The Economics of Technological Change and Adoption: A Review of the Literature

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December 2017

EARLHAM COLLEGE, DEPARTMENT OF ECONOMICS
SENIOR LITERATURE REVIEW

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Abstract

Technology has been the driver of economic growth throughout the industrial era, and presently promises an advanced robotic future. However, many worry about the consequences increasing technological adoption might have on labor markets and wages. From the burning of spindle machines in 1811 to the protection policies in early 20th century, rapid innovation and change has been met with both hearty acceptance and stark resistance. To address these anxieties and hopes alike, this paper surveys the existing literature on the impact of technology. The first two sections examines technology's role in the two industrial revolutions, analyses the determinants of technological adoption and discusses technological diffusion. The next three sections review technology's impact on productivity, growth, jobs wages and the future impact of technology.

JEL Classification Codes: O14, O31, O33, Q55

Keywords: technology, adoption, innovation, diffusion

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Introduction

The past two centuries have been marked with rapid developments in technology and information. We have observed machines do the job of men and the development of computers smart enough to beat a human at chess. While technology has been the key to increasing productivity and economic growth in the past, it has also led to the displacement of workers. In the early years of the industrial revolution, this displacement was countered by absorption of workers by other sectors of the economy as it expanded and new jobs were created. However, many speculate that mass unemployment could be a problem if growth in technical efficiency overtakes the rate at which economies find new uses for labor. The topic of technology's impact on the economy has received much attention in recent literature.

Understanding the impact of technology is important for a variety of reasons. People have had concerns about machines replacing skilled labor since as early as the 1500s. While some economists view technological advancement as a necessary cost that societies pay for the leap into 'technological modernity', others warn us about its impact on the job market and for good reason. Over the years, technological change has had an increasing impact on the labor market. This paper surveys the existing literature on technological change and adoption around two major themes: understanding how revolutionary technologies drastically change the economic landscape and the impact these changes have on productivity and jobs. Firstly, it is important that we understand how technological adoption occurs and new technologies spread across the various sectors of the economy. History is central to understanding patterns of technological advancements. A majority of historical literature is based around the study of General Purpose Technologies (GPT) in evaluating technology's impact on productivity and growth. GPTs are broad, revolutionary technologies such as steam-power, electricity and information technology that paved the way for rapid innovation and substantially affected the markets. Various influential papers use this GPT perspective to evaluate how technologies diffuse or spread throughout an economy. Because many recent papers look back at the GPT eras to explain the impact of recent technological advancement, the historical impact of GPTs on productivity and growth has been given importance in this review.

This review of literature is broken down into five major sections. Section I gives us some historical context as to the effects that technology has had on everyday life over the years. It builds a broad overview of the first and second industrial revolution and tracks the origins of technological unemployment within the historical literature. Section II talks about technology as a factor of production, general purpose technologies, determinants of technological adoption and technological diffusion. Section III uses the concepts discussed in the first two sections to look at the steam, electrification era, and the IT era broadly to discuss the impact technology has had on productivity and growth. It draws commonalities and parallels to help better our understanding of technology's impact on jobs. Section IV looks at the impact technology has had on jobs and wages over the years. Finally, Section V looks into the future impact of technological adoption given recent advancements in Machine Learning (ML), sensors and robotics.

The current published literature on technological change and adoption is far-reaching and encompasses a broad range of issues. I have covered only the essential topics and the most influential papers discussing these topics. This review omits topics of international trade impact of technology, knowledge spillovers and firm-level issues.

Section I- Brief historical context

Much of the historical literature on technology focuses on the industrial revolutions and the changes that took place during that era. Both Keynes (1930) and Mokyr (2005) agree that while technology has been relevant in the past, it did not have as big of an impact on the economy as during the first two industrial revolutions.

The First Industrial Revolution: Mankind's leap into Technological Modernity

From the invention of the wheel to breakthroughs in artificial intelligence, innovation and technological progress has been a dynamic continuum throughout human history. Many economic historians see humankind as inherently innovative and argue that technological progress is a guaranteed phenomenon. However, while many inventions and improvements were made for centuries prior to 1750, technology then accounted for a very small fraction towards growth and output. Before 1750, individuals and institutions lacked the collective knowledge required to bring about persistent technological progress needed to drastically improve productivity. In fact, much of pre-1750 growth can be said to have occurred due to commercial processes, better institutions, formulation of laws and the use of political power for redistribution of income. While this "Smithian growth" was vital to propelling society forward, it lacked sustained technological progress and investment towards innovation (Mokyr 2005).

Indeed, pre-1750 society was largely agricultural and observed an average of 0.2% annual growth in output. However, the pre-1750 society had paved the way for an era of "enlightenment" where people started to view knowledge as a means of improving mankind's standard of living rather than a tool to rectify religious doctrines. Starting in Europe, institutional changes such as intellectual property rights, protection for innovators and entrepreneurs and the supply of capital investments led to the generation and dispersion of "propositional knowledge" for technological applications. Fueled by a stable commodities and labor market, Europe saw waves of game changing macro-inventions followed by complimentary micro-inventions. Thus, the first machines were invented. Milling machines, mechanized spinning machines, steam power, and numerous improvements in metallurgy brought about economic growth on a scale never seen before (Mokyr 2005).

However, it wasn't any particular cluster of inventions but rather the persistence of technological change that marked the industrial era as a crossover towards the "technological modernity" for mankind. The first wave of inventions was quickly followed by another wave of improvements and discoveries in the 1820s. Mechanical weaving was perfected, the hot blast and electroplating revolutionized steel production, steam power was made more efficient, advancements were made in organic chemistry, the telegraph was invented and many more breakthroughs were made in precision engineering and machine tools. In short, the employment of useful knowledge towards practical application generated new tools and techniques that brought about enormous productivity and growth. Much of the 1.5% average annual growth that was seen in industrial nations during the industrial revolution can be attributed to technological change (Mokyr 2005).

The Second Industrial Revolution: Rapid Changes and Growing Anxieties

The First Industrial Revolution, which ended sometime around 1850, had set up the necessary infrastructure for expanding, manufacturing and production. The expansion of the railroad network and the telegraph facilitated the movement of people and knowledge on an incredibly large scale. This led to the Second Industrial Revolution, which lasted from 1870 till 1914. Often referred to as the "technological revolution", this time period saw the introduction and diffusion of paradigm changing innovations. Electrical power, telephones, the internal combustion engine, the Bessemer process for steel production and alternating current were some of the many cutting-edge technologies developed in this era (Muntone 2013).

While these innovations brought about immense gains in productivity and greatly reduced costs, they also kick-started a tidal wave of changes to factory structure and manufacturing processes. Cheaper energy, falling costs of machinery and improved factory structures led to record levels of technological adoption during this time period. By 1920, the value of investment towards industrial buildings had peaked to levels that remained unsurpassed until the start of the Second World War. Likewise, investments in machines and equipment during this period increased rapidly. However, while mass industrialization during the first revolution had led to minor displacement of workers from one sector to another, the second revolution replaced man with machines at a much higher rate, leading to what Keynes(1930) then described as "technological unemployment." Productivity grew by unprecedented levels as machines started taking over a range of tasks. While workers had been cautious of machines replacing them since early 1800s, it wasn't until the late 1920s that efficiency gains outpaced job creation.

Indeed, the first revolt against machines was seen as early as 1811 in a movement known as the Luddite movement. Groups of angry workers burned down textile machinery and factory equipment to protest job losses due to rapid changes. Their anger stemmed from technology leading to unemployment of skilled employees by cheaper and lesser skillful workers. The government soon suppressed the movement. Moreover, the economists of that era assured the anxious workers that while machine might replace labor, people are still needed to build those machines. Labor was undeniably required to build and operate these machines and by the end of the 19th century, real wages were three times higher than they were at beginning of the century. New areas of economic activity and innovation had sufficiently reabsorbed displaced workers until this period. Large investments towards the expansion of the manufacturing industry had kept the labor demand high enough. However, this optimism towards technology slowly disappeared towards the early 1920s.

As investments began to decline, increasing levels of productivity coupled with a slowdown of innovation-led economic activity caused substantial unemployment during 1920s. The unemployment rate hit a record high of 25% during 1933, along with the issue of rampant income inequality where the top one percent held more than 48% of the total wealth. While technological displacement was not the only cause for this fall in employment, it was a significant factor that slowed the pace of recovery. The output per man-hour kept increasing well into the Depression era; this shrank manufacturing employment and worsened the ongoing crisis (Fano 1991). The anxieties of the 1800s were now the reality of the 1930s.

Changing Attitudes: Too fast and too furious

"We are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come – namely, technological unemployment."– ***John Maynard Keynes (1930)***

According to Leontief (1952), two industrial revolutions had exponentially narrowed the gap between pure science and applied science. Leontief (1952) points out that the steam engine took a hundred years to establish it, electricity only took 50 years, the internal combustion engine around 30 years and within a span of 15 years, every American household had a vacuum tube. Keynes (1930) noted similar observations about the pace of technological advancements before and after the 16th century. Keynes (1930) argues that even though throughout much of the past two thousand years, humans have had access to almost the same bundle of resources, there had never been such rapid and far-reaching improvements in the standard of living and technology as was observed in the later parts of the 1800s. He attributes this great leap to the accumulation of capital along with the vast technological improvements that began in the 16th century and peaked during the latter half of the 18th century. In his essay, Keynes urges the general public to not be consumed by the ongoing "economic pessimism", but rather see it as a "temporary phase of maladjustment." For Keynes, the swiftness with which this economic transition took place blinded us to one vital problem—what if the growth in technical efficiency were to outpace the rate at which we found newer uses for labor?

Earlier economists such as Ricardo (1817) initially favored the adoption of technology within the premise that growing demand would offset its negative effects. Advancements in technology, for Riccardo were 'a general good' which brought with it additional advantages to the discoverer and raised net income as well the gross income of society. However, as Ricardo explored the subject further, he discovered that while improvements in technology might increase the net revenue of the country, those gains would go towards the landlords and capitalists, potentially worsening conditions for the worker. Ricardo concluded that while employing machinery leads to a fall in the demand for labor, the decision to not adopt could collapse this demand altogether as production would shift to other countries with higher net revenues. For Ricardo, technological unemployment was the lesser of two evils. Meanwhile, Leontief (1952) takes a different stance on the issue and suggests that as long as labor is able to maintain its relative share of national income, technological unemployment would not be as big of a problem as it was in the 19th century. Leontief (1952) believes automation simply accelerates the operation of forces that have shaped development so far and that it solves many problems, it also gives rise to newer and more difficult problems.

In order to better understand technological unemployment, we must explore technology as a factor of production. The next section explores the determinants of technological adoption and diffusion to help understand how us understand how technology impacts productivity and growth before exploring its impact on jobs.

Section II - Technology as a factor of production

If we were to look at technology as an input in the production process like land, labor and capital, we must factor in how it varies from the other three. For Romer (1990), technology or knowledge is simply research and development, costs that can be factored into the production function in terms of human labor hours spent on it. However, unlike human labor, if one were to view technology as a set of instructions for working with raw materials to create a product, these instructions once created can be used many times with no additional costs. Both Romer (1990) And Solow (1956) agree that technological change is vital to economic growth. When a human laborer passes away, the skill they posses is lost but research, knowledge and scientific discoveries not only survive time but also often improve for the better.

Romer (1990) views technology as an economic good with non-rival qualities and partial excludability and believes that technological change arises primarily because of intentional action taken by people who respond to market incentives. Most pieces of literature look at revolutionary technological advancements that paved the way for rapid innovation and changed the economic landscape rather than looking at individual pieces of technology. There are a number of factors that affect the rate of technological adoption and several models to help understand the process of diffusion of these technologies. Then, of course there are the macroeconomic effects of these technologies. I will first look into the concept of General Purpose Technologies (GPTs) and their impact on the market to explain the various determinants of technological adoption and the different models of technological diffusion.

Impact of General-purpose technologies

Jovanovic and Rousseau(2005) use the concept of a General Purpose Technology (GPT) to evaluate the various time periods during which a certain technology had an overarching impact in reshaping the economic landscape. In short, a GPT is any method of producing or inventing significant enough to have an expanded collective impact on society. GPTs are categorized by their ability to considerably change business models and improve productivity across sectors. Using this definition Jovanovic and Rousseau(2005) classify steam, electricity and information technology as the three most important GPTs of the past two centuries. Likewise, according to Bresnhan and Trajtenberg(1995), for a technology to be categorized as a GPT, it must possess three essential characteristics: the technology must spread across various sectors, it must improve as time passes, and it should bring about innovation of other products and processes.

Simon (1987) argues that it is not a single invention but rather a series of additional unexpected inventions, many equally as significant as the first one, that technology dramatically reshapes society. Likewise, Jovanovic and Rousseau (2005) believe that the periodic arrival of GPTs is often accompanied by some distinct changes in productivity, skill premium and market structure. Both Jovanovic and Rousseau (2005) and David (1990) believe that the initial output in the economy often tends to fall as markets adjust to these new technologies. However, this initial "productivity slowdown" is soon overcome as people develop skills to better utilize the new technology leading to periods of higher growth and prosperity. Since a new technology is often accompanied by technical demands for operating it, a skill premium for the skilled labors is observed as demand for them goes up. Bhak and Gort(1993) confirm this observation and note that it often takes several years before productivity peaks because of the initial hurdle in acquiring the skills needed for a new technology.

Moreover, on a more empirical note, Jovanovic and Rousseau (2005) found that GPTs are almost always accompanied by "creative disturbance" or fluctuating entry and exit of firms into the market. Upon evaluating the initial public offerings (IPO) data during the GPT eras, they found a significant amount of mergers, takeovers and changes in valuation in the stock exchange. They argue that since new firms often do not have the same costs sunk in old technologies and are better able to flexibly organize, adjust and hire for the latest technology, GPTs affect the overall market structure. This effect of entry and exit also accompanies waves of job reallocation, which will be discussed in the later sections. Number of firms entering and exiting the market can be seen at their highest during the later phases when prices of GPTs have fallen significantly because of improvements and innovations. David (1991) evaluates this issue from a pure investment perspective, arguing that the speed at which a GPT is adopted in the market is often subject to the quality of the investment pool and therefore the number of new firms entering the competitive market to utilize a GPT will depend on how well the economy is performing at the time. Moreover, for David (1991) the technological frontier remains subject to input costs and complementary products. Market entrants often choose to delay entry until their benefits justify these costs. We will explore more about this subject as we look into the determinants for adoption and diffusion of technology.

Adoption and Diffusion into the Market: Determinants of Technological Adoption

Hall and Khan (2003) believe that the contributions of a technology can only be realized when it is widely adopted; it is diffusion and not innovation that affects the pace of economic growth and brings about changes in productivity. Here, we look at the demand and supply side of the story when it comes to adoption of a new technology and then discuss the various models of diffusion. The diffusion process of GPTs usually takes the form of an S-shaped pattern signifying a slow initial adoption followed by an accelerating spread prices fall, eventually slowing down after the market saturates.

A number of factors affect a firm's choice to adopt a new technology. From demand-side determinants to supply-side developments and from investment decisions to network effects, a series of external and internal considerations drive technological adoption in the market. When it comes to technology, empirical evidence shows that the demand side plays a more significant role in decision-making than the costs and benefits offered by the supply side. If investing in a new technology were to be seen as incurring one additional fixed cost, firms and individuals weigh current uncertain costs against a stream of future uncertain benefits and then base their decision to adopt, improve or defer depending on how long it might take them to recover that fixed cost. Romer (1990) uses a one-sector neoclassical model with technological change as a factor input to look at endogenous reasons as to what determines the investment towards technology. He argues that the rate of technological change is sensitive to the rate of interest and that capital accumulation is a necessity for firms to take on research and development. However, to get a clearer picture, Hall and Khan (2003) lay out the various demand and supply side factors.

Like Romer, Hall and Khan (2003) believe that when deciding whether or not to adopt a new technology, firms factor in their availability of complementary skills and inputs and look at the stability of the demand for their goods in the future. A firm's technical capacity might aid or hinder the adoption of a special new technology. According to Rosenberg (1972), the state of the capital goods sector and the skill level of a firm's employee are the most important determinants for diffusion. Since the adoption of a new technology requires the purchase of the said technology, training of workers to operate the technology and updating of existing machinery around the new technology and having a stable demand for its products is a vital prerequisite for investment. These conclusions were backed by Coleman (2001), who looked at data from OECD countries for the period 1970 to 1990 and found education levels of workers, overall investment rates in the country and openness to manufacturing trade to be the most significant determinants for investment in computers. Likewise, the need to reorganize factories to utilize a new technology can be seen as a demand side hurdle. David (1990) also had the same conclusion as he points out that during the 1900s when the adoption of electricity was slow because factories then were built to run on mechanical shafts powered by steam engines.

Another significant factor that might affect the demand for a technology is the network effects associated with the technology. Network effect occurs when the value of a technology increases as the total number of users in the network increase. Direct network effects occur when each user's utility is increased as the network expands. Likewise, an indirect network effect of technology would be the wider availability of complementary goods for the technology as becomes more popular. For example, the larger availability of computer software as the sales of computers go up would be an indirect network effect while the utility from Internet as the network expands counts as a direct network effect.

Both David (1990) as well as Hall and Khan (2003) agree that network effects can be seen most where pieces of technology are highly connected to each other. This was especially true during the Information Technology era. Saloner and Shepard (1995) arrived to similar conclusions in their paper. Saloner and Shepard (1995) evaluated the importance of network effects on ATM machines and found that the value of banks go up when their ATM network grows. Furthermore, there also exists possible production economies of scale associated with technological adoption. This can be seen in large firms, which adopt new technologies sooner to shorten the learning and integration phase, and then spread it across a large number of units to spread the fixed costs associated. Majumdar and Svankatram (1998) studied the telecommunication industry and found that while production economies of scale are more important during the early stages of technological adoption, they tend to weaken over time. Meanwhile, network effects tend to be important during all phases.

As for the supply side, Rosenberg (1972) states that the three vital factors that affect the supply side are: the development of complementary inputs such as user skill and capital goods, the improvements made on the technology after it is first introduced and the invention of new uses for the technology. Rosenberg (1972) argues that when it comes to new technology, those with crude first models that are rigid in functionality and only do a specific task often lag behind in the rate of adoption. Moreover, the efficiency gains from a new technology are observed to be much larger during the enhancement phase than during the initial stage. As was observed with the case of high-density semiconductor chips, it was improvements in the materials used for manufacturing chips that paved the way for developing high-end semiconductor chips in conjunction with improvements within the chip itself.

Meanwhile, when presented with competition from a newer technology, firms often choose to make improvements to the old technologies thus slowing technological adoption. This case remains especially true when the existing technology is a close substitute. During early 1900s, factories delayed their switch to electricity until the benefits were much higher than costs. Lastly, the availability of complementary inputs from the supply side is also a vital factor. Producers of new technology often offer training courses for their buyers to encourage them to adopt. As Gruber and Verboven (2001) note, improvements in complementary inputs were a more important determinant than pricing when it came to the spread of the mobile telephone company in Europe. Now that we understand the underlying factors that determine the adoption of a technology, we must look at the various models for diffusion of a GPT in order to understand the impact they have on productivity and growth.

Models of Technological Diffusion

Diffusion is the process by which a something spreads throughout a population. When it comes to diffusion of technology, the diffusion pattern usually takes the form of an S-shaped curve. With GPTs, diffusion often starts out slow initially and accelerates as it spreads and then eventually slows down as it saturates. While several models exist to explain the diffusion process, most reinforce the S-shape curve and acknowledge that technological adoption is by and large an "absorption state".

Rosenberg (1972) discusses the adopter heterogeneity model, which assumes that different individuals value innovation differently. His model argues that the three factors that lead to this S-shaped curve are the constant or declining cost of a new technology over time, an even distribution of values placed for adoption, and adoption only occurring when the valuation placed by adopters is greater than the cost of the technology. Likewise, an alternative model presented by Stang and Soul (1998) looks at adopter learning and suggests that each new adopter learns about the technology from their neighbor leading to an increasing rate for adoption. While this learning or epidemic model is a more sociological approach, it also follows a S-shape curve.

On the other hand, Stoneman (2001) takes an investment based approach to explain the diffusion of technology. Stoneman (2001) views adoption of technology as investment under uncertainty, which can be evaluated using the real options framework. His model argues that there is an option value to delaying the investment along with uncertainty over future profits and possible sunk costs associated with the irreversible nature of certain technological adoptions. Since firms will chose to delay investment until their benefits somewhat exceed costs, the process of diffusion will be slow in the beginning. On the other hand, as technologies improve and future benefits are less uncertain, more investments will occur. Stoneman's (2001) model is backed by Luque's (1998) study of manufacturing plants where she found that decline in uncertainty over benefits correlated with higher adoption of robotic technologies in States.

Section III – Impact of technology on Productivity and Growth: Lessons from History

Now that we have studied how technology spreads as a factor of production and gotten some brief understanding to the effects it might have on productivity. Let us look at the different major GPTs and the study the impact they've had under a microscope. The goal of this section is to draw contrasts and parallels among these technologies to help up see the trajectory we might be headed towards. While there were other significant inventions in the past, I have decided to start my analysis on steam to understand the impact of GPTs in productivity and then on jobs and wages.

Steam: Kick Starting the Engines of growth

In many ways, the steam engine can be seen as one of the most significant inventions of the first industrial revolution. First patented by James Watt in 1769, steam power help set up the backbone of the industrial era by making railways and commercial steamships possible. However, steam was very slow to replace wind and water power and did not make much of an impact on productivity until 100 years after its invention when high-pressure steam engines were perfected (Crafts 2004).

This slow diffusion of steam engines can be partly attributed to the delay in its improvements. Atack (1979) looks at various energy sources with respect to the total horsepower each supplied and finds that steam energy only took off later in the 1850s once its costs had decreased significantly. The original low-pressure steam engines were highly inefficient and took up large amounts of coal, which was expensive during the 19th century. The high-pressure Lancashire boiler developed in the 1840s significantly reduced the cost of steam power, followed by Corliss engine in 1861 which allowed for continuous uniform flow of power and required only a fraction of the coal to generate the similar amounts of power. As steam engine designs got better, coal consumption by these engines had halved four folds by 1870 along with improvements in clustering of engines which brought with it various economies of scale (Crafts 2004).

While steam power was slow to improve, the invention in itself had made other crucial innovations possible. Railways were initially completely dependent on steam engines; the first major railway opened in Liverpool to Manchester in 1830 and by 1855, railways occupied a capital stock of 30% of the GDP in Britain. Furthermore, as coal consumption fell, it paved the way for commercial steam-ships in the 1850s. However, both railways and steamships only started contributing to growth after 1870 in the era of high-pressure steam engines. The impact of steam was very little during the industrial revolution itself and peaked in the third quarter of the 19th century. Estimates show that between 1780 and 1830, the British economy experienced an average of 0.3% growth in TFP (Total Factor Productivity). As Hawke (1970) points out, while the contribution of railways was noticeable, the sector was small relative to GDP until the mid 50s. In fact, it wasn't until the 1870s when steam power was largely used in mining and textiles along with transportation that it showed boosts in productivity. The productivity growth from steam peaked during the 1870s when it contributed to 0.41% of growth in TFP before slowing down. Despite being a significant GPT, at no point was steam power large enough to dominate productivity growth. Eventually the steam era ended around 1899 (Crafts 2004).

Electricity: Qualitative gains

The electrification era occurred between 1894 and 1930. Similar to the case of steam power, the diffusion of electricity only took off once costs of electricity went down considerably and growth in productivity was only observed later on as the invention matured. However, unlike steam, electricity was much quicker in establishing itself and brought with it a myriad of qualitative benefits that accelerated its diffusion into industries and households.

The first commercial power plant, the Edison central generating station in New York, was built in 1879, however, only 3% of US households used electricity in 1899. It wasn't until 1914-17 that electricity became the primary source of power for factories and brought gains in productivity. When regulated regional utility rates of electricity started to come down because of the many central power stations that were built, electricity started to replace mechanical power in factories. By the 1920s, about half of an average factory's mechanical drive was running on electricity. This shift from steam to electricity brought tremendous qualitative and quantitative gains (David 1990).

The output per man-hour increased to 3.1 percent after 1919 compared to the 1.3 percent before this period. David (1990) attributes more than half of the 5% acceleration in aggregate TFP growth rate seen later in the 1920s to the electric motor. These gains can be attributed to cheaper energy costs as well as to the indirect gains from factory reorganization. With steam-power, mechanical shafts ran bulkily through the factory floor and would often be run by one central steam engine. Electricity allowed for more flexibility in factory locations and design because they no longer had to be located in a large area near a water source. Moreover, factories were able to efficiently restructure their equipment to reduce costs. Individual segments of the factories could now be operated independently without running the entire factory to make use of a single portion. And, absent of a massive mechanical shaft running through the factory, they could be as small as a single storied building in design. Higher thermal efficiency from lower friction between mechanical parts greatly reduced power costs as well. Moreover, one would be foolish to discount the qualitative aspects of gains factories saw when they moved to electricity. With the invention of the "unit drive", individual motors could be used on machines of different sizes. This meant that workers had a cleaner workshop in the absence of many rotating belts and they also benefitted from greater workplace safety. While these qualitative improvements in the factories were not part of the production cost calculations, they were vital in fostering the industrial boom of that era. While the change to electricity was slow and gradual and initially met with much resistance because of the high cost of replacing previous machinery, over time they paid off greatly in terms of the productivity gains and other qualitative benefits (Devine 1983).

Unlike steam, which saw its peak contribution a hundred years after its invention, significant growth in productivity was observed, almost four decades after the first central power station had been built. Electricity saw its accelerating rate of diffusion slow down by 1905 and eventually the electrification era was over by 1930. The lessons from steam and electricity are important, the information technology era that we live in now saw these at a much more rapid rate.

Computers and Information Technology: Parallel pasts and possible futures

The time period from 1971 to present can be called the era of computers and Information Technology. The computer era shows many parallels and contrasts to the previous GPT eras and has raised many speculations about its future impact. Compared to the previous GPTs, computers evolved much more rapidly and produced a higher volume of innovations. Although the first computers were invented around the mid 1940s, the first commercial use of the computers began in 1960s and the first affordable Personal Computers were introduced in the 1980s, when the technology was less than 15 years old. Internet and ecommerce was introduced in the 1990s. The cost per computation declined at an annual average of 37% between 1945 and 1980 followed by the much more rapid decline of 65% per year well into the 1990s (Nordhaus 2007). By 2005, the prices of computers have fallen at a rate 100 times faster than that of electricity (Jovanovic and Rousseau 2005).

When we compare computers to electricity, we can better understand the scale of impact computers have had as a GPT. The main barrier to the adoption of electricity was the cost of setting up the initial wiring, once centralized power grids were established, electricity spread across all sectors at a much more rapid pace. Similarly, with computers, as the prices of computers went down and the Internet was introduced, computers took over swiftly. Indeed, the acceleration phase for the diffusion of computers was much longer than for electricity and did not end until 1997, while that of electricity ended by 1905. Moreover, as there is no sign of the diffusion of computers slowing down. Electricity was widely adopted across many sectors once the infrastructure was present, however, IT started out in high skill jobs and then spread across as more uses of computers were discovered. The initial barrier to computer adoption was the human aspect of learning to operate it, which is why computers were first, introduced to the workplace to complement jobs performed by high-skill workers.

Because of the initial learning hurdle, during early phases of adoption, computers slowed productivity growth. As Bessen (2002) finds, IT did cause large productivity slowdowns at first because of the skill required to learn how to operate it. The productivity slowdown was stronger at the start of the IT era compared to the previous GPT eras. This slowdown was so prominent that Solow (1987) famously remarked -*"we see computers everywhere except in the productivity statistics."* However many economists disagree with Solow arguing that empirical studies of the previous GPT eras have shown the nature of productivity slowdowns in the initial phases of adoption. Jovanovic and Rousseau (2005) claim that the full impact of this era is yet to be seen and that the true paradox was that so much was expected of ITC to begin with (Crafts 2004). Indeed, ITC had already shown a TFP of 0.68% during 1974-90, compared to 0.41% by electricity during its peak. Even in terms of capital stock, ITC during 1980s in United States occupied a larger share of the capital stock than steam engines, railways and steamships did by the third quarter of the 19th century (Crafts 2004). Brynjolfsson and Hitt (1995) concluded that not only does IT substitute for ordinary capital and labor, but also in many sectors it shows a higher return on IT investments relative to labor and capital.

SECTION IV - Impact of technology on Jobs and Wages

Now that we have viewed technology's effect on productivity, we can finally address the issue of technological unemployment. This section explores how technology impacts jobs and wages and briefly discusses what the future might hold for the labor market.

Ever since the Luddite movement of the 19th century and the mass unemployment during the 1920s, many have been fearful of the power of technology and automation to take over human labor and for good reason. The previous sections have shown us the impact on productivity brought about by waves of GPTs. Each of these successive waves swooped in and drastically changed factory organization and market structure. Moreover, each GPT era also caused the displacement of workers from various sectors of the economy. Every consecutive GPT has had an increasingly prominent effect on the labor markets and is the reason why the century old "automation anxiety" exists till this present day.

Technology intermingles with humans based on the type of work they perform to either complement their work or replace it. Based on the amount of education and technical proficiency required, jobs can be largely categorized high-skill, middle-skill, and low-skill jobs. High skill jobs include technical or managerial jobs that require a large degree of analytical skills, problem-solving capabilities, creativity and persuasion. Meanwhile, low skill jobs include those that require brute physical effort or the ability to understand and use language and also jobs within the service industry. Middle skill jobs are those within sales, clerical and administrative work that often routine and require different combinations of skills. Different technological eras have had a varying degree of effect on jobs based on the skill bracket they fall into. In order to understand how technology has affected the different categories, one must first understand how technology interacts with human labor.

Interactions: Working with or against machines

Autor (2015) argues that technology can either complement or replace human labor in performing a certain task depending on the nature of the work. Compared to humans, machines hold a comparative advantage in performing routine tasks that are codify-able into a number of programmable steps. Machines are consistent and often perform assigned tasks with pinpoint accuracy. On the other hand, humans excel at tasks that demand adaptability and creativity. Human comparative advantage rests in common sense, abstract reasoning and the ability to exercise judgment and intuition. While a machine can perform a million accurate calculations in a second, more often so, human supervision is required to make sense of the results. Routine tasks that rely mostly on human musculature are most easily replaced by mechanical power and machine consistency. In contrast, non-routine tasks requiring human supervision remain the least susceptible to replacement by machines, and, are often complimented by them. A machine cannot build a fully furnished house, but, the use of bulldozers, cranes and other machines help complete the work in a fraction of the time it would take if it were to be done using only human labor.

Most work processes require a variety of inputs in the form of labor, capital, creativity, simple repetition, intuition, technical skills and lingual skills. While each of these inputs plays an essential role, improvements in one does not replace the need for the others, in fact, the result is quite the contrary. In a work setting, the improvement in one set of tasks most often increases the economic value of a complementary set of tasks. This phenomenon can be better explained using the O-Ring production function put forth by Kremer (1993). Kremer states that if one step in the production were to fail, the entire production process fails, likewise, if the step were to improve, it increases the value of making improvements in other links in the chain. Similarly, if technology makes some steps of the work process cheaper, faster and more reliable, it increases the value of the remaining tasks performed by humans in the production chain. This framework helps us best understand technological unemployment from a historical perspective.

Impact on Jobs over the years

When we look at historical trends we can see that each technological era has affected different sectors of the economy. Before the first industrial revolution, production usually took place in workshops run by skilled artisans who would work on a product from start to finish. The industrial revolution saw the introduction of the factory system where the process of production was split into many smaller specialized chunks along with the division of labor. This method of production required more labors, but, since each unit was responsible for only a small part of the production chain, factories were able to utilize lesser skilled workers. Hounshell (1985) describes this process as “de-skilling” or the simplification of tasks to substitute for skill. This division of tasks led to the subsequent displacement of skilled artisans. However, since these factories required more labor, the growth in labor force along with gains from improved production meant that workers saw an increase in real wages. As Clark (2008) points out, it was the unskilled workers who were the beneficiaries of the First Industrial Revolution.

Eventually, as factories adopted steam power, the continuous-flow system was developed where workers could stand in one place and the task would be moved to them. Workers could now use specialized tools on mass produced components to quickly create a product. Ford Motor Company further improved this model to establish the first assembly line in 1913. Ford's assembly line, which was designed around machinery that could be operated by unskilled workers (Hounshell 1985), reduced overall work time by roughly 34% at the expense of more laborers (Bright 1958). As James and Skinner (1985) note, assembly lines started an age where physical capital complemented unskilled labor in replacing skilled workers.

However, the tides turned as factories moved from steam to electricity. Electricity made it possible for many stages of the production to be automated by facilitating the mechanization of assembly lines. Goldin and Katz (1998) argue that the continuous-process and batch production methods reduced the demand for unskilled manual workers required for carrying materials, assembling and conveying, and consequently led to higher demands for relatively skilled blue-collar production workers required in operating the machinery Furthermore, the shift to electrification along with the development of railroads facilitated the opening of new factories across various geographical locations. As factories expanded and management of employees and accounts got more complex, more workers for managerial jobs and clerks were sought after (Chandler 1977). Indeed, as Goldin and Kartz (1995) note, significant growth in white-collar workers with higher education and blue-collar workers was noticed during the twentieth century. Moreover, the early 1900s saw an increasing demand for office workers. As technology entered offices, the use of calculators, typewriters, Dictaphones, address machines reduced the cost of information processing and increased the demand for educated office workers (Beniger 1986). This trend continued well into 40s as managerial, professional as well as technical jobs saw an increase during this period and much higher growth during the 1980s. Moreover, increasing mechanization of farming equipment and advancements in the use of fertilizers led to a rapid decline in agricultural jobs as well. 41% of the jobs in the 1900s economy were in the agricultural sector compared to a mere 2% in 2014 (Autor 2014).

Job Polarization: Computerization and Skill-Biased Technological change

The next big impact to jobs came with the introduction of computers. As computation got cheaper and computers spread across the various sectors of the economy, many jobs were automated. When the first PC was introduced in the 1980s with word processing and spreadsheet functions, it eliminated typist occupations and facilitated the automation of repetitive calculations. While the early office technologies had increased the demand for clerks, by allowing automation, computers quickly reduced their demand. Furthermore, the development of airline reservation systems in the 1970s led the way for self-service, along with the introduction of the first industrial robots in the 1960s by General Motors (Gordon 2012). Telephone operators were no longer required and this loss of middle skill jobs continued well into the early 2000s.

Computers had dramatically increased the amount of information that can be processed by those in the high skill labor pool. High skill jobs often employ abstract reasoning to acquire and analyze information in order to interpret and apply it. Rapid improvements in computing power have helped workers performing these tasks to further specialize in their work, earning them a higher comparative advantage in the labor market. Furthermore, technology has helped their lower-skilled complementary counterparts, such as office assistants and nurses, work more efficiently. Likewise, low skilled jobs rely on very little data processing. Moreover, the demand for manual task is income elastic, and the demand for service work is fairly inelastic. Over the past few years, rising aggregate income has indirectly raised the demand for these jobs. As for middle skill jobs such as sales clerical, machines have increasingly codified the procedures involved in these "production and operative jobs" leading to a substantial fall in the employment pool over the decades. These trends are most clear when we look at the sectorial changes to jobs in the US labor market.

Wage polarization and the changing nature of jobs

All of Krushell(2000), Griliches (1969) and Nelson and Phelps (1966) also arrived to this same conclusion that new technologies raise the relative earnings of the skilled workers because of higher premiums in the early years. Author (2015) believes that labor supply responses, output and income elasticity of demand of their labor, are what determine whether wages increase or decrease because of technological change and automation. High skill jobs saw an increase in wages primarily because of the time-lag factor, easily taking up to 10 years to be a high skilled technician. Furthermore, the supply response from entrants into this bracket has not been sufficient enough to dampen the wage gains. However, if we look at the low skilled jobs, even though there was an increase in the demand for these jobs, there has been ample supply of labor from workers displaced from the middle skill pool. While the wages for the low skilled workers have gone up over time, overall wage gains have been limited and this bracket has not seen as large of gains compared to the high skilled workers.

On the other hand, the wage gain for the middle skilled workers has decelerated over time, along with the overall percentage of workforce employed in this skill bracket. However, as Autor (2015) points out, the nature of jobs has been changing over time in this sector. He uses the introduction of ATM machines as an example to explain how middle skill jobs have adapted around new innovations. Between 1995 and 2010, despite the number of ATM machines increasing by four folds, there was no reduction in the number of bank teller jobs. On one hand the ATM machines made it cheaper to operate a bank branch and thus more bank branches opened up. Meanwhile, the occupation of a bank teller evolved to become more a salesperson to maintain a relationship-banking model, to help develop customer client relationship and introduce credits and loans.

Many such middle skill jobs where vocational skills are combined with literacy, problem solving and people-skills are predicted to remain in the future. Jobs that combine the 'routine' tasks performed by a machine with the non-routine tasks, requiring human supervision and interaction, give the humans a comparative advantage but also significantly increase their output. Author (2015) believes that just as the farmers led the high school movement in the 19th century so that the next generation could operate farm machinery, societal advancements that enable future workers to learn and adapt must be made now to better equip the labor force.

SECTION V-The Future impact of technology

During the 1960s, the general public in the US was rightly concerned about the impact technology would have on the demand for labor. To address these fears of mass displacement of labor, the government at the time guaranteed a minimum income for each family with the government being the employer of last resort, along with a variety of vocational training programs to the average American worker to help them better adapt to the changing labor market (Author 2015).

According to Simon (1987), education was the key to preparing the labor force for the incoming impact of technological displacement. However, Frey and Osborne (2017) believe that as computerization spreads across more sectors and into more cognitive fields, it could displace even more workers in the decades to come. The technological future might not be as bright for some jobs as some suggest, and advanced algorithms could lead to the loss of more than a 140 million full time knowledge-based jobs worldwide (MGI 2013).

The past has shown us how technological progress has shifted the composition of employment. Historically, human labor has been able to adopt and acquire new skills by means of education (Goldin and Katz 2009). The impact of technology was confined to mechanization of manual tasks during the 20th century. Simon (1987) had noted the various hardware and software limitations that were yet to be overcome before computers could do cognitive work. However, recent years have seen computers increasingly challenge human labor in numerous cognitive tasks. Brynjolsson and McAfee (2011) argue that computers do not suffer from fatigue and biases like their human counterparts but its biggest advantage is scalability. Because of vast improvements in computational power and the rapid digitization of the economy, computerization is now spreading to jobs that were traditionally considered as non-routine.

This digitization has brought about an age of Big Data and advanced algorithms. Recent developments in Machine Learning (ML), Data Mining, Machine Vision, Computational Statistics and Artificial Intelligence have made breakthroughs in automating a range of cognitive tasks that were previously considered human dependent. Self-driving cars and handwriting recognition were considered as non-routine tasks less than 10 years ago, but can now be performed by a machine. Using increasingly large and complex data sets, machine-learning algorithms are able to employ enormous amounts of computational power to find patterns and reverse engineer the steps to solving a problem. A popular example noted by Tanner (2007) includes Google using the United Nation’s documents originally translated by humans to improve their translating algorithm. As more and more data is available, these algorithms get better and are entering many different sectors that were previously unaffected by computerization.

Machine Learning (ML) algorithms are often better at detecting patterns than humans and have seen increasing uses in the financial and healthcare sectors. Cohn (2013) gives us the example of IBM's Watson computers used in cancer care hospitals to find the best case treatment for patients based on symptoms, genetics, family history and medical past based on a set of 600,000 medical evidence reports and 1.5 million patient medical records. Markoff (2011) discusses the use of computers in legal and financial services where they are taking over a number of tasks performed by paralegals, and lawyers. Powerful computers scan and look for concepts using language analysis on thousands of legal documents to assist in pre-trial research. Likewise, trading AI algorithms have been trained to process news information, press releases and financial information so that decisions can be made much faster than a human reader (Mims 2010). Furthermore, even in skilled tasks such as software designing, ML helps a developer automatically detect bugs in their programs and optimizes design choices based on optimal parameters, with a reliability that cannot be matched by humans (Hoos 2012). Furthermore, advanced speech recognition has enabled computers to respond to a much wider range of human requests as was seen in the case of Apple's Siri; this has further reduced the demand for call center workers (CAA 2012).

Furthermore, Mobile robotics is another advanced field where the machines are catching up with human labor. Mobile robotics uses ML to do manual tasks where cutting-edge robots use sensors and manipulators to perform tasks with great dexterity. General Electric recently developed robots that can climb and maintain wind turbines (Robotics-VO 2013). In the transportation sector, onboard sensors and computers are now able to monitor all 360 degrees of a car's surrounding with greater precision and attention than most human drivers. Using LIDAR and GPS algorithms self-driving cars are now possible. The use of sensors has allowed for automatic meter reading in flow pipes reducing the need for workers to visit the site (MGI 2013).

Computerization has become an increasing part of everyday life and has established itself in almost every sector of the economy. Frey and Osborn (2015) believe that as these advanced technologies are increasingly able to perform non-routine tasks, they have seen an increasing impact on the low-skill jobs over the years. Frey and Osborn (2015) predict that an estimated 47% of jobs in the US are at risk of being computerized in the next two decades.

Concluding Remarks

The literature on the economics of technological change and adoption go as far behind as the history of technology itself. Over the past centuries, views within popular literature have constantly shifted between embracing and opposing technological change. With passing years and increasing availability of data, many have drawn parallels between previous technologies and the recent wave of computerization. Moreover, different views exist about the potential of technology to displace human labor in the future. However, very little has been done to evaluate investments in technology with respect to changing wages, especially for skilled workers. It would be interesting to study changes in demand for computer programmers with respect to increasing demand for technical proficiency.

Acknowledgements

The process of compiling this literature review has helped me a great deal in polishing my research and analysis skills. The subject of Economics is vast with many major topics and countless literature on each topic. The tools I have acquired over the course of this review will be vital to any research I might conduct in the future. A special word of gratitude is due to Rajaram Krishnan, who helped me guide my research for this literature review. I am also grateful to other members of the Economics Department at Earlham for helping me over the course of the semester and would like to express my deepest appreciation to Mark Lautzenheiser for helping me review my work as I progressed.

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