Stuck in the Middle:

The Substitution Effect of Digital Technology

on Middle Skilled Jobs

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Abstract

Since the 1980s, middle-skilled occupations have experienced a steady decline in the share of U.S. employment, a phenomenon often attributed to advances in digital technology. Among the explanations reported in the economic literature, the Autor Levy Murnane (ALM) hypothesis suggests that routine processes are most vulnerable to digital substitution – digital technology substitutes for routine occupations and compliments non-routine occupations. Tests have involved a division of occupations as routine vs. non-routine, which are subdivided further as manual, cognitive or analytic.

Unlike existing literature that examines the effect of digital technology on employment, this paper analyzes its effect on the unemployed. Using data from the Current Population Survey and the Dictionary of Occupational Titles, I find that routine cognitive workers are more likely to be unemployed than non-routine cognitive workers, thus reinforcing the ALM hypothesis. However, the effect of advancements in digital technology on the unemployment gap between routine cognitive and non-routine cognitive occupations depends on the type of technology. Using VAR techniques, I find that the net effect of advances in hardware technology on the unemployment gap is zero, while the net effect of advances in software technology is positive.

I. Introduction

Since the financial crisis in 2008 from which the U.S. economy spiraled into the deepest recession since The Great Depression, politicians and citizens await 'job creation'. Hoping that new jobs will be forthcoming, many also expect former jobs to return once the economy recovers. But what if those former jobs will not return? What if the labor market has structurally changed? Such that a job once occupied for over ten years has been filled not by someone else, but something else – digital technology.

The scope of digital technology is not limited to the implementation of personal computers, but also encompasses the application, diffusion and replication of software on computers, smartphones and tablets. Such diffusion has created online marketplaces – such as progromatic bidding – classrooms and applications that have reduced skills at the hands of dozens of workers into one screen. This paper aims to determine whether advancements in digital technology have historically led to the displacement of workers employed in routinized occupations.

It may be questioned whether advancing technology causes permanent net job shifts. The corollary to job displacements by technology is increased productivity and new job creation – per growth models ranging from Solow's to the Real Business Cycle model. Isn't this just another technology shock pushing aggregate demand outward?

In the last two decades, a vast array of literature has emerged citing one of two forces to structural changes in the labor market: Skill-Biased Technological Change (SBTC) and the Autor Levy Murnane (ALM) hypotheses – the latter emerging from the inadequacy of the former to explain the rising job polarization in Western labor markets. According to the SBTC hypothesis, technology increases the demand for skilled labor and reduces the demand for unskilled labor, resulting in a higher wage compensation for skilled relative to unskilled labor. Acemoglu (1998) and Kramarz (1998) establish the correlation between skill acquisition and technological change. Machin and Van Reenen (1998) supplement the SBTC hypothesis with empirical evidence that indicates faster skill upgrading is associated with higher industry research and development.

Yet, if the SBTC hypothesis was true, then in the last decade, one would expect positive growth rates of employment for middle and high-skilled labor, as well as a decline in low-skilled employment. However, this is not the case. As Autor, Katz and Kreuger (1998), Autor, Levy and Murane (2003), Goos & Manning (2007),

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Nedelkoska (2012) have stipulated, Western labor markets exhibit a polarizing trend that can only be explained in part by the SBTC hypothesis. Indeed, employment growth of high-skilled labor has increased, but so too has the growth of low-skilled employment. The individuals losing out are not unskilled workers, but 'middling workers' employed in routinized labor. Consequently, the SBTC hypothesis cannot fully explain the twin peaks phenomena of the labor market. Instead, the ALM hypothesis offers a nuanced view of the relationship between digital technology and the labor market, one that surpasses the binary categorization of labor as skilled and unskilled.

II. The SBTC & ALM Hypotheses

Technological shocks can stimulate economic growth, yet the impact of these shocks on the labor market requires closer scrutiny. In the short run, the effect of a change in technology – such as the invention of the railroad, computer or web browser – is palpable within the subsequent boost in real GDP. However, the impact of a technological change on the labor market reveals itself over a longer period of time. Often, the true impact – as with computerization – does not emerge until decades after the initial invention.

With increasing vigor, economists and citizens alike have raised alarm about widening job polarization in the U.S. economy, which they attribute to advancements in digital technology. The SBTC hypothesis generalizes the impact of technology upon all skill types as equivalent. Yet occupations within industries are characterized by varying types of skills. So much so that the Dictionary of Occupational Titles (DOT) assigns skill descriptions to twelve thousand unique jobs.

Contrary to the SBTC hypothesis, which categorizes occupations as skilled and unskilled, the ALM hypothesis applies two tiers of skill decomposition. First, the tasks of labor are segmented into routine and non-routine skills. Within these branches, tasks can be further broken down into cognitive and manual skills. The ALM hypothesis predicts that technology replaces routine cognitive and manual tasks, but complements non-routine cognitive tasks.¹ Once stated, this declaration seems obvious, especially since the assembly line epitomizes the replacement of manual labor by machines. However, we must reconsider our standard conception of a routine task. Routine tasks have become synonymous with manual tasks where the laborer repeats the same motion, whether that be smoothing the surfaces of ceramic toilet bowls or individually wrapping Galvadier chocolate truffles for packaging. Routine tasks, though, also include routine cognitive skills.

Prior to the invention of the computer, tasks that required repetitive information processing fell strictly within the mind's domain. With the invention of the computer, a machine whose primary function is to process information, the mind's domain has been encroached upon and in many cases usurped by another domain – the network domain. Computers and the bundles of software programs and communication capabilities packaged with them have expanded the replacement capabilities of technology to include human cognition. As Autor et. al (2003) articulate:

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¹ For non-routine manual tasks, the ALM hypothesis predicts that digital technology is a weak, or limited, compliment.

As symbolic processors-machines that store, retrieve, sort, and act upon information-computers augment or supplant human cognition in a vast set of information processing tasks that were historically the mind's exclusive dominion...Computers have increasingly substituted for the information processing, communications, and coordinating functions of bookkeepers, cashiers, telephone operators and other handlers of repetitive information processing tasks. (5)

Computers have expanded the types of tasks replaced by technology to include not only routine manual skills, but also routine cognitive skills. Thus, computers function as substitutes for routine manual and cognitive tasks and complements for non-routine cognitive tasks by increasing productivity.

Over the past three decades, the share of employment has shifted in favor of non-routine cognitive labor, as displayed in Figure 1.1. Furthermore, while the employment share of routine cognitive labor has fallen since 1970, the share of nonroutine manual labor remains constant over time. If the SBTC hypothesis was true, we would expect the share of the lowest skilled occupations to decline as technology advances. Yet – as the ALM hypothesis predicts – since computers function as a limited complement of non-routine manual labor, its share of employment remains stable as digital technology advances.



As with all substitution effects, the primary component that drives the replacement of one process for another is cost. In the decision to hire, a firm must choose whether the marginal product of labor of hiring an additional worker is equal to or exceeds the worker's marginal cost. A firm must also consider whether substitutes are available that offer a lower marginal cost for the same or greater marginal product of the worker. As substitutes, the price of computers and the quantity of **routine** cognitive labor employed are positively related. Conversely as compliments, the quantity of **non-routine** cognitive labor employed and the price of computers are inversely related. Given this relationship between the price of computers and its substitutes and compliments, as the price of computers declines, the quantity demanded of routine cognitive labor will decrease while the quantity of non-routine cognitive labor will increase. The corollary of this statement indicates that as computer prices decline, the number of individuals employed in routine cognitive labor will either become unemployed or switch occupations. In order for

Figure 1.1

this effect to be true, the price of computers must have declined since 1977. Indeed, as Bresnahan (2000) cites, the quality-adjusted price of computers has declined at a compound rate of twenty percent per year through the mid 1990s.²

These two functions of computers – as substitutes and compliments –are the central claim of the ALM hypothesis. If the ALM hypothesis models the interaction between the labor market and digital technology, we would expect within the data that routine cognitive workers represent an increasing share of the unemployed.

III. Hypotheses: Adding the Lens of Job Loss

The majority of the economic literature concerning the displacement of routinized workers by digital technology measures the share of employment differential that can be attributed to computers (Goos and Manning, 2007, Autor, Levy and Murnane, 2003, Autor, Katz and Kreuger, 1998). Such work attempts to determine the degree to which computers modify the tasks of a given occupation by examining those currently employed. In part, this is a result of the nature of the data, since most surveys only ask employed individuals whether they use a computer at work and for what purpose. Yet, by only measuring the effects of technology displacement on the employed, existing literature neglects the most important people of interest – the unemployed.

What happens to the individuals whose routinized jobs are usurped by digital technology? Do they find work elsewhere? Are they more likely to become unemployed? Must they accept a lower wage if changing occupations? Ljubica

² Figure 6.1 in the Appendix displays the steady decline of the computer price index since 2005.

Nedelkoska attempts to answer this very question for the case of another Western economic power: Germany. Nedelkoska (2012) attempts to track the adaptation process of German workers whose occupations require routine tasks. An individual whose skills become obsolete faces two choices: unemployment or occupational change. Nedelkoska concludes that workers performing routine tasks incur a higher probability of becoming unemployed and switching occupations. Similar to Nedelkoska's conclusions, I predict that workers performing routine cognitive tasks face a higher probability of unemployment compared to those performing nonroutine cognitive tasks.

A question that remains, however, pertains to the causality assertion. Is technology to blame for the decline of occupations requiring routine cognitive tasks? Nedelkoska concludes that if such directional causality exists, then it is a weak causal relationship in production and manufacturing, and for coding technologies other than computers, the relationship can even be complementary, proving that not all digital technologies interact uniformly with the labor market. Autor, Levy and Murnane (2003) conclude opposite results. Instead, within the most highly computerized industries, the trend exhibits an increase in labor input for non-routine cognitive skills and a decrease in labor input for routine cognitive skills. As with most relationships in economics, direct causality remains elusive. Association, at best, can be attained. Thus the second hypothesis to be tested is whether advancements in digital technology are historically followed by an expansion of the unemployment gap between routine cognitive and non-routine cognitive occupations.

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IV. Data Methodology

In order to measure the likelihood of unemployment for non-routine cognitive occupations compared to routine cognitive occupations and to test for causality between technological advancement and the unemployment gap, we require measures of skill task for all occupations. The National Academy of Sciences and Committee of Occupational Classification and Analysis aggregate Dictionary of Occupation Titles (DOT) characteristics for the 574 occupation categories of the 1970 U.S. Census. In the COC-DOT aggregation, Census Occupation Codes (COC) are assigned a score for General Education Development, Aptitudes and Temperaments measured in the DOT.

Using the same methodology as Autor, Levy and Murnane (2003), five

characteristics indicate the degree to which an occupation is non-routine or routine.

Non-routine Cognitive-Analytic: Mathematical General Education Development (GEDMATH) captures an occupation's quantitative and analytical reasoning skills.

Non-routine Cognitive-Interactive: Directional, Control, Planning (DCP) measures an occupation's communication and management skills.

Non-routine Manual: Eye-Hand-Foot Coordination (EYEHAND) takes on high values for occupations requiring a high degree of physical agility and spatial recognition.

Routine Cognitive: Set Limits, Tolerances or Standards (STP) indicates a worker's ability to adapt to work requiring set limits, tolerances or standards.

Routine Manual: Finger Dexterity (FINGDEX) captures the level of motor skills an occupation requires.

Based on the score of the DOT skill measures in the COC-DOT aggregation, I

calculated a weighted DOT mean task in order to assign one of the five skill

measures to each of the 574 Census Occupation Codes. In other words, I defined each occupation as non-routine cognitive-analytic, non-routine cognitiveinteractive, non-routine manual, routine cognitive or routine manual.

Although U.S. Census Data served to classify occupational codes by skill measure, I drew from the Current Population Survey (CPS) to analyze unemployment by skill measure. Since the U.S. Census and the CPS code occupations differently, I created a crosswalk using the CPS translation page to assign a skill measure to the CPS occupation codes with base year of 1970.³ By using the 1970 base year occupation codes, occupations are comparable over time. However, in using the base year, we assume that the task requirement of occupations remains constant overtime. Although this assumption could limit the regression results since technological advancement leads to changes in an occupation's tasks, the benefit of the assumption outweighs its limitations. By classifying each CPS occupation with a skill measure, characteristics of the occupation – instead of the individual – can be tracked overtime, in particular, unemployment status.

³ The Current Population Survey provides the translation page. The page categorizes CPS occupation codes by U.S. Census Occupation Codes for all years. The U.S. Census Occupation Codes are more detailed than the CPS occupation code. Thus to create the crosswalk, I matched the U.S. Census Occupation Codes to their CPS counterpart as defined by the translation page.

Probit Model

To measure the likelihood of unemployment of an individual with a routine cognitive or non-routine cognitive-analytic task, I created a probit model using CPS data from 1972-2013.⁴ The probit model is defined as follows:

1.
$$P(U_{i,T} = 1 | x_{i,T}, z_{i,T}) = F(\beta_0 + \alpha x_{i,T} + \gamma z_{i,T} + \epsilon_{i,T})$$

where $U_{i,T}$ is the likelihood of unemployment of individual *i* at year *T*, α is a vector of coefficients for a vector of characteristics $x_{i,T}$ that include age, sex, race, income, education and industry and γ is a vector of coefficients for a vector of dependent variables $z_{i,T}$ that include dummy variables defining the skill measure of an occupation.⁵

Vector Auto-regression (VAR) Model

Testing for Granger Causality through Vector Auto-regression is one method of determining whether a causal relationship exists between two forces. A casual relationship between digital technology and the unemployment rate of non-routine cognitive and routine cognitive jobs has yet to be established or refuted. If the probit model supports the hypothesis that individuals employed in routine cognitive occupations incur a greater likelihood of unemployment than those employed in non-routine cognitive work, then the question remains as to why this disparity

⁴ The sample consists of individuals between the ages of 18-65 who are in the labor force. For each year, *T*, the number of observations is between 40-90k individuals. See Table 1.2 in the Appendix for the probit model output.

⁵ Income is measured using an individual's wage. All measures of income are inflation adjusted using the CPI less food and energy with 2007 as the base year.

exists. The VAR model tests whether this difference in unemployment rates can be attributed to advancements in digital technology.

In order to create a VAR model, I converted the existing micro data from the CPS into time-series data. From 1972-2013, I calculated the annual unemployment rate for routine cognitive and non-routine cognitive jobs within the aggregate economy. Since the variable of concern is the disparity between the unemployment rate of routine and non-routine cognitive occupations, the dependent variable is the difference between the two unemployment rates. (Since I subtracted the unemployment rate of non-routine cognitive jobs from the unemployment rate of routine cognitive jobs, we would expect this difference to be positive).

For the primary explanatory variable, a measure of digital technology must be chosen. Investment in digital technology will serve as a proxy for technological advancement in the VAR model. The Bureau of Labor Statistics provides aggregate and industry level measures of digital technology investment in the National Income and Product Accounts (NIPA). Categories of investment include PC (personal computer), printers, hard drives, user-owned software, licensed software etc. I aggregated these sub-categories into two umbrella categories: hardware and software investment.

Although investment in durable and non-durable computer goods commenced during the same time period, the respective growth rates of investment vary significantly. Figure 1.2 and 1.3 displays the level of economic wide investment in hardware and software technology for the U.S. from 1972-2011. Accompanied with the graphs is a timeline that tracks the milestones of invention for the respective technologies.



Figure 1.2⁶ U.S. Hardware Investment, 1972-2011

⁶ The timeline of hardware and software technological advancements was compiled from the Computer History Museum.



Figure 1.3 U.S. Software Investment, 1972-2011

Investment in both hardware and software increase over time – as expected – yet for hardware investment, the growth rate remains fairly constant while software investment exhibits varying rates of exponential growth. Within the contours of these growth rates, the history of the digital technology revolution resides.

In 1989, Sir Timothy John Berners Lee invented the *World Wide Web* (it was released in 1990), but this invention alone did not spark the fastest rate of computer hardware investment from 1992-1996. Without a format to navigate, read and post content, the *World Wide Web* was inaccessible to widespread users. Once CERN uploaded the first website on August 6, 1991, the Internet became universally user-friendly, which sparked the highest growth rate of hardware investment. Software investment, however, did not respond in the same manner as hardware investment to the creation of the first website. Not until 2002 – following the DOT-COM bubble and the invention of the web-browser – did software investment finally takeoff.

Since hardware and software investment responded with varying growth rates to technological disturbances, they may also exhibit differing effects on unemployment for routine cognitive and non-routine cognitive occupations. Hence, the VAR model does not aggregate hardware and software investment.

The VAR model is as follows:

2.
$$D(U_{i,k,T}) = \beta_o + \delta I_{T-1} + \delta I_{T-2} + \eta Y_{T-1} + \eta Y_{T-2} + \lambda \pi_{T-1} + \lambda \pi_{T-2} + \beta D(U_{i,k,T-1}) + \beta D(U_{i,k,T-2}) + \varepsilon$$

where $D(U_{i,T})$ is the difference in the unemployment rate at time *T* between occupations with skill measures *i* and *k*, *I* is a vector consisting of the log of aggregate investment in hardware and software, *Y* is the log of real GDP and π is the log of the CPI less food and energy.

V. Results

Probit Model

The first hypothesis predicts that individuals employed in routine cognitive work incur a higher likelihood of unemployment than their counterparts in nonroutine cognitive occupations. If this hypothesis proves to be true and if we suspect that advancements in digital technology contribute to the result, then we would expect the shift of unemployment likelihood in favor of non-routine cognitive jobs to occur after 1977, when the Apple computer made its debut.⁷ Indeed, the probit model shows that routine cognitive workers become more likely to be unemployed than non-routine cognitive workers *after* the invention of personal computers.

⁷ Source: Autor (1998).

The coefficient of the dummy variable for routine cognitive labor, all else constant, becomes consistently significant in 1983, two years after the first IBM personal computer arrived on the market and at the beginning of the decade in which computer usage rapidly expanded across all industries. Figure 1.4 presents the marginal effect of the coefficient for routine cognitive occupations from 1968-2010.



From 1968-1983, the coefficient alternates between significance and nonsignificance in the probit model, indicating that skill measure is not a conclusive factor in predicting the probability an individual will be unemployed from one year to the next. Post 1983, individuals employed in routine cognitive occupations have a consistently higher probability of unemployment by 1-2 percentage points. In other words, the unemployment rate for routine cognitive occupations is 1-2 percentage points higher than for non-routine cognitive occupations (both analytic and interactive). This percent difference in the unemployment rate is consequential

Figure 1.4

 – especially considering the unemployment rate fluctuates within the bounds of 6 and 8 percent.

The only anomaly within the data occurs in the year 2000, when the marginal effect of routine cognitive occupations is not statistically significant. On March 10, 2000, the dot-com bubble burst, sending the job status of all Americans, regardless of skill type, into a tailspin of uncertainty. CPS data is collected at the end of March. Thus in 2000, CPS data was collected within weeks of the dot-com crash, which explains why all jobs, regardless of skill measure, incurred the same probability of unemployment.

The results of the probit model are consistent with the results of Nedelkoska (2012), where German individuals experienced a higher likelihood of unemployment given employment within a routine occupation. Nedelkoska had access to a panel data set in Germany, which allowed her to measure the probability of occupational changes of individuals across time. As expected, individuals occupied in routine work were more likely to switch occupations than those occupied in non-routine work. When comparing the likelihood of unemployment vs. the likelihood of occupational changes, individuals were significantly more likely to switch occupations than to become unemployed. Here lies the limitation of the CPS dataset: individuals cannot be tracked over time and consequently, occupational changes are not captured in the probit model. Although the probit model cannot capture the probability of occupational changes by skill measure, it must be recognized that advancements in digital technology do not necessarily displace a worker, but instead force an individual to change occupation.

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The question remains, however, whether the 1-2 percentage point difference in the likelihood of unemployment between routine cognitive and non-routine cognitive occupations is a result of advancement in digital technology. It cannot be assumed on the basis of skill measure alone that digital technology causes workers of routine cognitive occupations to face a higher unemployment rate than nonroutine cognitive workers. The VAR model attempts to supplement the results of the probit model by determining whether a statistical link exists between the unemployment gap and digital technology.

VAR Results

The VAR model measures whether advancements in digital technology are predictive of an expansion in the unemployment gap between routine cognitive and non-routine cognitive occupations. Digital technology has been categorized as hardware and software investment, since we expect the effect on the unemployment gap to depend on the type of technological advancement. In the VAR model, the unemployment gap is defined as the difference in the unemployment rate between routine cognitive and non-routine cognitive-analytic occupations. Figure 1.5 provides a visual representation of the unemployment gap.



Although one can imagine that other unemployment gaps exist – such as the gap between routine cognitive and non-routine cognitive-interactive or routine manual and non-routine manual unemployment – to avoid overcomplicating the empirical analysis, the unemployment gap will only pertain to the difference in routine cognitive and non-routine cognitive-analytic unemployment. Since Autor et. al (2003) concluded that technological advancements had the greatest impact on the share of employment of routine cognitive and non-routine cognitive-analytic occupations, I will restrict my analysis to the unemployment gap between those two skill measures. Furthermore, the empirical results of the other unemployment gaps did not generate significant findings.

Table 1.1 in the Appendix presents the results of the Granger Causality test ordered by Cholesky Factorization for the estimated VAR model.⁸ Before examining the model's estimated effects of hardware and software investment, we must first

⁸ The VAR model passes the unit root test and is stable. Furthermore, the lag exclusion test recommends the use of two lags.

determine whether the model exhibits expected relationships consistent with macroeconomic theory. In the VAR model, GDP is exogenous and significantly effects inflation, meaning that an unexpected rise in GDP is associated with rising inflation. Figure 2.1 displays the impulse response of the CPI to a shock in GDP.



The impulse response generates a shock at time zero in order to measure the response of one variable to an unanticipated rise in another variable, thus simulating the dynamic between the two variables. In Figure 2.1, an unexpected stimulus in GDP is followed by a rise in the CPI. Contrary to expectations, hardware and software investment do not function as complements. Instead, the model indicates that the primary driver of hardware and software investment is computer prices. This result is consistent with the conclusions of Autor et. al (2003). As demonstrated in the impulse response in Figure 3.1 and 3.2, an unexpected rise in prices is historically followed by a sudden decrease in software and hardware investment over the short run (approximately two years).



Once prices stabilize in the medium run, hardware and software investment return to their previous levels. Since the VAR model exudes the expected macroeconomic relationships supported by theory and existing empirical analysis, the VAR model has the potential to capture the dynamics between advancements in digital technology and the unemployment gap.

As stated by the ALM hypothesis, computer technology serves as substitutes for routine cognitive occupations and complements the work of non-routine cognitive-analytic occupations. If this hypothesis is true, then we would expect hardware and software investment to be associated with an expansion of the unemployment gap. The results of the Granger Causality test show that hardware and software investment, GDP and inflation are all significant contributors to the unemployment gap between routine cognitive and non-routine cognitive-analytic occupations over time.

The impulse response of the unemployment gap to a shock in GDP indicates that the gap responds in alignment with the expansions and contractions of the economy. During an economic expansion, the unemployment gap contracts and the reverse is true during an economic contraction. Moreover, the unemployment gap also exhibits the trade-off between unemployment and inflation predicted by the Phillips Curve. Figure 4.1 and 4.2 display the impulse response of the unemployment gap to a shock in GDP and inflation, respectively.



However, the unemployment gap cannot solely be attributed to the cyclical nature of the economy. Technological advancement contributes to the gap's persistence, yet not all technologies exacerbate the unemployment gap to the same degree. Contrary to expectations, an unanticipated rise in hardware and software investment leads to a contraction of the unemployment gap in the short-run (from year zero to year two), as displayed in Figure 5.1 and 5.2.



However, in the medium run, the effect of hardware and software investment on the unemployment gap differs. In response to a shock in hardware investment, the unemployment gap marginally rises above zero during the medium run (from year four to year seven). In contrast, a shock in software investment leads to an expansion of the unemployment gap in the medium run that exceeds the initial contraction in the short run. Thus the net change in the unemployment gap following a shock in software investment is positive, which means that advancements in software technology are historically followed by increased unemployment for routine cognitive workers and/or decreased unemployment for non-routine cognitive-analytic workers.

In order to account for the differing effects of hardware and software investment on the unemployment gap, two possible explanations arise. First, unlike automated devices responsible for replacing routine manual labor following the industrial revolution, the machine itself – the personal computer – may not fully substitute workers for routine cognitive tasks. The computer cannot produce output without software (hence they are complementary goods). Perhaps the substitution value lies not in the machine itself, but the application of the machine realized through software.

The computer acts as a mechanism upon which software – the true usefunction of the computer – can run. Without the creation of software, the widespread accessibility and usability of the machine would not have been realized. For example, during the infancy of the *World Wide Web*, its usability was diminished without a means of navigating its terrain. Until Netscape created the first userfriendly web-browser, the webpages and information contained upon those pages went unread, like lone signs along an unpaved highway.

Although the complementary nature of hardware and software lends itself to producing a good or service, digital technology's greatest contribution is its connective power – the ability to connect individuals and to create a seamless interlay of all units of a firm. As Bresnahan (2000) explains, advancement in digital technology alters the cost-effective structure and organization of a firm. For example, Business Workflow software fundamentally changed what was considered the most cost-effective scale of a firm, which led to large organizational changes. According to Bresnahan, large organizational changes, which often include the decentralization of decision-making, lateral communication and a greater emphasis on the need for autonomous workers, have a larger effect on the acquisition of higher skilled labor than the technological change alone.

Such mass organizational re-structuring does not come without a price – not only money, but also time. Restructuring a firm in order to incorporate advances in digital technology requires time. Consequently, a time-delay effect occurs that

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postpones the efficiency gains following the implementation of the organizational changes. The time-delay effect is precisely what occurs in the impulse response of the unemployment gap to a shock in software investment. As Figure 5.2 displays, the expansion of the unemployment gap does not occur until two years after the initial shock. Thus, the substitution effect of advances in digital technology on routine cognitive workers is not immediate. Only after firms achieve the implementation of new digital technology do computers begin to replace routine cognitive workers.

The substitution effect captured in the VAR model most likely underrepresents the magnitude of the actual substitution effect occurring in the U.S. labor market. Since the model only includes the number of unemployed workers for each skill measure, those workers partially replaced by digital technology are not included. 'Partially replaced' refers to occupations in which computers do not replace the entire worker, but only a subset of the worker's skills. Bresnahan (2000) labels this partial replacement effect as the 'limited substitutability' of digital technology. Due to the nature of the dependent variable, the model does not capture those routine cognitive workers who experienced a subset of their tasks replaced by computers. If the VAR model could capture those routine cognitive workers partially replaced by digital technology, we would expect the impulse response of the unemployment gap to be significantly larger.

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VI. Conclusion

The replacement effect of technology upon labor is nothing new, as this effect has occurred since the industrial revolution, during the creation of the assembly line and now, through advancements in digital technology. Previously, the Skill-Biased Technological Change hypothesis provided a widely accepted explanation for the effect of advancing technology upon the labor market: technology increases the demand for skilled labor and decreases the demand for unskilled labor.

Yet, this explanation fails to explain the recent decline of middle skilled labor in the last three decades – a decline that existing economic literature has attributed to advancements in digital technology. The Autor Levy Murnane (ALM) hypothesis provides a more nuanced view of the effect of technology on the labor market by categorizing labor within routine and non-routine occupations. Routine and nonroutine occupations can be further segmented by manual and cognitive occupations. The ALM hypothesis states that digital technology behaves as substitutes for routine cognitive occupations and as compliments for non-routine occupations. Insofar as the ALM hypothesis accurately explains the dynamic of the labor market and digital technology, the substitution effect of digital technology impacts a large share of the labor market, since routine cognitive occupations are concentrated within the middle class.

I tested two hypotheses: 1) Individuals employed in routine cognitive occupations incur a higher probability of unemployment than individuals employed in non-routine cognitive occupations and 2) The unemployment gap between routine cognitive and non-routine cognitive occupations can be attributed to

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advancements in digital technology. The probit model confirmed that since the 1980s, routine cognitive workers are more likely to become unemployed than nonroutine cognitive workers. In order to determine whether the unemployment gap between routine cognitive and non-routine cognitive occupations can be statistically linked to advancements in digital technology, a Vector Auto-regression Model (VAR) measured to what extent expansions in the unemployment gap can be explained by advancing digital technology.

Using hardware and software investment as a proxy for digital technology, the results of the VAR model conclude that the effect of digital technology upon the unemployment gap depends on the type of technology. Advancements in hardware technology are statistically significant, but the net effect on the unemployment gap over time is zero. In contrast, advancements in software technology lead to a contraction of the unemployment gap in the short run, but an expansion of the gap in the medium run that exceeds the initial contraction. Thus, the net effect of advancements in software technology on the unemployment gap is positive, which means that advancements in software technology are historically followed by an increase in unemployment for routine cognitive occupations and/or a decrease in unemployment for non-routine cognitive occupations.

The implications of these results indicate that as software technology advances, a greater number of routine cognitive occupations will either be fully displaced or partially displaced by digital technology. Partial displacement refers to the replacement of a subset of skills required within an occupation. Future research should be concerned with how to transition workers with middling skills towards

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higher skilled occupations that are complimented – not substituted – by digital technology. Such transition efforts in the form of job training, education and skillupgrading programs will be of greatest importance not for new entrants of the labor market (such as college graduates), but for existing laborers. As digital technology – especially software – advances at an increasing rate, our cultural expectation of a 'lifetime' career may be subject to evolution. In the near future, the norm may no longer be to remain in one occupation until retirement, but rather to reinvent our careers multiple times in order to adapt to a labor market, economy and world buffeted by constant waves of digital technological advancements.

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Appendix

Table 1.1: VAR Granger Causality Test Results

The table presents the p-values for the Granger Causality Test.

Independent Variable

	log(GDP)	log(CPI)	log(Hardware)	log(Software)	Urc - Unr- c/A
log(GDP)	***	-	-	-	-
log(CPI)	0.0256**	***	-	-	-
log(Hardware)	-	0.0015***	***	-	-
log(Software)	-	0.0091***	-	***	-
URC - UNR-C/A	0.0643*	0.0536*	0.0434**	0.0252**	***

Adjusted R-Squared	0.74
Observations	34

URC - UNR-C/A refers to the difference in the unemployment rate between routine cognitive (RC) and non-routine cognitive-analytic (NR-C/A) occupations.





Source: Federal Reserve Bank

Appendix

Table 1.2: Probit Model Output

Year	Observations	McFadden R-squared
1968	42775	0.1137
1969	43535	0.1072
1970	42267	0.0959
1971	42831	0.1145
1972	41590	0.1214
1973	41453	0.1013
1974	41266	0.1065
1975	40798	0.1315
1976	43277	0.1238
1977	52652	0.1129
1978	52062	0.1207
1979	52991	0.1090
1980	63459	0.1093
1981	64275	0.1286
1982	57580	0.1267
1983	57608	0.1355
1984	64670	0.1301
1985	65713	0.1367
1986	64571	0.1214
1987	64573	0.1263
1988	64831	0.1256
1989	60767	0.1120
1990	66902	0.1095
1991	66737	0.1072
1992	66042	0.1177
1993	65414	0.1131
1994	63469	0.1205
1995	63356	0.1048
1996	55167	0.1049
1997	56402	0.1144
1998	56709	0.1100
1999	57021	0.0904
2000	53425	0.0988
2001	87056	0.0937
2002	85818	0.0818
2003	83782	0.0761
2004	81627	0.0866
2005	80067	0.0864
2006	79311	0.0799
2007	78511	0.0842
2008	78099	0.0906
2009	77982	0.0913
2010	76535	0.1025
2011	73380	0.1027