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Just Out of Reach

THE ELUSIVE QUEST TO MEASURE THE DIGITAL ECONOMY

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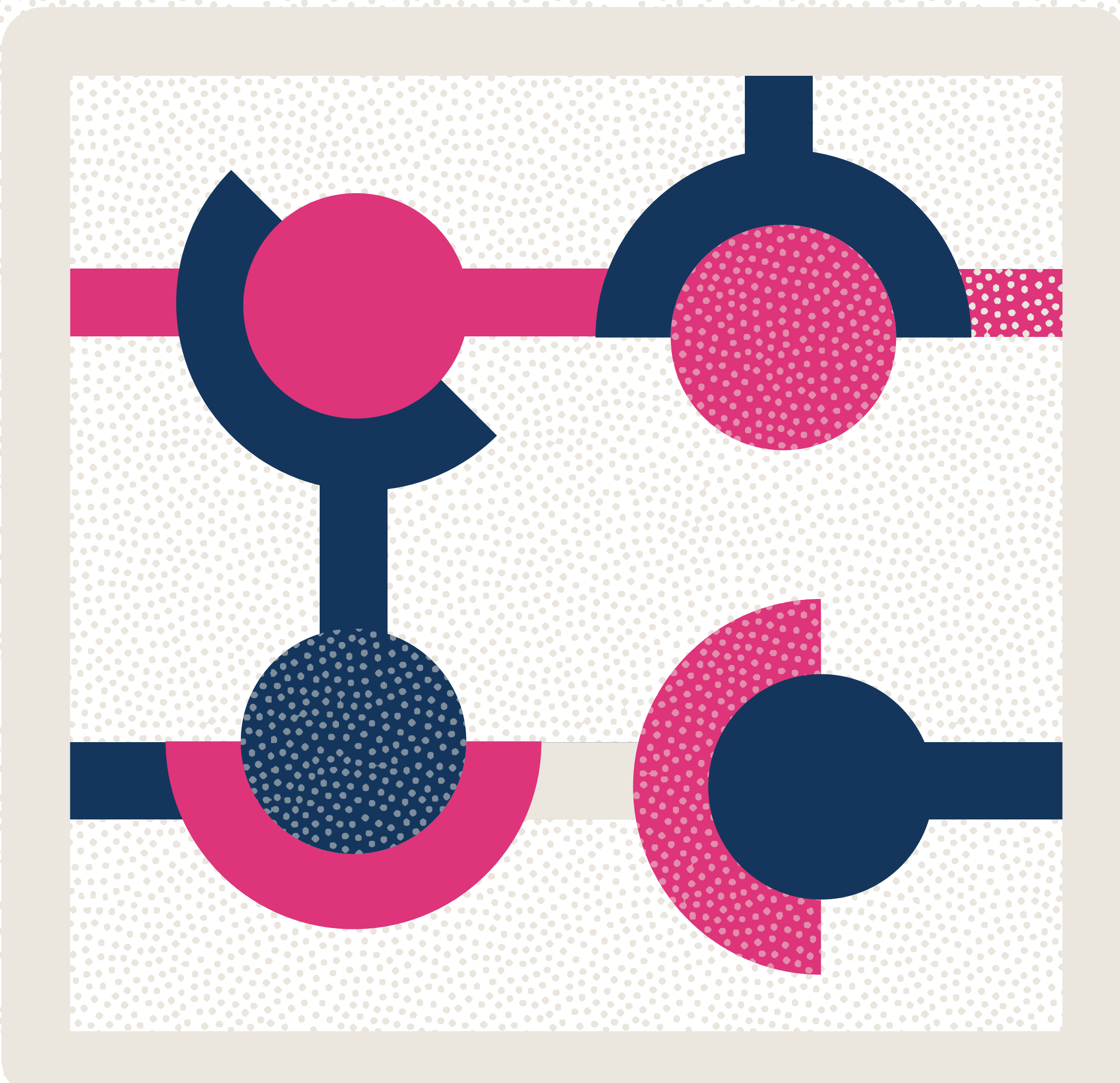

VIET VU
SENIOR ECONOMIST,
BROOKFIELD INSTITUTE

Viet is a Senior Economist at the Brookfield Institute for Innovation + Entrepreneurship. Viet is interested in how governments and companies can intentionally design policies and markets to drive human behaviour. He is also fascinated by how the world adapts to the emergence of new types of markets, as legal frameworks often lag behind. Viet holds a Master of Science in Economics from the London School of Economics & Political Science and a Bachelor of Arts in Economics with Honours from the University of British Columbia.

viet.vu@ryerson.ca | @vviet93

STEVEN DENNEY
POSTDOCTORAL FELLOW,
INNOVATION POLICY LAB

Steven is a Postdoctoral Research Fellow in the Innovation Policy Lab at Munk School of Global Affairs and Public Policy, University of Toronto, and a collaborator for the Brookfield Institute for Innovation + Entrepreneurship. His research spans the fields of comparative political economy and (im)migration and citizenship. Steven holds a PhD in Political Science from the University of Toronto, an MA in Global Affairs and Policy from Yonsei University, and a BA in Political Science from Harding University.

stevencdenney@gmail.com | @StevenDenney86

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20 Dundas St. W, Suite 921, Toronto, ON M5G 2C2

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Special Thanks + Acknowledgements

Principal Investigator
Mark Hazelden, Senior Director

Contributors

Shilbee Kim, Workstream Lead, Entrepreneurship Policy

Creig Lamb, Senior Policy Analyst

Sarah Doyle, Director, Policy + Research

Jessica Thomson, Marketing & Communications Specialist

Lisa Fielding, Copyeditor

Rachel Tennenhouse, Designer

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Introduction

TECHNOLOGICAL DEVELOPMENT is central to long-term economic growth and prosperity. In the past two decades, one particular form of technology has captured the attention of researchers as well as policy-makers: digital technology. Digital technology has created new methods for commerce to take place, from the introduction of new and more efficient modes of communication to entire digital platforms where buyers and sellers can interact. These changes mean that theoretical models and empirical measurements designed during and for the pre-digital era to understand economic dynamics fail to fully capture economic activities that happen digitally, obfuscating our ability to understand their broader impact.

One particular area where such considerations are needed is in how digital technology affects workers and labour. A number of conceptual problems present themselves, from estimating the value of a particular digital technology asset (especially concerning assets that are intangible, such as software, which is costless to replicate once produced) to challenges in delineating cases where digital technology *complements* workers and where it *replaces* workers.

As Canada and the rest of the world emerge from the COVID-19 pandemic, many workers have had to reconcile the dramatic impact of the pandemic on the way they work, as almost one in three workers in Canada worked most of their hours from home in 2020 (Mehdi & Morissette, 2021). Such changes were also felt by businesses, where one in 10 recorded half or more of their total sales online in 2020, an increase of almost 50% from 2019 (Statistics Canada, 2021). Such drastic changes also necessitated national statistical agencies to amend data collection methods to provide actionable insights for policy. As a result, Statistics Canada, , introduced the Canadian Survey on Business Conditions, the Canadian

Perspectives Survey Series, as well as introduced new measures into the Labour Force Survey and increased the frequency by which the Jobs Vacancy and Wages Surveys are released (monthly from quarterly). In Canada, this also meant that the way the 2021 census data collection was done was affected (Statistics Canada, 2020).

Now, more than ever, we need an approach to understand digital technology's impact on work and labour to capture the full range of economic activities that have and will take place. Through this knowledge synthesis, we will systematically review the conceptual ways in which technologies have been understood to impact economic processes, focusing especially on efforts and advancements made in the recent decade on how digital technologies impact work, labour, and the broader economy.

As this report lays out in detail, the way researchers have approached an understanding of technology and its impact on growth and development has evolved considerably in the past two decades, befitting the exponential growth of technology itself. The digital era, defined in large part by the proliferation of the personal computer and advances in computing power, has not only altered the structure of the economy but also significantly impacted the way we work and, subsequently, the methods employed to understand that change.

Long-run perspectives on why technological change and development is important to economic growth is not new, but the debate between exogenous and endogenous growth theories point to the growing sophistication of the discourse and the attention given to problems of job polarization and other inequities, such as gender-based and geographic disparities.

As focus shifted to endogenous growth theories, a new wave of research began to further explore and understand the uneven effects, tangent to explicit concerns with economic growth, that technological change has on labour, giving rise to theoretical frameworks to explain why some workers have not benefited (in the short run) from digital technology. This has led to the development of the theory of skill-biased technical change — or technological change that those who are "skilled" can fully take advantage of, while those who are not "skilled" lose out.

While the new skill-biased literature makes it clear that some "low-skilled" workers are losing out, this discourse left certain puzzles unanswered, such as the fact that despite what appeared to be clear gains going to technically trained and highly skilled workers, post-secondary students were not moving unidirectionally toward such training and occupations. From here, we see the rise of task-based approaches to understanding different types of skills (cognitive and manual) *and* tasks, be they routine (more open to automation) or non-routine (less open to automation). Herein we see the crucial contention that some types of labour (namely those defined by cognitive and non-routine tasks) are more clearly complemented by technological change (and automation) rather than replaced by it.

Although there have been great strides made in advancing and defining consistent and useful taxonomies and frameworks for types of skills and specific tasks, it is clear that the enormous variety of possible tasks makes measurement extremely difficult and thus data even harder to generate. Without this data scholars will struggle to conduct adequate research, and policy-makers will lack evidence to inform desirable policy objectives and their appropriate instruments.

This knowledge synthesis explores the discourse and literature on the digital economy, focusing on how we have come to know what we do about technology's impact on labour and the economy more broadly. Importantly, this report does not focus specifically on the findings of the research per se, although there is ample attention given to research findings, but rather attention is paid to the approaches, frameworks, and specific measurements devised to help conceptualize and ultimately measure the impact of technology, with specific attention to the ways technology either replaces labour or augments it.

Methodology

The specific method used for this knowledge synthesis project is a systematic review (cf. Higgins et al. 2019; Munn et al. 2018). The project team thoroughly reviewed, analyzed, and synthesized the existing literature that fit the twofold scope of the project: the augmentation and effect of digital technologies on the nature of work and the implications this has for Canada's economy. The synthesis was guided by two primary research questions, one focused on understanding competing (and complementary) theoretical frameworks and the other on the empirical aspects of research. They are:

1. **HOW HAVE THE THEORETICAL FRAMEWORKS** that seek to understand how (digital) technologies impact the economy evolved in the economic literature?

2. **WHAT MEASUREMENTS AND DATA HAVE BEEN** developed and made available to researchers as well as policy-makers to guide research and policy-making, especially in Canada?

Using this standard approach to systematic reviews, the knowledge synthesis will determine how the extant research links to the two questions specified in this proposal. Furthermore, given the research design and subject material focus of this broad literature, we have comprehensively reviewed within scope quantitative studies in order to identify all relevant evidence, understand practices and methods, consider conflicting findings, and recognize knowledge gaps and opportunities for additional research.

To accomplish the knowledge synthesis, the authors engaged in a bibliographic search using Google Scholar. The following keywords were used in the search: "digital labour", "digital skills", "skill-biased technical change", "measurement of digital labour", and "measurement of technology skills", as well as variations and combinations of the aforementioned terms. We restricted our search to papers written in (or translated into) English, and focused on research published from 2000 onwards, although some earlier papers were included when they provided a particularly compelling base that was relevant to the development of the current state of the literature.

Our literature search yielded many relevant and well-cited studies regarding how technology impacts labour. The sources fit into three categories: those that either (1) introduce or discuss a theoretical framework; (2) utilize a unique dataset; or (3) discuss measurement issues associated with empirically assessing established theories' predictions. For space consideration, and to review the topic at hand more fully, we specifically excluded studies that focus on welfare considerations and broader political and social concerns. We do not consider literature that focuses on precarious work enabled by technology platforms (i.e., "gig work"), for example, or studies that the consequences of digitization and automation on civic life, political liberties, and democracy. These studies are enormously important and directly relevant to the work examined here but focus more specifically on the impact of digital technologies, not on how we understand (as in measure) that impact. In the concluding paragraphs of this report, we devote some attention to the relationship between measurement and equity concerns, but the focus of this knowledge synthesis focuses on how we conceptualize, model, and measure the digital economy.

We then followed the citation chain of these papers (in both parent and child directions) to further expand the reach of our review. We also relied on an existing database of papers and reports in the authors' citation databases (developed for related research projects[1]) to identify additional relevant research. In total, 110 papers, reports, and other sources were examined.

Measuring Digital Maturity

Rise of computers and the era of digitization

Economists' focus on the impact of technological advancement on workers and the economy is not new. "I am convinced, that the substitution of machinery for human labour, is often very injurious to the interests of the class of labourers," wrote David Ricardo in 1821. However, the manifestation of technological advancement has changed considerably over the years. Brynjolfsson & McAfee (2016) demonstrates the difference between the current wave of technological advancements and previous waves, emphasizing the exponential rate of change experienced recently. Such changes have renewed discussions about the potential impact of technology on workers and the economy; for example, Autor & Salomons (2017) summarizes recent evidence and offers policy guidance to governments.

The rise in both computerization and digitization has also made available new research tools to tackle these very questions, often in the form of expansive datasets and improved computing power. For example, digitized data and algorithms leveraging the vast computing power available to analyze textual data in patents are used to study the dynamics of long-term technological innovation (Kelly, Papanikolaou, Seru & Taddy, 2018), while detailed administrative records of individuals are used to study the demographic dynamics of innovators (Bell, Chetty, Jaravel, Petkova & Van Reenen, 2019).

Though personal computers have existed for almost half a century, their use and prominence only took hold roughly 20 years ago. Consider that, in 1989, only 19.5% of households in Canada had a personal computer at home. By 1994, this number rose to 33.9% and then to 58.4% by 2000. And in 2016, 89% of households surveyed owned at least a desktop computer, laptop, or smartphone (General Social Survey, 1990, 1995, 2000, 2016).

Recent studies in Canada have also focused on understanding the impact of digitization and, more recently, automation, on the Canadian economy. For example, Birnbaum & Farrow (2018), through extensive respondent interviews and citizen engagement, describes the sentiment those in southwestern Ontario have toward the recent wave of automation technology.

As many of our economic activities shift to digital spaces, traditional measurements of these technologies have struggled not only to capture digitization's full impact but also to provide the data necessary to explain the process through which digital technology impacts the economy, prompting governments to develop new measurements (Statistics Canada, 2019). It is on this literature that we spent the bulk of

[1] These include Vu, Lamb & Willoughby (2019); Vu, Zafar & Lamb (2019); and Lamb, Munro & Vu (2018).

this knowledge synthesis, but before focusing on empirical studies that introduce or modify measurements, we considered how technology and technological change has affected how we think about economic growth.

Economic growth and technology: a long-run perspective

In understanding the issue of technological growth, economists have traditionally focused on the idea of long-run growth, a literature initiated by Solow (1956). This branch of the economics literature reflects little interest in the short-run fluctuation of the economy (such as those characterized in business cycles) but rather focuses on more fundamental, gradual, and long-run changes in the economy. Within this framework, technology is conceptualized as a force that augments the factors of production (canonically labour [L] and capital [K]). In the most basic model, technology (called total factor productivity, or TFP) augments both capital and labour (cf. Hulten 2010). This basic model can be extended to introduce factor-specific TFP (e.g., labour-augmenting technology).

The development of new models and the conceptualization of technology also had practical considerations. While the total stock of labour and capital, as well as output, were rightfully understood as measurable, technological levels (or TFP) were not. The new growth models allowed for an estimate of TFP using output levels and measurements of labour and capital. This meant that TFP was not estimated directly but was a "residual." In other words, TFP is what is left over after accounting for all factors — the now famously termed "Solow residual."[2]

Empirical approaches in this area are still evolving. Some papers introduce a more general econometric framework that allows for many factors of production, such as those in Mankiw, Romer & Weil (1992), or those that propose a firm-level measure of TFP growth, such as Levinsohn & Petrin (2003), which is extended by Wooldridge (2009).

Other models of long-term economic growth have been proposed, especially those that aim to include technological growth directly within the model (as opposed to having the model react to exogenous technological growth). Early work in this area includes the formulation of learning-by-doing in Arrow (1962), or those that incorporate the idea of creative destruction (through patent protection), such as Aghion & Howitt (1992).

Some have attempted to use the long-run economic growth models to explore the impact of recent technological change. Aghion, Jones & Jones (2017) is an example of one such endeavour. The authors outline necessary conditions for continuous exponential growth in the economy, with a specific formulation of a technological parameter.

Empirical investigation into the impact of digital technology, particularly the growth accounting literature, can be traced back to the work of Lichtenberg (1993) and Dewan & Min (1997). More recently, DeStefano, Kneller & Timmis (2020) examine the potential capital-saving effect of information and communication technology (ICT) using growth accounting.

Having established the general trajectory of the economics literature with regards to technology and growth, we now turn to the much more recent literature that focuses on how digital technologies impact labour, in addition to broader economic effects. Specifically, we focus on the heterogeneous effects, or "factor bias," that technological change has based on workers' skills, which is understood today as skill-biased technical change.

Skill-biased technological change

Interest in identifying the impact of digital technologies on the labour market and the economy writ large can be traced to an

[2] The original formulation (Solow, 1956) of total factor productivity (TFP) is the ratio of aggregate output to aggregate input. As it accounts for neither capital accumulation nor increase in labour input, it is necessarily a residual measure.

observational finding that showed increases in wage inequality in the US coinciding with wide adoption of personal computers in the work context in the 1980s (Levy & Murnane, 1992). Disaggregating this increase in wage inequality pointed to a consistent trend. Those who held a bachelor's degree or those who were considered in the literature to be "highly skilled" (compared to those without a high school diploma) experienced wage increases during this period. This literature then posited that the rise in wage inequality is attributable to technological change (namely, computerization) that has a particular bias for skilled workers. The term developed to describe the observed wage inequality was "skill-biased technical change" (SBTC) (Bound & Johnson, 1992). In many cases, such work also focused on the wage inequality between men and women (Katz & Murphy, 1992).

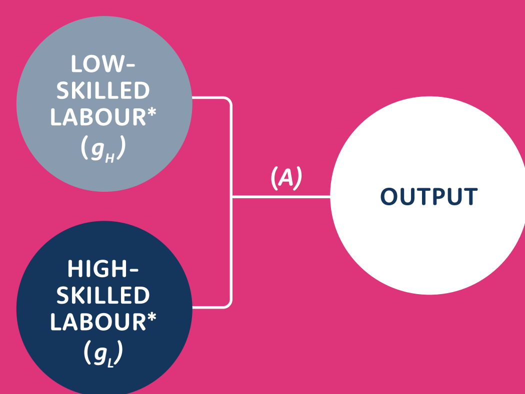
This literature, however, did not directly measure or model how digital technology was impacting labour. For worker skills, it tended to use education as a proxy (Katz, 2000), while capital investment into specific technologies (e.g., computers) was used to identify more technology-intensive industries for comparative analysis (Autor, Katz & Krueger, 1998).

A classic formulation of this strand of literature is similar to the way growth accounting is conducted, with the most basic models focusing on two distinct types of labour in a constant elasticity of substitution (CES) setup, which is a situation where the rate at which producers can substitute one type of labour for another remain constant, regardless of the size of the production (See Figure 1).

The key dynamic in the model involves the specific technology parameter for high-skilled and low-skilled labour, with SBTC only being relevant where the ratio between and increases. The ratio increasing implies that productivity improvements for high-skilled workers outstrips the productivity improvements for low-skilled workers. This is contrasted with an improvement in general technology (A) that does not bias itself against a specific type of labour (or that it improves the productivity of high-skilled labour as much as it improves the productivity of low-skilled labour). This simple model lends itself directly to connecting wage inequality to the differences in growth between technologies that affect various types of labour differently — namely, high-skilled labour, who become a lot more productive compared to low-skilled labour and get paid relatively more. The underlying point is that not all workers benefit equally from digitization. Even if technology's change has been beneficial on average, the benefits have not been distributed equally.

The hypothesis generated from this model spurred additional work that examines the role

Figure 1: Intuitive model dynamic of the CES function



These can be used interchangeably or "substituted" (but only imperfectly)

$$Y = f(N_H, N_L) = A[(g_H N_H)^{\frac{\sigma-1}{\sigma}} + (g_L N_L)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma-1}{\sigma}}$$

Y Output

N_H Number of "high-skilled" labour

N_L Number of "low-skilled" labour

A General technology parameter

g_H "High-skilled" labour specific technology

g_L "Low-skilled" labour specific technology

σ The elasticity of substitution parameter of digitization and labour demand. For example, Atasoy (2013) looks at the impact of differential investment in broadband internet on labour market outcomes; Ivus & Boland (2016) considers the impact of broadband deployment on Canadian service jobs and wage growth in Canada; and Pantea, Sabadash & Biagi (2017) looks at ICT more generally and its labour demand impact across seven European countries. For a more specific industry focus, Aubert-Tarby, Escobar & Rayna (2018) examines the impact of digitization on the news industry in France. The papers cited here are not exhaustive. Calvino & Spiezia (2020) provides a more comprehensive overview.

The SBTC conceptualization does not answer all questions and puzzles, however. Card & DiNardo (2002), for instance, provides a review of the analytical predictions SBTC literature makes and the actual observed changes in the economy. The authors identify two distinct puzzles that remain unresolved: one, where SBTC seemingly disappeared in the 1990s; and two, where the ratio between science-based graduates and humanities-based graduates decreases over time (while SBTC predicts this ratio to go up).

As the SBTC literature demonstrates, one particular focus of studies on how digital technology affects work is the potential for such technologies to replace labour — in part or in whole. These were the chief concerns discussed by David Ricardo in his work quoted above, and it has been a long-standing field of research. Expectedly, the discourse on the impact of automation technology on labour re-emerges whenever there is the introduction of a significant technology in the economy. It is to this literature that we know turn.

Task-based model of the economy

Scholarship on the problem of replacement due to technological change focuses on two issues in particular: (1) the effect of automating technologies in the manufacturing sector and (2) the impact of more general automation technologies in the broader labour market.

In tackling these issues, researchers are confronted with the inadequacy of previous models that characterized the interaction between capital and labour in the production process. In classical models, no clear mechanism is defined in how technology-enabled capital can replace labour in the production process. This changed in the early 2000s, when researchers started conceptualizing the production process as a combination of a multitude of tasks, of varying complexity, that can theoretically be performed by either labour or capital. The first well-known attempt to apply this approach to the automation context was Autor, Levy & Murnane (2003). The authors present a simple formal model that uses the concept of different types of labour that have advantages in different kinds of tasks.

This development meant that a conceptualization of skills *and* tasks had to be developed in a way that is both theoretically parsimonious and empirically measurable. Autor, Levy & Murnane

Table 1: Task framework from Autor, Levy & Murnane (2003)

	ROUTINE	NON-ROUTINE
Cognitive	Automation technology can **substitute** for these tasks	Automation technology **complements** these tasks
Manual	Automation technology can **substitute** for these tasks	Automation technology **neither complements nor substitutes** for these tasks

(2003) conceptualized recent digital technology to be particularly good in following a well-defined and consistent set of steps (the concept of an “algorithm”). This gave rise to the first dimension of their task matrix: routine versus non-routine. The researchers then introduce an additional dimension to their classification of tasks: cognitive versus manual tasks. Where previous research used educational levels as a proxy for skills (or as a measure of occupational skill demands), Autor, Levy & Murnane (2003) introduced a new methodology for making a distinction between skills and tasks. Table 1 summarizes the authors’ framework.

The delineation between skills and tasks is key, as routine tasks exist in both manual and cognitive tasks, but computerization and automation affect cognitive and manual tasks differently. In particular, non-routine manual tasks are conceptualized to be the kind that digital technologies neither substitute nor complement, while non-routine cognitive tasks are believed to be tasks that digital technologies likely complement. Further, non-routine cognitive tasks can be split between analytical tasks and interpersonal tasks. Some of the first hypotheses generated using this class of models were tested using broad task categories using US data in the authors’ paper.

However, the need for analytical tools that allow for more than two types of labour were soon needed. Using the framework developed by Autor, Levy & Murnane (2003), Goos & Manning (2007) identified a job polarization phenomenon in the US and the UK. Job polarization describes a situation where the automating technology becomes more efficient (than labour) at performing tasks in the “middle” of the task distribution, where both employment share and wages for “low” and “high” skilled workers increase.

Job polarization as a phenomenon is closely examined in different regional contexts and time periods, such as Autor, Katz & Kearney (2008); Goos, Manning & Salomons (2009); Autor & Dorn (2013); Michaels, Natraj & Van Reenen (2014); Beaudry, Green & Sand (2016); and Lu (2015). In Canada, the most well-known study is one by Green & Sand (2015), in which they demonstrate that wage polarization trends in Canada diverge greatly from those in the United States, possibly due to the industry structure of the Canadian economy. Notably, most papers that focus on examining job polarization make assumptions about pay associated with different groups of tasks. This assumption posits that there is a level of efficient sorting of labour and pay by different types of tasks, where non-routine manual jobs are proxied by low-income jobs and non-routine cognitive jobs are proxied by high-income jobs. This leads to a focus on a continuous wage distribution as opposed to a discrete number of job types.

The research on polarization is extended by focusing on demographic structures. Autor & Dorn (2009) brings attention to occupational age structures, while Cortes, Jaimovich, Nekarda & Siu (2020) decomposes the occupational change by demographic groups to separately identify the effect of demographic change, as well as the demographic-specific propensity to work in a particular occupation, highlighting the vulnerability faced by older men.

Such research prompted, at least in part, the development of a more general form of a task-based model, where job tasks were explicitly introduced. Acemoglu & Autor (2011), in chapter 12 of the *Handbook of Labor Economics,* summarize this model, cementing its position in the zeitgeist of the field. The classic formulation involves two main equations (See Figure 2).

Tasks within this framework are placed along a continuum, where there are key points that separate the space of tasks into three distinct areas: one, where "low-skilled" labour holds a comparative advantage; a second, where "middle-skilled" labour holds a comparative advantage; and a third, where "high-skilled" labour holds a comparative advantage. In other words, the ratio between task-specific productivity for each type of labour decreases along the task continuum:

$$\frac{\alpha_L(i)}{\alpha_M(i)}, \frac{\alpha_M(i)}{\alpha_H(i)} \text{ is strictly decreasing in } i$$

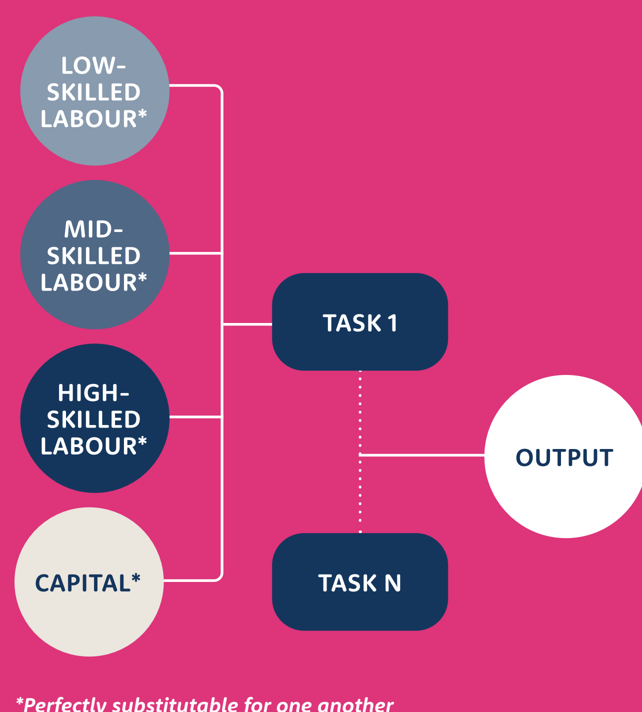
The task-based model differs from the SBTC model in a number of ways, but mainly where the substitution of differently skilled workers takes place. In the task-based model, each task has perfect substitutability between differently skilled workers (and capital). It becomes only natural, then, that each task is performed by one single type of worker, namely one that has the highest comparative advantage in that task (characterized by the task-specific productivity of differently skilled workers). The output from each of these individual tasks (called "intermediate goods") is then combined to create the final output.

Figure 2: Intuitive model dynamic of the task model

$$Y = e^{\int_0^1 \ln(y_i)di}$$

$$y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i)$$

Y	Output
y_i	i-th intermediate output, or discrete tasks
A_L, A_M, A_H, A_K	General productivity of low-skilled, mid-skilled, and high-skilled labour, and capital
$\alpha_L, \alpha_M, \alpha_H, \alpha_K$	Task-specific productivity for low-skilled, mid-skilled, and high-skilled labour, and capital
$l(i), m(i), h(i), k(i)$	Number of low-skilled, mid-skilled, and high-skilled labour, and capital performing task i



Manning (2004) explores some of these differences and attempts to reconcile the two literatures. Acemoglu & Restrepo (2017) and Acemoglu & Restrepo (2018) advance this discourse further, arguing for the distinct advantages presented by a task-based model compared to a factor-augmenting model (which is what SBTC is based on).

Though task-based models are now ubiquitous in labour economics, their origins stem from the long-term economic growth (and economic development) literature. The model presented in Acemoglu & Autor (2011) is a generalization of the model in Acemoglu & Zilibotti (2001), which sought to understand productivity differences among different nations in the development context. Even before this approach, however, Zeira (1998) proposed a task-based model with the underlying dynamic of labour-replacing technology to explain cross-country growth differences, while Kremer (1993) used a task-based model with a possibility of compounding mistakes made at each task (famously known as the "O-ring theory") to discuss the level of income inequality observed between different countries.

The task-based framework is useful, as it allows for a well-defined definition of "technological progress": the process through which the set of tasks in which it is more efficient for capital to perform expands. This framework also allows researchers to define different groups of workers with varying skill levels and those who hold comparative advantages in performing tasks of a specific complexity.

However, the task-based framework research stops short of measuring the *technical intensity* of the job tasks. It uses wages as a proxy measurement for workers' skill levels. Where technology is directly measured, it often focuses on identifying the level of investment in a particular technology (such as computers or industrial robots), as opposed to identifying the range of tasks performed in different sectors of the economy and the specific tasks performed by these technologies.

For example, in Acemoglu & Restrepo (2020), the authors focus on the total number of industrial robots (compiled by the International Federation of Robotics) that exist in the US (instrumented by the total stock of industrial robots in Europe) as a proxy for the level of job automation firms have been exposed to, finding employment reduction effects (in the manufacturing industry) of such introductions. They further supplement this measure by using data on "robot integrators," or businesses that install industrial robots in manufacturing plants, to measure the "exposure" to automating technology a company faces. A similar approach is used in Dauth, Findeisen, Suedekum & Woessner (2017) for Germany, and Graetz & Michaels (2018) for a cross-country context. Absent investment data, composite ICT indicators are used, such as in Evangelista, Guerrieri & Meliciani (2014). Godin (2003) examines the history and emergence of such indicators used by both governments and researchers.

However, Seamans & Raj (2018) points out that firm-level data has been lacking in this area of research and that data on automation is often aggregated at the industry or country level. Since then, several papers have extended the research to utilize firm-level investment data. Aghion, Antonin, Bunel & Jaravel (2020) focuses on the use of electricity at industrial plants (supplemented by valuations of industrial equipment at the plant level) in France as a proxy for automation technology. In Canada, Dixon, Hong & Wu (2020) uses detailed import data pertaining to industrial robots to measure the level of technological adoption at the firm level. Bessen, Goos, Salomons & van den Berge (2019) on the other hand, relies on detailed firm-level expenditures on automation technologies to estimate the employment impact at firms with higher levels of automation investment. Balsmeier & Woerter (2019) uses detailed firm surveys on digitization activity in Switzerland to estimate digitization's impact on the economy.

Other researchers focus on the work term and approximate task level or skill endowment through a variety of approaches. Böhm (2015) uses the US National Longitudinal Survey of Youth to understand skill endowment and then assumes self-sorting to different task groups to estimate the employment impact of routine-biased technical change. Michaels, Rauch & Redding (2018) uses unique verbs in the occupational description in the United States from 1880 to 2000 to characterize changes in the level of task specialization. Horton & Tambe (2020) explores the impact of a specific technology being discontinued through analyzing listed skill sets on an online labour market for developers. Gottschalk, Green & Sand (2015) estimates task-specific prices for the four broad types of tasks in the routine and cognitive-manual scale. Although it does not rely on the task-based theoretical foundation, Tambe & Hitt (2012) still uses IT labour data and technology investment to understand its effects on the economy and productivity.

Challenges in making direct empirical measurements of tasks are derived from two main sources: lack of comprehensive and reproducible data, and lack of a useful definition of a job task. On the second challenge, each production process likely utilizes tasks that are described in very different ways, making it nearly impossible to specify the full set of tasks involved in producing every distinct economic output. Further, even if such detailed descriptions exist, it is not trivial to then understand how a specific technology can be used to perform a particular task, or a set of tasks, as described. Autor (2013) outlines in detail the challenges associated with measuring tasks as a unit of production. Autor & Handel (2013) further tries to confront this limitation and bridge the gap using a model that specifies the process of task sorting between occupations.

Measurement challenges likely contribute to the lack of detailed and comprehensive task-level data on production processes. Classifying skills and how they relate to tasks is hard to measure precisely, as explained by Heckman & Kautz (2012), but there have been attempts. For example, the US Bureau of Labor Statistics, in partnership with the North Carolina Department of Commerce, publishes O*Net, a taxonomy of job attributes, ranging from skills and knowledge to detailed job tasks and job titles for almost 1,000 occupations that maps almost perfectly to the Dictionary of Occupational Titles (DOT) — the main taxonomy of occupations in the United States. Felten, Raj & Seamans (2017), for example, utilizes the O*Net database, along with technological advancement data from the Electronic Frontier Foundation, to study the impact of advances in AI technology on work.

Though O*Net is often considered to be the most comprehensive research data on job skills, as it is generated through interviews with job incumbents and those who are currently working in such occupations, similar endeavours exist. In Canada, Employment and Social Development Canada (ESDC) uses an "essential skills" framework: a set of nine skills considered to be "building blocks" that all 500 detailed occupations in the National Occupational Classification (NOC) require in performing the job. In addition, ESDC, in partnership with the Labour Market Information Council (LMIC) and Statistics Canada, is currently working on a much more comprehensive skills and task taxonomy for Canadian occupations (LMIC & ESDC, 2019), as Canada's lack of detailed task-level data is well described (Shortt, Robson & Sabat 2020). Tebrake (2018) describes the Canadian federal government's efforts in expanding measurement coverage to the digital economy in general.

Within the European context, task-level data is similarly scarce, though some does exist, with data quality rivalling that of O*Net. In certain countries with mandatory military service, detailed administrative data on men is useful, as demonstrated in Edin, Fredriksson, Nybom & Ockert (2017) for Sweden. Gathmann & Schönberg (2010) uses the German Qualification and Career Survey, a survey jointly administered by the Federal Institute for Vocational Education and Training and the Institute for Employment in understanding skill requirements of occupations. In Italy, the INAPP-ISTAT Survey on Italian Occupations provides detailed task-level information on occupations, as shown in Cirillo et al. (2020). In this paper, the authors create two related but different measures. The first measure focuses on identifying the routineness of a task, similar conceptually to the approach taken by Autor, Levy & Murnane (2003) in identifying job tasks highly susceptible to automation. The second measure focuses on the idea of digital exposure, or the degree to which an occupation is exposed to digital technology, similar to ideas found in Vu, Zafar & Lamb (2019) for Canada and Gallipoli & Makridis (2018) for the United States.

The approach that focuses on understanding the technological context that occupations work in has a number of applications. A direct implication of such work allows classification systems to distinguish between technical and non-technical occupations (and industries), guiding investment policies. Anderberg & Froeschle (2000), for example, focuses on identifying classification systems that would appropriately capture the impact of technological education in Texas. Another implication of focusing on an occupation-level measure is the ability to measure how occupational work context has changed over time. Muro, Liu, Whiton & Kulkarni (2017) demonstrates the level of change in technical context in occupations in the US using O*Net. Gallipoli & Makridis (2018) also uses this kind of classification in estimating the impact of across-industry differences in the elasticity of substitution between digital and non-digital labour on structural shifts in employment across industries over time.

The main disadvantage in using these occupational taxonomies is in the level of aggregation required for the data to be useful. They ignore within-occupation heterogeneity in task performance, an especially salient issue in considering those who work in the same occupation but in different industries. As a result, researchers engaging in this research must assume that all workers identified are working in a particular occupation and performing the same range of tasks, regardless of the context in which they are performing them. The problem becomes further entrenched when task measurements for occupations in one country or region are used (utilizing concordances tables between occupational taxonomies) to analyze labour trends in another, as task content of an occupation can vary significantly between different nations. Vu (2019), for a recent example, explores such implications in using O*Net data in the Canadian context.

In addition, such task-based measurement of occupations looks at tasks performed by humans, and we know of little data that examines tasks performed by machines (or digital technologies) in a production process. As task-based measurement data is updated irregularly, identifying changes in an occupation's task content is also challenging. Several approaches have been used as a result to measure the "routine" nature of specific job tasks and the resulting probability that a specific task or occupation is susceptible to automation. Autor, Levy & Murnane (2003) manually identify job attributes in the DOT data to capture routineness and non-routineness. Frey & Osborne (2017) use a radically different approach: Instead of hand-selecting key attributes, they gathered a group of AI and machine-learning experts to discuss and decide whether a limited number of occupations, as a whole, are automatable or not. They then use occupational attributes attached to these occupations as a training set to project such results onto the rest of the occupational categories using a Gaussian process. Arntz, Gregory & Zierahn (2017) take issue with the approach of using occupation-level automation predictions, citing a wide level of within-occupation heterogeneity in task contents. Duckworth, Graham, Frey & Osborne (2019) attempt to address this shortcoming by generating a probability estimate over the task space, as opposed to the occupation space, following similar procedures to Frey & Osborne (2017). Lamb (2016), as well as Lamb, Munro & Vu (2018) and Oschinski & Wyonch (2017), apply the Frey & Osborne (2017) approach to the Canadian labour market.

More recently, advancements have been made on the data availability constraint, with the emergence of job postings as a source of detailed (and varied) information that connects different job attributes, such as skills and tasks, in a particular context. The use of job posting in economic analysis is not new. As Abraham (1987) details, newspaper help-wanted ads have been useful in economic analysis for decades. Canada also conducts a quarterly (recently changed to monthly) survey of employers to gauge the level of job vacancies in the economy (Government of Canada, 2018). However, advancements in both technology and popularity of online job ads now allows for greater ease in collection and a greater volume of job ads accessible to researchers. Carnevale, Jayasundera & Repnikov (2014) and Cajner & Ratner (2016) outline considerations researchers should have in using online job-ad data in economic research. Burning Glass Technologies (2015, 2019), Nania, Bonella, Restuccia & Taska (2019), and Deming & Kahn (2018) describe in detail popular job postings data used by researchers. Atalay, Phongthiengtham, Sotelo & Tannenbaum (2017) convert raw text files for job postings in newspapers longitudinally, presenting another alternative for researchers engaged in using job ads.

However, job postings data is not without issues. Firstly, job postings are not generated using a consistent taxonomy, and many words and phrases can be used to refer to the exact same conceptual idea. To overcome such issues, recent advancement in computing capabilities and machine learning has been used to regularize this variation, allowing one to work with a much more contained set of job concepts. Secondly, it is important to consider the process through which job postings are generated. The naive view on job postings is that they are an accurate representation of the skills and tasks that are missing from a particular firm. In reality, they are an understanding by the individuals who wrote the job postings on what they believe is an entire job their firm needs at that moment. They may not reflect what the incumbent (once they successfully get the job) will end up performing. In Canada, a particularly unique challenge presents itself, as an algorithm will have to parse and connect between jobs that are posted in different languages, namely French and English, where effective translations between two skill terms is further complicated by cultural contexts.

One area in which job postings data excels is in identifying complementarities between different groups of skills, including between technical and non-technical skills. A seminal paper by David Deming (2017) focuses on the emergence of social skills as a key complementary skill to technological skills. Vu, Lamb & Willoughby (2019), along with Djumalieva & Sleeman (2018), conceptualize job postings as a directed bipartite graph (a network with two distinct types of nodes, in which edges are directional and always flow from one group to another), providing an analytically useful way to connect skills to occupations, especially in understanding similarities between occupations. Such an approach allows researchers to understand the broader context in which a skill appeared in a job posting, utilizing techniques from graph theory and network analytics. Using Canadian data, Vu, Lamb & Willoughby (2019) finds that job-context-specific knowledge in applying technology is also likely to show up as complementary skills. These data sources are especially relevant in understanding the kind of skills that are seen as being in complement to digital technology. Hershbein & Kahn (2018) directly leverage job-posting-level data to examine routine-biased technical change during the US recessions.

The sources reviewed in this section constitute the latest in the discourse on technology's varied impact on labour and the difficulties associated with measuring this impact. We now conclude with a summary of our findings and the implications this knowledge synthesis identifies for policy-makers, future research, and labour in general.

Conclusion & Discussion

Over the past two decades, advancements in theoretical and empirical research on how technology impacts work and labour have improved our understanding of the digital economy. These advancements treat technological change not as an abstract concept but rather as a phenomenon that affects mechanisms through which our economy functions. The most dominant framework used by researchers (and as a result, policy-makers) is one that breaks down a production process into a series of discrete tasks, each of which is potentially substituted with machines or complemented by them. This view is especially relevant to policy-makers focusing on understanding the change in work through the COVID-19 pandemic, as specific portions of a job, as opposed to an entire occupation, is affected by digitization and automation. This framework potentially implies a situation in which total reskilling of individual workers is not required, while partial expansion of skills they already possess will have a greater impact.

While significant advancements have been made in defining a consistent and useful taxonomy of tasks to aid researchers and policy-makers, the sheer variety of tasks that exist within the economy makes direct and useful measurement of such tasks difficult still and such data harder to generate. Absent such data, innovative workarounds are proposed that permit economists and other researchers to characterize the impact of digital technology on the way we work. Some of these involve direct attempts at conceptualizing a useful taxonomy in describing job tasks, whether through incumbent interviews or parsing job postings. Others abstract away from the actual implementation and specific use of digital technology to focus on using different levels of technological exposure firms' experience to understand technology's effects. Yet others, instead of describing and measuring each individual task, seek to characterize the general technology landscape that different workers operate in to determine a proxy measure for the likelihood that a job can be complemented by or substitutable with technology.

One of the more fundamental shifts within these advancements is in challenging the notion that those engaging in work considered to be "low skill" necessarily stand to lose in the face of technological advancements. Due, at least in part, to the observation that the share of those who receive the lowest wages (and thus are often seen to be "low skill") in an economy increase over time, this view challenges a linear view of employment change and the tasks associated with those changes. Work, in other words, is as complex and diverse across occupations as it is within them.

Indeed, one of the most pressing public policy issues of today, regarding current and future employment, is in determining how to best use technology to complement humans (and human labour) rather than replace them. This is the far more pressing issue than concerns about technology creating superintelligence (cf. Bostrom, 1998; Tegmark, 2017), yet, as Acemoglu (2021) contends, far too little attention is given to this crucial concern. "The causes of this broad pattern — more automation and less effort directed toward increasing worker productivity — are not well understood," he writes.

If the goal is to increase human productivity, close wage gaps, and create the conditions of shared prosperity, then new research methods, typologies, and frameworks are essential. We need, in short, a more sophisticated language through which we can discuss technology's impact on the economy and, ultimately, society writ large. We know that technology does not impact all workers within and across all occupations, skill sets, and job types in the same way, and that certain tasks and occupations stand to benefit more from technology augmentation (thereby increasing worker productivity) and others stand to be replaced. But the effects are not consistent or linear. We simply do not have a good enough analytical tool kit to understand why. The consequences of doubling down on automation out of ignorance are potentially disastrous. For example, tax regimes (in the United States, for instance) tend to favour capital over labour (Acemoglu, Manera & Restrepo, 2020). Greater automation will only serve to reinforce the belief that this approach is correct. Workers, especially those deemed "low skilled," stand to lose.

The ability to reconcile the diversity of work that exists within even a single occupation is central to future development in the field, as well as the development of a flexible yet workable taxonomy of tasks and skills that can be aggregated at different levels of detail and continuously incorporate new skills and job tasks that emerge in the economy. In Canada, this must be done for both English and French language, recognizing the complexity of cultural etymology of specific words that refer to job tasks. Further, the proposed body of work can become more impactful by incorporating the process through which workers gain comparative advantage in a specific set of tasks, informing potential policies the government can make to help those whose jobs are impacted negatively by automation.

Finally, though much work has been conducted, research that specifically focuses on Canada is still lacking. This is likely due to a combination of the relative lack of appropriate data to fully take advantage of the advancement in the field and the lack of intentional investment made in identifying potentially unique forces that shape the way technology impacts workers in Canada. We hope this present synthesis will help inspire development in both.

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