The Impact of Automation in the Manufacturing Industry:

An In-Depth Analysis of Global Unemployment Trends and Workforce Dynamics

By:

Raima Zaman

1006848100

raima.zaman@mail.utoronto.ca

Joseph Bradley

1007977682

joey.bradley@mail.utoronto.ca

ECO375: Applied Econometrics

University of Toronto

Department of Economics

21 November 2023

This research investigates the impact of automation in manufacturing industries on global unemployment rates over the past few decades. Amidst rising concerns about automation displacing jobs, we delve into an extensive analysis to discern its actual effects. Utilizing data from 32 countries over 21 years (2000-2020), including variables like automation contribution, unemployment rates, GDP growth, inflation, literacy, labor force participation, and R&D expenditure, we conduct regression analyses. Initial simple linear regression implies a modest decrease in unemployment rates associated with an increase in the use of automation. However, after incorporating various controls and fixed effects in multiple regressions, our results suggest a slight increase in unemployment rates linked to higher automation, particularly in developed nations. While statistically significant, these findings insinuate economic significance for countries during periods of economic stability, not accounting for times of volatility. Moreover, it should be noted that missing variables, inaccurate assumptions of linearity, and the dataset's overrepresentation of higher-income countries

could be skewing conclusions. Thus, while providing insights, the study advocates for further research using more sophisticated models such as time series analysis and a balanced sample representation for a comprehensive understanding of automation's intricate impact on global labor markets.

1 Introduction

Since the rise of automation in the mid-20th century (Hitomi 1994), there's been an exhilarating boom in the amount of robotics and machinery being used in manufacturing sectors. About 90% of firms that have been implementing these automotive technologies have experienced a boost in productivity, as reported by Nimawat and Shrivastava (2016). In fact, across Europe, the vast majority of manufacturing companies have been focusing on employing automation as a weapon against competition in the global market (Frohm et al. 2006).

Automation originally refers to the replacement of human labor by machines in tasks that had once been performed by human beings (Groover 2019). It allows for a system that is capable of operating without any human intervention. As such, since its implementation, there's been a growing and widespread fear of automation driving the average worker redundant, hence leading to higher labor turnover rates (Ivanov, Kuyumdzhiev, and Webster 2020). However, despite these biases against automation, several studies have found automation to aid in the creation of jobs, complementing labor rather than obstructing jobs. In his 2015 paper, MIT professor David H. Autor, while focusing his research on the US market from 1979 to 2012, subsequently found a distinct effect of increased productivity among assembly line workers, despite a relatively small displacement of middle-skill workers.

As such, in this paper, we dive into an in-depth analysis of the true potential effects of the implementation of automation in manufacturing industries on unemployment rates at a global scale. We ask whether automation has been aiding workers' productivity, or rather contributing to a greater rate of job loss and replacement of workers over the past few decades.

By default, we are also interested in observing the possibility of automation having no true effect on unemployment rates.

2 The Context and Data

For our analysis, we've extracted data from several online economic databases, ranging from the World Bank to the OECD. As we are primarily concerned with observing a global effect, we've compiled data from several different countries across the world. In particular, we focus on automation's potential effect across the last two decades. Our data thus exhibits as panel data ranging over 21 time periods, from 2000 to 2020, with a select focus on a sample of 32 countries that have kept consistent records of information relevant to our study. Each observation among the 672 observations in the data set represents a country-year observation.

As our primary interest is observing the potential effect of automation in the manufacturing industries of each country on unemployment rates, our key variables include a feature that captures the percentage of value added to the manufacturing industry of a specific country from the increased usage of automation, and a feature that measures the unemployment rate as a percentage of the labor force. However, as the unemployment rate of a country is a constituent affected by several economic conditions, factors, and demographic aspects of a country, our data thus consists of additional variables measuring such elements. These include a feature of annual GDP growth rate, a feature of annual inflation rate, measured as the annual change in the CPI (Consumer Price Index), a feature of the literacy rate, measured as a percentage of the population aged 15 years and above, a feature of the labor force participation rate (LFPR), and a feature for the R&D (Research and Development) expenditure of a country, measured as a percentage of GDP. While all these predictors exhibit continuous numeric distributions, we have an added feature that constitutes a binary variable classifying countries as developed (1) or developing (0). According to the World Bank, countries of high income are designated developed countries while countries of all other income levels are categorized as developing. We've thus grouped this dummy variable in accordance with the World Bank's income level classifications, set according to varying Gross National Income (GNI) per capita (in US dollars) groupings for each country; ranging from high income, upper middle income, and lower middle income to low income.

In Table 1, we include summary statistics for all our numerical variables, highlighting the overall averages and the distributions of each of these features. We find that on average, countries have observed a 38.57% addition in value in their manufacturing sectors from implementing automation. Indeed, each country has had at least some contribution to their manufacturing sectors by employing automation, as the minimum value displays as 7.11%, decidedly greater than zero. In Figure 1. a, while it is hard to decipher a distinct relationship between unemployment rates and automation, we can surmise a relatively inverse relationship. Further, in Figure 1. b, when we isolate the association of unemployment rates and automation contribution (% of value added in manufacturing) for a specific country (focusing on Canada), we can more clearly observe an inverse relationship. That is, for years with higher automation contribution, there appear to be lower rates of unemployment.

However, as this relationship is not apparent, we can assume there must be some other factors influencing the fluctuation of unemployment rates across time. In Figure 2. a, our scatterplot represents the dynamics of the unemployment rate in Canada over the years, exhibiting a clear mixture of a cyclical trend along with shock components. In Figure 2. b, when we plot the unemployment rate in Canada along with its GDP growth rate over time, we observe an inverse cyclical effect of the GDP growth with respect to the unemployment rate over time. From 2005 to early 2007, essentially preceding the Great Recession (late 2007 to 2009) (Weinberg 2013), unemployment rates and GDP growth rates revealed a positive correlation. As GDP growth rates decreased, so did unemployment rates. We inferred this to be a lagged effect; a hike in GDP growth precedes downward trends in unemployment rates, not reflective of the current decline in GDP growth. Following the onset of an economic shock, such as the Great Recession, we observed a negative correlation between these two factors; as GDP growth rates plummeted, unemployment rates shot up instantaneously. These intertwined fluctuations enhanced the idea that various factors affecting the economy also have an impact on unemployment rates.

Further, when distinguishing between developed and developing countries, we found a significant difference in the average effects of these economic and country-wise factors. From Figure 3.a, we found the vast majority of developed countries, to have lower rates of unemployment compared to developing countries (7.3% vs. 9.9%). Compared to our overall sample average of 7.78% in Table 1, developing countries have a decidedly greater unemployment rate, indicating an inherent difference among countries as a result of their income level classifications. In Figure 3.c, we similarly observe a lower average rate of GDP growth for developed countries (1.75%) compared to developing countries (3.78%) (Paprotny 2020). Further, Figure 3.d captures the difference in inflation rates between developed (on average 1.87%) and developing countries (on average 6.35%), corroborating the inherent difference between countries of varying income classifications. Figures 3.e-3.g, along with Tables 2.a and 2.b explore the fact that developed countries on average, have higher literacy rates (98.6%), higher labor force participation rates (73.1%), and spend a greater proportion of their budgets on R&D (1.94%) in comparison to developing countries (95.5%, 63.95%, and 0.57% respectively) (Roser and Ortiz-ospina 2018).

Further, research has found that the importance of the manufacturing sector has been declining since the 1990s in developing countries but has remained constant for developed countries (Pandian 2017). This in turn allowed us to assume overall fewer uses of automation in manufacturing in developing countries as a result of greater negligence to manufacturing sectors in general. This justifies what we found in Figure 3.b; developed countries exhibit greater proportions of automation contribution in their manufacturing sectors (on average 40.2%) compared to developing countries (on average 31.2%).

3 Regression analysis

3.1 Simple Linear Regression

Our baseline model focuses predominantly on the direct relationship between the contribution of automation to manufacturing industries and the respective dynamics of unemployment rates in those countries. As such, we can display our model as follows:

$$Unemployment_i = \beta_0 + \beta_1 Automation_i + u_i$$

Here, we employ automation as our predictor variable, and unemployment rate as our dependent variable. Further, the notation $\boldsymbol{u_i}$ represents the random error present in the model. $\boldsymbol{\beta_1}$ represents the slope coefficient of our model and $\boldsymbol{\beta_0}$ represents the coefficient for our model intercept. Plugging in the coefficients, we obtained:

$$Unemployment_i = 11.024 - 0.084\, Automation_i$$

From our simple linear regression in specification (1) from Table 3, we found a statistically significant estimated slope coefficient of -0.084 at a 1% significance level. Specifically, we can infer that a 10-percentage point increase in the percent of value added to GDP from employing automation in manufacturing is on average, associated with a 0.84 percentage point decrease in the unemployment rate of a given country in a given year, this correlates back to what we have hypothesized from our sparse scatterplots in Figures 1.a and 1.b. Further, a 0.84 percentage point increase in unemployment can be considered economically significant for countries during periods of economic stability, disregarding abrupt changes during periods of shock. We can deduce this to be the result of increased automation in manufacturing increasing productivity and efficiency of workers, thus allowing for the creation of jobs, rather than the feared destruction.

However, as we use a linear regression model to conduct our analyses, we must first ensure such a model is appropriate. Focusing on Table 1, once more, we can observe that there is significant variation in our independent variable, automation, as the table displays a minimum value of 7.1% contribution and a maximum of 65% contribution to the manufacturing sector. Thus, confirming ample variation in our predictor, we refer to Figure 5, which consists of a diagnostic plot of our residuals against our fitted response values. We observe a fanning pattern here, indicating a crucial problem with our assumptions. This pattern entails that our errors are influenced by variation in our predictor variable, thus, violating the uncorrelated errors, homoskedasticity, and independence assumptions. However, this is to be expected as we are working with panel data, which consists of observations of the same countries over time. The fluctuation in unemployment rates and automation implementation rates for a single country is likely to be correlated over time; unemployment rates of a given year will increase or decrease relative to their previous years' rates. This phenomenon of correlated effects is referred to as autocorrelation. Further, our observations consist of different countries over the same time period. This would mean, for example, that in the event of a worldwide epidemic, such as the COVID-19 pandemic, in a given year or a potential recession, as in the Great Recession, every country would be affected. As such, specification (1) suffers from an inflated sense of accuracy as the standard errors are smaller than they should be.

As we've already observed from our preliminary analysis, several other economic and demographic factors not only affect the unemployment rate of a country in a given year but also influence the magnitude of automation that will be implemented in their manufacturing sectors.

These factors can be categorized as confounding variables, exhibiting a hidden effect on both our variables of interest, and thus incurring the problem of omitted variable bias in our model. To account for these persisting factors, we extend our simple linear regression model by including them as omitted variables.

Additionally, in order to account for the differences in variation across time and across countries, we include dummy variables at both the country level and the year level, commonly referred to as year and country fixed effects. We also employ clustered standard errors at the country level in order to mitigate the distortion of standard errors from autocorrelation; clustered standard errors allow for heteroskedasticity and arbitrary autocorrelation within an entity but treat errors as uncorrelated across entities. These modifications allow for a more accurate interpretation of our relationship of interest by isolating the effect of automation on unemployment by holding all other factors constant.

3.2 Multiple linear regression

We gradually include alterations to our simple model to observe how each modification influences our relationship of interest. Extending from our simple model in specification (1), when we include fixed effects at the year level, in specification (2), we observe virtually no improvement in our model as our statistically significant coefficient for automation simply decreases from -0.084 to -0.086 while the standard errors minutely increase from 0.0127 to 0.0129. This allows us to infer that a 10-percentage point increase in automation contribution is associated with a 0.86 percentage point decrease in unemployment rates when holding constant variation over the years. This minor decrease in the slope coefficient essentially entails there is negligible variation in the effect of automation contribution on unemployment rates across countries. Instead, the bulk of the discrepancy in the effect of automation on unemployment rates originates from variations over time. Thus, in specification (3) in Table 3, we confirm this assumption, as including country-fixed effects instead results in a greater change in the slope coefficient. In specification (3), when we consider our simple model with country-fixed effects, the coefficient increases from -0.084 to -0.026 but is now statistically insignificant. That is, when we hold variation across countries constant, the contribution of automation in manufacturing has no true effect on unemployment rates. Further, in specification (4), we include both country-level and year-level fixed effects and obtain a statistically insignificant slope coefficient of -0.029. This entails, when holding variations across countries and over time fixed, implementation of automation no longer has a significant effect on unemployment rates. In order to account for unobserved heterogeneity within each year, specification (5) employs clustered standard errors on years and yields the same slope coefficient as specification (4) except with slightly higher standard errors. This increase in standard errors from clustering insinuates observations within the same year are more similar to each other than observations in different years.

Further, in specification (6), we include our omitted variables to our simple model with no fixed effects and obtain a statistically significant result at a 10% significance level, insinuating a 10-percentage point increase in the contribution of automation is on average associated with a 0.3 percentage point decrease in unemployment. While the slope coefficient is stagnant in comparison to specification (5), our standard errors greatly decreased when we considered omitted variables potentially incurring bias in our model. Including year and country fixed effects, along with time clustered standard errors, specification (7) produces a statistically insignificant slope coefficient on the contribution of automation. We can infer that when we include omitted variables to our model and hold these factors constant over time and across countries, there is no significant effect of automation on unemployment rates.

However, as we had previously observed inherent differences between countries as a result of their income level classifications, we incorporated this feature into our model in specification (8). When including an interaction term between income level classifications of countries and the proportion of the contribution of automation in the manufacturing sectors in those countries, we obtained a statistically significant slope coefficient at the 5% level. Specification (8) thus allows us to conclude that a 10-percentage point increase in automation contribution is on average associated with a 0.67 percentage point increase in unemployment rates when holding variation over time and across countries constant. For any specific country at any given time of stability, these results may be deemed economically significant, though the same cannot be said during periods of economic shock. That is, unemployment rates generally exhibit minor fluctuations during periods of economic stability; from Figure 2.a, we can observe unemployment rates in Canada declining gradually between 2010 to 2012, approximately from 8.1% to 7.6% to 7.3%. It is only during periods of economic shock, that we observed abrupt changes, such as the period between 2008 to

2009, when unemployment rates shot up from 6.2% to 8.4%. Further, the slope coefficient on our interaction term insinuates that developed countries on average have 0.1 percentage point higher unemployment rates as a result of an increase in the proportion of the contribution of automation. That is, when we hold constant the factor of a country having no differences in terms of income level at the baseline, taking into account influences from GDP growth rates, inflation rates, literacy rates, labor force participation rates, and R&D expenditure rates, and hold variation over time and across countries constant, we observe the contribution of automation in manufacturing industries to incur higher unemployment rates globally.

4 Limitations of results

In the beginning of our research, we were curious to know how the implementation of automation in manufacturing industries affected unemployment rates specifically within the manufacturing industry. However, due to limited data on industry specific unemployment rates across countries and years observed, we were compelled to look at the general unemployment rates of each country. If we were able to look at industry specific unemployment rates, perhaps automation in manufacturing industries would display a bigger impact on the unemployment specifically in the manufacturing industry. Moreover, we must consider the possibility of additional omitted variables missing in our model, potentially preventing the isolation of the effect of automation contribution on manufacturing industries on unemployment rates. On top of that, it is just as likely that the relationship presented while significant, may not be linear, thus inhibiting our linear regression model's ability to capture the true degree of effect.

Additionally, it must be noted that as our model consists mainly of higher-income countries, possibly skewing our results. Critically, from Figure 4, we found that there is an overrepresentation of developed countries in our data, indicating our data captures on average, lower unemployment rates, higher automation contribution rates, lower GDP growth rates, lower inflation rates, higher literacy rates, higher labor force participation rates, and higher research and development expenditure rates. This limitation likely skewed our model to present an increase in unemployment rates from increased automation contribution whereas a sample with a greater representation of developing countries could yield instead a decrease in unemployment rates as a result of increased automation contribution in manufacturing industries.

5 Conclusion

Our findings yield insights yet come with limitations. Initially, our simple linear regression suggested a significant decrease in unemployment rates associated with increased automation, consistent with prior studies like that of David Autor in the US market. However, as we expanded our analysis to multiple linear regression models, incorporating diverse economic and demographic factors while adjusting for baseline differences, along with country and year-fixed effects, our results instead suggested a substantial increase in unemployment rates associated with an increase in automation. That is, developed countries exhibited higher unemployment rates associated with heightened automation, contrary to developed countries. This suggests a nuanced relationship, indicating potentially divergent effects based on a country's income level classification.

Despite statistically significant results in some model specifications, the study acknowledges several limitations. The potential presence of additional unobserved variables and the assumption of a linear relationship along with overrepresentation of higher-income countries in the dataset might skew findings, obscuring the true impact of automation.

In conclusion, while the study reveals nuanced insights into the interplay between automation and unemployment rates, the complexity of this relationship warrants further exploration. Addressing the limitations and employing more sophisticated modeling approaches, such as time series analysis to capture effects of autocorrelation, could offer a more refined understanding of automation's multifaceted impact on global labor markets. However, based on our research and findings, we arrive at the conclusion that automation in the manufacturing industry has a significant effect for countries during any given period of economic stability, not accounting for abrupt fluctuations during periods of economic uncertainty.

References

Autor, David H. 2015. “Why Are There Still so Many Jobs? The History and Future of Workplace Automation.” *Journal of Economic Perspectives* 29 (3): 3–30. https://doi.org/10.1257/jep.29.3.3.

Frohm, J., V. Lindström, M Winroth, and J. Stahre. 2006. “THE INDUSTRY’S VIEW on AUTOMATION in MANUFACTURING.” *IFAC Proceedings Volumes* 39 (4): 453–58. https://doi.org/10.3182/20060522-3-fr-2904.00073.

Groover, Mikell . 2019. “Automation.” In *Encyclopædia Britannica*. https://www.britannica.com/technology/automation.

Hitomi, Katsundo. 1994. “Automation — Its Concept and a Short History.” *Technovation* 14 (2): 121–28. https://doi.org/10.1016/0166-4972(94)90101-5.

Ivanov, Stanislav, Mihail Kuyumdzhiev, and Craig Webster. 2020. “Automation Fears: Drivers and Solutions.” *Technology in Society* 63 (November): 101431. https://doi.org/10.1016/j.techsoc.2020.101431.

Nimawat, Dheeraj, and Ashish Shrivastava. 2016. “Increasing Productivity through Automation.” *European Journal of Advances in Engineering and Technology* 3 (2): 45–47. https://ejaet.com/PDF/3-2/EJAET-3-2-45-47.pdf.

Pandian, Roshan K. 2017. “Does Manufacturing Matter for Economic Growth in the Era of Globalization?” *Social Forces* 95 (3): 909–40. https://www.jstor.org/stable/26166858.

Paprotny, Dominik. 2020. “Convergence between Developed and Developing Countries: A Centennial Perspective.” *Social Indicators Research*, September. https://doi.org/10.1007/s11205-020-02488-4.

Roser, Max, and Esteban Ortiz-ospina. 2018. “Literacy.” Our World in Data. September 20, 2018. https://ourworldindata.org/literacy.

Weinberg, John. 2013. “The Great Recession and Its Aftermath.” Federal Reserve History. November 22, 2013. https://www.federalreservehistory.org/essays/great-recession-and-its-aftermath.

World Bank. 2020. “COVID-19 to Plunge Global Economy into Worst Recession since World War II.” World Bank. June 8, 2020. https://www.worldbank.org/en/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii.

Appendix

Table1: Overall Descriptive Summary Statistics

	Mean	SD	Min	Max
Unemployment Rate	7.778	4.120	1. 9	27.825
Automation Contribution	38.567	13.051	7.106	65.396
GDP Growth Rate	2.111	3.24	-14.839	24.370
Inflation Rate	2.664	4.018	-4.478	54.915
Literacy Rate	98.038	3.058	48.134	100
Labor Force Participation Rate	71.459	6.288	48.551	82.93
R&D Expenditure	1.699	0.95	0. 131	4.796
N	672			

Figure 1.a:

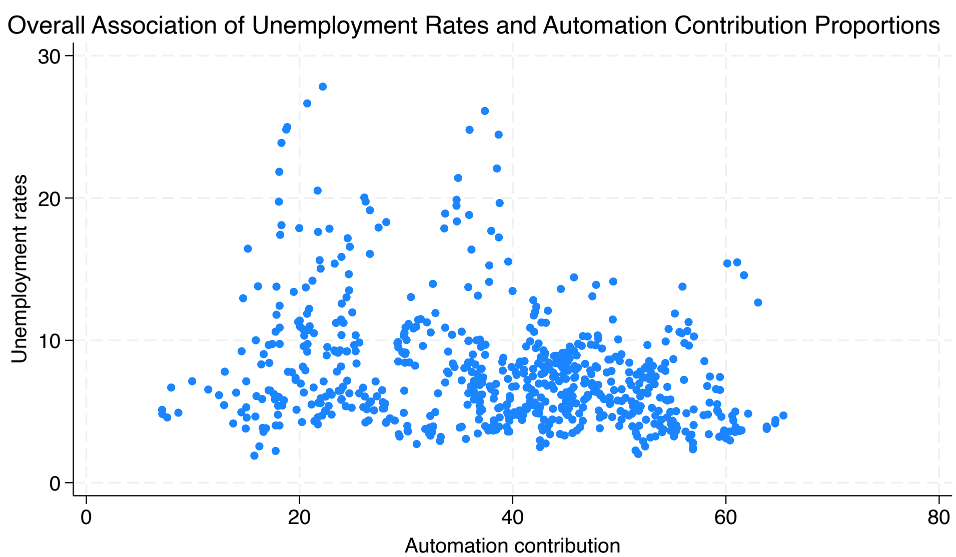


Figure 1.b:

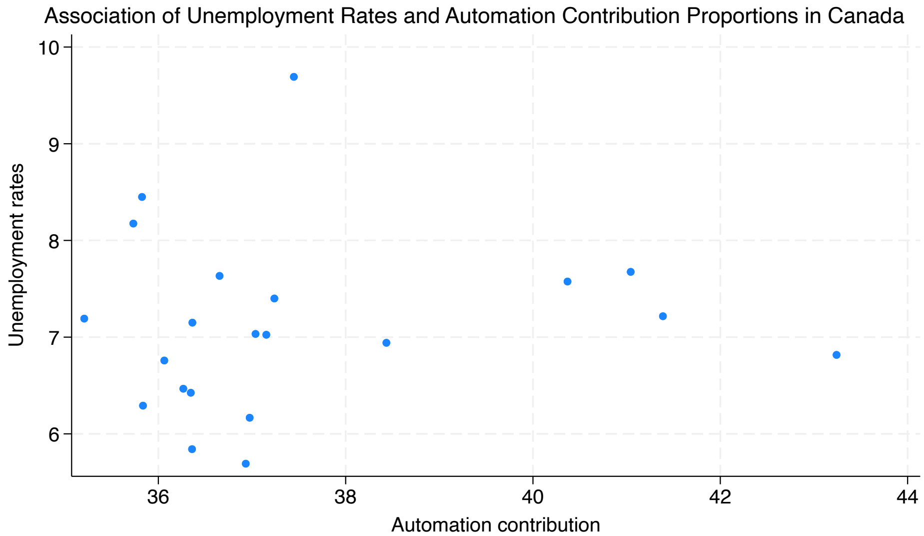


Figure 2.a:

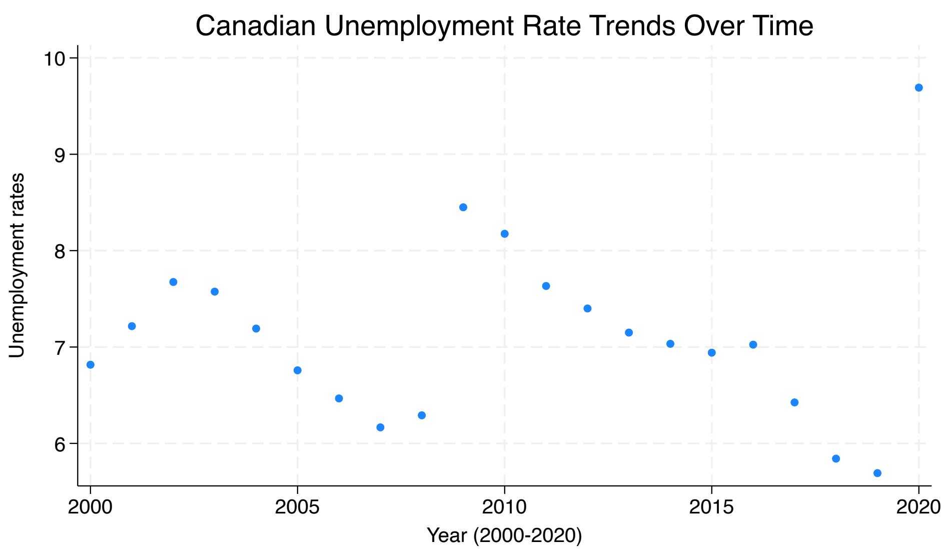
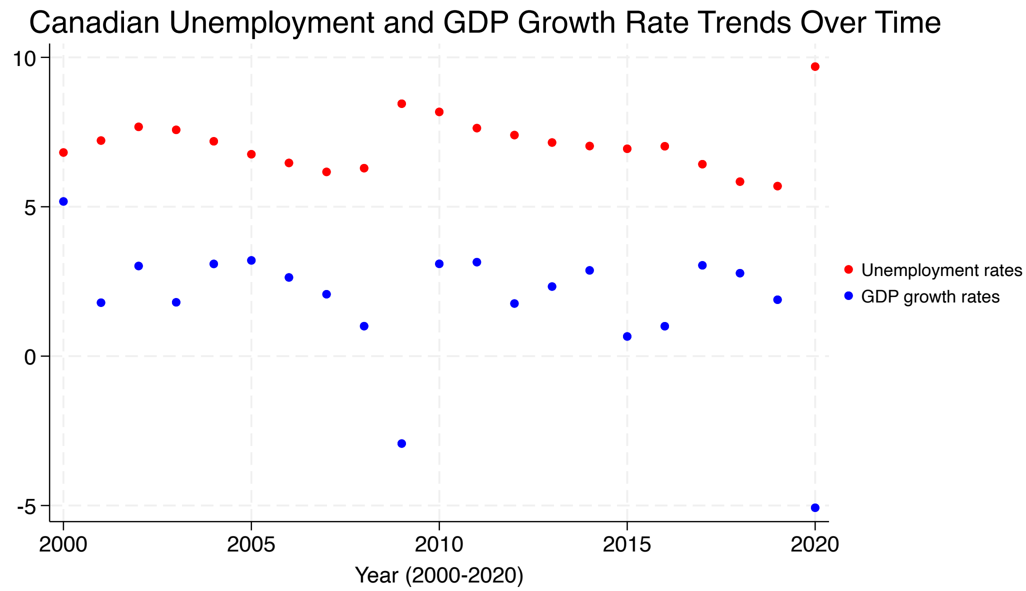


Figure 2.b:



<u>Table 2.a:</u> Descriptive Summary Statistics for Developed Countries (1)

	Mean	**SD**	**Min**	**Max**
Unemployment Rate	7.315	3.868	1. 9	27.825
Automation Contribution	40.159	13.006	7.106	65.396
GDP Growth Rate	1.752	3.022	-11.325	24.370
Inflation Rate	1.872	1.438	-4.478	8.912
Literacy Rate	98.577	2.678	48.134	100
Labor Force Participation Rate	73.075	4.905	60.359	82.93
R&D Expenditure	1.941	0.862	0.342	4.796
N	553			

Table 2.b: Descriptive Summary Statistics for Developing Countries (0)

	Mean	**SD**	**Min**	**Max**
Unemployment Rate	9.926	4.570	2.506	20.520
Automation Contribution	31.169	10.502	9.932	56.525
GDP Growth Rate	3.776	3.683	-14.839	11.200
Inflation Rate	6.345	8.094	-1.134	54.915
Literacy Rate	95.532	3.457	87.000	99.816
Labor Force Participation Rate	63.947	6.566	48.551	73.641
R&D Expenditure	0.575	0.324	0.131	2.125
N	119			

Figure 3.a:

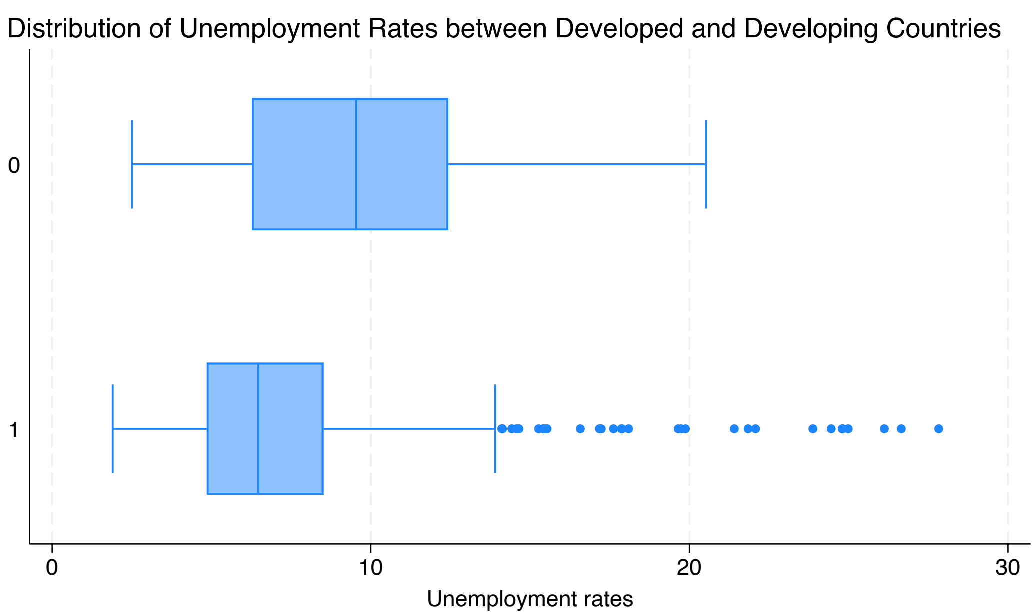


Figure 3.b:

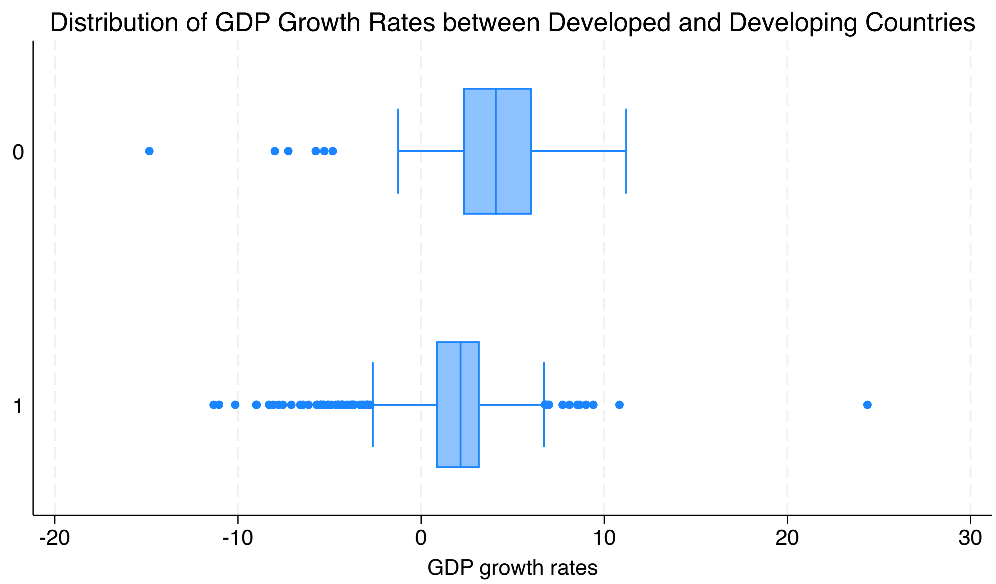


Figure 3.c:

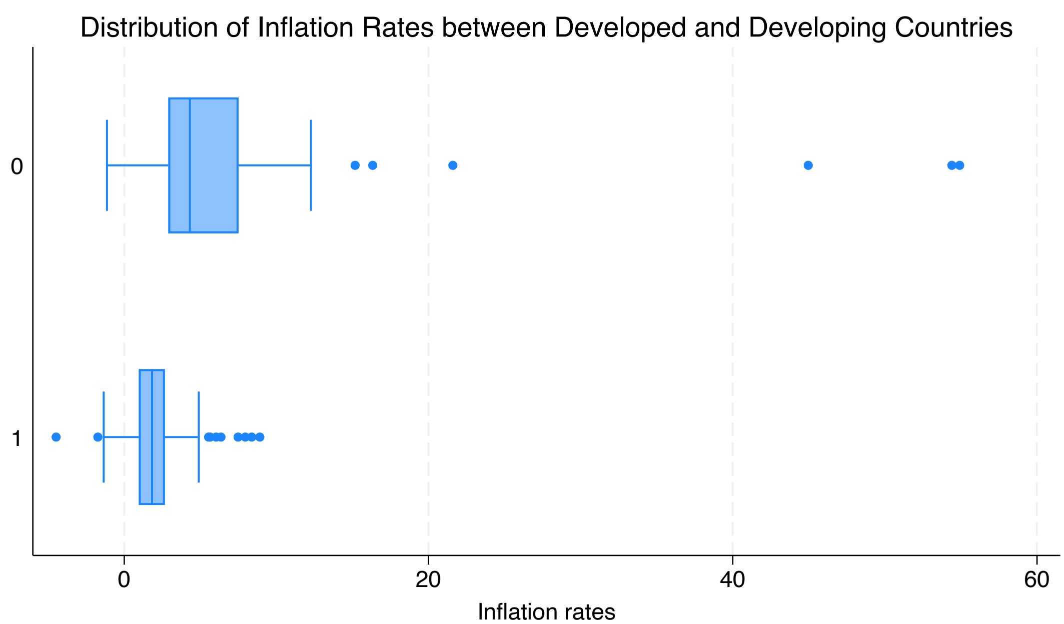


Figure 3.d:

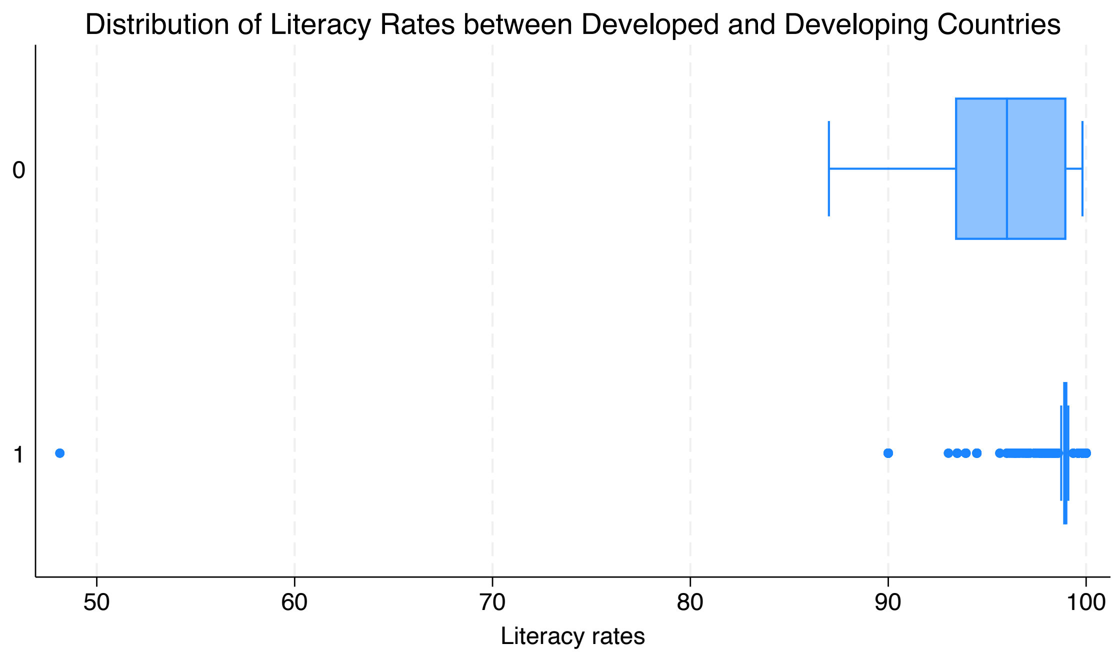


Figure 3.e:

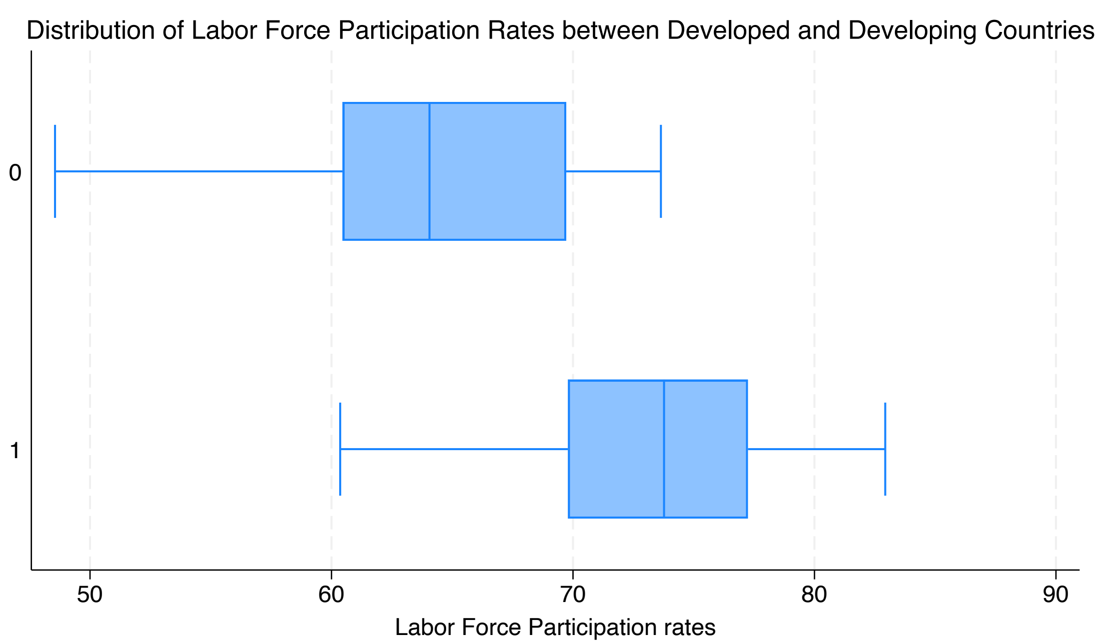


Figure 3.f:

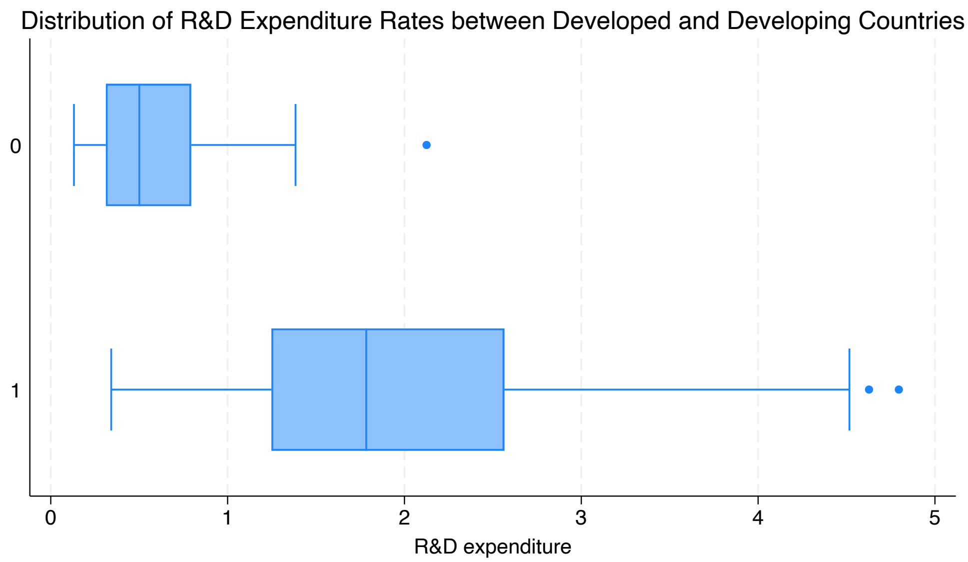


Figure 3.g:

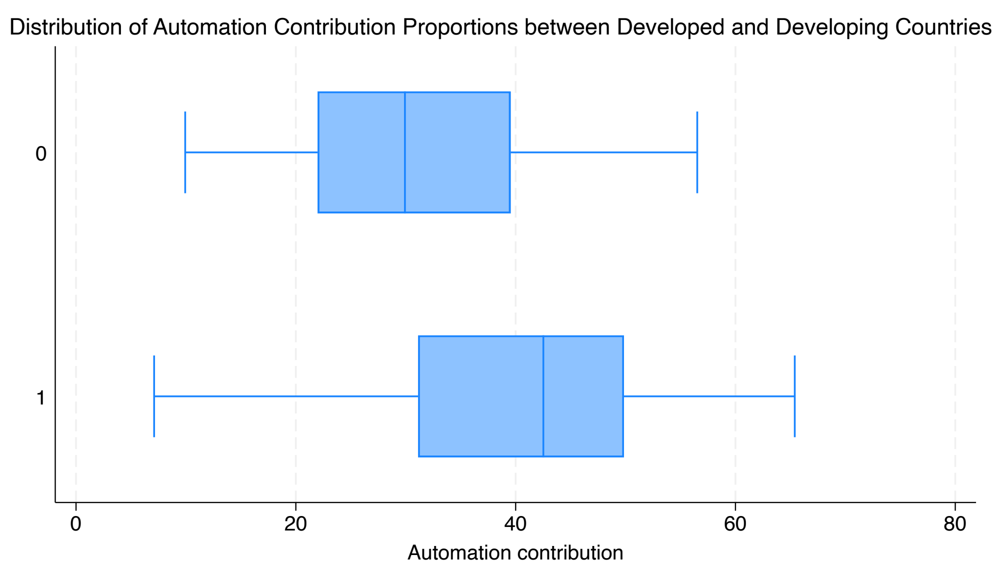


Figure 4:

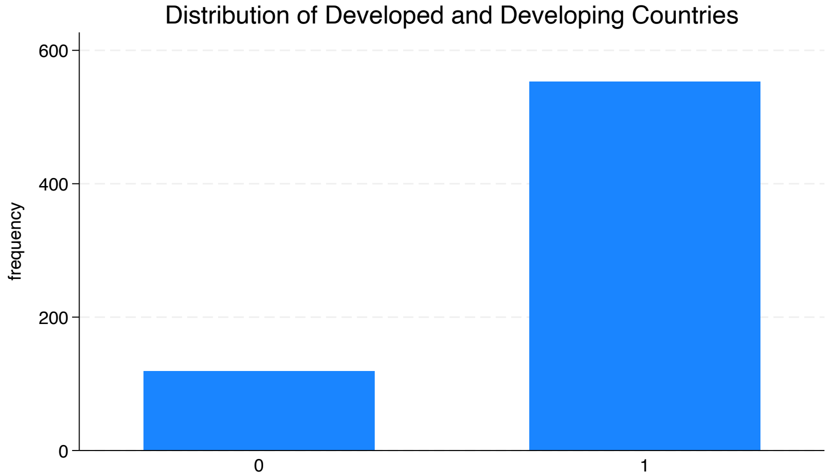


Figure 5:

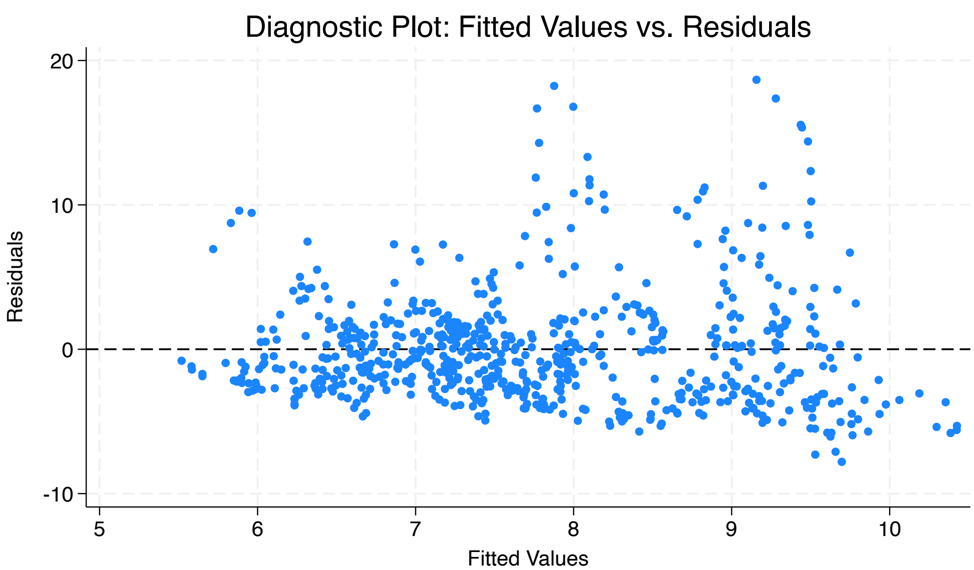


Table 3:

	Unemployment rates				
	(1)	(2)	(3)	(4)	(5)
Automation contribution	-0.0842***	-0.0855***	-0.0258	-0.0290	-0.0290
	(0.0127)	(0.0129)	(0.0279)	(0.0287)	(0.0322)
Constant	11.02***	10.85***	7.212***	6.922***	6.922***
	(0.576)	(0.857)	(1.395)	(1.580)	(1.582)
Year FE	No	Yes	No	Yes	Yes
Country FE	No	No	Yes	Yes	Yes
Clustered SEs (Year)	No	No	No	No	Yes
Adjusted R^2	0.0711	0.129	0.593	0.651	0.651
Observations	672	672	672	672	672

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4:

	Unemployment Rates		
	(6)	(7)	(8)
Automation contribution	-0.0316^{*}	-0.0421	0.0672^{**}
	(0.0161)	(0.0303)	(0.0291)
GDP growth rates	-0.218^{***}	-0.293^{***}	-0.312^{***}
	(0.0541)	(0.0923)	(0.0912)
Inflation rates	-0.125^{***}	-0.103^{***}	-0.107^{***}
	(0.0432)	(0.0227)	(0.0266)
Literacy rates	0.0477	0.108^{*}	0.0669
	(0.0425)	(0.0607)	(0.0475)
Labor Force Participation rates	-0.122^{***}	-0.200^{**}	-0.0956
	(0.0261)	(0.0799)	(0.0752)
Automation contribution * Developing			-0.100^{***}
			(0.0168)
Constant	15.98^{***}	10.88	6.351
	(4.058)	(7.702)	(6.696)
Year FE	No	Yes	Yes
Country FE	No	Yes	Yes
Clustered SEs (Year)	No	Yes	Yes
Adjusted R^2	0.190	0.683	0.711
Observations	672	672	672

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$