# An Incentive for Investment Hurting Growth?: An Analysis of Section 179 Expensing and its Impact on Job Growth Through Related Capital Investment

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*This paper examines the economic impacts of Section 179 expensing in the Federal Tax Code. More specifically, it examines the impact of this incentive on automation and technological unemployment through a system dynamics simulation involving the professional industry, the manufacturing industry, and the rest of the United States economy. It also provides an overview of current trends towards automation, along with Recommendations for responsive tax policies to combat problems that could arise. Based on the results of the model and the analysis of current trends, both the professional and manufacturing industries face potential risks from automation, due to an increase in the Section 179 allowance, but the economy as a whole will benefit.*

*Keywords: economic impact, Section 179 expensing, automation and technological unemployment, system dynamics*

## INTRODUCTION

Passed in December 2017, the Act of Congress Public Law 115-97, otherwise known as the Tax Cuts and Jobs Act, or Trump Tax Cuts (U.S. Department of the Treasury Internal Revenue Service, 2021a), created significant amendments to the Internal Revenue Code of 1986. Most notably, this reform to the tax law raised the standard deduction and lowered individual tax rates. On the corporate side, the tax rate was lowered from a marginal 35% to a flat rate of 21%, and the Section 179 election and bonus depreciation limitations were increased for small businesses. On the surface, the changes seemed generally to encourage economic growth for Americans and domestic businesses (Lee, 2021; Abbas and Klemm, 2013); however, alterations in tax regulations and the corresponding economic implications are a multifaceted phenomenon (Bordignon et al., 2001). This study utilized a simulation model to examine the complexities of the Section 179 election.

Along with the analytical approach to this topic, this paper offers an economic overview of the rise of automation and its impact on job growth and technological unemployment. In light of both of these, the assessments indicate that some of the changes to the tax law will have an impact on job growth and require responsive federal action. More specifically, with the projected rise of the Section 179 election from the newly expanded bonus depreciation limitations, businesses will have a stronger incentive to invest in equipment and automation. This, in turn, will affect job growth by driving technological unemployment, which will require a strong tax policy to combat.

It is understood that there are numerous other factors associated with economics and business; thus, the assumption made here is that all other factors are held constant (*ceteris paribus*). Along with this, the outcomes presented are not a highly probable occurrence, seeing as the discussion about automation replacing labour has been around since the Industrial Revolution, but outcomes tend to be played off as a Luddite Fallacy. This paper emphasizes a hypothetical situation based on projections from corporate and federal data. It is still important to note, however, that this change in the Tax Cuts and Jobs Act is not necessarily an entirely positive amendment.

The remainder of this paper is organized as follows: Section two presents an overview of the literature on accelerated depreciation, system dynamics applications in investments, and technological unemployment. Section three provides information about Section 179 expensing. Section four outlines the methodological approach of this study. Section five describes our system dynamics model and presents the results. Section six discusses automation and technological unemployment. Section seven examines the potentials of incentive-based and penalty-based policies, and the last two sections discuss possible implications of the findings and make suggestions for further study.

## LITERATURE REVIEW

Currently, there is no published research analyzing the impact of accelerated depreciation on technological unemployment. There is, however, extensive research on other aspects of this phenomenon, such as research addressing the impact of accelerated depreciation on the economy, research relating to technological unemployment, and analyses of investment using system dynamics models.

### Accelerated Depreciation and the Economy

Ever since the introduction of Section 179, scholars have examined the economic impacts of accelerated depreciation. Hall and Jorgenson (1967), for instance, examined different aspects of tax policy from the 1950s and 60s, including Section 179, and determined that investment had substantial effects. Yuan and Oriaku (2016) observed a positive correlation between GDP and Section 179 deductions, which stemmed from an increase in investment. A number of accelerated depreciation studies relate specifically to agricultural machinery. Hadrich et al. (2013), for instance, found that Section 179 had the largest positive effect on purchases when compared to other factors. Similarly, Polzin et al. (2018) used a model to show how accelerated depreciation used by commercial farms lowers the cost of capital and thus encourages equipment investment, and Williamson and Stutzman (2016) found statistically significant investment demand elasticities with respect to Section 179 expensing, whereas bonus depreciation, on average, had little impact on capital investment.

Despite these findings highlighting the successful impacts of Section 179, there is also research with contrary findings. Keane (2016) pointed to conflicting evidence for the economic benefits of accelerated depreciation; the few analyses she conducted, however, focused mainly on bonus depreciation and its lack of impact. Section 179 is not as controversial. For this reason, and in light of Williamson and Stutzman's research, this study did not examine bonus depreciation along with Section 179. Margalioth (2007) argued that ideas about accelerated depreciation are based on Evsey Domar's economic growth theory, which has misguided politicians for decades; however, this argument is based on theory instead of on hard data, such as those informing research supporting the claim that accelerated depreciation has an impact on investment.

### Investment and System Dynamics

Using system dynamics, this paper examines technological unemployment associated with Section 179. Chow's (2015) research method is the closest to the method in this study, especially because it uses PI+, a forecasting model, to test the impacts from permanent Section 179 expensing at $500,000, the amount it was at the time of study. Chow argued that Section 179 would create an increase of investment and thus an increase in employment. This research, however, did not examine the automation and technological unemployment aspect that are examined in this paper. Other studies have also studied investment using system dynamics, specifically with respect to investment in energy, including Alishahi et al. (2012), Assili et al. (2008), and Liu and Zeng (2017). Liao et al. (2015) examined the dynamics between organizational IT investment strategy and market performance. All of these studies show how system dynamics can be used to determine the economic impacts of investment.

### Analyses of Technological Unemployment

Of the aspects of the effects of Section 179 considered in this paper, research on technological unemployment seems to be the most abundantly studied. Acemoglu and Restrepo (2018) claimed that machines will replace human labour but that new tasks will be created by humans, reversing this effect and generating a long-term equilibrium. They then extended this argument to address the relation between this stability and the distribution of income and employment, showing that there will still be inequality and, ultimately, harmful economic consequences from technological advancement. This paper looks into specific industries that might not experience this growth of new tasks. Similarly, Vermeulen et al. (2018) studied the impact of automation on employment and argued that potential job losses would be counterbalanced by job creation. This conclusion is also based on a whole view of the economy instead of a focus on specific industries, but the research does offer forecasts at the industry level, showing how some industries will suffer, while others will grow.

Other studies emphasize the likelihood of technological unemployment. Postel-Vinay (2002) compared the short- and long-term effects of technological progress on employment, with the long-term showing an acceleration of job obsolescence. Frey and Osborne (2017), cited in numerous studies, investigated jobs that would likely be at risk from future computerization and concluded that they would constitute about 47% of total U.S. employment. Chui et al. (2016) looked at the feasibility of automation in activities at the industry level. They focused more on work activities, like data processing and managing others, rather than on particular occupations, but they still measured the likelihood of how each industry would be affected by technological unemployment. Other research that supports this study is addressed in the section "Automation and Technological Unemployment."

Our research provides empirical contributions in this area of study. Judging from our review of the literature, the impact of accelerated depreciation on technological unemployment has never been studied. Even though system dynamics is commonly used to analyze investment decisions, it has not been used as a tool to model the complexity of the economic impacts of Section 179, and the current findings in the literature on this subject are inconsistent. We think that this study of the professional and manufacturing industries, which are very likely to experience adverse effects, with its holistic view of overall economic impacts, provides clear and valuable information for policy makers.

### Background on Section 179

Over the years, numerous changes have occurred in the Section 179 election. This incentive is directed towards small businesses, with the aim of growing the economy, specifically through capital investment. Instead of capitalizing and depreciating the cost of property over time, the taxpayer can elect to deduct the cost as an expense, with certain limitations.

The introduction of the Internal Revenue Code's (IRC) Section 179 occurred in 1958 through the Small Business Tax Revision Act of 1958 (P.L. 85-866), in hopes of encouraging capital investment. It allowed a deduction of up to $2,000 (or $4,000 in the case of a married couple filing a joint return) of the cost of new or used business machines and equipment with a tax life of six or more years that were acquired and placed in service in a tax year. It was not changed until 1981 under President Ronald Reagan's Economic Recovery

Tax Act (ERTA). According to a Senate Finance Committee Report, "The rules for determining depreciation allowances … need to be replaced because they do not provide the investment stimulus that is essential for economic expansion" (Joint Committee on Taxation, 2005). Section 179 "permits an election to 'expense' a portion of the cost" of qualified property, with specific limitations. This included "$5,000 in 1982 and 1983, $7,500 in 1984 and 1985, and $10,000 in 1986 and later years" (Jordan, 1982). The maximum allowance is reduced, dollar for dollar but not below zero, by the amount by which the cost of the property exceeds a threshold. The initial threshold was $200,000.

The general idea behind this tax addition was to encourage investment in equipment, even if there was a restriction to the type of property that qualified. Originally, *qualified property* referred to any property that was depreciable by the taxpayer, had an estimated useful life of at least three years, and was tangible personal property or "tangible property … used as an integral part of manufacturing, production," or other specific trade or businesses (U.S. Department of Treasury, 2002). For instance, if a firm purchased a machine for $7,000 in 1983, only $5,000 could be expensed under Section 179, while the remaining $2,000 could be depreciated with the MACRS method (U.S. Department of the Treasury Internal Revenue Service, 2021b). If the firm waited to purchase and use the machine in the following year, all $7,000 could be expensed under Section 179.

One may ask, "What is the benefit of expensing a portion of the property instead of depreciating it over its useful life?" Depending on the tax rate and other variables, one option may be more advantageous than the other. In general, if a taxpayer is trying to reduce taxes in the current year as much as possible, then electing to use Section 179 expensing will lead to lower taxes. In contrast, depending on their preferences regarding cash flow, some firms might want to claim lower deductions in each year of a property's useful life, instead of one deduction in the year of purchase. For example, in 2018, suppose the ABC Corporation and the XYZ Corporation both purchase equipment amounting to $50,000, with a seven-year recovery period. ABC elects Section 179 expensing, while XYZ uses MACRS depreciation with a 200% declining balance. ABC expenses all $50,000 in the first year, while XYZ can deduct only $7,143 (14.286% of $50,000). In year two, however, ABC can claim no depreciation on this equipment, but XYZ deducts $12,245 (24.49% of $50,000). Assuming all else is equal, ABC has a much lower tax bill in year one, while XYZ has a lower tax bill in years two and after. In this case, ABC cares more about its cash flow in year one, whereas XYZ believes it can use the deductions more effectively throughout the useful life of the equipment. Due to their struggles with cash flow, most small businesses try to improve it wherever they can, so a large majority elect to lower their current tax bill and have more cash flow in the current year, instead of benefiting from small increments over time (Ernst, 2019). In other words, it makes sense that most small businesses would prefer to expense using Section 179 rather than MACRS.

The original amendment to the ruling on Section 179 remained until 1993, when there was a 75% increase of the limitation from $10,000 to $17,500. The growth then continued year after year (Table 1). In 2018, President Trump's Tax Cuts and Jobs Act raised the maximum Section 179 expensing allowance to $1,000,000 from the previous year's $500,000. The threshold was also increased, and the definition for qualified property was modified. Notably, computer software was added as qualified property, along with "improvement property and some improvements to nonresidential real property—including roofs; heating, ventilation, and air-conditioning property; fire protection and alarm systems; and security systems" (KPMG, 2019).

**TABLE 1**
**MAXIMUM ALLOWANCES AND THRESHOLDS FOR SECTION 179 EXPENSING, ADJUSTED BASED ON THE CONSUMER PRICING INDEX (CPI), BY YEAR**

| Year | Maximum Allowance | Threshold | Maximum Allowance Adjusted Based on CPI | Threshold Adjusted Based on CPI |
|---|---|---|---|---|
| 1987 | $ 10,000 | $ 200,000 | $ 24,734 | $ 494,679 |
| 1993 | $ 17,500 | $ 200,000 | $ 33,822 | $ 386,533 |
| 1997 | $ 18,000 | $ 200,000 | $ 31,120 | $ 345,775 |
| 1998 | $ 18,500 | $ 200,000 | $ 31,265 | $ 338,001 |
| 1999 | $ 19,000 | $ 200,000 | $ 31,604 | $ 332,678 |
| 2000 | $ 20,000 | $ 200,000 | $ 32,552 | $ 325,517 |
| 2001 | $ 24,000 | $ 200,000 | $ 37,778 | $ 314,813 |
| 2003 | $ 100,000 | $ 400,000 | $ 150,708 | $ 602,832 |
| 2004 | $ 102,000 | $ 410,000 | $ 150,266 | $ 604,010 |
| 2005 | $ 105,000 | $ 420,000 | $ 150,619 | $ 602,475 |
| 2006 | $ 108,000 | $ 430,000 | $ 149,828 | $ 596,538 |
| 2007 | $ 125,000 | $ 450,000 | $ 168,035 | $ 604,926 |
| 2008 | $ 250,000 | $ 800,000 | $ 326,599 | $ 1,045,116 |
| 2010 | $ 500,000 | $ 2,000,000 | $ 631,812 | $ 2,527,247 |
| 2018 | $ 1,000,000 | $ 2,500,000 | $ 1,105,578 | $ 2,763,946 |
| 2022 | $ 1,080,000 | $ 2,700,000 | $ 1,080,000 | $ 2,700,000 |

**System Dynamics Model**

One of the tools than can be used to analyze the economic impacts of Section 179 is system dynamics simulations. The following will explain system dynamics and the methodology used to determine the outcomes.

*Overview of System Dynamics*

System dynamics is a branch of systems theory. Originally developed in the 1950s by MIT Professor Jay W. Forrester, it is a modeling technique used to understand the dynamic behaviour of complex systems. Forrester's *Industrial Dynamics* (1961) provided an alternative perspective on management science, but the field expanded later as system dynamics became an acceptable method for approaching other types of policy decisions [Brailsford et al., (2014), p. 26-27]. System dynamics models present results with changes over time that occur within the system boundary. In other words, the conclusions ignore outside factors unless they are included in the process. Since this simplifies complex systems, there is a fine line between what should and should not be included.

*Section 179 System Dynamics: Methodology*

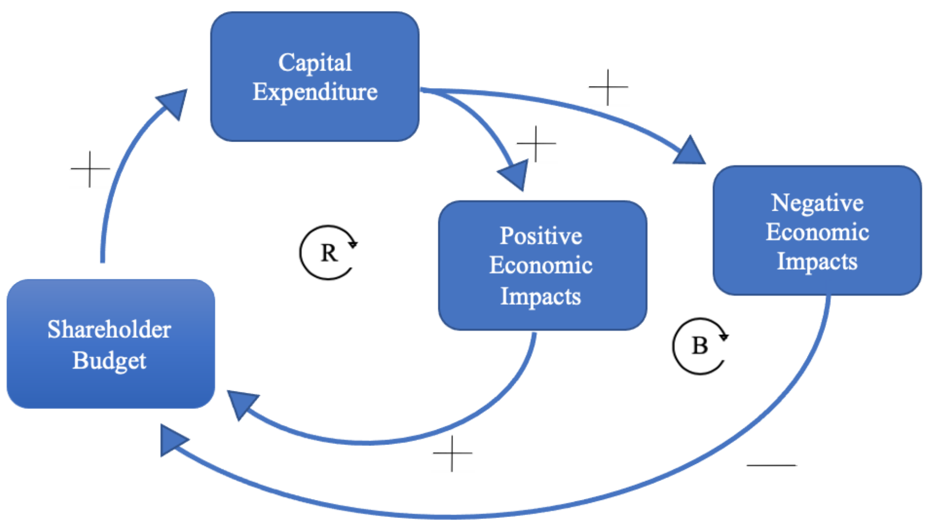
Using the Section 179 model, this research study integrates system dynamics and multi-industry input-output analysis to model and assess the relationships among Section 179, capital expenditures, and their associated economic impacts. The objective is to understand the impact the Section 179 allowance has on the economy, especially on employment, and provide recommendations for the government, business owners, and professionals to help prevent negative results. Simulation was chosen as the methodology, due to the complexity of the phenomena and the limited availability of data. The model examines both short-term (less than five years) and long-term (35 years or more) economic impacts associated with the change in the Section 179 allowance, focusing on allowance amounts of $0 (no allowance), $1 million, $2 million,

$3 million, $4 million, $5 million, and $10 million. The economic impacts measured were sales, employment (Emp), employee earnings (EE), proprietary income (PropInc), other property-type income (OPTI), and indirect business tax (IndBusTax). The industries analyzed (with their relative NAICS codes) were the professions (54), manufacturing (31-33), and the rest of the economy (Other). The analysis of the professional industry highlights the potential impacts of automation on accounting and other skilled labour. Manufacturing was analyzed since it is an industry that has been associated with automation since the first Industrial Revolution and is one of the areas most susceptible to negative impacts (Chui et al., 2016). The results were derived from historical data and scholarly research. The software utilized to conduct the study was AnyLogic 7.3.

*Section 179 System Dynamics: Model Formulation*

As mentioned previously, the model was formulated to investigate the relationship between the Section 179 tax policy and its associated economic impacts. Figure 1 shows a causal loop diagram that provides a basic understanding of the model, reflecting its general nature and the structure of relations between agents.

**FIGURE 1**
**CAUSAL LOOP DIAGRAM OF SECTION 179 AND ITS IMPACTS**




As evidenced by the diagram, there are both reinforcing and balancing feedback loops. As for the former, as Capital Expenditure increases, so does Positive Economic Impacts. This then causes an increase in Shareholder Budget, which will further increase Capital Expenditure.

The balancing loop is similar; however, as Capital Expenditure increase, there is a negative economic impact on Shareholder Budget, which decreases. This, in turn, decreases Capital Expenditure, which reduces the negative economic impacts and increases Shareholder Budget. These two loops operate at the same time.

This thought process is built into the model (Appendix A1). In general, Capital Expenditure causes positive and negative economic impacts (on Sales, Emp, EE, PropInc, OPTI, and IndBusTax), which results in a change to Tax Revenue and Budget Shareholder. Budget Shareholder then impacts Capital Expenditure for the following year. Table 2 presents the data sources for each model parameter.

**TABLE 2**
**DATA SOURCES**

| Description | Parameter | Source |
|---|---|---|
| Automation potential | $\rho_i$ | Chui et al. (2016) |
| Direct employment due to capital expenditure multiplier | $\alpha_{i,j}$ | IMPLAN (2020) |
| Direct employment due to direct sales multiplier | $\beta_{i,j}$ | Ferrari (2017), Statista Research Department (2022), St. Louis FED (2021) |
| Total sales multiplier due to direct sales | $\gamma_{i,j}$ | IMPLAN (2020) |
| Total sales multiplier due to capital expenditure | $\eta_{i,j}$ | IRS (2018) |
| Total economic impact | $\zeta_j^k$ | IMPLAN (2020) |
| Tax rate | $\upsilon_j^r$ | U.S. BLS (2021a), U.S. Department of the Treasury Internal Revenue Service (2021a) |
| Total sales in 2019 | $s_i(t)$ | |
| Total cash flow in 2019 | $q_j(t)$ | IRS (2018) |
| Total budget in 2019 | $b_j(t)$ | IRS (2018) |
| Number of days in the year | $d = 365$ | - |
| Historical average of total depreciation | $\overline{g_\iota}$ | BEA (2020) |
| Historical average of depreciation duration | $\overline{\tau_\iota}$ | BEA (2020) |

The model uses numerous equations, all of which are impacted by the amount of the Section 179 allowance. Equation 1 calculates the adverse direct employment for each industry, based on the automation potential and the amount of capital expenditures for each industry. This adverse direct employment impacts the amount of direct sales generated (see Equation 2). Equation 3 calculates the adverse total sales, based on the adverse direct sales for each industry. Equation 4 represents the positive total sales impact, but this is determined directly by the capital expenditures of an industry. The overall sales impact is then calculated (Equation 5) and is used to determine the economic impacts for each industry (see Equation 6). Equation 7 calculates the cash flow generated as a function of the Section 179 allowance, and it is also impacted by the corporate tax rate and the ratio of the impact of overall sales (Equation 5) to base-year sales. The total tax revenue is calculated to examine how the different economic impacts might affect the government's budget. It is determined by multiplying certain economic impacts (EE, PropInc, and OPTI) by their relative tax rates, adding the tax already calculated through other economic impacts, and then removing the cash flow supplied to a business (Equation 7) because of the Section 179 allowance. Equation 9 calculates the change in Shareholder Budget caused by certain economic impacts (PropInc, OPTI) and the ratio of current cash flow to base-year cash flow. Next, Shareholder Budget is determined (see Equation 10). Equation 11 represents Capital Expenditure calculated as a function of Shareholder Budget. Finally, Equations 12-14 supply the data for the stock-flow diagram; they calculate Net Property, Plant, and Equipment (NetPPE) (Equation 12), the inflow of daily capital expenditure (Equation 13), and the outflow of depreciaion (Equation 14). Depending on the time, this depreciation is determined by the industry's historical depreciation, daily capital expenditures, and the duration of historical average depreciation, or the total depreciation in a duration. The model formulation is as follows:

**TABLE 3**
**SETS, VARIABLES, AND PARAMETERS**

| | |
|---|---|
| **Sets** | |
| $i \in I$ | Set of industries $i$ = {1: professions, 2: manufacturing, 3: other} |
| $j \in J$ | Set of industries $j$ = {1: professions, 2: manufacturing, 3: other} |
| $t \in T$ | Set of years |
| $k \in K$ | Set of multiplier types $k$ = {1: employment, 2: employee earnings, 3: proprietary income, 4: other property-type income, 5: indirect business tax} |
| $l \in L$ | Set of allowance decision alternatives $l$ = {\$1M, \$2M, \$3M, \$4M, \$5M, \$10M} |
| $r \in R$ | Set of tax rates $r$ = {1: corporate, 2: employee earnings, 3: proprietary income, 4: other property type income} |
| $y \in \mathbb{R}_{\geq 0}$ | Set of time values |
| **Decision Variable** | |
| $A_l$ | Section 179 Allowance |
| **Variables** | |
| $C_{i,l}(t)$ | Capital expenditures of industry *i* due to the Section 179 allowance amount, *l*, in year *t* |
| $\Psi_{i,l}(t)$ | Adverse direct employment impact of industry *i* due to the Section 179 allowance amount, *l*, in year *t* |
| $\Theta_{i,l}(t)$ | Adverse direct sales impact due to the adverse direct employment impact of industry *i*, due to the Section 179 allowance amount, *l*, in year *t* |
| $\Phi_{j,l}(t)$ | Adverse total sales impact of industry *j* due to adverse direct sales impact of industry $i \in I$, due to the Section 179 allowance amount, *l*, in year *t* |
| $\mathrm{X}_{j,l}(t)$ | Positive total sales impact of industry *j* due to capital expenditures of industry $i \in I$, due to the Section 179 allowance amount, *l*, in year *t* |
| $\Omega_{j,l}(t)$ | Total sales impact of industry *j* due to the Section 179 allowance amount, *l*, in year *t* |
| $E_{j,l}^{k}(t)$ | Total economic impact, *k*, of industry *j* due to the Section 179 allowance amount, *l*, in year *t* |
| $f_j(A_l)$ | Regression function for Section 179 expense deductions of industry *j*, based on the Section 179 allowance, $A_l$ |
| $f_j(B_{j,l}(t))$ | Regression function for capital expenditures of industry *j*, based on the shareholder budget for industry *j* due to the Section 179 allowance amount, *l*, in year *t* |
| $\mathrm{Q}_{j,l}(t)$ | Cash flow due to the Section 179 allowance amount, *l*, in year *t* |
| $\mathrm{T}_{j,l}(t)$ | Total tax revenue for industry *j*, based on the Section 179 allowance amount, *l*, in year *t* |
| $\Delta B_{j,l}(t)$ | Shareholder budget change for industry *j* due to the Section 179 allowance amount, *l*, in year *t* |
| $B_{j,l}(t)$ | Shareholder budget for industry *j* due to the Section 179 allowance amount, *l*, in year *t* |
| $NPPE_{i,l}(t)$ | Net property, plant, and equipment of industry *i* due to the Section 179 allowance amount, *l*, in year *t* |
| $\omega_{i,l}(t)$ | Total depreciation in duration of industry *i*, based on the Section 179 allowance amount, *l*, in year *t* |

| Parameters | |
|---|---|
| $\rho_i$ | Automation potential of an industry *i* |
| $\alpha_{i,j}$ | Direct employment multiplier of industry *j* due to the capital expenditures of industry *i* |
| $\beta_{i,j}$ | Direct sales multiplier of industry *j* due to the direct employment of industry *i* |
| $\gamma_{i,j}$ | Total sales multiplier of industry *j* due to the direct sales of industry *i* |
| $\eta_{i,j}$ | Total sales multiplier of industry *j* due to the capital expenditures of industry *i* |
| $\zeta_j^k$ | Total economic impact multiplier, *k*, of industry *j* |
| $\upsilon_j^r$ | Tax rate, *r*, of industry *j* |
| $s_i(t)$ | Total sales of industry *i* in base year *t* (= 2019) |
| $q_j(t)$ | Total cash flow of industry *j* in base year *t* (= 2019) |
| $b_j(t)$ | Total budget of industry *j* in base year *t* (= 2019) |
| d | Number of days in a year |
| $\overline{g_\iota}$ | Historical average of total depreciation of industry *i* |
| $\overline{\tau_\iota}$ | Historical average of depreciation duration of industry *i* |

**TABLE 4**
**MODEL FORMULATION**

**Model**

$$\Psi_{i,l}(t) = \alpha_{i,j}\, \rho_i\, C_{i,l}(t) \quad \forall i \epsilon I; \forall l \epsilon L; \forall t \epsilon T; i = j \tag{1}$$

$$\Theta_{i,l}(t) = \beta_{i,j}\, \Psi_{i,l}(t) \quad \forall i \epsilon I; \forall l \epsilon L; \forall t \epsilon T; i = j \tag{2}$$

$$\Phi_{j,l}(t) = \sum_{i \epsilon I} \gamma_{i,j}\, \Theta_{i,l}(t) \quad \forall i \epsilon I; \forall j \epsilon J; \forall l \epsilon L; \forall t \epsilon T \tag{3}$$

$$\mathrm{X}_{j,l}(t) = \sum_{i \epsilon I} \eta_{i,j}\, C_{i,l}(t) \quad \forall i \epsilon I; \forall j \epsilon J; \forall l \epsilon L; \forall t \epsilon T \tag{4}$$

$$\Omega_{j,l}(t) = \mathrm{X}_{j,l}(t) - \Phi_{j,l}(t) \quad \forall j \epsilon J; \forall l \epsilon L; \forall t \epsilon T \tag{5}$$

$$E_{j,l}^k(t) = \zeta_j^k\, \Omega_{j,l}(t) \quad \forall j \epsilon J; \forall k \epsilon K; \forall l \epsilon L; \forall t \epsilon T \tag{6}$$

$$\mathrm{Q}_{j,l}(t) = \frac{f_j(A_l)\, \Omega_{j,l}(t)\, \upsilon_j^1}{s_i(t)} \quad \forall i \epsilon I; \forall l \epsilon L; \forall t \epsilon T; i = j \tag{7}$$

$$\mathrm{T}_{j,l}(t) = \sum_{k \epsilon K} \upsilon_j^r\, E_{j,l}^k(t) + E_{j,l}^5(t) - \mathrm{Q}_{j,l}(t) \quad \forall j \epsilon J; \forall l \epsilon L; \forall t \epsilon T; 2 \leq k \leq 4; r = k \tag{8}$$

$$\Delta B_{j,l}(t) = \frac{\sum_{k \epsilon K} E_{j,l}^k(t) + \mathrm{Q}_{j,l}(t)}{q_j(t)} \quad \forall j \epsilon J;\ \forall l \epsilon L; \forall t \epsilon T; 3 \leq k \leq 4 \tag{9}$$

$$B_{j,l}(t) = b_j(t)\,\Delta B_{j,l}(t) \quad \forall j\epsilon J; \forall l\epsilon L; \forall t\epsilon T \tag{10}$$

$$C_{i,l}(t) = f_j(B_{j,l}(t)) \quad \forall i\epsilon I; \forall l\epsilon L; \forall t\epsilon T; i = j \tag{11}$$

$$NPPE_{i,l}(y) = \int_{t-1}^{t} \left(Inflow_{i,l}(y) - Outflow_{i,l}(y)\right) dy + NPPE_{i,l}(0) \quad \forall i\epsilon I; \forall l\epsilon L;\ \forall t\epsilon T; \forall y\epsilon Y \tag{12}$$

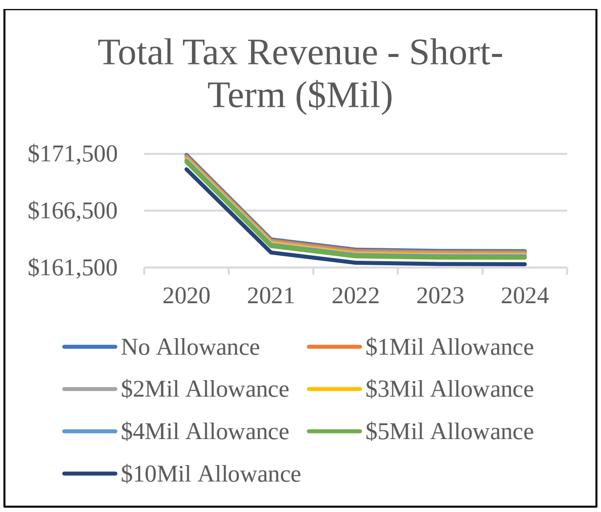
$$Inflow_{i,l}(y) = \frac{C_{i,l}(t)}{d} \quad \forall i\epsilon I; \forall l\epsilon L;\ \forall t\epsilon T; \forall y\epsilon Y \tag{13}$$

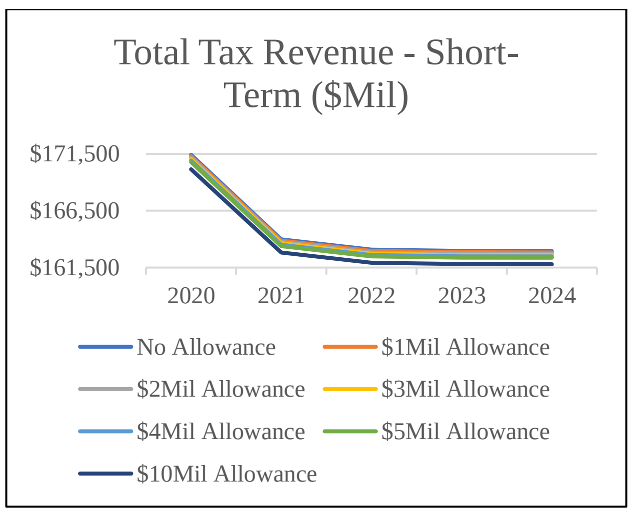
$$Outflow_{i,l}(y) = \begin{cases} \bar{g}_l & t < \bar{\tau}_l; \forall i\epsilon \mathrm{I};\ \forall l\epsilon L;\ \forall \mathrm{y}\epsilon \mathrm{Y} \\ \dfrac{C_{i,l}(t)}{\frac{\bar{\tau}_l}{\mathrm{d}}} & \bar{\tau}_l < t \leq \mathrm{d}\bar{\tau}_l + \mathrm{d}; \forall i\epsilon \mathrm{I};\ \forall l\epsilon L;\ \forall \mathrm{y}\epsilon \mathrm{Y} \\ \omega_{i,l}(t-1) + C_{i,l}(t) & t \geq \mathrm{d}\bar{\tau}_l + \mathrm{d}; \forall i\epsilon \mathrm{I};\ \forall l\epsilon L;\ \forall \mathrm{y}\epsilon \mathrm{Y} \end{cases} \tag{14}$$

**Section 179 System Dynamics: Results**

After the simulation was run with the different amounts of allowances, noticeable trends were observed in the short term. Since the model reached equilibrium early, only the short-term results registered general trends. The different results tracked were total tax revenue, total sales, total employment from CapEx, and loss of employment from automation (as a percentage of the total possible loss of employment) for each industry.

**FIGURE 2**
**TOTAL TAX REVENUE**



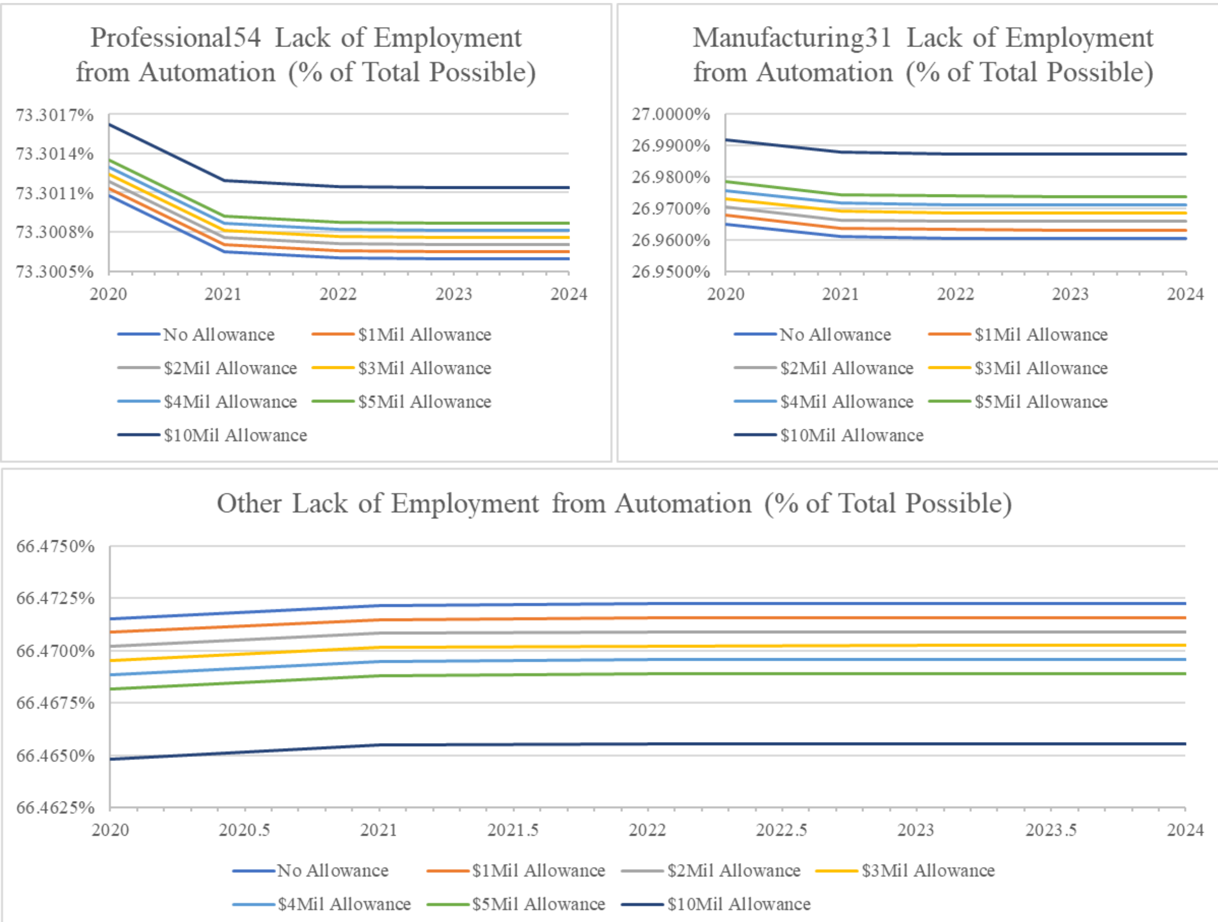




The following charts show the total tax revenue generated by the model. According to the short- and long-term results, tax revenue starts to decrease for the first few years until it levels off. As is evident in the long-term graph, the model reaches equilibrium around 2024. The graphs indicate that increasing the allowance will generate a decrease in tax revenue, and as time goes on, in the short run, there will also continue to decrease. This could be due to increases in Section 179 expense deductions, as more businesses are created from the resulting economic growth.

**FIGURE 3**
**TOTAL SALES**


The graphs in Figure 3 represent a similar downward trend as the model reaches equilibrium. As the Section 179 allowance is increased, total sales and total employment both increase. The long-term results are not presented, since the the model reaches equilibrium early and no change occurs after. Given the results presented so far, the findings from the model run counter to the hypothesis in this paper. The economy seems to be propsering from the increases in the allowance, and jobs do not seem to be threatened. What follows, however, reveals that certain industries may not be improving as much as the overall economy. A table of the economic impacts is included in Appendix A2 to provide an understanding of the total benefits, based on the current value of the dollar.

**FIGURE 4**
**LOSS OF EMPLOYMENT FROM AUTOMATION**




These graphs show a loss of employment in each industry due to automation. For the purposes of the model, the worst is assumed, namely, that all jobs at risk of being automated are automated. Loss of Employment is calculated by dividing the Adverse Employment Impact by the Positive Employment Impact generated from Capital Expenditure. This Positive Employment Impact is equivalent to the total possible employment from capital expenditures if adverse effects (in this case, automation) are ignored. For example, suppose $10,000 is invested in capital expenditures. Without the potential of automation, this investment creates 100 jobs. With automation, however, it actually creates only 40 jobs, which means that there is a 60% loss of employment from automation. The results were also started at 2021 to provide an expanded view.

Certain numbers seem high and unlikely, like 73.3% for professional industry, but this is a worst-case scenario. The assumption is that every job that could be automated would be. This percentage is also an effect of the Direct Employment Due to Capital Expenditure multiplier, which indicates that for every dollar invested in capital expenditures, X number of jobs are created. For instance, when accounting firms purchase more computers, they are able to hire more entry-level employees. Compared to the other industries in the model, the professional industry has a much higher multipler.

The argument here is that, as the allowance increases, the percentage of loss of employment from automation would also increase, since the greater the allowance, the more potential there is for automation. As the charts indicate, this is the case for the professional and manufacturing industries. Other studies, however, show that increasing the allowance decreases the overall adverse effect on the economy, which means that employment in the economy as a whole benefits from the increases in the Section 179 allowance; however, certain industries experience a negative effect. In general, the model shows that the effects of changes in the Section 179 allowance are not drastic, but as previous research shows, this investment incentive has signifcant impacts on the economy.

It should be noted that the data for this study were collected during the COVID-19 pandemic, a time of substantial economic downturn. Since its inception, the purpose of Section 179 and other bonus depreciation has been to stimulate the economy and employment through asset investment during periods of economic downturn, and this has historically been the case. Therefore, in analyses of economic growth, as the economy recovers, it is expected that there would be significant periods of investment and increased automation, followed eventually by a period of equilibrium, where investment levels off as the recovery continues. These investments in automation are long-term and will have prolonged impacts on the employment trends of a company and on its strategic direction. Moreover, historically, it is rare for a company to reverse direction by automating a process, then shifting back over time to manual production. If anything, in the wake of these investments, automation will continue to increase as processes are further streamlined. Based on the historical trends, the authors believe that the results from the models in this study will apply to future periods, post-COVID-19.

*Section 179 System Dynamics: Future Work*

Currently, the model supports the argument of this paper. There is, however, future work that could provide more accurate results and lead to different conclusions. For instance, the current model does not consider the types of jobs created and replaced. This relates to Frey and Osborne (2017) and Chui et al. (2016), who distinguish skilled versus unskilled jobs. Also, non-economic factors must be considered when considering economic development, including social and technological advancements (Martins and Veiga, 2014).

Future work might also incorporate stock flow into the simulation. This is not needed to run the simulation, but it might eliminate the equilibrium seen here and could alter the results altogether. A candidate stock for this model would be NetPPE. It could be incorporated by making Capital Expenditure a function of both Budget Shareholder and NetPPE or Depreciation (the outflow). As the value of NetPPE decreases and depreciation continues (the age of machinery and equipment), Capital Expenditure should increase (since shareholders should decide they need newer equipment). The only reason it was not used in this model is that there was a lack of statistical significance in this relationship with the current numbers; however, a regression analysis might indicate a way to incorporate this stock.

There is also room to expand on the technological impacts. Rate of Adoption, for instance, could be incorporated, or Automation Potential could be a function dependent on Employment Level. For instance, in an extreme case, suppose 100 jobs are created on day, one with an 80% likelihood that those jobs would be automated, and, as it turns out, 80 of the jobs are. The next day, there should be a 0% likelihood that the remaining jobs will be automated since technology does not evolve that fast. It would also be interesting to conduct a sensitivity analysis of Automation Potential.

Furthermore, the model does not account for supply and demand. For instance, a demand for products should be considered in an analysis of total sales. Even though a company may invest in capital expenditures to increase production, it does not necessarily mean that everything produced will be sold. The supply of employees and the job market should also be considered. Just because there is an increase in jobs created does not mean there are enough workers to fill those jobs. Also, people may not want certain kinds of jobs, so that automation would be needed to replace the positions.

Other future research might include more causal loops. The Section 179 allowance, for instance, could be endogenous and depend on the tax revenue generated, on the current status of the economy, or even on the current political structure. If the economy is doing well, policy makers may not prioritize boosting the Section 179 allowance, or the majority of Congress might be opposed to tax incentives if they feel a need to generate more tax revenue for other programs. There might also be a connection between Tax Revenue and Capital Expenditure or Adverse Employment Impact since the government budget plays a role in the economy and is not merely an outcome.

Finally, another suggestion for future research is to test this model three to five years after the COVID-19 pandemic to evaluate its sustainability, holding other external variables constant during the test period. Based on prior trends, it could be expected that under better economic conditions, the impact would be weaker than during the period covered in this study, but that the model would still apply.

## Automation and Technological Unemployment

The main intention of Section 179 is to increase capital investment. If it is successful, more businesses, preferably ones with smaller assets or profit, will purchase equipment, software, and other qualified property, since they can take a larger tax break the year of the purchases. The combination of technological improvement and an increase in the incentive to invest in capital should cause a rise in automation. This, in turn, would result in technological unemployment, and at least a portion of the economy would suffer.

### *Definitions*

To start, a definition of automation is in order. According to Julius Rezler, a 20th-century sociologist, automation can be defined as "the latest phase of mechanization in which the human operator is replaced by automatic controls" [Rezler (1969), p. 6]. Note that all mechanization is not necessarily automation. For instance, a librarian usually has to climb a ladder to reach the top-shelf. With the technological improvement of an automatic lift, or even a robotic arm, that can extend and grab, the task of climbing the ladder is replaced. The librarian, however, must still perform the task; that is, the human operator has not been replaced.

Along with changes to the definition of qualified property, Rezler has coined the term *cybernation*, "a type of automation [… that] refers to the application of computers to the production process in both the office and the factory" [Rezler (1969), p. 6]. With the fourth industrial revolution underway, cybernation has become more pertinent (Oztemel and Gursev, 2018; Deloitte, 2015). In terms of Section 179, with the introduction of software as qualified property, the coincidence of cybernation with automation is an issue – both can result in technological unemployment. Technological unemployment "differs from other types of unemployment [… in that] jobs themselves are eliminated and the unemployed, even if rehired, cannot return to the same job because it no longer exists." It may also "last longer than other types" of unemployment, like cyclical or seasonal unemployment, where "the worker temporarily loses his employment, but his job is not eliminated" [Rezler (1969), p. 25-26].

### *The Struggle Between the Sides: A Quick Overview of the Debate*

The debate over whether automation causes technological unemployment has been around since the first industrial revolution. As one can infer from an argument that has lasted this long, there is no distinct answer. Even experts draw different conclusions, since "the very same statistical data may be subject to different interpretations depending on the economic philosphy or ideology" [Rezler (1969), p. 23]. For instance, economists using a microeconomic view in one study "reported that no technological unemployment of importance was noticed in the firms." Experts with a macroeconomic perspective, however, "have found large-scale technological unemployment" [Rezler (1969), p. 14-15]. One main argument of the macroeconomists is that the "rise in output per man-hour [should be] accompanied by an equivalent increase in output [or else] employment (measured in terms of total hours employed) will decline." Based on this assumption, scholars found that automation "eliminates 30,000 to 50,000 jobs weekly, or between 1.5 million and 2 million jobs yearly" [Rezler (1969), p. 39-40]. As mentioned previously, however, arguments against this view still rise. For instance, opponents have argued that "displacement is not equivalent to unemployment," that an increase in productivity is not completely attributable to technological change (since it can also stem from an increase in efficency or changes in management styles), and even that the issue is too complicated to use such a simple assumption [Rezler (1969), p. 39-40].

Scholars and experts in industry disagree on these points. For example, if automation promises higher profits, corporate managers are more likely to manipulate data to show that the amount of technological unemployment is insignificant, or even that there is job growth. Union leaders, on the other hand, might use opposing arguments to promote hiring over investing in automation, in hopes of expanding union membership. Either way, one must take into account the biases of experts when it comes to such a broad topic of debate.

*History of Technological Unemployment Resulting From Automation*

One key indicator of technological unemployment stemming from automation can be seen throughout history. Multiple industries over the past century (and even beyond) have felt the effects of automation. This section will look at different instances when an industry has been impacted by the introduction of automation.

Even though examples of automation date back for decades, the first one that will be noted here occurred in the years preceding the Great Depression. During the 1920s and late 1930s, the steel industry introduced a revolutionary innovation into its manufacturing process, the continuous-strip method. Developed in 1918, this method transformed steel production. Steel was in high demand, mainly due to the blossoming automobile industry, so the improvement was seen as a positive on the surface. This change, however, resulted in an "increase in the amount of steel manufactured … from 181,000 net tons in 1925 to 10 million tons in 1937, doing away with the need for hundreds of workers per ton" [Bix (2002), p. 19]. Newspapers even took notice, as evidenced by an article titled "Continous Mills Voracious in Cost, but How They Produce!" The Temporary National Economic Committee researched the issue in 1939. Their hearings, published as *Investigation of Concentration of Economic Power: Technology and Concentration of Economic Power*, stated that "126 men in automatic steel mills can produce the same tonnage as 4,512 men in hand mills [which] represents a 97 percent reduction in man-hours.… Human labour is practically eliminated in the hot-strip mills. Electrical power is substituted …. The strip mills are displacing 84,770 workers" [Temporary National Economic Committee (1939), p. 16459]. After finishing the hearings, "TNEC's members … [concluded] that the adoption of continous-strip mills ultimately cost jobs" [Bix (2002), p. 21].

The 1950s and 1960s faced similar instances. In 1955, for instance, Bank of America's electronic recording machine-accounting (ERMA) threatened the bookkeeping industry. The new technology required only nine operators, and "ERMA reportedly performed the functions of fifty bookkeepers," creating a net loss of employment opportunities [Bix (2002), p. 242]. Switchboard operators also saw a decline due to technology. With the introduction of dial systems, "the Bureau [of Labor Statistics] concluded technical changes in phone services had eliminated 71,824 jobs, a 33 percent labour force reduction" [Bix (2002), p. 23]. Even in the late 1990s, the last of the former switchboard opeators were still struggling to compete with this system, showing the long-term effects industrial change can have on the technological unemployed (Rimer, 1996).

Along with these services, manufacturing still felt the pressure. In the 1960s, Rezler (1969) observed, "[I]n the industries that have adopted automated technology, the employment of production workers in the past decade has either declined or remained stationary despite a sharp increase in the volume of production" [Rezler (1969), p. 37]. This emphasizes the disproportion between production and employment that derives from technology and the continued technological impact on the manufacturing industry.

Sadly, an era of relief for the manufacturing industry had yet to come. Following the 1960s, industrial robots began to become more prevelant. For instance, "Chrysler adopted dozens of spot-welding robots that reportedly did the jobs of 200 men" [Bix (2002), p. 276]. Likewise, General Electric's spray-paint and adhesive robots displaced "one or two workers at each step" of the process[Bix (2002), p. 276]. Even automation in the production, bottling, canning, and packing processes would lead to an estimated "drop [of] a thousand jobs over the next five years" [Bix (2002), p. 255].

As evidenced by the steel industry in the 1920s-1930s, by services in the 1950s and 1960s, and by manufacturing from the 1970s onward, technological unemployment has been an issue in the United States, and, as one could predict, today is no exception.

## Potential Technological Unemployment in the Future

With today's seemingly endless improvements in artificial intelligence (AI), industries will be impacted by technology in ways society has never seen before. The sections that follow examine the professional industry closely in regard to the threats to labor posed by AI, along with possible implications deriving from the Section 179 allowance.

### *Accountants*

At first glance, the professions may seem to be the occupations furthest from the reach of automation by AI. Events in the past decade, however, have shown signs of potential technological threats, especially to accountants, doctors, and lawyers.

As mentioned previously, there has already been a threat to the accounting industry, especially to bookkeepers, with Bank of America's introduction of ERMA. The employment of accountants and auditors, however, has shown no clear sign of suffering from increased automation in the industry. It is even projected to grow by 6% from 2018 to 2028, according to the U.S. Bureau of Labor Statistics. The Bureau also mentions, however, that "technological change is expected to affect the role of accountants over the next 10 years. As platforms such as cloud computing become more widespread, some routine accounting tasks may become automated" (U.S. Bureau of Labor Statistics, 2021a). Alongside this, other technologies, like robotic process automation (RPA), artificial intelligence (AI), the Internet of Things (IoT), and advances in Big Data are being implemented in this profession.

As one of the rising technologies, RPA has multiple capabilities in the realm of accounting. It can automatically log in and keep passwords secure, retrieve large amounts of data from the internet, and automatically input Excel information into an interactive PDF file, such as a W-4 form (Keys and Zhang 2020). This "bot" is capable of being implemented in the public tax environment. Mezzio (2019) mentions that RPA creates a "time savings of 70%" by automating the preparation, conversion, and submission of tax documents, a process tax staff are very familiar with. While RPA handles mundane and repetitive tasks, AI expands beyond this by making cognitive decisions. Petkov (2020) provides numerous examples of how AI can replace the human functions of accounting, including preparing automatic journal entries for multiple financial statement accounts and analyzing the financial statements of invested companies to determine the most advantageous. The IoT, the network of objects connected through the internet, follows suit with these changes. In terms of accounting, implementation of this technology offers "enormous potential" because it can replace manual inventory counts and assist with other accounting measures (Brown-Liburd and Vasarhelyi, 2015; Vasarhelyi et al., 2015).

Although this technology is expansive in its capabilities, there are mixed responses from employers and experts. With RPA, for instance, some anticipate there will be no change to hiring, while others believe there is potential for a reduction in hiring at the lower levels (Cooper et al., 2019). Accounting firms also tend to stick to the status quo, due to their "developed structures" (Schmidt et al., 2020). They can be resistant to change, as is evident in their "persistent lag behind their clients in their adoption of earlier technological advances" (Alles, 2015) and their "obsolete methods of business measurement and regulations" (Romero, 2012). Licensed professionals in general are threatened "as professional work is increasingly automated, its mystique is dissolved, and the work is increasingly executed by paraprofessionals using smart technologies" (Sutton et al., 2018). Conversely, others see this technology as a complement to accounting knowledge. In opposition to the opinions of Frey and Osborne (2017), some hold that accountants will be able to focus their attention on more opportunistic ways of providing value and, thus, will not be subject to as high a risk of automation as the profession adapts (Richins et al., 2017). As stated previously, however, this depends on the profession's no longer resisting this change and being open to evolving soon.

### *Doctors*

Other professionals who are susceptible to technological advancements in AI are medical specialists. In 2019 alone, there have been numerous advancements towards AI in medical fields, ranging all the way from the prediction of readmissions to the automation of scribing and transcription (Park, 2019). In particular, radiologists and pathologists have seen significant pathways paved for automation.

Radiologists interpret medical imaging to diagnose and treat injuries and diseases. They examine x-rays; computed tomography, MRI and PET scans; and ultrasounds. AI, however, has shown the capability to do the same thing. For instance, researchers at Google have developed an algorithm that can detect lung cancer as well as radiologists. It even outperformed six radiologists "with absolute reductions of 11% in false positives and 5% in false negatives.…This creates an opportunity to optimize the screening process via computer assistance and automation" (Ardila et al., 2019). An article from the *New England Journal of Medicine* stated three years before Google even tested their algorithm that "machine learning will displace much of the work of radiologists" [Obermeyer and Emanuel (2016), p. 1218]. Some researchers even go as far to say that radiologists are "doomed for extinction" (Budd, 2019).

Along with radiologists, pathologists have experienced the emergence of AI. Germano De Sousa, an oncology laboratory in Portugal, recently incorporated IBM Watson into their operations. IBM Watson is an AI system that uses deep learning and layered algorithms to create an artificial neural network. It constantly learns and improves, providing businesses with tailored solutions. In a promotional video for IBM Watson, a biologist at this lab states that this AI system can "speed up and scale that process of interpretation and report production, while maintaining the quality." She also claims that she trusts the computer, despite knowing "how difficult it is to annotate the sequencing data" (IBM Watson Health, 2019). Pathologists at this lab are the ones who interpret data and generate reports, so IBM Watson is doing the work they would normally tackle. Later in the video, the Director of the Molecular Pathology Lab at this company, José Germano de Sousa, MD, mentions that he can perform other tasks, because IBM Watson produces reports more quickly (IBM Watson Health, 2019). However, expanding the capabilities of AI will soon cause a lack of need for people to perform other tasks.

### *Lawyers*

Law is subjective, so it is highly improbable that a computer will be representing a plaintiff in court or defending a corporation. There is, however, the possibility of AI's replacing humans who conduct pre-trial research. Kira Systems, for instance, uses AI technology to scan contracts and summarize relevant content. Specifically, it "predicts the relevance of clauses and information in a fraction of the time it would take a lawyer or paralegal" [Agrawal et al., (2019), p. 34]. Similarly, Symantec's Clearwell system "can present the results graphically and proved capable of analyzing and sorting more than 570,000 documents in two days" [Frey and Osborne (2017), p. 17]. Both systems are capable of finding relevant pre-trial information far more quickly than a human. This research is usually done by entry-level lawyers, so they face a greater risk of technological unemployment than established lawyers.

There are multiple instances of professions facing potential obsolescence, but the professional industry seems less likely to face automation from AI compared to the transportation and retail industries. It will affect all industries, but especially when seeking professional advice, humans feel a sense of comfort receiving it from another human rather than from a computer. This means there will highly likely be a need for these professions for years to come and that technology will not replace humans in these industries as soon as in others. Entry-level professionals are the most susceptible, but like safety drivers in the front seats of autonomous cars, people in these positions will be needed to monitor and verify sensitive and impactful information. They differ from safety drivers, however, in that the laws and rules are constantly changing in these professions (as is evident in Section 179), whereas traffic signs and roads tend to remain stable.

### *Relation to Section 179 and Model Results*

Having examined how the professions might experience technological unemployment due to automation and AI, it becomes possible to relate these technological investments to the Section 179 deduction.

A look at the professions suggests that some would benefit from Section 179. In the 2017 amendment, computer software was added as qualified property, which means, for instance, that advanced accounting software can be expensed. This is also true of Clearwell's eDiscovery System and Kira Systems. Exact prices cannot be given due to different specifications for acquiring a purchase quote, but in general, software packages like these high-end AI tools are not cheap; therefore, providing relief for the year of purchase through the smaller tax bill can help a company. As with these software packages, an exact price for IBM Watson is hard to come by, but as one source claims, just to manufacture it can cost up to $3 million (Gustin, 2011). Nevertheless, as can be seen in the example of IBM Watson given above, medical centers can greatly benefit from this technology.

The Section 179 model shows that, at the current allowance, the professional industry faces a potential loss of employment from automation of 73.304%. As mentioned previously, this number seems fairly high, but it reflects a worst-case scenario. As of 2019, there are 1,436,100 accountants and auditors (U.S. Bureau of Labor Statistics, 2021a) and 62,600 tax preparers in the United States (U.S. Bureau of Labor Statistics, 2021b). Assuming that the use of automation would be distributed evenly over the whole professional industry, this would mean 1,098,607 jobs would be automated. However, obviously, it is not that simple, because certain occupations, like auditor, may be less susceptible than others, like bookkeeper. Future research that further breaks down the professional industry may provide better insights into the potential loss of employment from automation.

**What Makes Today Different?**

The history and possible future of technological unemployment have been addressed, but important questions arise: What makes today different? Why should these concerns not be considered subject to the Luddite Fallacy, as automation has been in the past? There are two factors that make the mass movement towards automation and AI a real threat: the short time frame in which the innovations have been occurring and the total reach of the technology.

The 20$^{th}$ century saw the second and third industrial revolutions. This paper discusses these eras and the time between where technological unemployment occurred. Overall, unemployment fluctuated, but it is hard to single out technology as the main reason. This is not to say that people did not experience technological unemployment, but the country as a whole was able to find ways to address the problems and move past them. Even before, when the first machines replaced human labor, there was a long period of time for the situation to develop. Today, however, advancements in automation and AI are happening much more quickly. A writer from the *Washington Post* wrote, “The industrial revolution unfolded over centuries. Today’s technology revolutions are happening within years.” He then refers to self-driving cars, manufacturing, professionals, and other examples of the rise of AI (Wadhwa, 2015). The risks of job loss to AI seem to be coming faster than expected. For example, “A University of Oxford study from 2013 estimated that 47% of U.S. jobs may be at risk within the next two decades because of advances in artificial intelligence and automation. The White House Council of Economic Advisers estimate that workers making below $20 an hour would have an 83% chance of losing their jobs to robots in that span” [Dillow and Rainwater (2017), p. 70].

There is also concern on the part of some of the world’s smartest individuals, as is evidenced by their signatures on an open letter titled “Research Priorities for Robust and Beneficial Artificial Intelligence: An Open Letter.” Signed by Elon Musk, Stephen Hawking, Steve Wozniak, and numerous other influential people, the letter argues the need to focus AI on beneficial activities and to be wary of pitfalls. More specifically, there is “valuable research to be done on how to … mitigate adverse effects, which could include increased inequality and unemployment” [Russel, et al., (2015), p. 106]. Obviously, there is concern over how rapidly automation and AI are being implemented.

A second reason why these concerns should not be considered a Luddite Fallacy is the expansive reach of technology. With Big Data and the new capabilities of machine learning, there is the potential to affect a broad range of industries. This can be seen just by looking at the industries analyzed earlier. As they begin to experience technological unemployment, “workers won’t be able to shift to new kinds of predictable, routine work, because it’s exactly that kind of work that’s being automated, not just in agriculture or manufacturing or service industries but across all of them simultaneously” [Russel et al., (2015), p. 72]. In other words, since all industries are being affected concurrently, there is no industry for the unemployed to transition to.

After examining the history of technological unemployment and some industries that could face technological unemployment, one can conclude that the technological unemployment resulting from AI introduction will be different from anything experienced in the past and should be cause for concern. It is also important to note that businesses are given an extra incentive to invest in AI by Section 179, which provides them with tax relief, resulting in a greater chance that technological unemployment will follow.

**Recovery Policy**

As just noted, with the increased incentive from Section 179 for companies to invest in automation and AI, workers will start to experience technological unemployment. To combat potential job losses, policies will be required, and one approach is tax policy.

When it comes to tax policy, there are two main approaches: incentive-based and penalty-based. To address the problem, policy makers can promote employment through retraining tax credits, employment credits, and even transportation credits. They may also discourage too much investment in automation through a techno-tax on either the companies purchasing the replacement equipment or on the companies that manufacture the equipment.

*Incentive-Based Tax Policies*

Three main incentive-based tax policies are retraining credits, employment tax credits, and tax breaks for transportation. Although all focus on aspects like education, growth, and connection, they all directly or indirectly promote employment.

Discussions about, and legislation for, retraining have been around since World War II. Usually, there is an emphasis on federally funded programs. One state, however, has implemented a tax credit that focuses on education by employers. In 1994, politicians established the Georgia Business Expansion and Support Act (BEST). Part of the BEST Act allows any Georgian company to take a tax credit of 50% for direct training expenses, including the cost of instructor and teaching materials, employee wages during retraining, and reasonable travel expenses. This credit can be used to offset up to 50% of a company's tax liability and can be applied to future tax liability for up to 10 years (Georgia Department of Revenue, 2010). This creates an incentive for employers to educate their employees and have a system in place to promote rising status. Limited data are available on the success of this credit, however. Also, Georgia's unemployment rates and employee turnover rates from 1994 onward do not differ significantly from those of the United States in general, so it is hard to conclude whether the credit was successful. Nevertheless, a tax credit could benefit smaller businesses. For instance, a study in 1998 mentioned how "smaller employers were much less likely to provide formal training programs than employers in larger establishments" (Lynch and Black, 1998). These are the same businesses that Section 179 is targeting, so a tax credit that promotes holding onto employees and retraining them will benefit smaller companies. This, in turn, will result in less technological unemployment since employees can advance past the jobs AI and automation are taking over.

A second type of incentive-based tax policy is to provide a tax credit for employment by a company. Once described as a "labour differential tax," it means that "all employers would receive tax credits based on the amount of wages paid, balanced by extra taxes on employers who enjoyed profits deemed 'excessively large as compared with total wage payments'" [Bix (2002), p. 78]. Although this tax may seem to be directed more at businesses that are not paying sufficient wages, it also benefits businesses that have a higher payroll-to-gross-profit ratio. Companies can qualify for this credit by increasing employee wages or by hiring more employees and increasing payroll through additions to the system. Although the former seems more likely, both are viable options. It also discourages companies from letting employees go, because it lowers their payroll expense and increases their chances of having to pay a tax instead of receiving the credit.

Currently, there are forty states that have credits like this, employment tax credits that are based on new payroll costs or the number of net jobs created, and they have proved to be effective. For instance, Ohio's Job Creation Tax Credit, established during the early 1990s, "had a positive impact on job creation in Ohio between 1993 and 1995, with between 63 and 68 percent of new jobs (2764 to 3976 jobs)" [Faulk (2002), p. 264]. Likewise, Georgia saw improvements due to the tax credit, as firms that took the credit generated

"24.5 to 27.6 percent more jobs (1870 to 2196 jobs) than eligible firms not taking the credit between 1993 and 1995" [Faulk (2002), p. 264]. A working paper created in 2016 concluded that the overall "cumulative effect of [Job Creation Tax Credits] is positive, but the effect takes two to three years to be fully observed in the data" [Chirinko and Wilson (2016), p. 44]. Obviously, there is an employment benefit from these tax credits, so establishing a credit at the federal level or seeing the remaining states create their own employment tax credit could help combat any technological unemployment that may arise from AI and automation. States that have this tax credit could also increase the amount or raise the minimum requirements for eligibility.

A third type of incentive-based tax policy involves connections, specifically between areas of residency and locations with potential business growth. If the federal and/or state governments encourage investment in areas facing unemployment through large tax breaks, these areas will see a rise in job opportunities. For instance, a high-speed rail line from Syracuse to New York City has the potential to create jobs, while slashing travel times. This idea was first examined in 2012, when "one study showed, high-speed rail could help create at least 21,000 new jobs" (Weiner, 2012). Not only would infrastructure like this extend the reach of potential employees, but the development of the railroad would create jobs in itself. This idea also reflects a positive perspective towards technological advancement since high-speed rail transportation is an innovative technology.

After examining these incentive-based tax policies, credits for retraining programs and the hiring of new employees and tax breaks for connective transportation seem like viable options, with the potential to counter the technological unemployment arising from the introduction of AI.

*Penalty-Based Tax Policies*

The other approach to tax policy, penalty-based legislation, would limit the amount of automation businesses want to invest in, which in turn would decrease technological unemployment. This can be done through a techno-tax on companies that purchase equipment for automation or on the companies that produce it.

The idea of a techno-tax was first brought up during President Franklin Delano Roosevelt's administration. Facing technological unemployment, experts suggested a tax on companies that were replacing human laborers with machines. This penalty would "tax profits on machine-made goods to provide relief for affected workers … taxing technology according to how many workers it replaced" [Bix (2002), p. 76-77]. Machines that perform jobs humans could not physically do would be exempt. In short, this would be a tax on an employer's intentional displacement of workers by acquiring machinery. There was also a suggestion from the International Association of Machinists in their draft of a "New Technology Bill of Rights," proposing that "the state and nation have the right to require employers to pay a replacement tax on all machinery, equipment, robots, and production systems that displace workers" [Bix (2002), p. 277]. Canada's Green Party recently proposed a robot tax, which would require a company to pay a tax equivalent to the income tax paid by the employees being replaced by automation, and the revenue generated would be used to fund retraining programs (Colón, 2019).

There are some concerns about this approach, however. First, large legal battles could occur between the taxed corporations and the IRS over definitions of what types of technology the tax should apply to. The IRS would also have to determine when the tax applies, since job displacement does not necessarily happen simultaneously with the purchase of automation. Usually, the duties of the affected employee erode until the position becomes obsolete and is no longer needed. This penalty would also discourage investment in any automation at all, limiting the technological growth of a business and leading to a lack of competitive advantage. Some scholars have examined these issues in the case of the robot tax. Goulder mentions several policy responses to inevitable automation, including the creation of a federal regulatory agency, an imputed salary assigned to a machine that would be equivalent to the salary of a worker doing the same task, and restrictions on amortization to discourage certain kinds of investment (Goulder, 2019). Either way, he believes politicians will continue to focus on a robot tax, since it provides "a tax that can be increased with minimal political risk … [T]hey can tax the hell out of it without significant repercussions" [Goulder (2019), p. 1206]. Soled and Thomas (2018) argue that the tax system needs a complete overhaul. They recommend that Congress “reconfigure its anachronistic 20th-century approach to taxing 21st-century income” by applying the same tax rate to all income, including labour income, trade and business profits, investment income, and capital gains; by removing subsidized tax expenditures that promote capital usage; and by investing in tax expenditures that cultivate human capital.

The other option for penalty-based tax policy would be to tax companies that create automation technology. Punishing technological innovation seems like a stretch in a capitalist society, but there is potential for this strategy. This is most evident in Andrew Yang’s proposal of a Freedom Dividend, whose main goal would be to provide every U.S. citizen with a universal basic income (UBI). Yang claims that the money could come from “the biggest winners from AI and new technologies” through a value-added tax (Yang, 2019). Essentially, the government would take from the companies that cause technological unemployment from automation and distribute the wealth to everyone. UBI is not a new idea, and there have been recent advancements towards this proposition. For instance, there has been experimentation with UBI in a dozen countries, including Spain, Kenya, the Netherlands, Uganda, and India. Influential leaders like Mark Zuckerberg, Elon Musk, Pierre Omidyar (eBay’s founder), and Chris Hughes (a Facebook co-founder), have all mentioned or explored the concept of a UBI (Dillow and Rainwater, 2017).

Of course, there are issues with the idea of a UBI. One significant concern relates to the Silicon Valley supporters of UBI. First, it seems contradictory for the leaders of tech companies to back a tax that would reduce their profits. One article questions Elon Musk and Mark Zuckerberg’s “profit-maximizing decisions to employ sub-contracted, precarious, over-worked and minimally paid workers” and mentions how they avoid taxes through offshoring profits and tax havens (Fouksman and Klein, 2019). It seems ironic that they want the government to supply money to the less fortunate, while they show no sign of caring for the less fortunate in their own business dealings and while they are able to avoid taxes altogether through their tax strategies. There is also the cynical viewpoint that these Silicon Valley supporters are trying to get more profit into their own pockets. Since they have such a large influence on society and consumers, these leaders could persuade consumers to purchase their goods with the new monthly dividend. For instance, imagine Apple marketing its newest iPhone as affordable by everyone, with monthly payments coming directly from their government dividend.

Techno-taxes have the potential to assist with an unemployment crisis stemming from automation. There are drawbacks, however, to penalty-based policies, like the discouragement of investment in any automation or a possible backlash against a UBI. At the moment, tax credits seem to be the more approachable alternative.

*Proceeding With Caution*

After reviewing their tax options, politicians could move to stop technological unemployment. With the global pandemic and newly appointed Biden administration, however, a large amount of focus has been on coronavirus-related relief and stimulus. There has been talk about repealing aspects of the Tax Cuts and Jobs Act, albeit this does not include Section 179. President Biden has proposed multiple reforms, including raising corporate tax rates from 21% to 28%, instituting a payroll tax, and imposing a “10% Offshoring Penalty surtax” (Watson et al., 2020; Joe Biden Campaign, 2020).

In regard to post-pandemic recovery, some economists have proposed full expensing. This would essentially replace Section 179 and allow all capital investment to be expensed in the first year. One economic report suggests keeping taxes low and promoting “pro-growth structural reforms, such as full expensing, … preventing scheduled tax increases and constraining spending growth” (Michel, 2020). This approach, however, would run counter to President Biden’s plan to raise corporate taxes. Other economists believe that full expensing “offers a cost-effective solution to encourage additional investment over the long run” (York and Huaqun, 2020) and would cause “employment [to] grow by more than 1 million full-time equivalent jobs” (York, 2020). However, these jobs, as discussed previously, may not necessarily be filled by human labour. Given President Biden’s tax reforms and the proposals for permanent full expensing, corporations might find investing in automation their best option to avoid paying high taxes.

### Possible Implications

The findings of this study have different implications for different stakeholders, including the government, small businesses, entry-level professionals, and senior-level or managerial professionals. These are as follows:

*Government*

For the government, tax policy, preferably incentive-based proposals like retraining credits, employment tax credits, tax breaks for transportation, or a combination of the three, has the power to combat the technological unemployment faced by industries in the future. A techno-tax or the institution of a UBI could also reduce some adverse effects. With either approach, legislators should be proactive. Signs of the potential negative impact of automation are evident, and it would be foolish to solely incentivize investment in automation. The trend of increasing the Section 179 allowance is aimed at encouraging economic growth, but it should be accompanied by policies that assist the workers who may be replaced by automation. There is a relationship between this allowance and automation, and politicians should acknowledge it.

*Small Businesses*

One of the groups most strongly impacted by the Section 179 allowance is small businesses. The intent of Section 179 is to encourage growth. For owners and managers of these businesses, it makes sense to take advantage of this allowance, since it provides more cash flow in the year following the capital expenditures. As technology becomes more available to small businesses, their investments in automation could increase their cash flow and lead to an increase of efficiency for their customers. As should be evident by this paper, however, small business leaders should be cautious about the potential detrimental impacts of investing in automation.

*Entry-Level Professionals*

On the adverse side of this model, entry-level professionals face the biggest threat. Realistically, professionals beginning their career are more likely to be replaced by automation than higher-level professionals. A couple of recommendations for this demographic would be to focus on soft skills or to get an education in an additional field. Having skills or knowledge that transcends the merely technical aspects of a job can go a long way.

*Senior-Level and Managerial Professionals*

While entry-level professionals are more susceptible to job loss from automation, senior-level and managerial professionals are still at risk. With the kinds of technology being developed now, all have the potential to be replaced. Like their less experienced counterparts, they would benefit from skills and qualities apart from the technical aspects of their jobs. Continued education, which is a requirement in many professions, also makes a difference when counteracting this threat.

Higher-leveled professionals, like small business owners, should be mindful of the potential adverse effects of investing in automation over human labour. They should understand both the benefits and the costs when proceeding with newer technology. Entry-level workers are needed to some extent to keep an industry alive, so it is a good idea to design internships and starting positions for less regimented tasks. For instance, interns at a tax firm could focus more on tax research than on filing returns. That way, managerial professionals could continue to work while their organizations remain competitive by investing in new technology.

## CONCLUSION

With President Trump's Tax Cuts and Jobs Act, Section 179 increased allowance for expensing from $500,000 to $1,000,000. After analyzing how Section 179 may impact technological unemployment with a simulation model, it is concluded that overall, the economy may benefit as a whole with an increase in the Section 179 allowance, but certain industries, like the professions and manufacturing, stand a great chance of experiencing adverse effects. Further examination of technological unemployment in the past, as well as of its likelihood in the future, could highlight how the impending growth of automation and artificial intelligence, and consequent job loss, are objects of real concern that should not be played off as a Luddite Fallacy, especially given the speed and reach of current technological developments; in a word, there are different implications for different industries.

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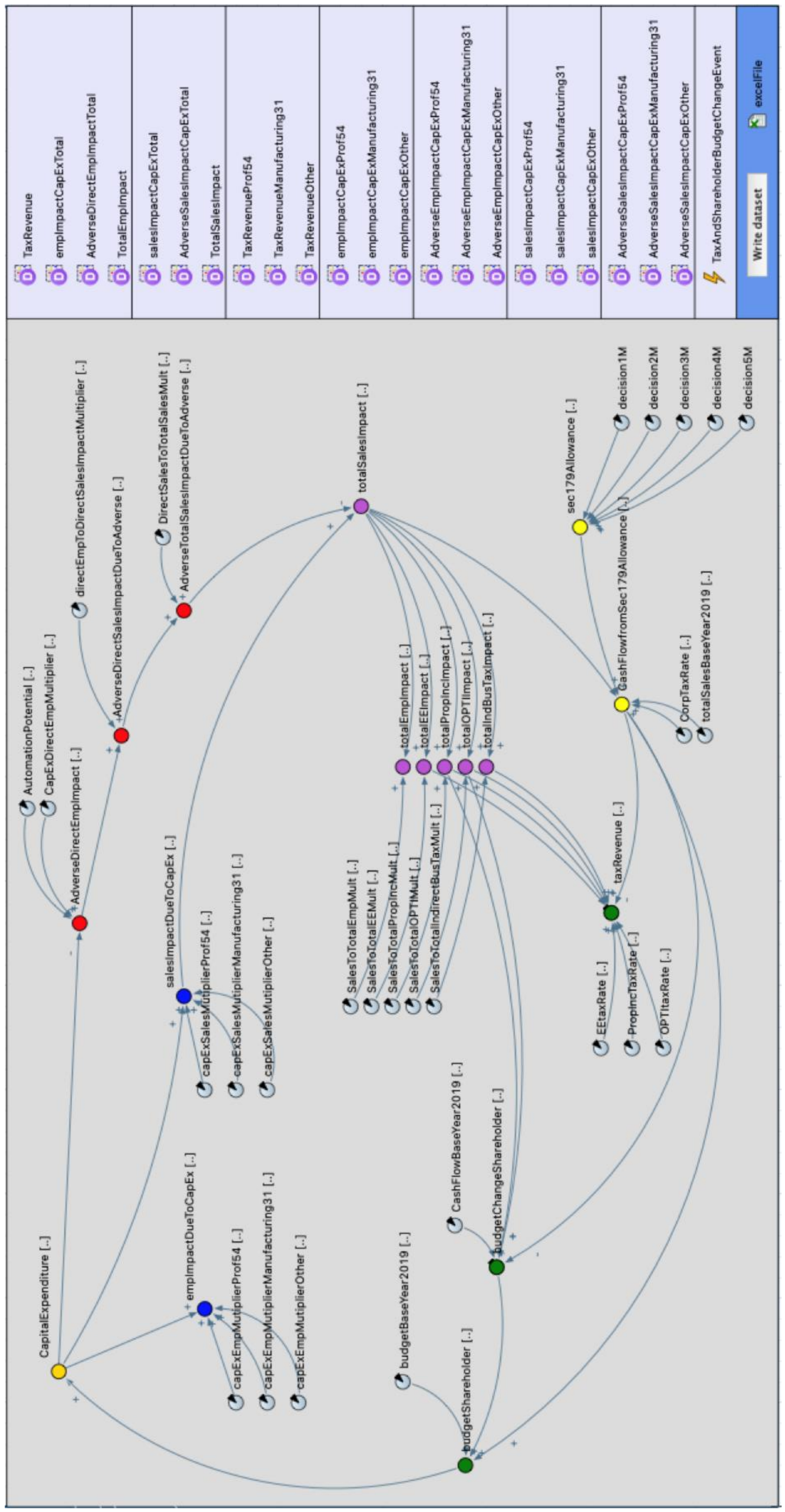
## APPENDIX 1: SYSTEM DYNAMICS SIMULATION MODEL



## APPENDIX 2: DETAILED RESULTS

| | | No Allowance | $1Mil Allowance | $2Mil Allowance | $3Mil Allowance | $4Mil Allowance | $5Mil Allowance | $10Mil Allowance |
|---|---|---|---|---|---|---|---|---|
| Total Employment | Professions54 | 76,750,896 | 76,752,959 | 76,755,022 | 76,757,086 | 76,759,150 | 76,761,214 | 76,771,535 |
| | Manufacturing31 | 24,874,375 | 24,875,229 | 24,876,084 | 24,876,938 | 24,877,793 | 24,878,647 | 24,882,922 |
| | Other | 152,948,620 | 152,954,183 | 152,959,746 | 152,965,309 | 152,970,873 | 152,976,437 | 153,004,264 |
| | Total | 254,573,891 | 254,582,371 | 254,590,852 | 254,599,334 | 254,607,816 | 254,616,298 | 254,658,720 |
| Avg Employment (per year) | Professions54 | 2,192,883 | 2,192,942 | 2,193,001 | 2,193,060 | 2,193,119 | 2,193,178 | 2,193,472 |
| | Manufacturing31 | 710,696 | 710,721 | 710,745 | 710,770 | 710,794 | 710,818 | 710,941 |
| | Other | 4,369,961 | 4,370,120 | 4,370,278 | 4,370,437 | 4,370,596 | 4,370,755 | 4,371,550 |
| | Total | 7,273,540 | 7,273,782 | 7,274,024 | 7,274,267 | 7,274,509 | 7,274,751 | 7,275,963 |
| Total Sales ($million_npv) | Professions54 | $22,886,490.83 | $28,770,396.99 | $28,771,160.47 | $28,771,924.00 | $28,772,687.58 | $28,773,451.21 | $28,777,270.10 |
| | Manufacturing31 | $7,869,257.89 | $22,887,267.19 | $22,888,043.59 | $22,888,820.05 | $22,889,596.55 | $22,890,373.12 | $22,894,256.71 |
| | Other | $59,525,382.28 | $7,869,540.53 | $7,869,823.20 | $7,870,105.88 | $7,870,388.58 | $7,870,671.31 | $7,872,085.19 |
| | Total | $90,281,131.00 | $59,527,204.71 | $59,529,027.26 | $59,530,849.93 | $59,532,672.72 | $59,534,495.64 | $59,543,612.00 |
| Avg Sales ($million_npv_per year) | Professions54 | $653,899.74 | $822,011.34 | $822,033.16 | $822,054.97 | $822,076.79 | $822,098.61 | $822,207.72 |
| | Manufacturing31 | $224,835.94 | $653,921.92 | $653,944.10 | $653,966.29 | $653,988.47 | $654,010.66 | $654,121.62 |
| | Other | $1,700,725.21 | $224,844.02 | $224,852.09 | $224,860.17 | $224,868.25 | $224,876.32 | $224,916.72 |
| | Total | $2,579,460.89 | $1,700,777.28 | $1,700,829.35 | $1,700,881.43 | $1,700,933.51 | $1,700,985.59 | $1,701,246.06 |
| Total Tax Revenue ($million_npv) | Professions54 | $920,838.19 | $919,543.33 | $918,248.40 | $916,953.40 | $915,658.34 | $914,363.20 | $907,886.50 |
| | Manufacturing31 | $612,380.57 | $611,056.27 | $609,731.88 | $608,407.40 | $607,082.83 | $605,758.18 | $599,133.53 |
| | Other | $2,549,516.78 | $2,549,244.85 | $2,548,972.91 | $2,548,700.94 | $2,548,428.95 | $2,548,156.95 | $2,546,796.62 |
| | Total | $4,082,735.54 | $4,079,844.45 | $4,076,953.19 | $4,074,061.75 | $4,071,170.12 | $4,068,278.33 | $4,053,816.66 |
| Avg Tax Revenue ($million_npv per year) | Professions54 | $27,083.48 | $27,045.39 | $27,007.31 | $26,969.22 | $26,931.13 | $26,893.04 | $26,702.54 |
| | Manufacturing31 | $18,011.19 | $17,972.24 | $17,933.29 | $17,894.34 | $17,855.38 | $17,816.42 | $17,621.57 |
| | Other | $74,985.79 | $74,977.79 | $74,969.79 | $74,961.79 | $74,953.79 | $74,945.79 | $74,905.78 |
| | Total | $120,080.46 | $119,995.43 | $119,910.39 | $119,825.35 | $119,740.30 | $119,655.24 | $119,229.90 |

## APPENDIX 3: LEVELS OF DRIVING AUTOMATION