

Evaluating the impact of autonomous long-haul trucking deployment in California using USAGE-Hwy

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Executive summary

This study runs simulations to determine the economic impacts of adopting automation in long-haul trucking in California. It describes the simulation results under “fast,” “medium,” and “slow” adoption scenarios, using the Centre of Policy Studies’ purpose-built USAGE-Hwy Computable General Equilibrium (CGE) model.

Much of the technology for full autonomous trucking is still being developed and is not yet ready for large scale deployment. However, there are numerous examples where “level 4” Automated Driving Systems (ADS) have already been deployed with safety drivers. Numerous AV developers carry loads for customers using level 4 autonomous technology on routes in the Southwest, while other companies have completed road tests in China and Europe.¹

This study focuses on the impact of automation in long-haul trucking for several reasons. First, long-haul trucking occurs on limited access highways that are less-complex driving environments than surface streets. Second, unlike short-haul trucking, long-haul driving involves sustained and uninterrupted highway driving with few non-driving responsibilities.

Upgrading a Class 8 tractor for automation that allows it to operate without human intervention involves outfitting vehicles with lidar, sensors, and other technology. Given uncertainty over the timeline for adoption of ADS, we simulate the impacts of automation in long-haul trucking over the period 2020-2050 under a fast, medium or slow adoption scenario where after 15 years, about 95 per cent, 65 per cent or 35 per cent of the fleet of long-haul truck tractors is converted to accommodate Level 4 automation, respectively. The “fast” scenario (with automation technology being deployed in 2021) has not played out in reality, as Level 4 automation is not currently permitted in California. However, this “fast” scenario can be considered an outer boundary of possible impacts.

To simulate the impact of the automation of long-haul trucking in California, we use data from the Bureau of Labor Statistics (BLS) data and other sources. We find that in all scenarios, the introduction of ADS in California will increase state GDP, capital, employment, wages, and welfare in the billions of dollars. In particular, we find that the deployment of autonomous long-haul trucking in California would:

- **Contribute to an annual increase in real GDP and welfare in California** of about 0.35 per cent relative to baseline, equivalent to about \$7.9b of 2019 GDP under the “fast” adoption scenario, or about 0.28 per cent relative to baseline, equivalent to about \$6.5b of 2019 GDP under the “slow” adoption scenario.
- **Increase output of the “For-hire” trucking industry** by about 4 percent relative to baseline.
- **Preserve long-haul trucking jobs** under the “medium” or “slow” adoption scenarios in California. Layoffs of long-haul truck drivers would only occur nationwide under the “fast” adoption scenario and only over the period 2032-2036. This further assumes that autonomous trucking deployment were to begin in 2021, which is unlikely given the lack of enabling regulations. Further, lower employment levels for long-haul truck drivers will largely be offset with natural occupational turnover and growth in short-haul trucking.
- **Lead to improved fuel efficiency and reductions in fatalities and safety costs** due to a reduction in large truck crashes. The most direct impact of the adoption of

¹ See <https://www.azmirror.com/2019/08/16/autonomous-semi-trucks-arizona-ups-tusimple/> and <https://edition.cnn.com/2021/07/14/world/tusimple-autonomous-truck-spc-intl/index.html>.

automation in long-haul trucking would be an improvement in labor productivity in the trucking industries.

- **Increase California’s total employment** in all adoption scenarios. California’s total employment would increase by approximately 2,400 jobs during the “fast” adoption scenario analysis period, despite decreases in employment for long-haul truck drivers.

Evaluating the impact of autonomous long-haul trucking deployment in the United States using USAGE-Hwy

This report evaluates the macroeconomic effects of the introduction of automation in the long-haul trucking sectors in the United States using USAGE-Hwy v1.2, with a focus on the regional impacts in California. This involves a revision of work published as US Department of Transportation (Jan. 2021) by the Office of the Assistant Secretary for Research and Technology. That work used USAGE-Hwy v1.1 with a base year of 2016. In this current revised work, USAGE-Hwy v1.1 has been updated to v1.2 with all data reflecting an updated base year of 2018. The primary reference for USAGE-Hwy is Dixon, Rimmer and Waschik (2017). All model simulations are set up and solved using the Centre of Policy Studies’ purpose-built GEMPACK software, documented in Horridge *et al.* (2018).

A summary of the truck transport industries in USAGE-Hwy and the strategy for modeling the impact of automation in long-haul trucking is contained in Section 1. Section 2 details the shocks applied to USAGE-Hwy that reflect the impact of automation in the long-haul trucking sectors. The base year for these data and all simulations is 2018. Section 3 sets out the macroeconomic results from simulations that evaluate the impact of automation in long-haul trucking and justifies them via back-of-the-envelope (BOTE) theory and calculations, specifically looking at California. Concluding remarks and possible directions for future research are given in Section 4.

1. Modeling the impacts of autonomous long-haul trucking deployment

This section provides a summary of the different aspects of the Truck Transport industries in which we model automation in long-haul trucking as having an impact. These include labor-saving technological change, as automation allows trucks to be operated without drivers. Automation is also expected to impact the productivity of capital in the trucking industry, since driverless trucks can be operated for much longer periods without drivers who would otherwise need rest. Automation should also improve fuel efficiency and should also impact road safety with implications for fatalities and safety costs.

1.1 Automation and the 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 or Private transport industries, one of which modeled industry 47OT.484 “In-house truck transportation”. Another task involved updating the database behind USAGE-Hwy from 2012 to 2018. As a result, data for the two truck transport industries in USAGE-Hwy

v1.2 reflect 2018 BEA and TSA data that were used in the update process. Activity in these industries in USAGE-Hwy was calibrated to be consistent with total demand for “For-hire truck transportation” 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 1.1 below summarizes the two truck transport industries in USAGE-Hwy v1.2.

Table 1.1: Truck Transport industries in USAGE-Hwy v1.2 (\$m)

AICS industry	Intermediate inputs	Compensation of employees	Gross operating surplus	Taxes	Value of industry output	Value of commodity sales
484 For-hire truck transportation	265,894	99,266	57,957	6,687	432,339	372,061
47OT.484 In-house truck transportation	255,701	116,837	68,216	0	440,755	440,755

The specific focus of this report is the impact of automation in long-haul trucking. We assume that the long-haul segment of this industry will be the first to be impacted (compared to other segments of 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 ADS is engaged and the vehicle is within its operational design domain (ODD). The driver could potentially receive their 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). Either way, the most direct impact of the adoption of automation in long-haul trucking would be an improvement in labor productivity in the trucking industries.

Labor-saving technological change:

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 1.1 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/special.requests/oesm18in4.zip>). 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). As a result, we assume that 58.9% [= $(47400 \cdot 895670) / (47400 \cdot 1521590)$] of the “Compensation of employees” listed in Table 1.1 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 private trucking sectors (ie: USAGE-Hwy industries TruckingServices and InHouse Trucking), 51.52% [= $(6.1+12.5) / (33.1+3.0)$] and 8.13% [= $(3.5+1.7) / (41.3+22.7)$] were long-haul truck drivers, respectively.

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%. This 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. This reflects the fact that even long-haul truck drivers execute non-driving tasks that may be difficult to replace through automation, including “checking vehicles, following safety procedures, inspecting loads, maintaining logs, and securing cargo” (Gittleman and Monaco 2020:12).

Before finishing this subsection, we estimate the number of truck drivers in both the For Hire or TruckingServ sector and the Private or InHouse Trucking sector, since we will be interested in how automation in long-haul trucking could lead to layoffs of labor in the trucking industry. BLS Occupational Employment Statistics reported that in 2018, 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. Following Gittleman and Monaco (2020:16-18), we 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 in 2018, there were 461,481 [= $895,670 \cdot 0.5152$] and 77,738 [= $956,780 \cdot 0.0813$] Long Distance Tractor-trailer Drivers in the “Trucking Services” and “In-house Trucking” sectors, respectively.

These are the number of driving jobs that may be at risk of elimination due to adoption of automation in long-haul trucking.

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.² 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 5 to 5.5% fuel savings expected from mandated speed controls³ and the 15% realized fuel savings claimed by TuSimple.⁴

Capital-saving technological change:

Automation in long haul trucking should lead to a reduction in labor costs, and should also lead to fuel cost savings. 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.

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 Transport (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 Transport (Sept 2020) People Table

² <https://www.nationalgeographic.com/news/energy/2011/09/110923-fuel-economy-for-trucks/>

³ <https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/speed-limiter-pria-082016.pdf>

⁴ <https://venturebeat.com/2019/09/17/tusimple-raises-120-million-to-expand-its-fleet-of-driverless-delivery-trucks/>

14).⁵ Of these single large truck fatalities, we estimate that 29.11 per cent involved long-haul trucks.⁶ 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 [= $970 \cdot (2897/4415) \cdot 0.87 \cdot 0.2911$] 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 1.49.⁷ As a result, we assume that automation would save \$97.2 million [= $17000 \cdot (2897/4415) \cdot 0.87 \cdot 0.2911 \cdot 22934 \cdot 1.49$] in annual (2018) medical costs.

2. Constructing shocks to simulate automation in long-haul trucking

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 described in Section 1. 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 per cent, reflecting the following baseline behaviour in USAGE-Hwy macroeconomic aggregates:

- 2.7 per cent annual growth in aggregate real consumption
- 1.7 per cent annual growth in aggregate real investment
- 1.7 per cent annual growth in aggregate real government spending
- 5.2 per cent annual growth in aggregate real exports
- 4.8 per cent 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 per cent per year. Aggregate labor market behaviour is characterized by:

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

We assume that the annual increase in the U.S. population is 0.936 per cent.

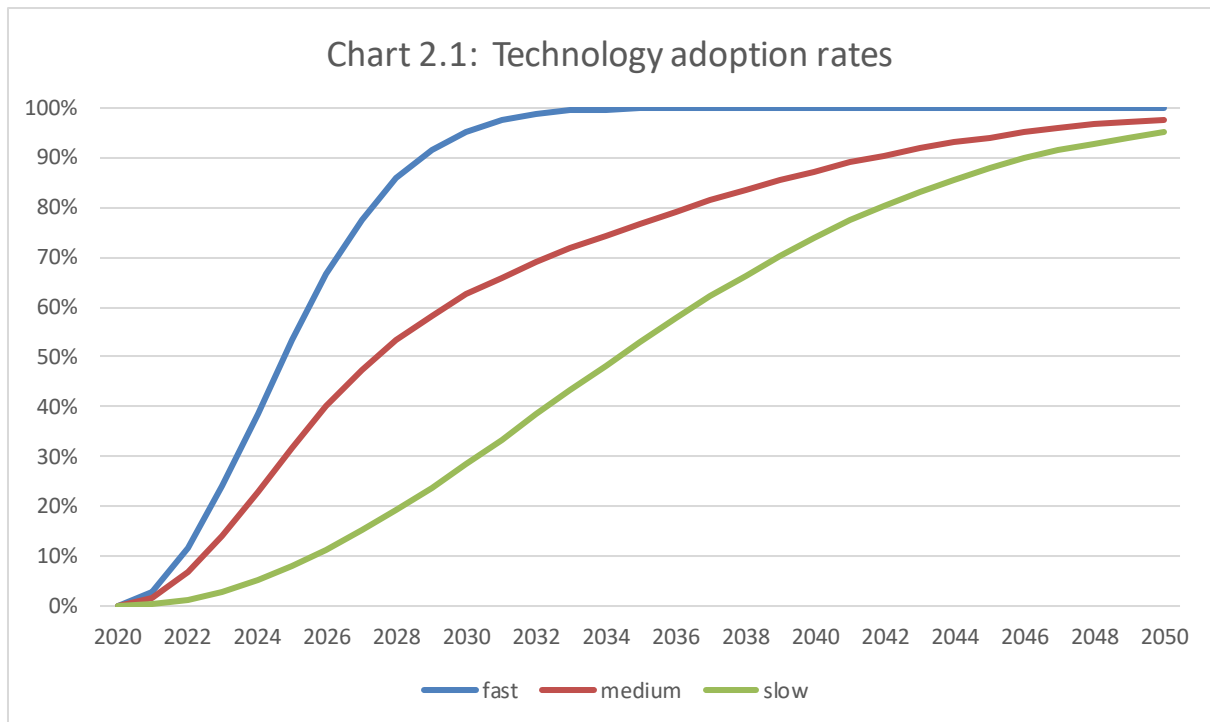
USAGE-Hwy v1.2 represents an initial 2018 equilibrium. We suppose that the first firms in the trucking industry begin adopting automation in long-haul trucking starting in 2021. This

⁵ 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.

⁶ A detailed derivation of this share is provided in subsection 2.2 below, near the middle of p.11.

⁷ This US health care inflation rate is compounded over 2005-2018 using data from https://ycharts.com/indicators/us_health_care_inflation_rate.

assumption allows us to explore the possible economic consequences of automation. In truth, Level 4 automation is not currently 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 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. 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.



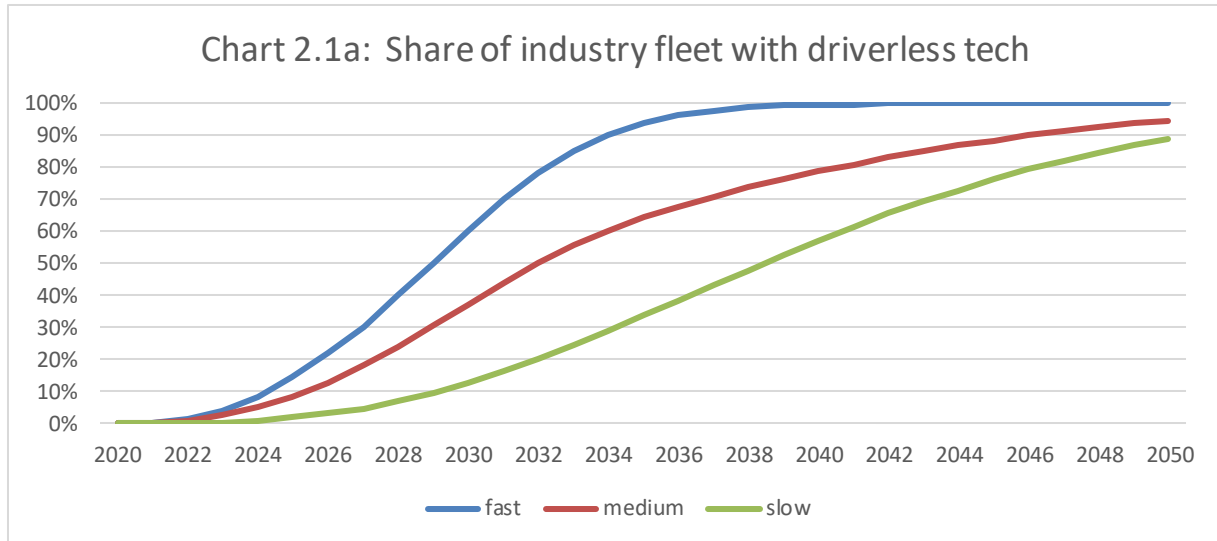
Under the “fast” adoption path, all firms in the for-hire and private trucking sectors will have begun adopting automation in long-haul trucking within 10-15 years, so that after 10-15 years over 90% of new investment in trucks will be on trucks with driverless capability. Under the “medium” and “slow” 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 tractor⁸ 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.⁹ Based on this information, we assume the lifespan of the existing

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

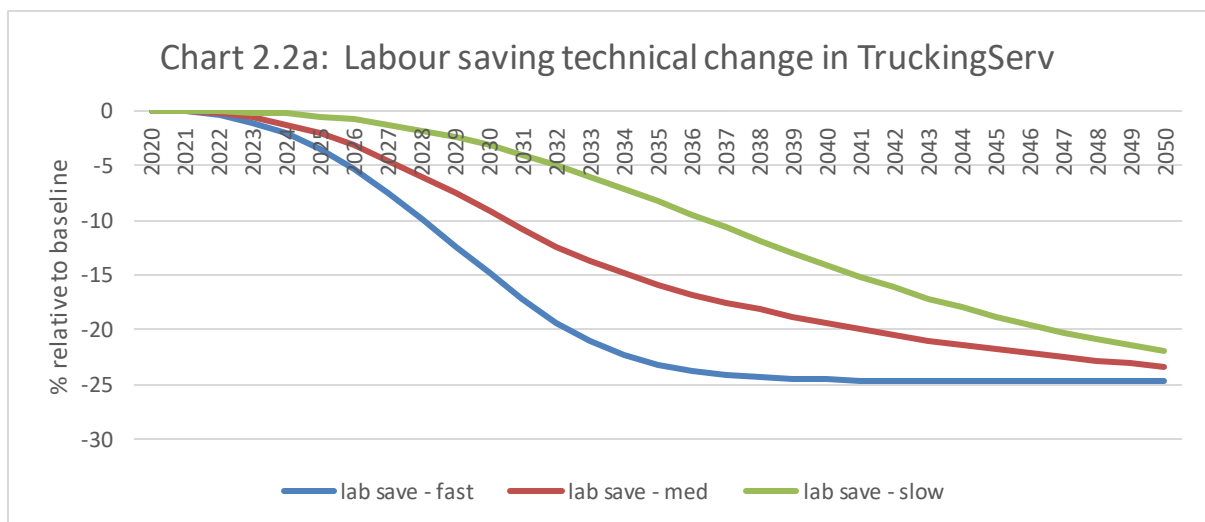
⁹ Kenny Veith (president, ACT Research) in conversation by phone with the U.S. DOT, June 3, 2019.

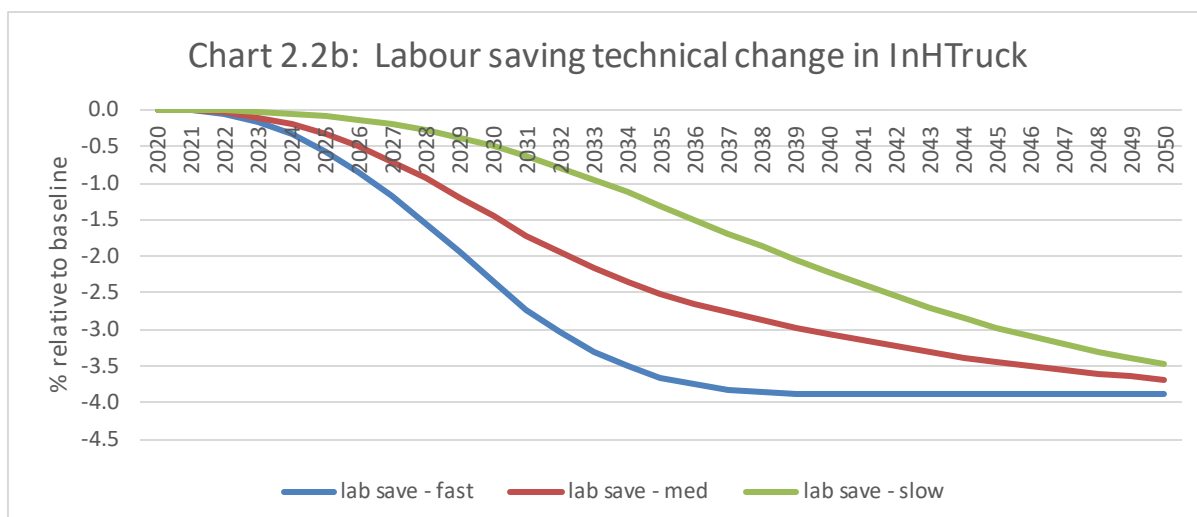
fleet of long-haul trucks to be nine years. On average, in any given year, any firm that has begun adopting automation technology will convert 1/9th of its fleet. This implies that the share in year t of the fleet of long-haul trucks in the trucking industry that will have been converted to accommodate 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. These shares are plotted in Chart 2.1a.



2.1 Labor saving technical change

The first set of shocks reflect the impact that automation in long-haul trucking is expected to have on labor productivity. 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 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.





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 Section 1 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 McKinsey estimate of maximum automation potential in Heavy Truck and Tractor-Trailer Operators (81.4%) and the share of the industry fleet that has adopted automation from Chart 2.1a. For example, under the “fast” scenario, by 2030, just over 60% 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 $-14.6\% [= -100 \cdot 60.46\% \cdot 58.80\% \cdot 51.52\% \cdot 81.4\%]$ and $-2.31\% [= -100 \cdot 60.46\% \cdot 58.80\% \cdot 8.13\% \cdot 81.4\%]$, 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 37% 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 $-9.07\% [= -100 \cdot 37.44\% \cdot 58.80\% \cdot 51.52\% \cdot 81.4\%]$ and $-1.43\% [= -100 \cdot 37.44\% \cdot 58.80\% \cdot 8.13\% \cdot 81.4\%]$, respectively.

2.2 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 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.¹⁰ “Already, companies have made fully autonomous beer deliveries and struck

¹⁰ 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>.

alliances to operate ATs jointly. The rigs these companies are using are typically new medium- and heavy-duty trucks, outfitted with lidars,¹¹ 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). 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 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 (ie: 1 minus) of the technology adoption rates in Chart 2.1a, to a minimum of 50%. 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.

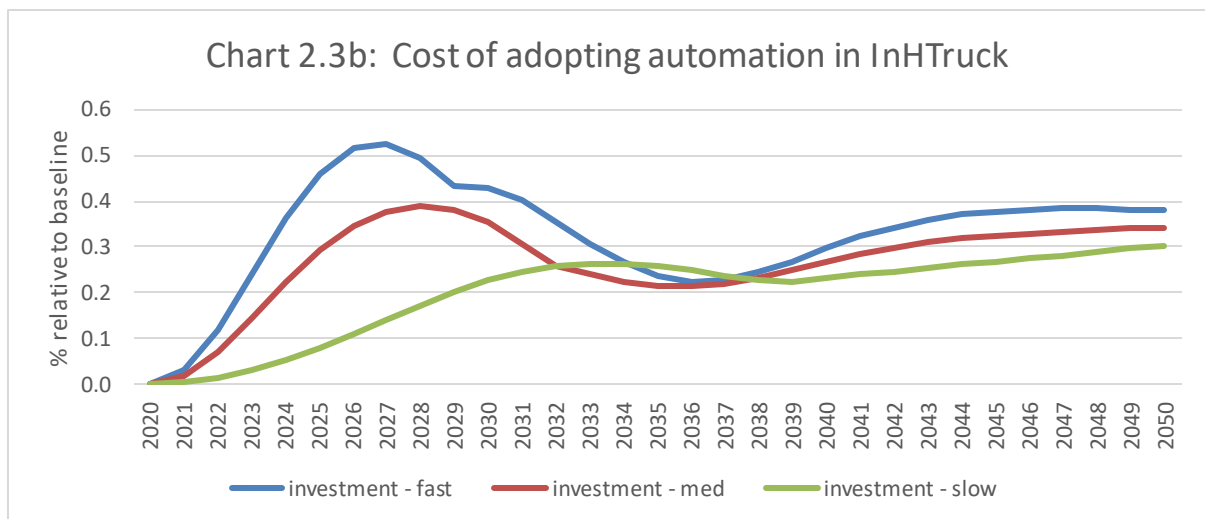
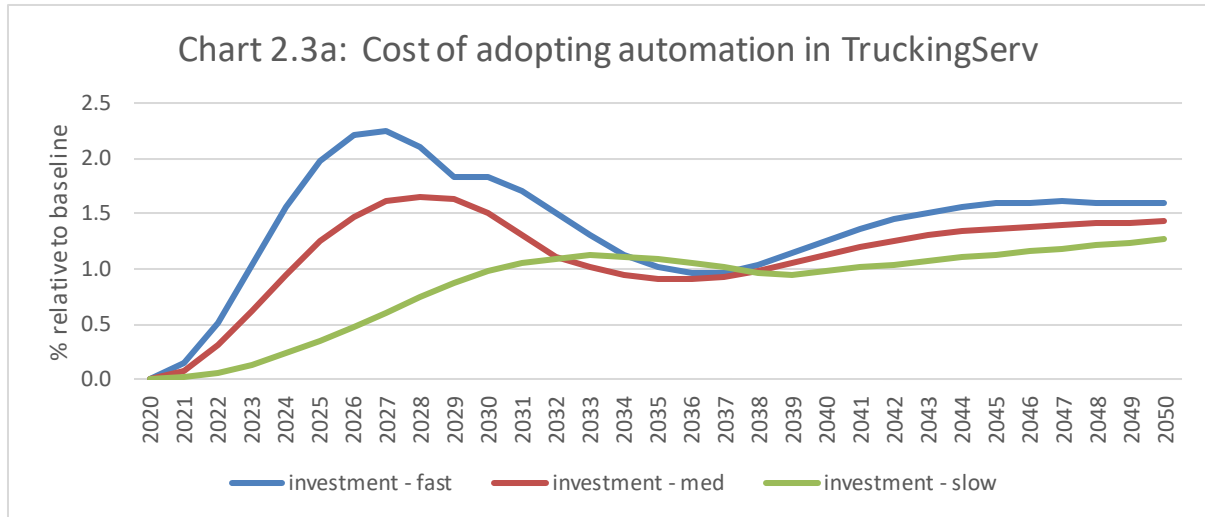
To estimate the share of the fleet of tractor-trailers that is involved in long-haul trucking, we start with BLS data on occupation 53-3032 Heavy and Tractor-Trailer Truck Drivers, May 2019 (available from <https://www.bls.gov/oes/tables.htm>) which showed that total national employment of Heavy and Tractor-Trailer Truck Drivers was 1,852,450. Of these, 895,670 were employed in the Truck transportation (TruckingServ) industry. We presume that the remaining 956,780 were employed in the Private Trucking (InHTruck) sector. We noted earlier in Section 1 that 51.52 per cent and 8.13 per cent of “Heavy truck and tractor-trailer operators” in the TruckingServ and InHTruck sectors were “Long-distance tractor-trailer drivers”, respectively. We conclude that 29.11 per cent [= $(895670 \cdot 0.5152 + 956780 \cdot 0.0813) / 1852450$] 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 [= $2,000,000 \cdot 0.2911$]. Over the simulation period, we assume that the size of the fleet of long-haul trucks grows, following the increase in Truck vehicle-miles-travelled over the same period as reported in the latest forecast provided by the US Department of Transportation.¹²

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 autonomous operation (\$0.1m), discounted by 1 minus the technology adoption rate in 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, 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 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 baseline output (number of trucks) in the industry. Under the “fast” adoption scenario, this shock is highest in 2027 when 8.62 per cent of the fleet is converted to allow for autonomous operation, bringing the total share of the fleet converted by 2027 to 30.51 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 \$111,237m and \$114,910m for the TruckingServ and InHTruck industries, respectively. So in 2027, the investment shock is 2.25 per cent [= $100 \cdot 691959 \cdot 0.0862 \cdot 0.1$

¹¹ LIDAR stands for *Light Detection and Ranging*, a [remote sensing](https://oceanservice.noaa.gov/facts/lidar.html) method that uses light in the form of a pulsed laser to measure ranges (variable distances). See <https://oceanservice.noaa.gov/facts/lidar.html>.

¹² 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.

· $(1-0.3051) \cdot 0.864 / 159296$] in the Trucking Serv sector and 0.53 per cent [= $100 \cdot 691959 \cdot 0.0862 \cdot 0.1 \cdot (1-0.3051) \cdot 0.136 / 109398$] in the InHTruck sector. This equates to an additional \$3,579m in the Trucking Serv sector and \$564m in the InHTruck sector of investment spending for the 8.62 per cent of the fleet being converted in 2027 to allow for autonomous operation in 2027.



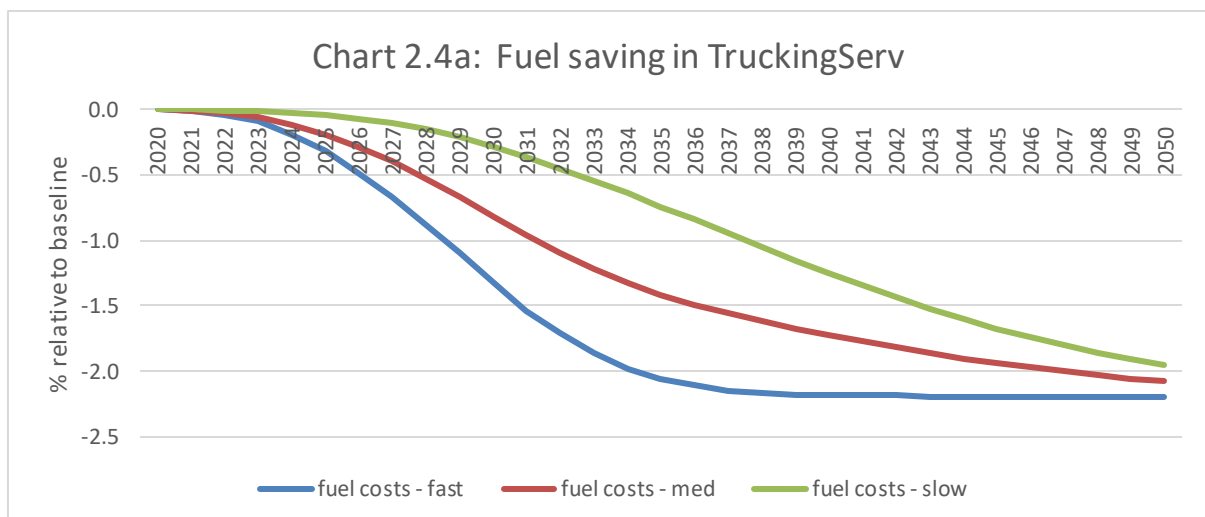
After 2029, the first trucks that were upgraded in 2020 will be 9 years old and will need to be replaced. This explains why the curves in Charts 2.3a and 2.3b never return to baseline. For example, under the “fast” adoption scenario, the baseline growth in vehicle miles travelled suggests that the number 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 \$306b by 2050, the cost of adopting automation in the Trucking Services sector reaches almost 1.6 per cent [= $(1/9) \cdot \text{number of trucks } (1,020,751) \cdot \text{TruckServ share } (0.86) \cdot \$50\text{k per truck} / \text{Investment in TruckServ } (\$306\text{b})$] above baseline by 2050.

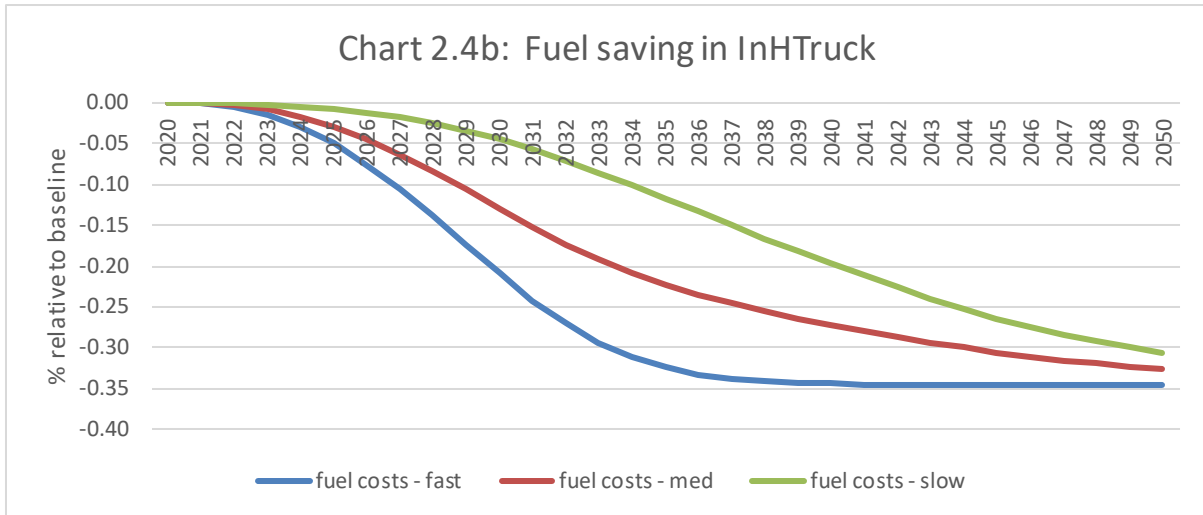
Again Charts 2.3a and 2.3b have the same shape, since they both reflect the same adoption paths in Chart 2.1a, and they both presume the same cost that needs to be incurred to replace a long-haul truck with one that is fitted to allow for autonomous operation. By the end of the

simulation period, baseline investment in the TruckingServ industry is about 50 per cent higher than that in the InHTruck industry in USAGE-Hwy (ie: the denominator in the shocks in Charts 2.3a and 2.3b are dissimilar by 2050). Also, 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 features 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 2.25 per cent) and the scale on Chart 2.3b (where the largest investment shock in InHTruck under the “fast” adoption scenario in 2027 is 0.53 per cent).

2.3 Fuel cost savings

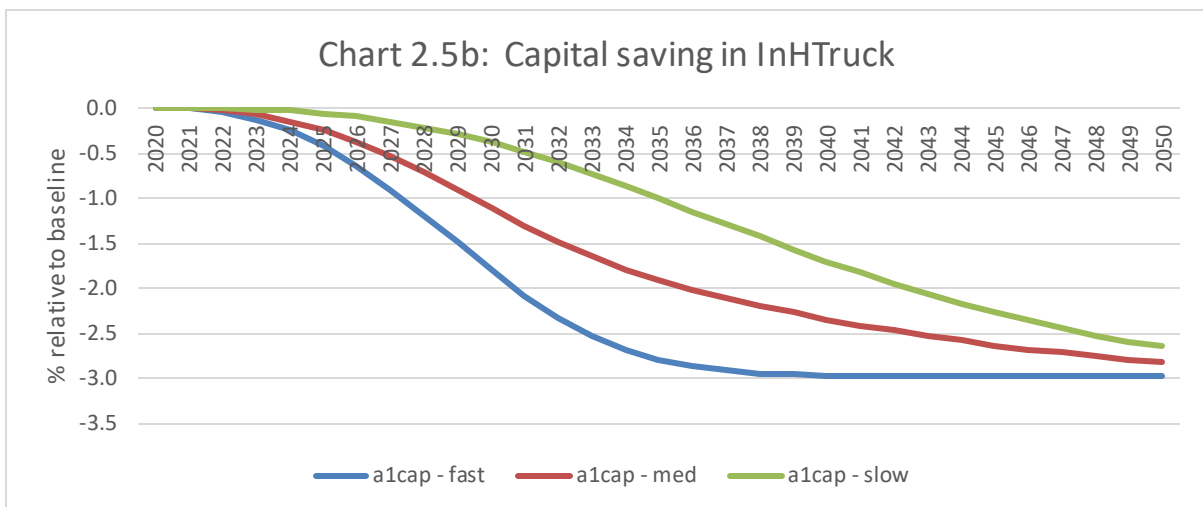
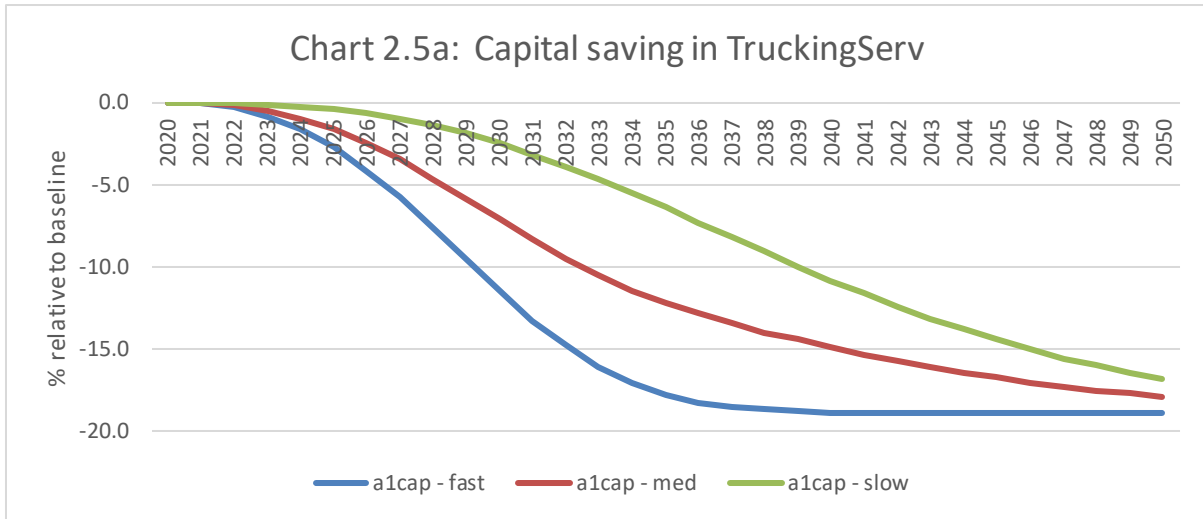
Charts 2.4a and 2.4b present the percentage reductions in fuel use per unit of output that are anticipated upon adoption of automation in long-haul trucking. Given the evidence summarized in Section 1, we assume that fuel costs fall by 5.22% for those firms that adopt automation in long-haul trucking. As a result, the shocks in Charts 2.4a and 2.4b for the TruckingServ and InHTruck industries in USAGE-Hwy reflect 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 -2.18% [= $-100 \cdot 0.0522 \cdot 0.5152 \cdot 0.814$] in the TruckingServ industry and -0.34% [= $-100 \cdot 0.0522 \cdot 0.0813 \cdot 0.814$] in the InHTruck industry, reflecting the share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum Technical Automation Potential of 81.4% for “Heavy and Tractor-trailer Truck Drivers” from McKinsey Global Institute (2015). 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.





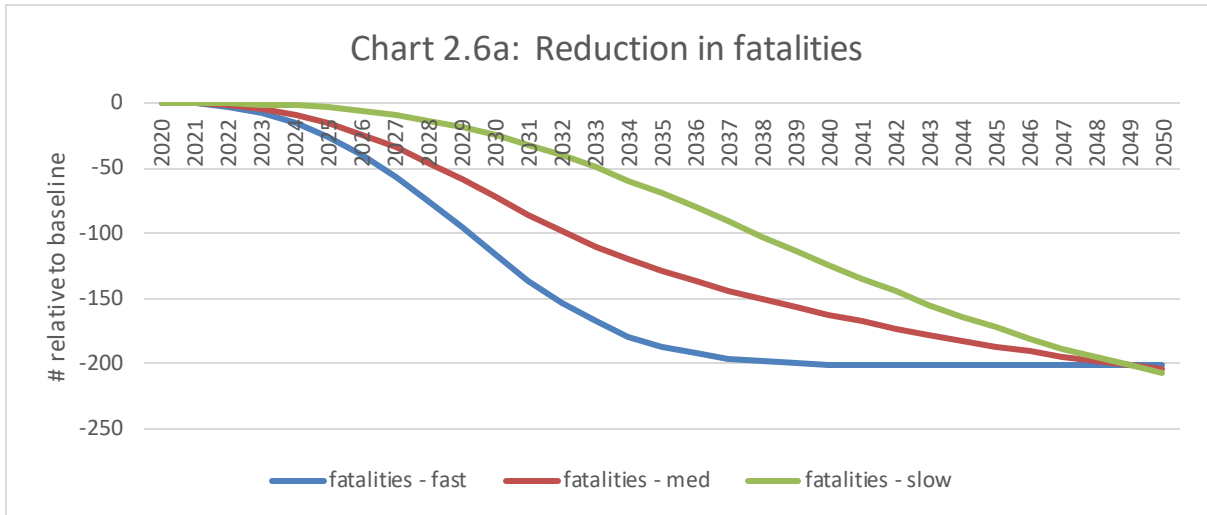
2.4 Capital-saving technological change

Charts 2.5a and 2.5b 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 2.5a and 2.5b 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 drivers in private or in-house trucking engage in long-haul trucking than 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 -18.8 per cent [= $-100 \cdot 0.45 \cdot 0.814 \cdot 0.5152$] and -3.0 per cent [= $-100 \cdot 0.45 \cdot 0.814 \cdot 0.0813$] in TruckingServ and InHTrucking, respectively, reflecting the share of Heavy Truck and Tractor-Trailer Operators that are Long Distance Tractor-trailer Drivers and the maximum Technical Automation Potential of 81.4% for “Heavy and Tractor-trailer Truck Drivers” from McKinsey Global Institute (2015). 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.

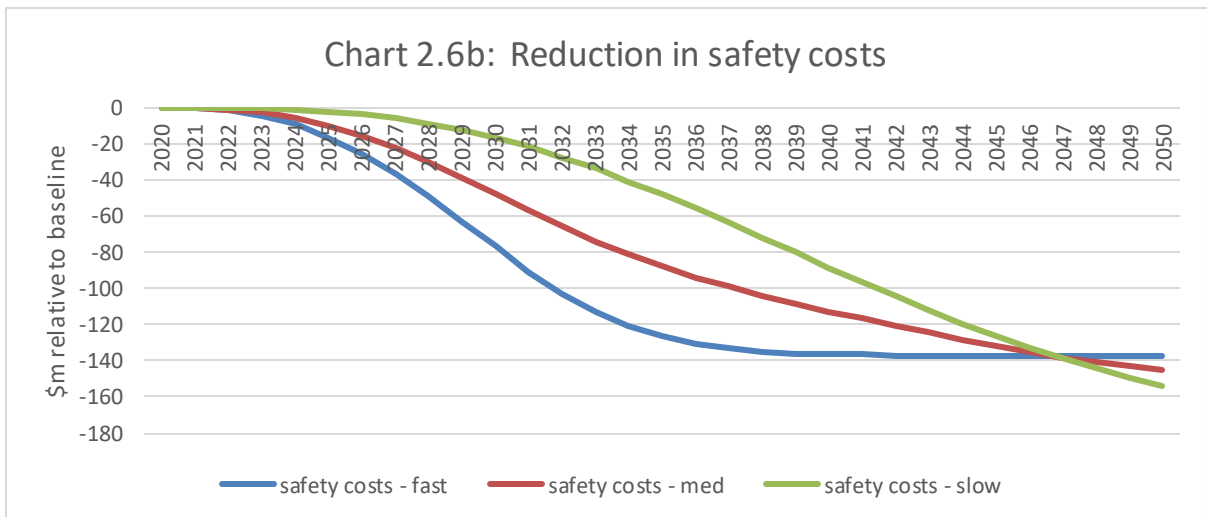


2.5 Fatalities and safety costs

The final shocks reflects 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 information from Section 1, we begin with our estimates 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 forecast by the Department of Transportation. 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. As in previous work with USAGE-Hwy, each extra fatality is valued at \$10.5m, following guidance on Value of Statistical Life available from <https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis>).



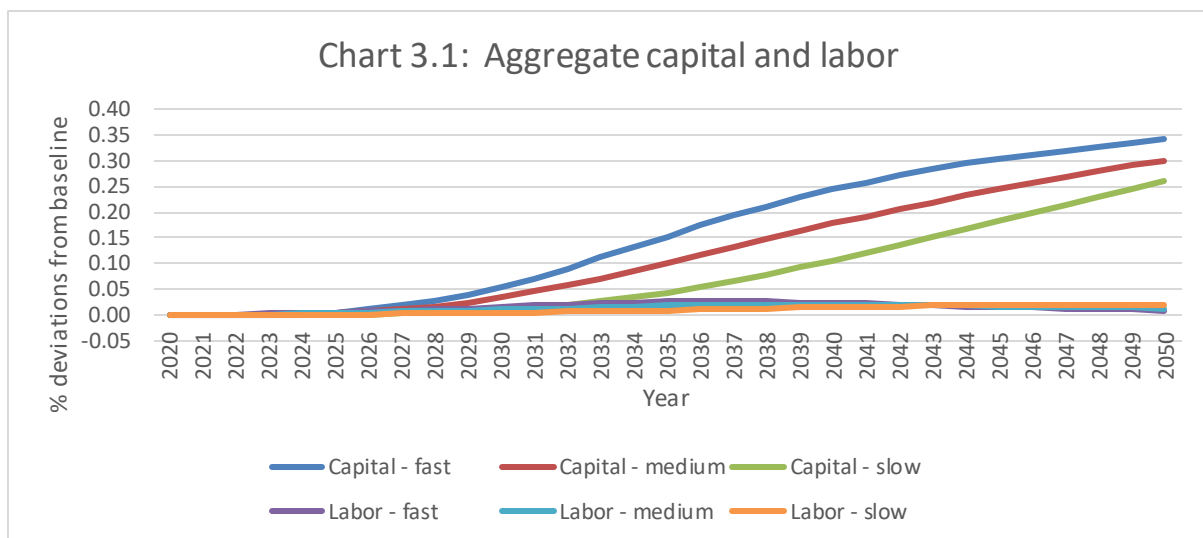
The reduction in safety costs (in \$m) per unit of output due to the reduction in truck crashes and associated injuries upon adoption of automation in long-haul trucking are presented in Chart 2.6b under either fast, medium or slow adoption rates. The shape of these curves is similar to those in Chart 2.6a since both are based upon the same adoption rates in Chart 2.1a. In 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.



3. Effects of automation in long-haul trucking

3.1 Macroeconomic results

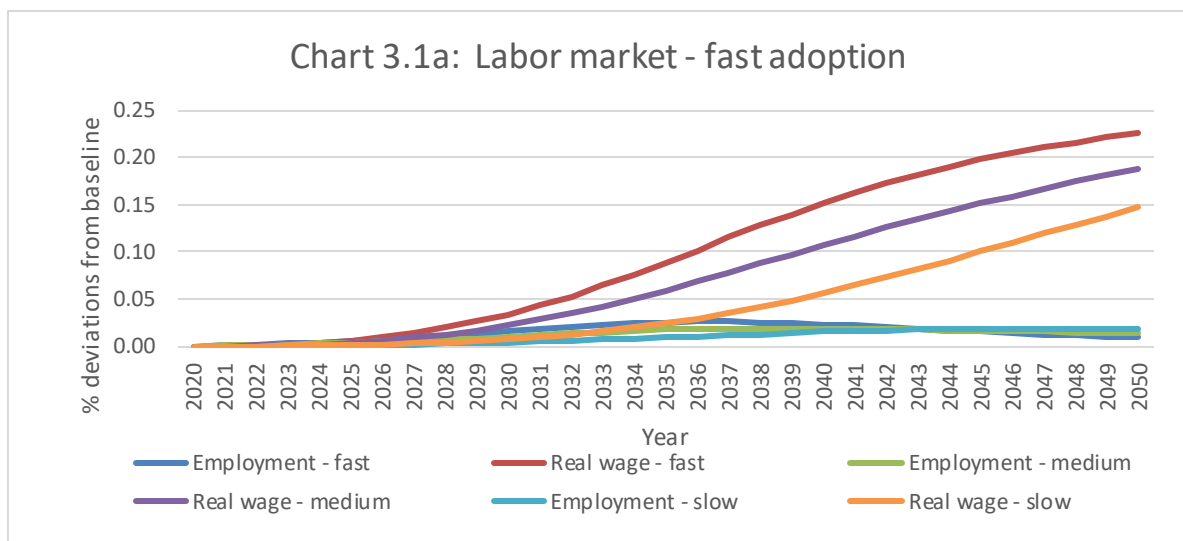
To begin our analysis of the impact of these shocks that represent the adoption of automation in long-haul trucking, we look at the direct consequences of the increase in investment spending in the TruckingServ and In-House Trucking industries. Over the simulation period, under the “fast” adoption scenario, replacing the long-haul trucking fleet with stock that is equipped for automated operation results in an extra \$107b of aggregate investment spending in the US economy relative to baseline. As illustrated in Chart 3.1, this increased investment translates into an increase in aggregate capital that reaches almost 0.35 per cent above baseline by 2050. Under the “medium” and “slow” adoption scenarios, this increase in capital reaches just over 0.3 and 0.25 per cent above baseline by 2050 since less than 100 per cent of the fleet is converted for the adoption of automation by 2050 under the “medium” and “slow” scenarios.



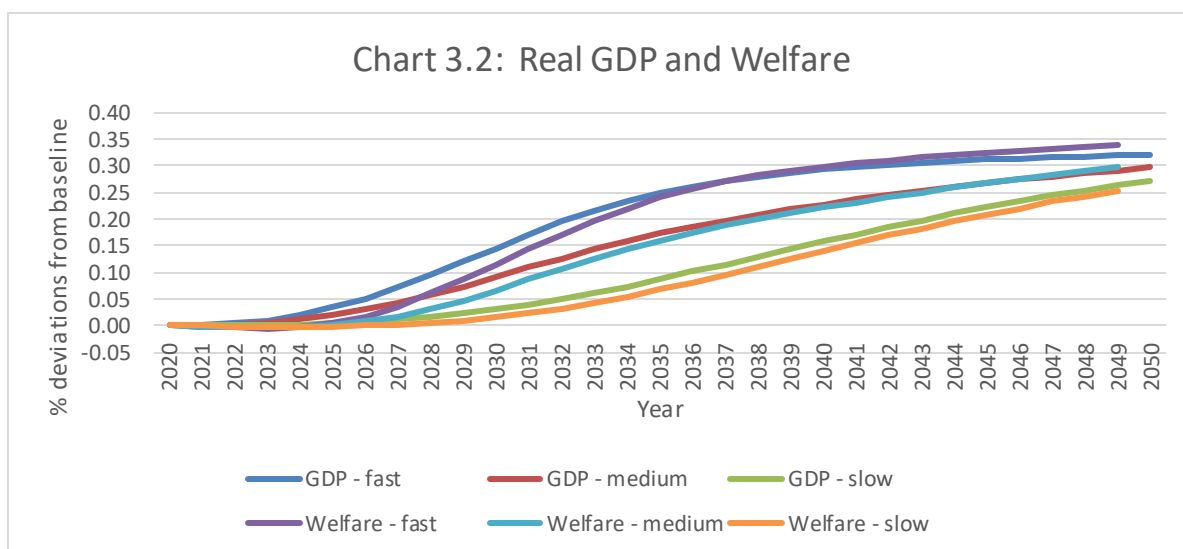
If the same amount of labor in the economy can now be combined with more capital, then labor productivity will increase. This effect is distinct from and additional to the direct impact that automation has on labor productivity in the trucking sectors: The increase in aggregate capital will make the average unit of labor across the whole economy more productive. At a given real wage, this increases the demand for labor. Chart 3.1 illustrates this increase in labor demand or employment over the simulation period while capital is increasing. The operation of the labor market in USAGE-Hwy is illustrated in more detail in Chart 3.1a below for the “fast” adoption scenario. Employment (labor demand) increases as capital increases, reaching a peak around 2036. In USAGE-Hwy, labor supply is exogenous, determined by exogenous changes in population and participation rates. Hence, the investment in the adoption of automation in long-haul trucking that stimulates labor demand causes an excess demand for labor. This results in the increase in the real wage illustrated in Chart 3.1a. 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

increase more and earlier, reaching almost 0.026 per cent above baseline in 2036. 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 US employment in 2019, the average annual gain in employment over the simulation period is equivalent to about 23,700 jobs.

Under the “slow” adoption scenario (see Chart 3.1 above), 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 of only 0.019 per cent above baseline, and the average annual gain in employment over the simulation period is 15,200 jobs.



How do these changes in capital and labor translate into changes in real GDP and welfare? Chart 3.2 below shows how real GDP and welfare change as automation in long-haul trucking is adopted under the three different scenarios.



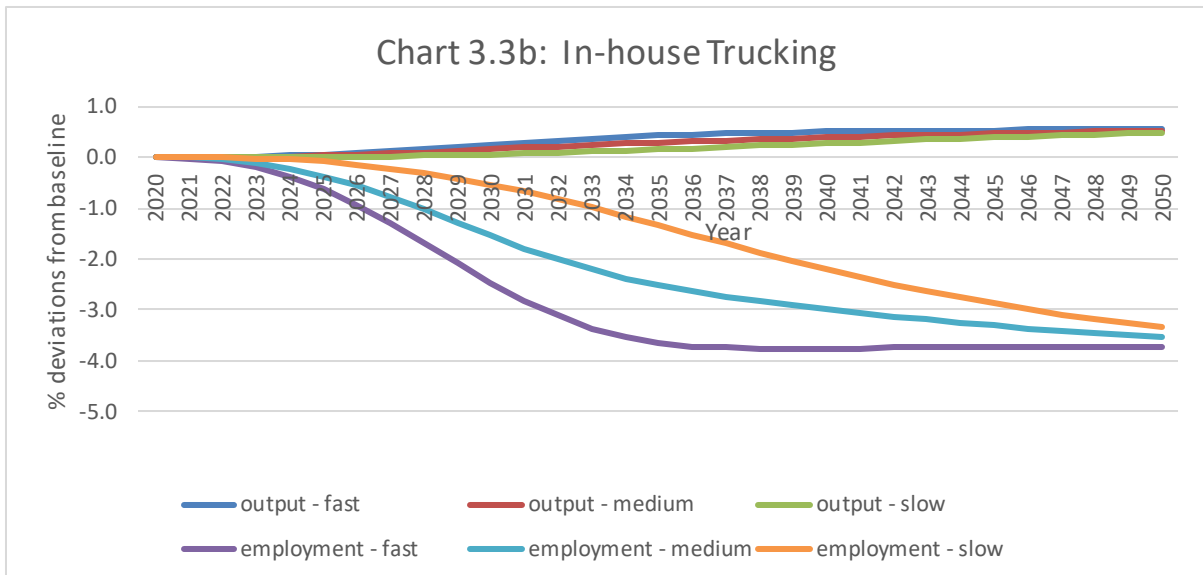
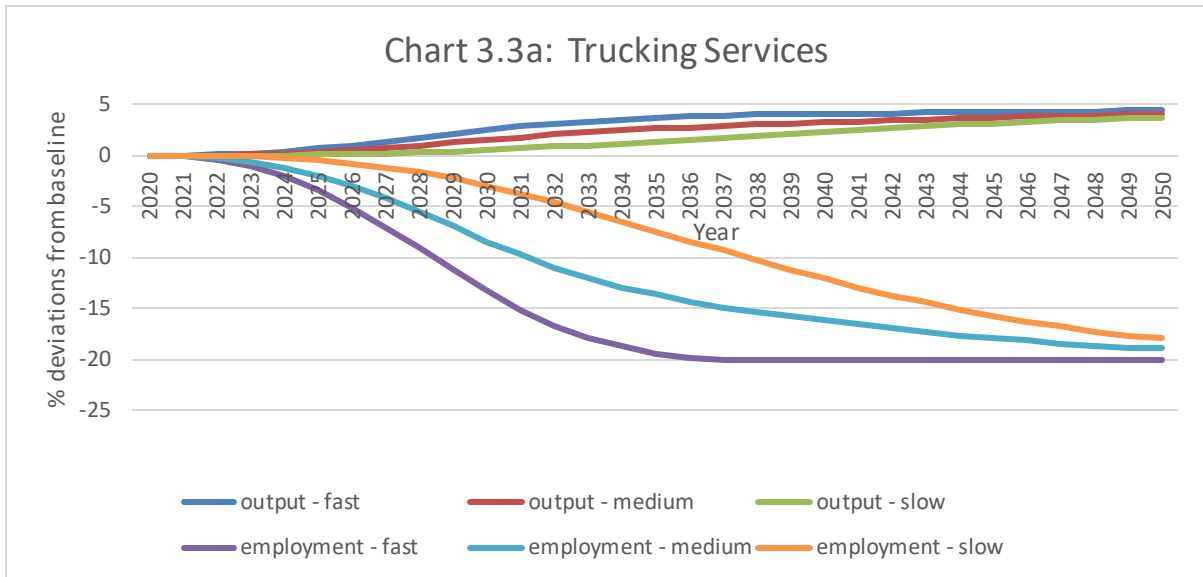
By 2050, under the “fast” adoption scenario, GDP reaches 0.32 per cent above baseline, equivalent to just over \$66b relative to 2019 GDP. Where does this improvement in real GDP come from? By 2050, labor has almost returned to baseline, so the contribution of labor to this real GDP gain is negligible. At 0.34 per cent above baseline, capital growth contributes almost 0.12 per cent of the real GDP gain. 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 just under 0.18 per cent to the real GDP gain.¹³ 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 3.2 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 2037. 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 2037 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 0.3446 per cent by 2050 under the “fast” adoption scenario, equivalent to about \$39b in 2019 prices. The average yearly welfare increase is just over 0.19 per cent, equivalent to about \$22.2b in 2019 prices. Under the “slow” scenario, the corresponding figures are 0.25 per cent by the end of the simulation period, equivalent to almost \$29b in 2019 prices. The average yearly welfare increase is 0.09 per cent, equivalent to about \$10.4b in 2019 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 3.3a shows that the adoption of automation in long-haul trucking leads to an increase in output of the Trucking Services sector that reaches over 4 per cent above baseline by 2050. Chart 3.3b shows that the increase in the In-House Trucking sector reaches only 0.6 per cent above baseline by 2050.

¹³ By 2050, labor and capital in the TruckingServ sector account for about 0.57 and 0.09 per cent of GDP, while in InHouse Trucking, they account for 0.67 and 0.11 per cent of GDP, respectively. From Chart 2.2 and Chart 2.5, labor- and capital-saving technical change is 25 per cent and 19 per cent in the TruckingServ sector, and 4 and 3 per cent in the InHouse Trucking sector, respectively.

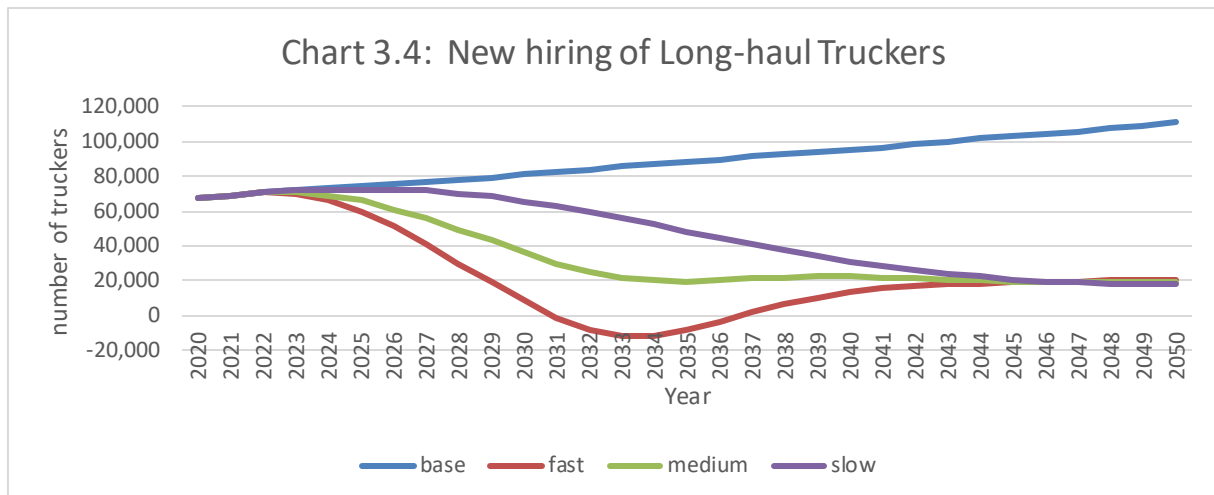


Along with the increase in output in the TruckingServ and InHTruck sectors, Chart 3.3a and Chart 3.3b also report a large decrease in employment in these industries. These are consistent with the labor-saving technical change shocks reported in Chart 2.2a and Chart 2.2b. As firms in these sectors adopt automation technologies, by 2050, employment in the TruckingServ and InHTrucking sectors falls by 18-20 per cent and 3-4 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 3.4 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:

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

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 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 Trucking¹⁴), increasing to 570,037 in 2021. As a result, Chart 3.4 reports baseline annual new hiring of long-haul truck drivers in 2021 of 69,120 [= 570,037 – 559,683 + 0.105 · 559,683], rising to over 110,000 by 2050.

The impact of the adoption of automation on the hiring of long-haul truckers is illustrated in Chart 3.4. There are no layoffs under the “medium” and “slow” adoption scenarios, since net hiring is always positive. But under the “fast” adoption scenario, after 2029 (by which point just over 50 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 about -11,600 in 2033, about 1.6 percent of baseline employment of long-haul truckers in 2033. 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 81.4 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.

¹⁴ Using BLS Occupational Employment Statistics and evidence from Gittleman and Monaco (2020:16-18), we argued earlier 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.

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.

3.3 California Regional Impacts

Thus far we have used USAGE-Hwy to illustrate the impacts of autonomous long-haul trucking deployment on the national economy. Here, we turn our attention to California impacts, using USAGE-Hwy in conjunction with regional modules in a top-down fashion. A top-down approach is appropriate for analyzing policies or shocks that do not have identifiable effects on relative production costs across regions. The impacts of autonomous long-haul trucking deployment fall into this category. By contrast, policies or shocks like changes in regional or state-level taxes that are implemented at the regional level require the use of a bottom-up model such as USAGE-TERM (for example, see Wittwer (2017)). Top-down modelling allows computations to be carried out with far greater commodity and regional detail than bottom-up.

Given uncertainty over the timeline for adoption of ADS, we simulated the impacts of automation in long-haul trucking in California from 2020-2050 under fast, medium or slow adoption scenarios. In the fast scenario, 95 per cent of long-haul truck tractors are converted to Level 4 automation in 15 years, while 65 per cent or 35 per cent of the fleet of truck tractors is converted to within that same time for the medium and slow adoption scenarios, respectively. In all scenarios, the introduction of ADS would increase California's GDP, capital, employment, wages, and welfare that can be monetized into billions of dollars. The "fast" scenario - with automation technology deployment commencing in 2021 and reaching its maximal level by 2040 - does not reflect reality, because Level 4 automation is not currently permitted in California. However, this scenario is helpful for understanding the outer boundary of possible impacts.

In distributing results from the national level to the states, the regional module takes account of three factors. The most important is the industrial composition of activity in each state. If employment in a state is heavily concentrated in industries that are relatively helped (harmed) by the national shock under consideration - here, the deployment of autonomous long-haul trucking - then the regional module will generate relatively large positive (negative) results for that state. The second factor is interstate trade. If a state relies heavily on exports to states that are positively (negatively) impacted by the shock under consideration, then the regional module will generate positive (negative) effects for that state. Finally, the regional module encompasses local multiplier effects. If traded-goods industries in a state are relatively positively (negatively) affected by the first two factors, then in the regional module, nontraded-goods industries (e.g. Retail trade) will also be relatively positively (negatively) affected.

We explain a state's percentage gain relative to the national gain as a function of two factors: (1) its mix of industries and (2) the performance of its industries relative to the national performance of those industries. A state does well relative to the nation if: (i) it has a mix of industries containing a relatively high share of gaining industries; and (ii) its industries in general do better than their counterparts in the rest of the U.S. To disentangle these two factors, we start by writing the relative percentage gain for a state r as:

$$\text{Relative gain}(r) = e(r) - e(\text{nation}), \quad (3.1)$$

where: $e(r)$ is the percentage gain for state r ; and
 $e(\text{nation})$ is the national percentage gain of 0.023 per cent.

Next we express the state and national gains as weighted averages of the state and national gains at the industry level. This leads to

$$\text{Relative gain}(r) = \sum_j \text{JSh}(j, r) \cdot e(j, r) - \sum_j \text{JSh}(j) \cdot e(j, \text{nation}) \quad (3.2)$$

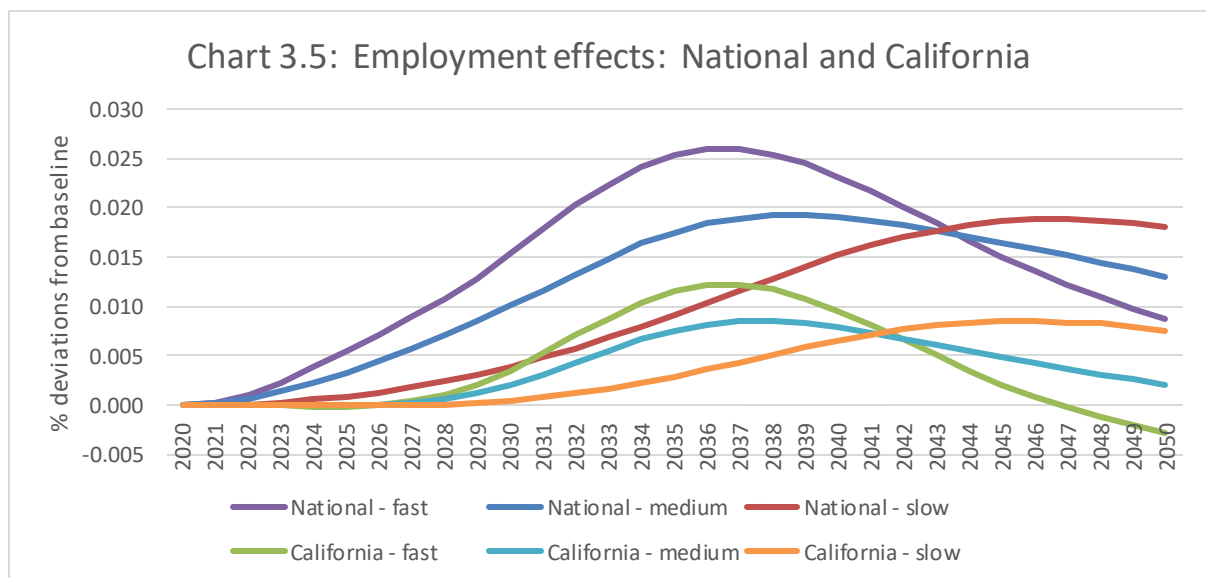
where: $\text{JSh}(j, r)$ is industry j 's share in jobs in state r ;
 $\text{JSh}(j)$ is industry j 's share in jobs in the nation;
 $e(j, r)$ is the percentage change in jobs in industry j in state r ; and
 $e(j, \text{nation})$ is the national percentage change in jobs in industry j .

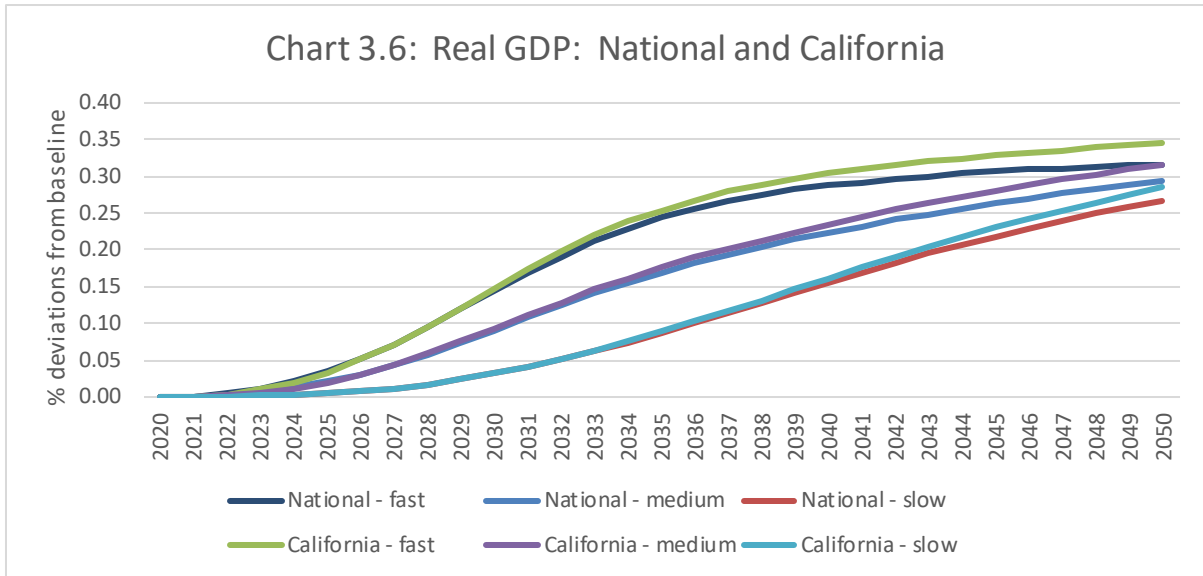
Equation (3.2) can be rewritten as:

$$\text{Relative gain}(r) = \sum_j [\text{JSh}(j, r) - \text{JSh}(j)] \cdot e(j, \text{nation}) + \sum_j \text{JSh}(j, r) \cdot [e(j, r) - e(j, \text{nation})] \quad (3.3)$$

The first term on the right hand side of equation (3.3) is the mix effect. It is positive if state r has a relatively high share of its jobs in industries that do well at the national level and a relatively low share in industries that do poorly at the national level. The second term on the right hand side is the relative performance effect. It is positive if state r has sufficient industries j that do better than the national performance of j [$e(j, r) > e(j, \text{nation})$]. To a large extent the performance effect magnifies the mix effect. If a state has a favorable mix of industries, then multiplier effects will help all of the industries in the state towards a percentage expansion greater than that for the nation.

Under the “fast” adoption scenario of autonomous long-haul trucking, we find an increase of 45,475 jobs at the national level, equivalent to an increase of 0.023 percent. In California, there are 2,394 jobs created under this scenario – an increase of 0.010 percent. In Charts 3.5 and 3.6, we report regional employment and real GDP effects, respectively, over the whole simulation period for California and for the nation as a whole.





The employment and real GDP effects reported in Charts 3.5-3.6 for California are only slightly different from the National results. The results demonstrate an annual increase in real GDP and welfare in the US of about 0.33 per cent relative to baseline, equivalent to about \$66b of 2019 GDP. The real GDP increase in California is a bit higher, at 0.35 per cent relative to baseline, equivalent to about \$7.9B of 2019 GDP under the “fast” adoption scenario, or about 0.28 per cent relative to baseline, equivalent to about \$6.5B of 2019 GDP under the “slow” adoption scenario.

4. Concluding remarks and directions for the future

Our results indicate that the automation of long-haul trucking will benefit the national and state economies. California will see increases in GDP, welfare, capital, and labor in the billions of dollars. Additionally, our model concluded that these economic benefits will accrue without mass layoffs of long-haul truck drivers. In California, not accounting for acute shortages, there are no expected layoffs in the slow, medium or fast adoption scenarios. Assuming the occupational turnover remains near today’s levels, automation of long-haul truck driving will lead to layoffs of at most 1.7 percent only across the US over a five-year period and only under the most ambitious adoption scenario. Further, these drivers should be able to find employment as short-haul drivers. Under the slow and medium adoption scenarios nationwide, the overall impact of trucking layoffs is further minimized. Trucker shortages are likely to further reduce any projected layoffs.

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 regarding the technology’s development. Also, accurate and current 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.

As California moves to allow L4 testing and deployment in the state, technologies will mature and business models will be better understood, providing an ongoing opportunity for examining impacts on the state's transportation workforce. A re-examination of this topic will

provide valuable insight into the impacts of driving automation on the Nation's transportation workforce.

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