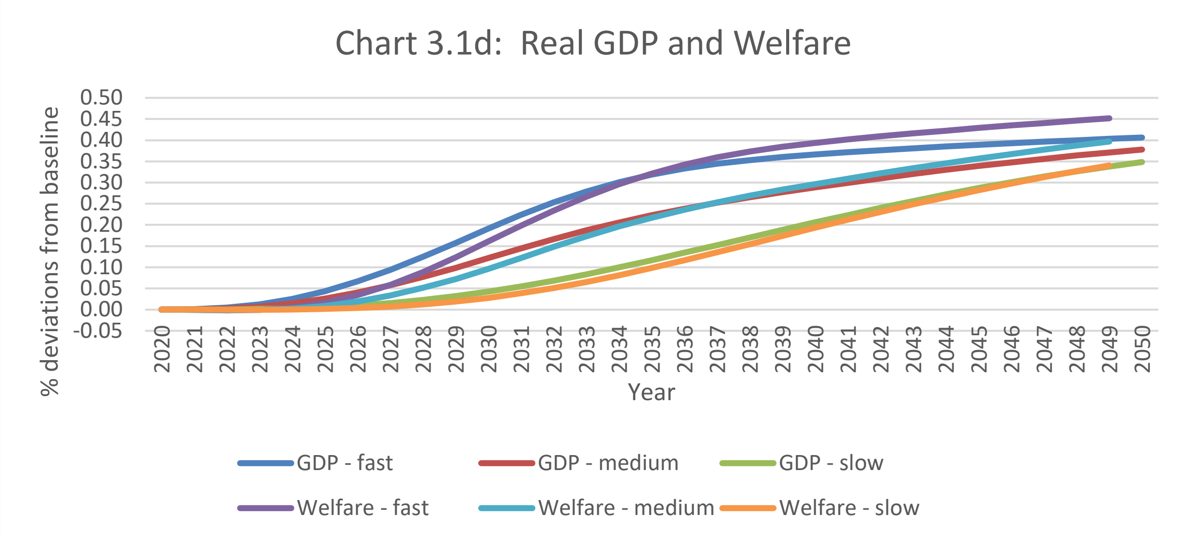
The operation of the labor market in USAGE-Hwy is illustrated in Charts 3.1b and 3.1c below. Relative to baseline, if the same amount of labor in the economy can now be combined with more capital, then labor productivity will increase. This effect is distinct from and additional to the direct impact 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. Chart 3.1b 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 2034. In USAGE-Hwy, labor supply is exogenous, determined in the baseline by exogenous changes in population and participation rates. Hence, when the investment in the adoption of automation in long-haul trucking stimulates labor demand, this causes an excess demand for labor. This results in the increase in the real wage illustrated in Chart 3.1c. As long as employment remains above labor supply, the excess demand for labor puts upward pressure on wages, and 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 increase more and earlier, reaching almost 0.06 per cent above baseline in 2034. Thereafter, employment drifts back towards 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 base period (2018) US employment, the average annual gain in employment over the simulation period is about 0.03 per cent, equivalent to about 48,300 jobs.

Under the "slow" adoption scenario, the rate of growth of capital is not as rapid, and by 2050, capital is still growing, while it has flattened by 2050 under the "fast" scenario. As a result, under the "slow" scenario, labor demand is still growing steadily by 2050, but reaches a maximum just below 0.04 per cent above baseline, with an average annual gain in employment over the simulation period of just over 0.02 per cent, equivalent to about 35,800 jobs relative to 2018 employment.





How do these changes in capital and labor translate into changes in real GDP and welfare? Chart 3.1d below shows how real GDP and welfare change as automation in long-haul trucking is adopted under the three different scenarios.



By 2050, under the "fast" adoption scenario, real GDP reaches just over 0.4 per cent above baseline, equivalent to \$84b relative to 2018 GDP. We can make sense of this result using the impacts of automation on capital and labour reported in Charts 3.1a and 3.1b and the technology shocks reported in Section 2. By 2050, labor has almost returned to baseline, so the contribution of labor to this real GDP gain is negligible. But aggregate capital is just over 0.49 per cent above baseline by 2050. Since capital accounts for almost 35 per cent of GDP by 2050, capital growth contributes 0.17 per cent [=0.4937·0.3456] of the real GDP gain. The largest share of real GDP gain is accounted for by technical change. By 2050, labor-saving, capital-saving and fuel-saving technical change associated with the adoption of automation in long-haul trucking contribute 0.23 per cent to the real GDP gain.[16] 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 more steadily throughout the simulation period under the "slow" adoption scenario.

Chart 3.1d also 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 Charts 2.6, 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 2035. This is so 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 2035 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

[16] By 2050, the labor and capital employed in the TruckingServ sector account for about 0.57 and 0.29 per cent of GDP, while in InHouse Trucking, they account for 0.67 and 0.44 per cent of GDP, respectively. From Chart 2.2 and Chart 2.4, labor- and capital-saving technical change in 2050 is 24.2 per cent and 18.6 per cent in the TruckingServ sector, and 3.8 and 2.9 per cent in the InHouse Trucking sector, respectively. The overall contribution of technical change to real GDP is 0.23 per cent.

measures are not part of GDP. The increase in welfare reaches just over 0.45 per cent by 2050 under the “fast ” adoption scenario, equivalent to about $63b in 2018 prices. The average yearly welfare increase is almost 0.26 per cent, equivalent to almost $36b in 2018 prices. Under the “slow” scenario, the corresponding figures are 0.34 per cent by the end of the simulation period, equivalent to almost $47b in 2018 prices. The average yearly welfare increase is 0.13 per cent, equivalent to almost $18b in 2018 prices.

3.2 Industry results

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 Trucking Services and In-House Trucking sectors. The adoption of automation has a much larger impact on the Trucking Services industry compared to the In-house Trucking sector, since there are so many more long-haul truck drivers in the Trucking Services industry. As a result, Chart 3.2a shows that the adoption of automation in long-haul trucking leads to an increase in output of the Trucking Services sector that reaches over 8 per cent above baseline by 2050. Chart 3.2b shows that the increase in the In-House Trucking sector reaches only 0.7 per cent above baseline by 2050. The largest decrease in output is in the RailroadServ industry. As users substitute towards more efficient Truck transport away from comparatively less efficient Rail transport, output of the RailroadServ industry falls by -10.5 per cent by 2050 (complete industry results under the “fast” adoption scenario are presented in Table A1 at the end of the Report). The WaterTrans and AirTrans industries see a more modest decrease in output of -4.5 and -1.6 per cent, respectively, by 2050. Other industries typically see small positive increases in output over the simulation period.

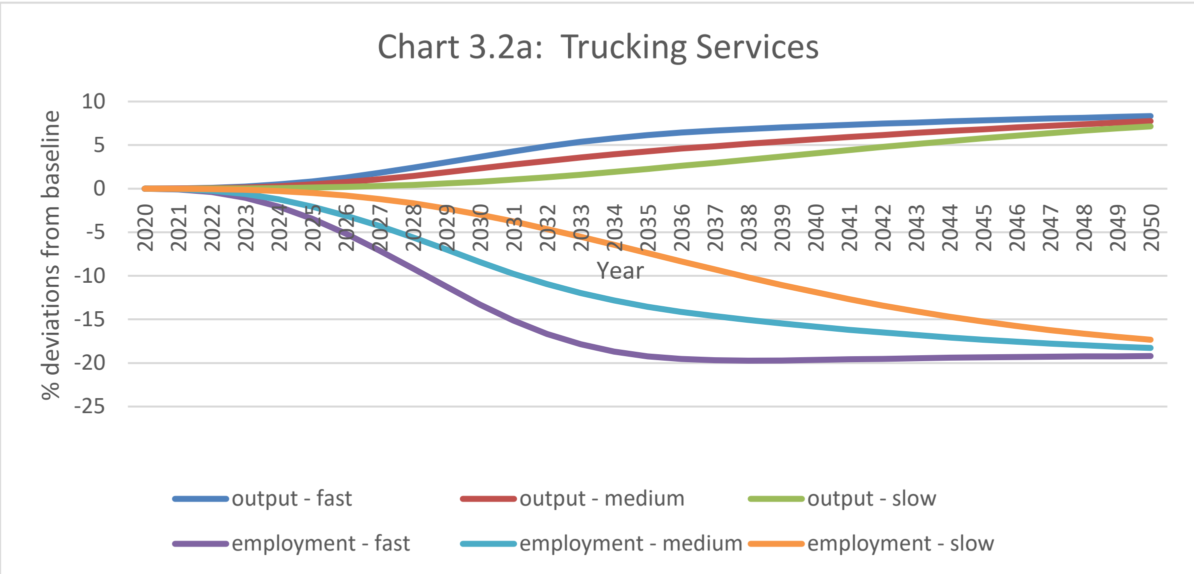
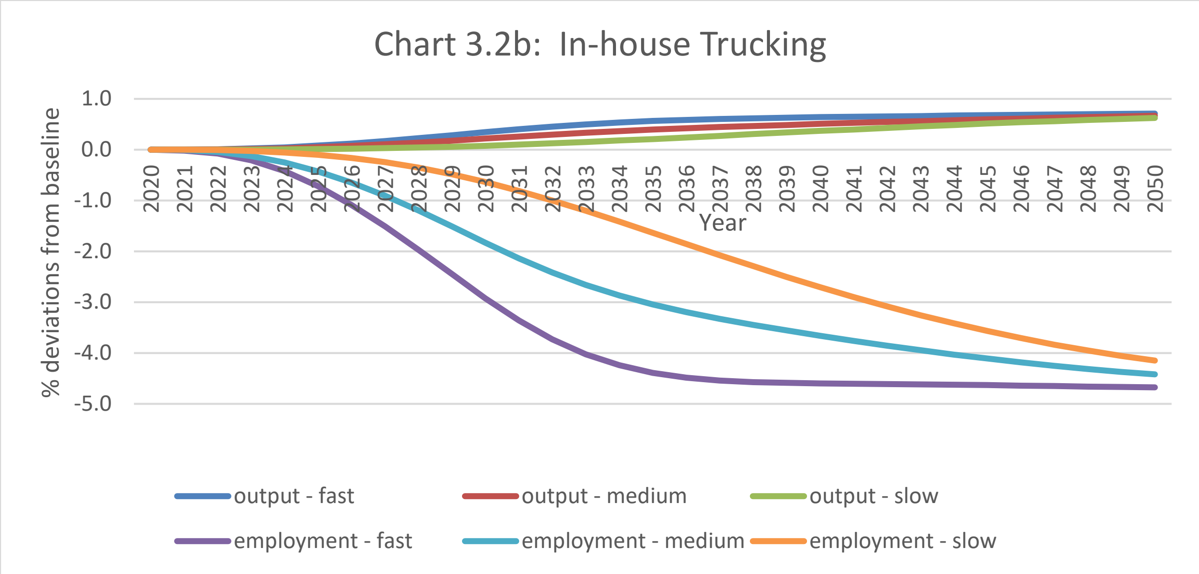


Chart 3.2a: Trucking Services

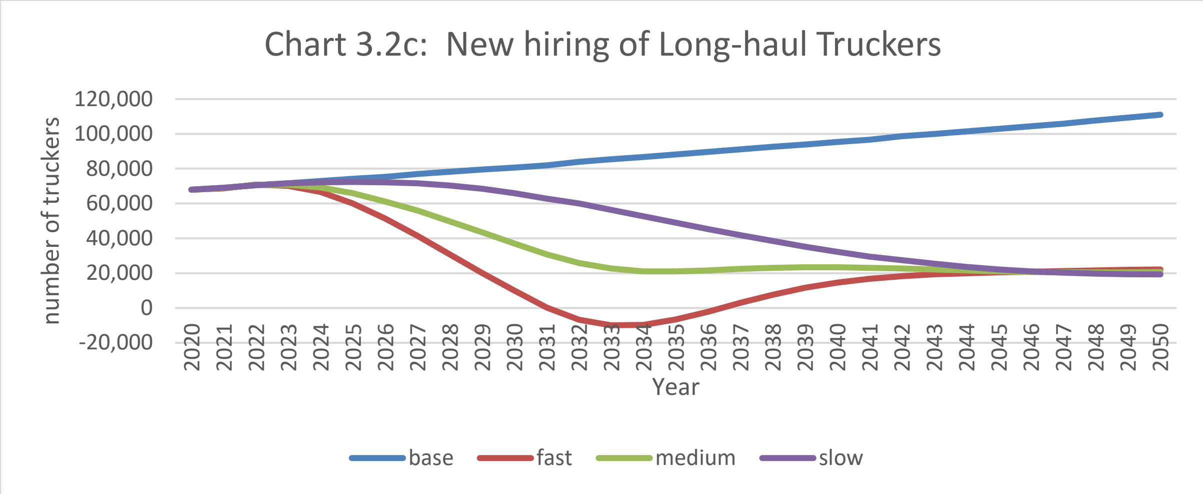


Along with the increase in output in the TruckingServ and InHTruck sectors, Chart 3.2a and Chart 3.2b also report a large decrease in employment in these industries. These are consistent with the labor-saving technical change shocks reported in Chart 2.2a and Chart 2.2b. As firms in these sectors adopt automation technologies, by 2050, employment in the TruckingServ and InHTrucking sectors falls by 17-20 per cent and 4-5 per cent, respectively.

Finally we consider the impact of the adoption of automation in long-haul trucking on employment 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 layoffs of drivers of long-haul trucks. Chart 3.2c 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:

New hiring = employment (t) – employment (t-1) + employment (t-1) · 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 retired. Groshen *et al*. (2018) cite BLS occupational turnover projections to argue for the use of an annual occupational turnover rate of 10.5 per cent for long-haul truck drivers (see Groshen *et al*. (2018) pp.12 and 41).



In 2020, the USAGE-Hwy baseline suggests employment of 559,683 long-haul truck drivers (478,995 in the TruckingServ industry and 80,688 in InHouse Trucking[17]), increasing to 570,038 in 2021. As a result, Chart 3.4 reports baseline annual new hiring of long-haul truck drivers in 2021 of 69,121 [= 570,038 – 559,683 + 0.105 · 559,683], rising to over 111,000 by 2050.

The impact of the adoption of automation on the hiring of long-haul truckers is illustrated in Chart 3.2c. There are no layoffs under the "medium" and "slow" adoption scenarios, since net hiring is always positive. But under the "fast" adoption scenario, after 2031 (by which point just over 56 per cent 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 layoffs of long-haul truckers. Net hiring reaches a minimum of almost -10,000 in 2033, about 1.4 percent of baseline employment of long-haul truckers. But by the time the whole fleet has been converted to accommodate automation, net hiring ultimately trends to about +20,000. This long-term net hiring by 2050 reflects our assumption that the Maximum Automation Potential in the long-haul trucking industry is 80 per cent, so of the 110,000 net hires of long-haul truckers under the baseline by 2050, 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 1,852,450 "Heavy and Tractor-Trailer Drivers" in 2018, of whom 461,481 and 77,738 were Long Distance Tractor-trailer Drivers in the "Trucking Services" and "In-house Trucking" sectors, respectively. Using the same annual occupational turnover rate of 10.5 per cent for all truck drivers, this suggests an annual turnover of 137,889 [= (1852450-461481-77738) · 0.105] short-haul truck drivers in 2018. This turnover is an order of magnitude greater than the largest layoffs of long-haul truck drivers. As a result, we conclude that long-haul truck drivers should always be able to find employment as short-haul truck drivers, so properly managed, the issue of layoffs should not be a significant concern when considering the adoption of automation in long-haul trucking.

[17] Using BLS Occupational Employment Statistics and evidence from Gittleman and Monaco (2020:16-18), we argued at the end of Section 2.2 that in 2018, there were 461,481 and 77,738 Long Distance Tractor-trailer Drivers in the "Trucking Services" and "In-house Trucking" sectors, respectively.

4. Concluding remarks and directions for the future

The adoption of driving automation will change long-haul trucking jobs in diverse ways, including job responsibilities, wages, and quality of life. As noted throughout, there are considerable uncertainties at this point in the technology's development and accurate, up-to-date data are not fully available. The specific ways in which these jobs will change may vary significantly across market segments and operating environments and will be influenced by contemporaneous changes in related industries.

Our model indicated that overall, the automation of long-haul trucking will be beneficial to the US economy, with increases in GDP, welfare, capital, and labor that can be monetized into billions of dollars. Additionally, our model concluded that these economic benefits can be reaped without mass layoffs of long-haul truck drivers. Assuming the occupational turnover remains near today's levels, automation of long-haul truck driving will force annual layoffs of at most 1.4 percent only over a five-year period and only under the most ambitious adoption scenario, and all of these drivers should be able to find employment as short-haul drivers.

As technologies mature and business models are better understood, re-examination of this topic will provide valuable insight into the impacts of driving automation on the Nation's transportation workforce. An interesting avenue for further research would involve extending the analysis to take account of the impact of automation in long-haul trucking on the value of travel time. For example, Wadud (2017) notes that "full automation can relieve the driver of his/her driving duties so that the driving time can now be used for other in-vehicle activities." Automation also allows for a truck to be run for more hours per day, decreasing the amount of time that it would take for a load to reach its destination. USAGE-Hwy already has the ability to account for the value of travel time, so if reliable estimates of travel time savings due to automation could be found, these could be incorporated into subsequent analysis of the impacts of automation.

References

Acemoglu, D. and P. Restrepo (2017), "Robots and Jobs: Evidence from US labor markets", NBER Working Paper 23285. http://www.nber.org/papers/w23285.

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

Bessen, J. (2019), "Automation and jobs: when technology boosts employment", *Economic Policy* 34(100), pp. 589–626.

Chottani, A., G. Hastings, J. Murnane and F. Neuhaus (2018), "Distraction or disruption? Autonomous trucks gain ground in US logistics", McKinsey & Company Report. Available from https://www.mckinsey.com/industries/travel-logistics-and-transport-infrastructure/our-insights/distraction-or-disruption-autonomous-trucks-gain-ground-in-us-logistics.

Clements, L.M. and K.M. Kockelman (2017), "Economic Effects of Automated Vehicles", *Transportation Research Record* 2606, pp. 106–114. http://dx.doi.org/10.3141/2606-14

Costello, B. (2017), "Truck Driver Shortage Analysis 2017", American Trucking Associations, https://www.trucking.org/ATA%20Docs/News%20and%20Information/Reports%20Trends%20and%20Statistics/ATAs%20Driver%20Shortage%20Report%202019%20with%20cover.pdf

Craft, Ralph, "Why Trucks and Cars Collide," July 31, 2008, Traffic Records Forum. Based on the FMCSA Large Truck Crash Causation Study (LTCCS).

Dixon, P. B., M. T. Rimmer, and R. Waschik (2017), "Linking CGE and specialist models: Deriving the implications of highway policy using USAGE-Hwy", *Economic Modelling* 66, pp.1-18. https://doi.org/10.1016/j.econmod.2017.04.022

Engholm, A. I. Kristoffersson and A. Pernestål (2021), "Impacts of large-scale driverless truck adoption on the freight transport system", *Transportation Research Part A* 154, pp.227–254. https://doi.org/10.1016/j.tra.2021.10.014

Engholm, A., A. Pernestål and I. Kristoffersson (2020), "Cost Analysis of Driverless Truck Operations", *Transportation Research Record* 2674(9), pp.511–524.

Fagnant, D.J. and K Kockelman (2015), "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations", *Transportation Research Part A* 77, pp.167-181.

Frey, C.B. and M.A. Osborne (2017), "The future of employment: How susceptible are jobs to computerisation?", *Technological Forecasting and Social Change* 114, pp.254-80. https://doi.org/10.1016/j.techfore.2016.08.01

Gittleman, M. and K. Monaco (Jan. 2020), "Truck-driving jobs: Are they headed for rapid elimination?", *ILR Review* 73(1), pp.3-24. https://doi.org/10.1177/0019793919858079

Groshen, E.L., S. Helper, J.P. MacDuffie and C. Carson (June 2018), "Preparing U.S. workers and employers for an autonomous vehicle future", Securing America's Future. https://avworkforce.secureenergy.org/wp-content/uploads/2018/06/Groshen-et-al-Report-June-2018-1.pdf

Hooper, A. and D. Murray (Oct. 2018), "An Analysis of the Operational Costs of Trucking: 2018 Update", American Transportation Research Institute, http://truckingresearch.org/wp-content/uploads/2018/10/ATRI-Operational-Costs-of-Trucking-2018.pdf

Horridge J.M., Jerie M., Mustakinov D. & Schiffmann F. (2018), GEMPACK manual, GEMPACK Software, Centre of Policy Studies, Victoria University, Melbourne, ISBN 978-1-921654-34-3.

Huang, Y. and K.M. Kockelman (2020), "What will autonomous trucking do to U.S. trade flows? Application of the random-utility-based multi-regional input–output model", *Transportation* 47, pp.2529–2556. https://doi.org/10.1007/s11116-019-10027-5

McKinsey (2018), "Route 2030: The Fast Track to the Future of the Commercial Vehicle Industry", McKinsey Center for Future Mobility Report, available from https://www.mckinsey.com/~/media/McKinsey/Industries/Automotive%20and%20Assembly/Our%20Insights/Route%202030%20The%20fast%20track%20to%20the%20future%20of%20the%20commercial%20vehicle%20industry/Route%202030%20-%20The%20fast%20track%20to%20the%20future%20of%20the%20commercial%20vehicle%20industry_vf.ashx.

McKinsey (2017), “A Future that Works: Automation, Employment and Productivity”, McKinsey Global Institute, 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.

McKinsey Global Institute (2015), “Automation Potential and Wages for US Jobs”, available from McKinsey Global Institute.

Raj, A., J.A. Kumar and P. Bansal (2020), “A multicriteria decision making approach to study barriers to the adoption of autonomous vehicles”, *Transportation Research Part A* 133, pp.122-137.

SAE International (2018), “Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles”, document J3016_201806, available from https://www.sae.org/standards/content/j3016_201806/.

Shladover, S. *et al.* (2018), “Cooperative Adaptive Cruise Control (CACC) for Partially Automated Truck Platooning: Final Report”, Federal Highways Association, Cooperative Agreement No. DTFH61-13-H-00012, available from https://escholarship.org/uc/item/260060w4.

Simpson, J.R., S. Mishra, A. Talebian and M.M. Golias (2019), "An estimation of the future adoption rate of autonomous trucks by freight organizations", *Research in Transportation Economics* 76. https://doi.org/10.1016/j.retrec.2019.100737

US Department of Transportation (Sept. 2020), “Large truck and bus crash facts 2018”, Federal Motor Carrier Safety Administration: Analysis Division. Available from https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2018-pdf.

US Department of Transportation (Aug. 2016), “Speed Limiting Devices”, National Highway Traffic Safety administration Report FMVSS No.140, available from https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/speed-limiter-pria-082016.pdf.

US Department of Transportation (Mar. 2007), “Unit Costs of Medium and Heavy Truck Crashes”, Federal Motor Carrier Safety Administration, available from https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/UnitCostsTruck%20Crashes2007.pdf

Vermeullen, B., J. Kesselhut, A. Pyka and P.P. Saviotti (2018), “The Impact of Automation on Employment: Just the Usual Structural Change?”, *Sustainability* 10, 1661. doi:10.3390/su10051661

Waschik, R., C.L. Taylor, D. Friedman and J. Boatner (Jan. 2021), “Macroeconomic Impacts of Automated Driving Systems in Long-Haul Trucking”, Report No. FHWA-JPO-21-847; available from https://rosap.ntl.bts.gov/view/dot/54596.

Table A1: Average annual change in industry output (percent change relative to baseline)

Industry \ Year	2021-25	2026-30	2031-35	2036-40	2041-45	2046-50
Agriculture	0.1	0.3	0.6	0.8	0.9	1.0
Mining	0.1	0.6	1.0	1.2	1.4	1.5
Crude	0.0	0.1	0.1	0.1	0.1	0.1
NatGAS	0.0	0.0	0.0	0.1	0.2	0.2
Construct	0.1	0.3	0.5	0.5	0.5	0.5
DairySugar	0.0	0.2	0.5	0.6	0.7	0.8
Meatprods	0.1	0.3	0.7	0.8	0.9	1.0
Foodmanu	0.1	0.4	0.7	1.0	1.1	1.2
TobaccoProd	0.0	0.2	0.4	0.5	0.5	0.5
Apparel	0.1	0.2	0.3	0.3	0.3	0.3
Textiles	0.1	0.6	1.0	1.2	1.3	1.4
WoodFurn	0.1	0.5	0.7	0.8	0.9	1.0
PaperPub	0.1	0.6	1.0	1.2	1.4	1.5
Chemicals	0.2	0.9	1.6	1.9	2.1	2.2
Petrolprods	0.1	0.3	0.5	0.6	0.6	0.7
Footwear	0.1	0.4	0.5	0.6	0.6	0.6
MetalProds	0.2	0.7	1.1	1.4	1.7	1.9
Machinery	0.2	0.6	0.9	1.0	1.1	1.2
Computers	0.1	0.4	0.5	0.5	0.5	0.5
ElectMach	0.1	0.3	0.4	0.4	0.4	0.5
MotorVeh	0.2	0.6	0.8	0.9	1.0	1.0
Aircraft	0.0	-0.1	-0.1	0.0	0.0	0.1
AircrftEngin	0.1	0.1	0.1	0.1	0.2	0.2
AircrftEquip	0.1	0.2	0.3	0.4	0.4	0.5
TransEquip	0.0	-0.2	-0.2	-0.2	-0.1	-0.1
NavigEquip	-0.1	-0.2	-0.3	-0.3	-0.3	-0.2
ManuNEC	0.2	0.7	1.3	1.6	1.8	1.9
FreightForw	0.2	0.7	1.0	1.1	1.1	1.1
ArrangPTrans	0.0	0.0	-0.1	-0.2	-0.2	-0.2
Communicat	0.0	0.2	0.4	0.6	0.6	0.6
Utilities	0.1	0.5	0.8	1.0	1.1	1.1
TradMarg	0.1	0.4	0.6	0.7	0.7	0.7
OwnoccDwell	0.0	0.0	0.1	0.2	0.2	0.3
ComputerServ	0.1	0.2	0.3	0.3	0.3	0.3
Advertising	0.1	0.3	0.5	0.6	0.6	0.7
Legalserv	0.0	0.2	0.3	0.3	0.3	0.3
BusFinServ	0.0	0.2	0.2	0.3	0.3	0.3
EatDrinkPlce	0.0	0.2	0.4	0.5	0.5	0.5
MedicServ	0.0	0.0	0.0	0.0	0.0	0.0
Education	0.0	0.1	0.2	0.2	0.2	0.2
SocialServ	0.0	0.2	0.3	0.4	0.4	0.4
Enterprise	0.1	0.2	0.4	0.4	0.5	0.5

NoncompImps	0.2	0.7	1.1	1.2	1.2	1.2
Scrap	1.4	4.2	5.6	5.7	5.5	5.4
Used2ndhGds	0.0	0.0	0.0	0.0	0.0	0.0
MiscServ	0.1	0.3	0.4	0.5	0.5	0.6
RoadBrid	0.0	0.0	0.0	0.1	0.1	0.1
StreetRep	0.0	0.0	0.0	0.0	0.0	0.0
PrivRoadTrans	0.0	0.2	0.3	0.3	0.3	0.3
VacationTrans	0.1	0.3	0.4	0.3	0.2	0.1
EVT	0.0	0.1	0.1	0.1	0.0	0.0
CommuteTrans	0.0	0.0	0.1	0.0	0.0	0.0
CarRepairs	0.0	0.2	0.3	0.3	0.3	0.3
GovtServ	0.0	0.0	0.0	0.0	0.0	0.0
Holiday	0.1	0.3	0.4	0.3	0.2	0.1
FgnHol	0.0	0.4	0.7	0.9	0.9	0.8
ExpTour	0.1	0.0	0.0	0.0	0.0	0.1
OthNonRes	0.0	0.2	0.4	0.5	0.5	0.6
Railroadserv	-1.0	-4.1	-7.2	-8.9	-9.9	-10.4
PassengTrans	0.0	0.1	0.2	0.2	0.2	0.2
TruckingServ	0.9	3.6	6.1	7.2	7.8	8.2
WaterTrans	-0.8	-2.6	-3.8	-4.1	-4.3	-4.4
AirTrans	-0.1	-0.6	-1.1	-1.4	-1.5	-1.6
PipelinExng	0.0	0.1	0.2	0.3	0.4	0.4
NatgasTransp	0.0	0.0	0.1	0.1	0.2	0.3
Wat2	0.2	0.6	0.9	1.0	1.0	0.9
Air2	0.1	0.2	0.4	0.6	0.7	0.8
InHAir	0.0	0.0	0.0	0.0	0.0	0.0
InHRail	0.1	0.6	1.0	1.2	1.4	1.5
InHWater	0.1	0.3	0.5	0.6	0.6	0.7
InHTruck	0.1	0.3	0.6	0.6	0.7	0.7