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Technology and jobs: A systematic literature review

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Deliverable 6.1 systematically reviews the empirical literature on the impact of technological change on employment since the 1980s. This academic article distinguishes between five measures of technological change (ICT, robots, innovation, productivity, other) and investigates through which mechanisms technology either reduces or increases the demand for labor.

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Technology and jobs: A systematic literature review

Kerstin Hötte[1], Melline Somers[2], Angelos Theodorakopoulos[1]*

[1] Oxford Martin School, University of Oxford, 34 Broad Street, Oxford OX1 3BD, UK
[2] Research Centre for Education and the Labour Market, Maastricht University, Tongersestraat 49, 6211 LM, NL

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Does technological change destroy or create jobs? This question is subject to a longstanding debate and has been investigated in many empirical studies. New technologies may replace human workers, but simultaneously reinstate new jobs if workers are needed to operate these machines or if new fields of economic activity emerge. Further, technology-driven productivity growth may increase disposable income, which stimulates a demand-induced expansion of output which creates additional employment. In this article, we systematically review the literature on the nexus of technology and employment in the post 1980s to synthesize the empirical knowledge of these three effects. We distinguish five types of technological change (ICT, robots, innovation, productivity, other). The majority of studies supports the two labor creating effects, i.e. the reinstatement and real income effect. A somewhat smaller number of studies supports the replacement effect. We conclude that, according to the literature, the labor saving effect of technology is more than offset by compensating mechanisms. This holds for most types of technologies. Nevertheless, this review highlights that especially low skilled, production, and manufacturing workers have been adversely affected by technological change, and effective up- and reskilling strategies should remain at the forefront of policymaking along with targeted social support systems.

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Contact information: kerstin.hotte@oxfordmartin.ox.ac.uk; melline.somers@maastrichtuniversity.nl; angelos.theodorakopoulos@oxfordmartin.ox.ac.uk

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1 Introduction

Concerns that automation and technological advancement will make human labor obsolete is not a recent phenomenon. Already during the first Industrial Revolution, the adoption of power looms and mechanical knitting frames gave rise to the Luddite movement. The Luddites protested against disruptive technology by destroying textile machinery out of fear of job loss and skill obsolescence. The idea that technological change can render many workers redundant, at least in the short run, has been supported by influential economists like Karl Marx and David Ricardo in the nineteenth century (Marx, 1988; Ricardo, 1821). Others, such as Thomas Mortimer, believed that machines could displace labor more permanently (Mortimer, 1772). More recent concerns about massive job losses (Smith and Anderson, 2017) stem from improved computing power, decreasing costs and advances in machine learning and robotics (Brynjolfsson and McAfee, 2014). The current debate on the labor market impact of technological change has also been fed by a number of influential studies predicting the extent to which jobs are susceptible to automation (Arntz et al., 2017; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018).

Although there is little evidence that automation has led to widespread unemployment over the centuries, job losses due to technological progress have been significant. Indeed, most technologies are designed to save labor, i.e. to replace human workers by machinery. Where tractors were introduced to substitute mechanical power for human musculature, assembly lines replaced human handiwork by machine-consistency. As the price of computing power has fallen in recent decades (Nordhaus, 2007), computer assisted technologies have increasingly displaced workers in performing explicit and codifiable tasks.

However, economic theory points out that several compensation mechanisms can indirectly counterbalance the initial labor saving impact of new technologies (e.g. Vivarelli, 2014; Acemoglu and Restrepo, 2019). First, technological change can increase the demand for labor by creating new jobs that are directly associated with the new technology. This mechanism is also referred to as the reinstatement effect. Second, technology can also increase the demand for labor through the demand side. Technological progress is generally expected to boost productivity, which in turn can lead to lower production costs and lower consumer prices. It can also raise the marginal product of labor and capital, and subsequently increase relative wages and returns to capital. All of these effects contribute to a rise in real income and if demand is elastic, and positively responds to increases in income and decreases in prices, we would expect to observe an increase in aggregate output.

The objective of this paper is to offer an empirical basis for the policy and scientific debate about the employment impact of technological change in developed countries. We do this by means of a systematic review of the literature. To offer a complete picture of the technology impact on employment, we synthesize the empirical evidence by the mechanisms through which technology can either decrease or increase the demand for labor.

Our study is not the first to review the existing evidence on the effect of technology on employment, but our systematic approach covering 127 studies contributes in several ways: First, most reviews are narrative which may be subject to the authors' bias (Bruckner et al., 2017; Brown and Campbell, 2002; Calvino and Virgillito, 2018; Goos, 2018; Mondolo, 2021; Vivarelli, 2014). Second, earlier studies that provide systematic reviews of the literature focus on short periods of time (1980-2013 for Ugur et al. (2018), 2005-2017 for Balliester Reis and Elsheikhi (2018), 2000-2021 for Perez-Arce and Prados (2021)), while our review covers 33 years from 1988-2021. Third, in contrast to Ugur and Mitra (2017) who synthesize the evidence on technology adoption on employment in less developed countries, we focus our review on developed countries assuming to capture the impact of the technological change at the frontier. Fourth, while most earlier reviews restricted their analysis to specific types of technology, we analyze how employment effects differ across alternative types of technological change. In particular, we distinguish between five broader categories of technological change measured by (1) ICT and (2) robot diffusion, (3) innovation surveys, (4) productivity growths, and (5) various alternative indicators. Fifth, to be as inclusive as possible, we do not limit our analysis to specific measurements of employment. Although evidence from different models (e.g. derived labor demand, skill/wage share, and decomposition analyses) do not necessarily yield comparable estimates, they are informative about the direction of the employment effect.

The findings of our systematic review can be summarized as follows. A somewhat larger number of studies finds support for the labor creating mechanisms of technological change than for the labor saving channel. For most types of technology, we find that the number of studies supporting the replacement effect is roughly balanced by the number of studies supporting the reinstatement and real income effect. Only for studies that rely on innovation as a measure of technology, the employment impact seems to depend on the type of innovation. The empirical evidence suggests that product innovation is mostly labor creating, while the evidence concerning the employment impact of process innovation is somewhat inconclusive. It is important to note that the real income effect is difficult to analyze as it requires studies to examine technology-labor interactions while simultaneously taking the productivity and wealth effects of technology into account. In fact, only a small number of studies allow us to draw more definitive conclusions on the real income effect. Hence, although we find more support for the labor creating effects of technological change, we are careful in concluding that technology has a positive effect on net employment. However, we do safely conclude that the labor replacing effect of technology is more than offset by a range of compensating mechanisms. Hence, there does not appear to be an empirical foundation for the widespread anxiety over technological unemployment.

This paper is structured as follows. Section 2 presents the conceptual framework and discusses the mechanisms through which technological change can increase or decrease the demand for labor. In Section 3, we discuss our methodology and Section 4 presents the results. Section 5 discusses the findings and Section 6 concludes.

2 Conceptual framework

The interactions between technological change and labor are complex. In this study, we rely on a three-stage framework to analyze the empirical evidence on the labor market effects of technology. The three stages are mechanisms on how technology interacts with labor, that become increasingly complex and indirect.

Before outlining this framework, a note on our interpretation of technology needs to be made. In this research, we rely on a very generic understanding of technology: Technology is the capability to transform a given set of inputs into outputs, and technological change happens when the quantity and/or quality of inputs or outputs change (Saviotti and Pyka, 2013; Ruttan, 1959). For example, new technologies may make production processes more efficient which enables a firm to produce the same good with a lower amount of labor or material inputs. It can be also reflected in the outputs when technologies enable a firm to bring a new product to the market.

How does this interact with labor? Here, we focus on three key mechanisms on how technological change affects the demand for labor. These mechanisms are incrementally more indirect.

To illustrate these mechanisms, let us introduce a stylized model. A very generic production function is give by:

$$Q = A^Q f(A^L L, A^X X) \tag{1}$$

where Q is an output good measured in prices, L is the amount of labor that is used in combination with other inputs X to produce Q. Other inputs can be capital goods, material and intermediate inputs, or different forms of labor (e.g. different occupations or differently skilled workers). The parameters A^L, A^K, and A^Q represent the production technology. Generally, the production function is non-decreasing in its arguments A^L, L, A^K, and K: a higher level of technology or production inputs leads to an increase in the value of output Q. Technological change may enter in different forms, changing the levels of A^L, A^X, and/or A^Q.

2.1 The replacement effect

The most direct impact of technology on employment is the so-called "replacement effect". This effect occurs when the adoption of a new technology enables a firms to save labor inputs for the production of a given quantity of output.

In the stylized model above, replacement happens if A^L increases and Q is constant, i.e. $dQ = 0$. This means that less labor is used but everything else remains equal. However, not every type of technological change leads to an increase of A^L, and even if technological change increases A^L, it only replaces labor if output Q does not expand to a sufficient extent.

Other forms of technological change can lead to an increase in A^X which means that the same amount of output can be produced with lower input requirements X. An example for an A^X-increasing technology is a technology that helps save energy in the production process. Technological change may also lead to an increase in A^Q which increases the value of output Q while keeping the input requirements constant. An example is a product innovation such as the introduction of a new design. This enables a firm to bring a new and more valuable product to the market while not changing it's input requirements.[1]

Empirically, it is challenging to measure whether or not technological change is labor replacing. Whether or not it is may be heterogeneous across industries and occupations, and often it is difficult to measure this at a sufficiently granular level. Moreover, different forms of technological change may be interdependent: for example, the introduction of a product innovation may require other skills of workers making previous product lines and the workers who produced these lines redundant. It may also be that labor saving technological change does not lead to layoffs, but those employees that are no more used to produce Q find other useful tasks within the same firm.

In this research, we critically evaluate and systematize the empirical evidence to find out whether or not technological change since the 1980s had been labor-replacing, i.e. whether or not technological change has increased A^L.

In the literature, we identify various indicators that allow to draw conclusions about the existence of the replacement effect. At all levels of analysis (macro, meso, micro, regional, other), changes in employment are one key indicator: Empirical support for the replacement effect exists if we observe a technology-induced decrease in employment in those firms and industries where the technology is used. Measures of employment include the employment rate, number of workers, hours worked, and the labor share of income even though the labor share is only indicative, but not sufficient to provide evidence for the labor saving impact of technology. Moreover, a number of studies at different aggregation levels examines changes in the relative employment of different occupational groups which we also consider as support for the replacement effect. For example, a technology-induced increase in the ratio of high over low skilled labor use may indicate the replacement of certain types of labor. We consider this as supporting evidence for the replacement effect, even though we acknowledge that technology-induced changes in the relative demand for labor are not sufficient as evidence for replacement.[2]

We also interpret micro (worker or firm) level studies that assess the relationship between the type of tasks performed by workers (some are more susceptible to automation than others) and the likelihood of being displaced as indicative for the replacement effect. If the likelihood that certain jobs displaced increases in response to technological change, technology may have contributed to the obsolescence of these occupations if they can be replaced by machinery.

Another indicator of the replacement effect are changes in the elasticity of substitution of labor and capital or other inputs X. Technological change may alter this elasticity.

[1]Note that it would be irrational for a firm to introduce a product innovation if it does not increase its value of output.

[2]For example, technology-induced changes in the relative demand for low skilled labor at the aggregate level, do not necessarily mean that labor was replaced. It may be that technological change enabled the emergence of a new industry that uses differently skilled labor. This may induce a shift in the relative demand, but in absolute terms not a single worker was replaced by machinery.

A technology-induced increase in the elasticity indicates that technological change has improved the technological possibilities to replace labor by other inputs. We interpret this as supporting evidence for the replacement effect.

2.2 The reinstatement effect

The reinstatement effect is the next indirect effect of technological change. It occurs if the adoption of new technology induces new jobs that are directly associated with the new technology, regardless of whether or not technological change happens via A^L, A^X, or A^Q. Generally, a pre-condition of the reinstatement effect is an increase in Q, otherwise technological change would be only input saving even though the effects may be heterogeneous across different groups of employees.

For example, an input saving (A^L or A^X) may induce the creation of new jobs within the same firm for technology maintenance. A firm may also start supplying new customer services that became affordable due to the introduction of an input saving technology or necessary if a new technology A^Q changes the quality of the output Q. For instance, the introduction of computers at the workplace creates new tasks, such as those related to programming, the maintenance of soft- and hardware, and data management. Dependent on the level of aggregation, the reinstatement effect also refers to jobs created up- or downstream the supply chain, i.e. jobs associated with the production of X. For example, the suppliers of capital or intermediate inputs required to operate the new technology may increase their demand for labor if X is increasingly used. Also downstream customers of the technology adopting firm may start offer new services along with the product produced with new technology. Hence, the reinstatement effect exists if $\partial L/\partial A > 0$ for any $A = A^L, A^X, A^Q$.

Here, we screen the empirical literature whether or not it provides supporting evidence for the existence of this effect. Again, the empirical measurement of the reinstatement effect is complex as the technology-induced replacement of new jobs may happen at different levels of aggregation: Reinstatement may happen in the same firm and/or in other industries, and studies limited to a subset of firms or industries can not capture the reinstatement of labor elsewhere.

An increasing demand for labor is the key indicator of supporting evidence for the reinstatement effect. This is reflected in lower unemployment, an increasing number of employees and hours worked. We also consider a higher labor share of income and rising wages as supporting evidence for an increasing demand for labor. Note that the reinstatement effect does not need to be equally distributed across different types of labor. To support the existence of this effect, it is sufficient if we observe an increase for at least one group. We also consider changes in the relative demand for labor as hint that supports the existence of the reinstatement effect, as it may be driven by an increase in the demand for certain types of labor.

Whether or not the net impact of technology on employment is positive or negative depends on the balance between labor replacement and reinstatement.

2.3 The real-income effect

The two effects introduced above mainly refer to the impact of technology on the production side when it changes the use of inputs in absolute and relative terms. Technological change also affects labor through an indirect channel that mostly operates through the demand side.

Assuming rational technology adoption decisions, technological change is always associated with productivity improvements; otherwise it would not be rational to adopt a new technology. Productivity improvements enable firms to produce a given value of output at lower costs which would be reflected in lower consumer prices if these input costs savings are transmitted to consumers. Moreover, if technological change raises the marginal product of certain types of labor, we would also expect relative wages to rise. If technological change raises the marginal product of capital, we would expect higher rents to capital which are another source of income. All these effects (lower prices, higher wages, higher returns to capital) contribute to a rise in real income. If demand is elastic and positively responds to increases in income and decreases in prices, we observe an expansion of aggregate output Q. It should be noted that the real income gains are not necessarily equally distributed. This may have an impact on the demand reaction as the propensity to consume is heterogeneous across income groups and products. The expansion of output driven by a technology-induced real income effect may lead to a higher demand for labor.

As the real income effect on labor is very indirect, we interpret a study as empirically supportive for the real income effect if it provides empirical support for one of the underlying mechanisms, that are: an increase in (1) productivity, (2) lower prices, (3) higher levels of income and wages, (4) rising levels of output and a positive relationship between labor and output.

We interpret studies that report insights on at least one of these mechanisms as supportive for the real-income effect while being aware that support for one of these mechanisms does not necessarily imply that the full chain of causal arguments holds. For example, productivity gains may not be forwarded to consumers in terms of lower prices if distorted competition prevents this, and rising levels of income do not necessarily imply a higher demand for consumption.

3 Methods

The aim of this review is to answer the question: *What is the net employment effect of technological change since the 1980s in developed countries?* To answer this question, we review the empirical evidence of studies published between 1988 - April 2021.

3.1 Search strategy

We closely followed the PRISMA 2020 guidelines to ensure the quality of the systematic search process (Page et al., 2021). A scoping review was used to identify relevant search terms in widely cited studies. Subsequently, a computerized search was performed using a set of search terms that appeared either in the title, abstract, or list of keywords of studies, namely: ‘automation’, ‘technology*’, ‘digiti$ation’, ‘robot*’ or ‘artificial intelligence’, combined with ‘labo$r’ or ‘employment’.[3]

The search was conducted in the Web of Science Core Collection database. We opted for Web of Science because of its proven suitability as a principal search engine for systematic reviews (Gusenbauer and Haddaway, 2020). We only included records from the Social Sciences Citation Index (SSCI) of Web of Science to exclude studies in the sciences as our research is concerned with the effects of technological change and not its technical realization. Moreover, to further exclude irrelevant literature, we limited our search to the following Web of Science categories: Economics; Management; Business; Business, Finance; Sociology; Industrial Relations & Labor; Development Studies; Social Sciences, Interdisciplinary; History; Social Issues; Urban Studies; and Geography. Furthermore, the search was restricted to the most relevant document types and include articles, book chapters, early access documents, proceeding studies, and reviews.[4] Documents were also restricted to the English language due to the researchers’ collective abilities. Although we did not impose any restriction on the search period, our search covered the time period 1988-April 2021. The initial year was the earliest year in Web of Science to which our research team had access. The final year was determined by the start of our research project in the second quarter of 2021.

Figure A.1 gives an overview of the selection process of relevant studies. Web of Science initially provided us with 8,699 studies that were published between 1 January 1988 and 21 April 2021. Six independent researchers were involved in the process of selecting the relevant records for the policy report. The procedure was structured in such a way that each researcher evaluated 1/6 of the retrieved records in a first round, i.e. approximately 1,450 per person. In a second round, the six sets of records were rotated so that a second researcher assessed the records previously screened by someone else. The setup of the procedure ensured that in the second round, two separate researchers were assigned to the set of records of the original screener to avoid bias. To illustrate: if researcher A screened articles 1 to 1,450 in the first round, then in the second round, researcher B screened articles 1 to 725 and researcher C screened articles 726 to 1,450. The first and second screening rounds were conducted independently such that the assessment of the first assessor was unknown to the second assessor prior to finalizing their set of records.

Based on the title and abstract, every researcher screened and indicated for each record whether they considered it relevant for the paper (by indicating “yes”), whether it was potentially relevant (by indicating “maybe”), or whether the record was considered irrelevant (by indicating “no”). In this first step, studies were considered relevant if the independent variable is related to technology and the dependent variable is related to (un)employment (inclusion criterion 1). In a second step, records that were considered relevant by both researchers (“yes”/ “yes”) were automatically kept. Likewise, records that were deemed irrelevant by both researchers (“no”/“no”) were immediately disre-

[3]The exact search string can be found in Appendix A.1.

[4]Our final selection of studies were only comprised of articles as other types of documents did not meet our inclusion criteria.

garded. Due to the sheer mass of literature, "yes"/"maybe" combinations were changed into a definite "yes" and were retained. Likewise, "no"/"maybe" combinations were excluded from the review. Mutual uncertainties ("maybe"/ "maybe") and strong disagreements ("yes"/"no") were subjected to further reviewing. Each of these remaining records were further evaluated by a randomly assigned third reviewer, who made the final decision to include or exclude the articles in question.

In step 3, the remaining 252 studies were assigned to three researchers who each independently assessed 1/3 of the remaining records against the following inclusion criteria: (1) the study examines the effect of technological progress on (un)employment; (2) the study has an empirical element; and (3) the study focuses on at least one developed country.[5] With respect to inclusion criterion (1), we include studies that either use a direct or indirect measure of technological progress. Direct measures include proxies (for the diffusion) of specific types of technologies including information and computer technologies (henceforth ICT) and industrial robots. Other measures include total factor productivity (henceforth TFP) and innovation indicators (both product and process innovation). We also include studies that do not directly measure technological change, e.g. studies that indirectly infer the impact of technology by investigating the employment change for routine jobs that are assumed to be automatable (Autor et al., 2003). Concerning the outcome measure of interest, we include studies using different measures of (un)employment, e.g. hours worked, number of employees at the firm, the percentage of unemployed individuals of the total workforce, employment to population ratio, labor's share of income, or high skill to low skill labor ratio. Inclusion criterion (2) implies that we exclude purely theoretical studies, but include studies that make an empirical contribution (i.e. regression, descriptive, and decomposition analyses). Finally, we did not impose any specific restrictions on the level of analyses. Therefore, our final selection of studies investigates the impact of technological progress at various levels, i.e. at the macro (e.g. country), meso (e.g. sectors, industries), micro (e.g. firms, individuals), regional (e.g. regions, states, cities), and other (e.g. skills, occupations) levels of data aggregation.

Step 4 of the systematic search led to the inclusion of 127 studies. These studies were coded along a variety of dimensions. First, we recorded information on how technological change was measured. Furthermore, we recorded the country or countries studied, the period studied, the outcome variable(s) studied, and mechanisms explaining the relation between technological change and employment (i.e. replacement, reinstatement, and real income effect). With respect to (un)employment indicators and underlying mechanisms, we also described how it was measured. The data that were extracted also include the data source(s), the level of analysis (e.g. firm, sector, region or country), the sample size, the study design, and whether the study investigates heterogeneous effects. We recorded the main findings in terms of (un)employment effects and whether the authors find support for the replacement, reinstatement and real income effect. Finally, we kept track of the author(s)' names, the year of publication, source (e.g. name journal), and type of publication (e.g. article).

[5] Here, countries are defined as developed if classified as high-income by the World Bank, 2021.

4 Results

In this section, we begin with an overview of the basic descriptive statistics for the 127 studies that remain in our sample after the step-wise selection procedure. Subsequently, we describe and contextualize the subset of studies that report empirical results for each of the three effects introduced above: replacement; reinstatement; and real-income (see Section 2).

4.1 Overview

An overview of the studies covering the different effects is provided in Table 1. The vast majority (81%) of the studies in our analysis is related to the replacement effect. Another 62% report results about the reinstatement of labor and 26% about the real-income effect. More than half of the studies (59%) report results for at least two of the three effects and 16 studies (13%) for all three effects.

Table 1: Studies by type of effect examined

	(1) replacement	(2) reinstatement	(3) real income	(4) overlap
share	0.81	0.62	0.26	0.59
#	103	79	33	75

Notes: Columns (1), (2) and (3) present the share and number (#) of studies examining the replacement, real income and reinstatement effect, respectively. Column (4) presents the share and # of studies exploring at least two of the effects in (1)-(3). The total # of studies is 127.

The studies in our sample differ by the technologies studied and the empirical indicators used to them. However, we observe sufficient common thematic patterns which point to broader technology classifications. To that end, we define four broad groups of technologies (ICT, robot, innovation, and TFP-style) plus one residual category (other/indirect) for technology types that are used by a small number of studies and are rather heterogeneous to form separate technology groups.

Table 2: Studies by technology group

	(1) ICT	(2) Robots	(3) Innovation	(4) TFP-style	(5) Other	(6) Overlap
share	0.35	0.13	0.13	0.14	0.30	0.06
#	45	17	17	18	38	8

Notes: Columns (1)-(5) present the share and number (#) of studies examining ICT, robots, innovation, TFP-style and Other technology groups, respectively. 'Other' refers to technologies measured indirectly through prices, automation risks, etc. Column (6) presents the share and # of studies examining at least two of the technology groups in (1)-(5). The total # of studies is 127.

In Table 2, we find that roughly one third (35%) of the studies analyze the impact of ICT on employment. The diffusion of ICT is measured in different ways. On the one hand, some studies use measures of ICT investments or capital, as for example found in (EUKLEMS, 2019) and other comparable data bases which are mostly publicly available. On the other hand, other studies rely on survey data of computer use and ICT investment at the firm level, or measures of exposure to computerization at the occupation level.

The impact of robots is analyzed by 13% of the studies. The diffusion of this technology group is mostly measured using data for industrial robots from the International Federation of robotics (henceforth IFR) (IFR, 2020) which, as far as we are aware of, is the only source consistently covering a large set of countries, time-periods and all relevant industries where industrial robots are adopted. Rs received much attention because they are commonly interpreted as a pure automation technology, and thus substitute for manual tasks.

Another 13% analyze the employment effects of innovation. These studies typically use data from the Community Innovation Survey (henceforth CIS) or comparable surveys for non-European countries. These surveys are regularly conducted by statistical offices to assess the innovativeness of firms and regions. Typically, these surveys allow to distinguish between process and product innovation and, in some cases, organizational innovation. Process innovation is measured by survey questions asking firms to report whether they implemented a new improved production method. Similarly, the introduction of product innovation is evaluated based on a survey question asking firms whether they recently introduced a new product. Organizational innovation is measured through a question asking for the implementation of new organizational methods in business practices, workplace organization or external relations (Arundel and Smith, 2013).

Next, 14% of the studies consider different measures of productivity enhancements to capture technological change that we categorize as TFP-style. TFP-style methods mostly rely on estimates of productivity (TFP or labor productivity) or changes in substitution elasticities. Some of these studies use readily available estimates provided by statistical offices or other relevant external data sources. Others explicitly estimate productivity or substitution elasticities on the basis of otherwise unexplained variation in the production function and sometimes also distinguish between different types of input biased technological change.

Table 3: Studies by level of analysis

	(1) macro	(2) meso	(3) micro	(4) regional	(5) overlap
share	0.35	0.32	0.30	0.12	0.09
#	45	41	38	15	12

Notes: Columns (1)-(4) present the share and number (#) of studies where the analysis is conducted at the macro (e.g. country, over-time), meso (e.g. sectors, industries), micro (e.g. firms, individuals), and regional (e.g. regions, states, cities) level of data aggregation, respectively. Column (5) presents the share and # of studies where the analysis is conducted in at least two of the previous levels of analysis. The total # of studies is 127.

We further classify the studies by the level of analysis which reflects the degree of aggregation of the data used for estimations.[6] In Table 3, we find that the coverage of macro, meso and micro level studies is roughly balanced with 35%, 32% and 30%, respectively, while only 12% of the studies have a regional focus. Macro level studies rely on country-level data and variation over time and/or countries. Meso level studies usually include industry or sector level data, while micro level studies are at the more granular level—mostly at the firm or individual employee level. Finally, regional level studies use variation across regional dimensions (e.g. commuting zones, NUTS regions, counties, world regions, etc.).[7]

Table 4: Studies by the type of empirical methodology used in the analysis for any and each effect explored

	(1) Descriptive	(2) Regression	(3) Simulation
Any effect			
share	0.14	0.80	0.06
#	18	102	7
Replacement			
share	0.15	0.83	0.03
#	15	85	3
Reinstatement			
share	0.16	0.80	0.04
#	13	63	3
Real income			
share	0.12	0.85	0.03
#	4	28	1
Total employment			
share	0.15	0.81	0.04
#	13	72	4

Notes: Columns (1)-(3) present the share and number (#) of studies by the primary type of empirical methodology used in each study to identify the effect(s) of interest. 'Descriptive' refers to studies using descriptive statistics and conceptual analyses that link macro level stylized facts to empirically reported technology-trends at the micro level. 'Regression' refers to any regression-based analysis or other quantitative inferential methods with empirical foundation. 'Simulation' captures simulation methods, e.g. DSGE. These statistics are reported in each row panel within any, replacement, reinstatement, real income, and total employment effect reported, respectively. Note that there is no overlap in methods reported, i.e. more than one primary method used in each study, and thus the shares across columns add up to one, up to rounding.

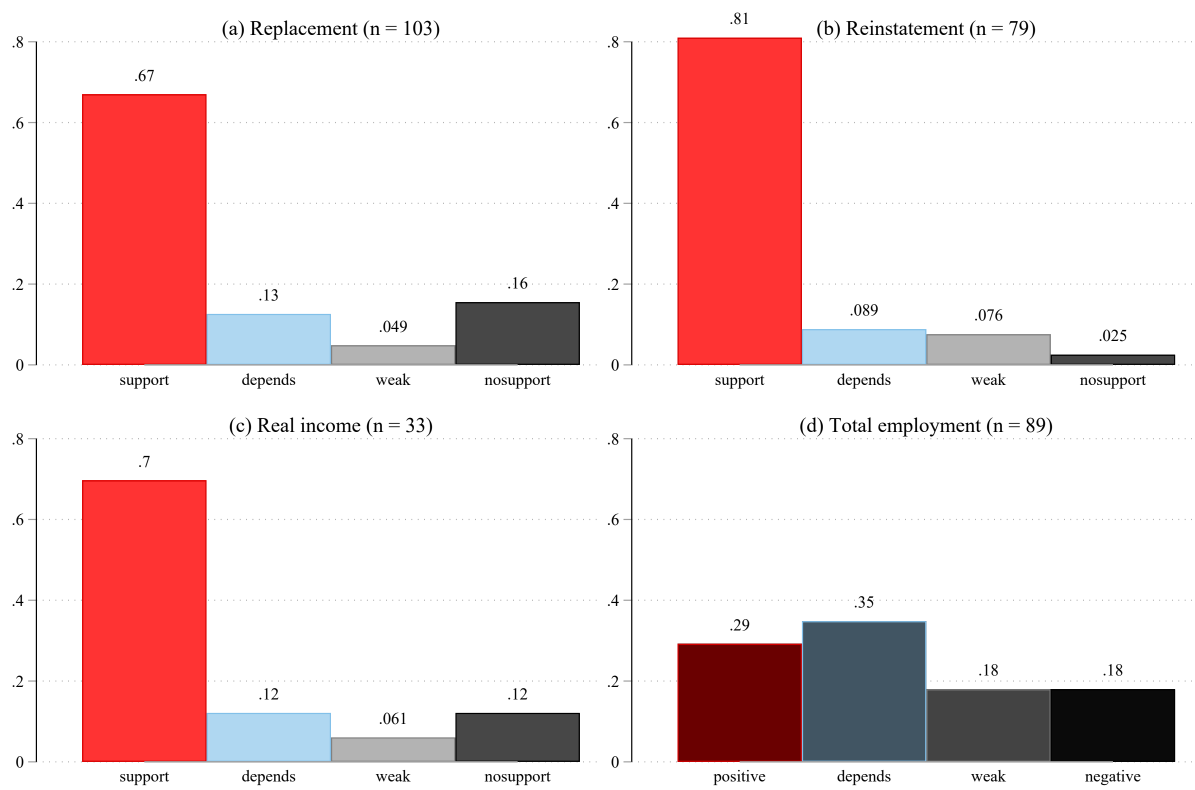
We use three categories to classify and distinguish between studies based on: de-

[6]For a handful of studies that rely on calibration and simulation methods, the level of analysis refers to the level of aggregation of the results/predictions.

[7]Note that only a small share of studies (9%) provides results at multiple levels of analysis, which in most cases comes in the form of additional robustness checks.

scriptive analyses (labeled “Descriptive”); regressions and similar forms of inferential statistics (labeled “Regression”); and studies that rely on simulation or calibration exercises (labeled “Simulation”). Simulation studies were only included if a substantial part of the study includes a significant amount of empirical data analysis, e.g. to motivate, calibrate, and/or estimate a simulation model. Table 4 gives on overview of the methods used. Specifically, irrespective of the effect explored, more than 80% of the studies rely on regression methods and between 12-16% on descriptive analyses. Only a small fraction (3-6%) uses simulation methods.

Figure 1: Share of studies by type of result reported for each effect examined



Source: Author’s calculations based on 127 studies collected from systematic literature review.
Notes: Panels (a)-(d) present the share of studies by each type of result reported for the replacement, reinstatement, real income and total employment effect, respectively. Specifically, in panels (a)-(c) a study is classified as ‘support’ if it finds a significant empirical effect that supports the effect of interest examined, i.e. replacement, reinstatement, real income, respectively. ‘Depends’ refers to the set of studies that find varying effects depending on the type of technology or the (sub)sample analyzed (e.g. type of sector or labor). Studies reporting effects that are negligible in terms of the magnitude were classified as ‘weak’. Studies were labeled as ‘no support’ if they investigate the effect of interest, but documented insignificant or opposite effects. Similarly, in panel (d), ‘positive’ and ‘negative’ refer to studies which find for total employment a significant empirical effect that is positive and negative, respectively, while ‘depends’and ‘weak’ are defined similarly to those above. A study can investigate more than one type of effect, but the assigned groups of results (i.e. support, depends, weak or no support and positive, depends, weak or negative) are mutually exclusive within each effect explored. In each panel, ‘n’ is the number of studies examining the relevant effect.

In Figure 1, we provide an overview of whether the findings reported in the studies support the different effects. Specifically, we classified a study as "support" if it provides results that offer data-based support for the existence of the effect of interest examined, i.e. replacement, reinstatement, and real income. Some studies find that the effects vary depending on the type of technology or the (sub)sample analyzed, for example distinguishing between industries, demographic groups, occupations, and types of labor. In this case we assigned the group "depends". Studies that report negligible effects in terms of the magnitude or effects of low statistical significance were classified as "weak". Finally, studies were labeled as "no support" if they find that the effect of interest is insignificant or opposite to what was hypothesized. Note that a study can investigate more than one type of effect, but the assigned labels, i.e. support, depends, weak or no support, are mutually exclusive within each effect.

In panel (a) of Figure 1, we can see that roughly two thirds (67%) of the studies that report results on the replacement effect find support for this effect, while only 16% provide no support. A small share (13%) of studies suggest that whether or not the technology is labor replacing depends on specific factors, such as the industry, country, or type of labor considered. The remainder (4.9%) reports weak or inconclusive results.

Panel (b) shows that among those studies that report results on the reinstatement effect, 81% support that technological change creates new jobs either within the same firm, the same industry or elsewhere in the economy. Only a small fraction of the studies (2.5%) find no support. Again, a minor fraction of the studies (16.5%) find that the effect is conditional on the specification or focus of the analysis.

When looking in panel (c), similarly striking is the high support for the real income effect among those studies that report any results on this effect. Generally, it should be highlighted that the number (n) of studies in this subsample is much smaller compared to the rest of the effects, i.e. 33 versus 103 and 79 studies. Again, roughly 70% of the studies provide empirical support for the existence of this effect. This indicates that technological change increases real income levels which may lead to a higher demand and expansion of output with positive employment effects.

As explained above in Section 2, this effect is the most indirect which makes the empirical analysis challenging. Here, we report all studies as supporting the real income effect if they provide empirical evidence for the existence of at least one mechanism that underlies the real income effect, i.e. productivity enhancement, price reductions, increases in net income, output expansion, or a positive association between output and employment. A small share of studies does not find any support for the real income effect, namely, 12%. Another 12% of the studies document that the presence of a real income effect depends on other factors, while only 6% of the studies present weak evidence over such an effect.

Panel (d) in Figure 1 summarizes the results from our evaluation of the net effect of technological change on employment. In total, 29% of studies document a net positive effect, 18% a negative effect, and 18% report ambiguous or inconclusive results. The majority of studies (35%) shows that the net employment effect is conditional.[8]

[8] In Appendix Table A.1, we summarize the findings for each effect in absolute frequencies.

4.2 Replacement effect

Table 5: Studies by findings on replacement

	(1) support	(2) depends	(3) weak	(4) no support
share	0.67	0.13	0.05	0.16
#	69	13	5	16

Notes: Columns (1)-(4) present the share and number (#) of studies with empirical results that support, depend (on various characteristics, e.g. technology type, analysis level, etc.), are weak, and do not support the presence of a replacement effect, respectively. The total # of studies in the sample is 127 of which 103 examine the replacement effect.

4.2.1 Overview, methods and technical issues

Does technology replace human labor? The majority of studies exploring the replacement effect suggest that it does, but we also find a relatively small share of studies that do not support or suggest ambiguous effects (see Table 5). For a deeper understanding, we systematize the empirical evidence for this effect by the finding (support, no support, depends) and other characteristics of each study.

Before diving into the results, we summarize a few general aspects. A large number of studies build on the neoclassical framework of skill or task biased technological change as a basis for the empirical analysis. The majority of studies (83%) use regression analyses or other quantitative inferential methods to assess the impact of technology on labor, fifteen studies (15%) are based on descriptive statistics and conceptual analyses that link macro level stylized facts to empirically reported technology-trends at the micro level, and the remaining three studies (3%) use simulation methods (see Table 4).

Key indicators to evaluate the existence of the replacement effect are labor demand (measured in employment and hours worked) at the firm, industry, country, skill or occupation level. Other closely related measures which are informative to understand the extent to which technology replaces labor, include: the labor share; the probability of unemployment; labor-capital substitution elasticities; and employment shares of heterogeneous groups of employees.

In column (1) of Table 6, we present the fraction of studies using different measures to capture technology and the remaining columns display for each of the technology groups considered whether or not these studies offer empirical support for the replacement effect. The largest fraction of replacement studies (36%) studies the impact of ICT. Next, a commonly used technology measure in recent studies is robots (15%), followed by innovation (12%) and TFP-style with 17%. Of the selected studies, 29% use other measures of technology which do not directly relate to any of the aforementioned technology groups or serve as an indirect measure of technological change (e.g. price changes, automation risks, etc.).

Column (2) in Table 6 illustrates that we find high support rates for the replacement effect across all technology types except for innovation. The strongest support comes from studies that use robots (87%), TPF-style (76%), Other (73%), and ICT (62%) as technology measures, where the percentage in parentheses indicates the share of replacement studies that study the respective technology and find support. Differently from the other technologies, the findings from ICT-based studies appear to be the most controversial showing simultaneously a high number of studies that support (62%) and do not support (24%) the effect, but only a few studies that report conditional or weak effects.

Table 6: Studies by findings on replacement effect for each technology group considered

	(1)	(2)	(3)	(4)	(5)
			by finding		
	total	support	depends	weak	no support
ICT					
share	0.36	0.62	0.08	0.05	0.24
#	37	23	3	2	9
Robots					
share	0.15	0.87	0	0	0.13
#	15	13	0	0	2
Innovation					
share	0.12	0.25	0.58	0	0.17
#	12	3	7	0	2
TFP-style					
share	0.17	0.76	0.12	0.06	0.06
#	17	13	2	1	1
Other					
share	0.29	0.73	0.10	0.07	0.10
#	30	22	3	2	3

Notes: Column (1) presents the share and number (#) of studies by the technology group considered in each row panel relative to the total number of studies examining the replacement effect. The row-sum of shares in column (1) does not add up to one since there are studies considering more than one technology group. Columns (2)-(4) present the share and # of studies by the set of findings reported on the replacement effect for each type of technology considered in each row panel. For findings, a study is classified as 'support' if it finds a significant empirical effect that supports the replacement effect examined. 'Depends' refers to the set of studies that find varying effects depending on the type of technology or the (sub)sample analyzed (e.g. type of sector or labor). Studies reporting effects that are negligible in terms of the magnitude were classified as 'weak'. Studies were labeled as 'no support' if they investigate the effect of interest, but documented insignificant or opposite effects. The technology types reported include ICT, robots, innovation, TFP-style and Other types of technologies (e.g. indirectly measured through prices, automation risks), respectively. Note that there is no overlap in findings reported, i.e. more than one primary finding in each study, and thus the shares across columns add up to one, up to rounding. The total # of studies in the sample is 127 of which 103 examine the replacement effect.

Studies relying on innovation show the weakest support rate for the replacement effect, but seem consensual about the conditionality of the effect. Only one quarter of the replacement ICT studies (25%) support this effect and another 17% does not find any empirical support, while 58% of the studies report that the effect is conditional on the type of innovation (e.g. product or process innovation) and other relevant dimensions, such as the characteristics of the employees and firms.

4.2.2 Studies supporting the replacement effect

The highest number of studies (n=23) that support the existence of a replacement effect rely on ICT as a measure of technological change, often proxied by investment in computer capital or survey data on computer use (Autor et al., 2002; Autor et al., 2003; Autor and Dorn, 2013; Baddeley, 2008; Balsmeier and Woerter, 2019; Dengler and Matthes, 2018; Diaz and Tomas, 2002; Eden and Gaggl, 2018; Fonseca et al., 2018; Fossen and Sorgner, 2021; Morrison Paul and Siegel, 2001; Wolff, 2009; Addison et al., 2000; Autor, 2015; Berman et al., 1994; Luker and Lyons, 1997; Autor et al., 2015; Blanas et al., 2019; Goaied and Sassi, 2019; Kristal, 2013; Kaiser, 2001; Jerbashian, 2019; Morrison, 1997). Most of these studies examine changes in firm or industry level labor demand, unemployment rates in certain industries, and occupations.

The large majority builds on theories of skill or task biased technological change and find support that ICT technologies replace human labor in low skill jobs and occupations or (regions with) industries that are intensive in routine tasks. For example, support for the replacement effect is usually reflected by empirically observed shifts in employment shares across industries, occupations, and demographic groups. The majority of studies are at the meso level of analysis, followed by studies at the micro level (Balsmeier and Woerter, 2019; Dengler and Matthes, 2018; Fonseca et al., 2018; Fossen and Sorgner, 2021; Addison et al., 2000; Kaiser, 2001) and macro level Baddeley (2008), Eden and Gaggl (2018), Wolff (2009), Autor (2015), and Goaied and Sassi (2019). Only Autor and Dorn (2013) and Autor et al. (2015) show ICT-induced replacement effects at the regional level.

Among the studies looking at the replacement effect, the highest relative support for this effect comes from studies using robots as a technology measure, i.e. the following thirteen out of a total of fifteen studies support the effect (Borjas and Freeman, 2019; Camina et al., 2020; de Vries et al., 2020; Edler and Ribakova, 1994; Faber, 2020; Jung and Lim, 2020; Compagnucci et al., 2019; Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2020; Dodel and Mesch, 2020; Blanas et al., 2019; Graetz and Michaels, 2018; Labaj and Vitaloš, 2020). Most of the robot studies cover a period between the mid 90s until 2016 and mainly look at European countries or the US. The most commonly used data sets with information on industrial robot penetration come from the IFR or national associations of robot manufacturers, e.g. for Japan (Dekle, 2020) and Denmark (Graetz and Michaels, 2018). In a similar fashion, the studies by Camina et al. (2020) and Edler and Ribakova (1994) rely on survey data on robot use in Spanish manufacturing and German firms, respectively, in pre-selected industries. An interesting alternative is that from Blanas et al. (2019) who use detailed data on trade in robots and ICT products, while Dodel and Mesch (2020) use survey data on self-reported job losses in response to workplace automation among US employees.

Almost all of these robot studies are at the meso level and explore the presence of employment effects mainly at the industry level, followed by a handful of studies at the regional and micro level, i.e. individuals/firms. These studies find a negative association between robot diffusion and employment, labor income shares, and/or higher probabilities of self-reported job losses. Some studies additionally report the effect of robots on wages which are ambiguous and heterogeneous across skill groups. Generally, the impact tends to be more negative for certain manufacturing industries, for women, for medium-aged employees and for low skill employment. Compagnucci et al. (2019) report a positive effect on wages which is outweighed by employment losses, yielding a net negative effect on the wage bill.

Faber (2020) and Acemoglu and Restrepo (2020) study the impact of robots on the regional (commuting zone) employment-population ratio. Acemoglu and Restrepo (2020) use a long difference regression approach and report a negative relationship between robot exposure and employment where the effects are strongest in routine manual occupations and blue collar jobs. In the same spirit, Borjas and Freeman (2019) rely on similar data sets to examine the impact of robots and immigrants on hourly wages and employment at the state-industry level. They observe a negative association of robots and employment and wages. The study by Faber (2020) is an interesting exception since it examines the impact of robots used in an offshoring country. He finds that robot adoption in offshoring industries in the US has a negative employment effect on regions in Mexico that heavily rely on exports to the US. This result supports the idea that the diffusion of automation technologies may have cross-regional spillovers. Specifically, when regions whose comparative advantage in the production of tradable goods is based on low labor costs may lose this advantage since the tasks performed by cheap labor can now be performed by machinery.

The one study in this technology group performed at the macro level is by Labaj and Vitaloš (2020) who examine the impact of robots, measured by the number of robots per thousand workers, on changes in the country-level wage bill. They find evidence for the existence of the replacement effect, but simultaneously report that negative employment effects are overcompensated by the reinstatement of new labor.

Another set of studies (n=13) that mostly support the existence of the replacement effect use production function-based indicators as measures of technological change, which we group as TFP-style (Angelini et al., 2020; Ergül and Göksel, 2020; Gregory et al., 2001; Ho, 2008; Baltagi and Rich, 2005; Bloch, 2010; Chen and Yu, 2014; Autor and Salomons, 2018; Bessen, 2020; Graham and Spence, 2000; Whelan, 2009; Huh and Kim, 2019; Kim and Kim, 2020). These studies mostly report shifts in labor demand, particularly across industries and across different types of labor, such as shifts from production to non-production labor. Angelini et al. (2020), Ho (2008), Baltagi and Rich (2005), and Gregory et al. (2001) provide evidence that technological change is skill biased by showing that lower skilled labor tends to be replaced by high skill labor. Bessen (2020), Chen and Yu (2014), and Bloch (2010) evaluate the factor bias of technological change and document patterns of labor saving and capital-using technologies over the past decades with considerable heterogeneity across industries and countries. Autor and Salomons (2018) additionally document that industry level growth in TFP was associated with a decrease in wages, hours worked, the wage bill, and in the labor share in major industrial countries since the 1970s. Whelan (2009) and Huh and Kim (2019) study cyclical macroeconomic fluctuations and show that positive TFP-style shocks tend to be negatively related to hours worked. Ergül and Göksel (2020) and Kim and Kim (2020) sugest that technology-induced shocks are associated with decreases in the labor share of income, albeit potentially being only transitory, while Graham and Spence, 2000 find that some of the industry-region employment losses can be attributed to technological changes.

The studies using "other/indirect" technology measures can be roughly grouped into three categories. A first bundle of studies (Peng et al., 2018; Gardberg et al., 2020; Blien et al., 2021; Grigoli et al., 2020; Arntz et al., 2017) capture the exposure to technological change of certain industries, demographic groups and regions relying on measures of automation risk which are based on the approach and metrics developed by Frey and Osborne (2017), i.e. estimates of the probability that certain tasks performed by human labor are prone to be automated. These studies exploit variation in regional, industrial and/or occupational susceptibility to automation and provide evidence that automation risk indices help to explain employment losses and the longer unemployment spells for workers in certain jobs.

A second category of "other/indirect" technology measures includes capital and high-tech equipment investments used by Morrison (1997), Wemy (2019), and Ho (2008) as proxies for technological change. Also Gera et al. (2001) infer the pace of technological change from shifts in the age of the capital stock, as more recent capital indicates more dynamic patterns of technology investment. Kim and Kim (2020), Gera et al. (2001), Morrison Paul and Siegel (2001), and Vainiomaki and Laaksonen (1999) approximate technological change via an input-based innovation indicator (R&D spending), while Gera et al. (2001) and Feldmann (2013) use an output-based innovation indicator (patents). Most of these studies are at the macro or industry level and find declines in the labor share of income and employment. Further, Gera et al. (2001) provide support for skill biased technological change, i.e. more negative consequences in terms of employment and income for low skilled labor. The skill bias is also supported from the descriptive analyses by Oesch and Rodriguez Menes (2010) and Buyst et al. (2018) who provide detailed description of occupational shifts across industries that are in turn verbally linked to existing trends in technology. Similarly, the detailed historical analysis from Padalino and Vivarelli (1997) documents changes in the employment-GDP elasticity in G7 countries for the period 1964-94. The authors find for the post-Fordist era a negative correlation between GDP growth and employment in manufacturing, but not for employment in the whole economy. They also highlight that this relationship was reverse during the Fordist era.

The third category of studies focuses on skill biased technological change and all are at the macro level except for one regional level study (Reshef, 2013; Padalino and Vivarelli, 1997; Manning, 2004; Hoskins, 2000; Hoskins, 2002; Madariaga, 2018; Reijnders and J., 2018). The measures of technology employed are heterogeneous and vary from the use of the Leontief inverse matrix as a proxy for changes in production techniques to changes in occupational efficiency. All studies provide suggestive evidence that technological change decreased the (relative) demand for unskilled workers or routine jobs.

Continuing, only three studies among those that provide empirical support for the replacement effect study the impact of innovation as it can be identified by CIS-like data (Vivarelli et al., 1996; Cirillo, 2017; Dachs et al., 2017). Vivarelli et al. (1996) study the impact of product and process innovation in Italian manufacturing firms during the 1980-1990s. They find clear support for labor displacement driven by the dominant role of process innovation. Cirillo (2017) and Dachs et al. (2017) make the same observation in different European countries, but also highlight the presence of heterogeneity in their findings. Specifically, process innovation appears to be more relevant for high-tech industries and the effects tend to be stronger in Northern European countries.

Interestingly, when evaluating studies that support the existence of the replacement effect, we observe that, irrespective of the technology-type studied, only a small fraction provides insights on positive aggregate employment effects, while the vast majority shows ambiguous results. Balsmeier and Woerter (2019), Camina et al. (2020), Dachs et al. (2017), Manning (2004), Diaz and Tomas (2002), Luker and Lyons (1997), and Padalino and Vivarelli (1997) report a net positive effect on total employment while Arntz et al. (2017), Jung and Lim (2020), Chen and Yu (2014), Compagnucci et al. (2019), Addison et al. (2000), Autor and Salomons (2018), Acemoglu and Restrepo (2020), Gardberg et al. (2020), Goaied and Sassi (2019), Whelan (2009), Hoskins (2002), Huh and Kim (2019), and Wemy (2019) find a negative effect.

4.2.3 Studies not supporting the replacement effect

The number of studies that provide evidence against any significant impact of technology on employment is somewhat smaller. In particular, only sixteen out of sixty-nine studies do not support the effect. Among these studies, nine evaluate the impact of ICT, two measure technological change by robot diffusion and another two by innovation. Three studies rely on indicators that fall into the residual category “other/indirect”, while only one study examines the TFP-style technology type. Eight of these studies are at the micro level, four at the macro level, and two for each of the meso and regional level. From the micro studies, Aubert-Tarby et al. (2018) and Scholl and Hanson (2020) make the analysis at the worker and occupation level, respectively, while the remaining focus at the firm level.

The ICT category includes five studies that apply firm-level regression analyses (Aubert-Tarby et al., 2018; Fung, 2006; Pantea et al., 2017; Atasoy et al., 2016; Gaggl and Wright, 2017), one performing industry level regressions (Biagi and Falk, 2017), one that applies descriptive economic history analysis at the macro level (Borland and Coelli, 2017), and two studies using regression analyses at the regional level, which cover cities (Behaghel and Moschion, 2016) and economic regions (Ivus and Boland, 2015).

Among the micro level studies, Fung (2006) proxies ICT technologies by expenses on IT and computer data processing and examines whether these technologies had a labor saving impact on the US banking industry between 1992-2002. The author rejects the presence of labor saving effects for the technologies considered, since the findings suggest that the more technology intensive firms actually increase their employment. Similarly, Aubert-Tarby et al. (2018) analyze whether digitilization in the French newspaper and magazine press industry creates or destroys jobs, and how this affects the quality of labor contracts. Overall, they find that digitalization is associated with a reduction in the probability to be laid off and also with higher wages. Pantea et al. (2017), Atasoy et al. (2016), and Gaggl and Wright (2017) make similar observations for EU countries and Turkey looking at different firm level ICT usage indicators. They estimate either insignificant or positive effects of these technologies on employment in SMEs. Additionally, Gaggl and Wright (2017) show that the introduction of these technologies is associated with changes in the composition of tasks performed by workers.

In line with the findings above, Biagi and Falk (2017) and Ivus and Boland (2015) do not find any significant effect of ICT on employment in European industries and Canadian regions, respectively. Likewise, Behaghel and Moschion (2016) do not observe that ICT diffusion increases the probability of dismissals in French cities. If anything, they provide only weak support of increased job instability for high-school dropouts. Borland and Coelli (2017) provide a descriptive historical analysis, whereby they document a decrease in routine labor which does not deviate from historical patterns. They fail to identify any noteworthy relationship between ICT diffusion and employment changes.

Dekle (2020) and Fu et al. (2021) evaluate the impact of robot adoption on employment. Fu et al. (2021) study a sample of seventy-four countries, including the EU-27 and twenty-nine developing countries. They find insignificant employment effects in developing countries and even positive effects on aggregate employment accompanied with positive productivity effects in developed countries. The authors also report heterogeneity by gender, but even in this dimension they do not find any evidence for large-scale robot-induced replacement. Dekle (2020) analyze the impact of robot diffusion during 1979-2012 in twenty Japanese industries, but do not identify any significant negative effects on employment.

Among those studies that distinguish the impact of product and process innovation, the literature review by Calvino and Virgillito (2018) concludes that the relationship between product innovation and employment is rather positive if statistically significant at all. On the other hand, the impact of process innovation remains controversial, but the authors also emphasize that the existing evidence is insufficient to support the existence of a replacement effect. Next to the impact of ICT, Fung (2006) also report the impact of in-house process innovation in the banking sector. But similarly to ICT, they cannot find any support that these innovations are labor saving.

Three studies that do not find support for the replacement effect consider technologies that fall in our residual category "other/indirect". The study by Scholl and Hanson (2020) relies on measures of automation risks based on expert judgments à la Frey and Osborne (2017). Using a regression framework, they do not find that the automation risk measures are in any way significantly related to changes in pay or employment. Sargent (2000) assumes that changes in economic regularities, such as the relationship between unemployment rates and vacancies, are an indication of technological change. Implicitly this approach takes for granted that technological change affects and hence is directly linked with this regularity. The author finds descriptive evidence that such shifts occurred and he links these patterns to employment shifts across industries, occupations and educational groups. Nevertheless, the author does not find that these patterns of change in the structural relationships are associated with an increase in unemployment rates. Finally, the study by Raval (2019) explores plant level information to examine whether capital-labor substitution possibilities have changed between 1987-2007. They report that the estimated capital-labor elasticities have been very persistent over the time period covered.

4.2.4 Studies with ambiguous findings and indirect evidence

Ambiguity about the existence of the replacement effect is reported in twenty studies and comes in the following decreasing order in terms of the number of studies using as a technology measure: innovation, ICT, other/indirect, and TFP-style. No study on the impact of robots reports weak or conditional results. Among the studies with ambiguous results, some of these—classified as "weak"—provide only indirect evidence that may or may not be consistent with the replacement effect. The remaining studies—classified as "depends"—provide contradicting evidence when using different technology measures. In both cases and irrespective of the technology type, all of these studies remain inconclusive on whether or not technology replaces labor.

A subset of these studies argues that there is a re-allocation of employment from one group of occupations to another which provides suggestive evidence for the replacement effect (Autor et al., 1998; Breemersch et al., 2019; Flug and Hercowitz, 2000; Gallipoli and Makridis, 2018; Green and Sand, 2015; Maurin and Thesmar, 2004). Similarly, Fort et al. (2018) and Boyle and McCormack (2002) look at the reallocation of employment within and between manufacturing. However, as is also recognized in most of these studies, employment patterns such as job polarization may also be driven by changes in wages, demographic change or other relevant factors of influence that may be correlated with technology.

Another subset of these studies investigates whether the decline in the labor share can be explained by technology (Dixon and Lim, 2020; O'Mahony et al., 2021). The decline of the labor share does not necessarily imply that jobs have been replaced by technology, but it may indicate technology-induced pressure on the labor market if the relative factor remuneration for labor declines. Hence, we understand this as indirect support for the replacement effect.

Next, when looking at the ICT studies, Gallipoli and Makridis (2018) provide indirect support for the replacement of non-IT by IT intensive occupations with a higher wage premium. Breemersch et al. (2019) show that ICT adoption is associated with increased polarization towards high pay jobs within manufacturing industries only, but with minimal contributions between manufacturing and non-manufacturing industries. Maurin and Thesmar (2004) show that the share of skilled labor increased in response to ICT adoption which may be accompanied with the simultaneous replacement of unskilled labor. Autor et al. (1998) find rapid skill upgrading processes since 1970 and provide suggestive evidence that these processes evolve faster in computer intense industries. These studies point to a declining employment share of certain types of jobs, i.e. mostly routine task intensive, low skill, and low wage jobs. However, it is not necessarily true that changes in employment shares are accompanied by the replacement or "phasing out" of certain occupations. O'Mahony et al. (2021) study the impact of ICT and innovation-related capital investments, but do not find any conclusive results on whether the labor share is positively or negatively affected. Intangible investments related to innovation tend to have a positive impact, while investments related to firm organization tend to show the opposite pattern. In tendency, low and intermediate skilled workers appear to be more negatively affected.

Three studies of those relying on TFP-style measures report ambiguous results (Boyle and McCormack, 2002; Dixon and Lim, 2020; Fort et al., 2018). Fort et al. (2018) offer a detailed descriptive analysis showing a negative relationship between TFP growth and employment in some but not all manufacturing industries. Interestingly, they report that this does not realize through the shut-down of existing plants but through lower shares of labor input in plants that are new entrants. Boyle and McCormack (2002) and Dixon and Lim (2020) do not directly evaluate the impact of TFP on labor, but show that the decline in the labor share can be partly attributed to labor saving technological change.

Seven of the studies that document ambiguous results for the replacement effect rely on innovation (product and process) as a measure of technology (Bogliacino and Pianta, 2010; Falk, 2015; Cozzarin, 2016; Evangelista and Vezzani, 2012; Pellegrino et al., 2019; Van Reenen, 1997; Kwon et al., 2015). All of them rely on analysis at the firm level - except for the industry level study by Bogliacino and Pianta (2010) - and explore whether there is a significant relationship between the introduction of process/product innovation and labor demand. In addition, Falk (2015), Evangelista and Vezzani (2012), and Kwon et al. (2015) provide further explorations on the impact of organizational innovation. All these studies do not find any significant impact of product and organizational innovation on labor. Similarly, for process innovation, Pellegrino et al. (2019) and Van Reenen (1997) either present weakly statistically significant negative effects or findings that depend on the size of firms.

Falk (2015) shows a negative association between process innovation for labor, but this only holds for a subset of industries. Cozzarin (2016), next to product and process innovation, studies the impact of advanced manufacturing technologies (AMT) and finds ambiguous evidence depending on the type of innovation and technology considered: for example, he finds no effect of AMT, a negative effect of product innovation, and a positive effect of process innovation. Evangelista and Vezzani (2012) find weak evidence of a labor saving impact of organizational product innovation in manufacturing but not in services. Next to the labor saving effect, they also observe an innovation-induced increase in sales which may offset the negative effect on employment. Also, Kwon et al. (2015) find a negative impact of process but not product innovation.

Among those studies that rely on technology measures that fall in our residual category "other/indirect", three use investment in high-tech capital or R&D as technology proxies (Breemersch et al., 2019; Flug and Hercowitz, 2000; Idris et al., 2021) and one relies on knowledge-based assets (O'Mahony et al., 2021). Idris et al. (2021) cannot identify any impact of high-tech on employment and Flug and Hercowitz (2000) and Breemersch et al. (2019) document that technologies may be associated with wage and skill polarization patterns in the labor market. However, Breemersch et al. (2019) emphasize that technology plays a rather minor role in explaining polarization patterns in the labor market. Furthermore, O'Mahony et al. (2021) find heterogeneity in the results depending on the exact type of the technology considered: R&D-based knowledge investments mitigate the ICT-driven declining trend in the labor share, while innovation-related intangible investments are related to increases in the labor share which is opposite to the effect found from organization-related investments.

Finally, Green and Sand (2015) provide a descriptive analysis of technology trends but without a direct measurement. They explore polarization patterns in the Canadian labor market since the 1970s, but cannot confirm any hypothesis about skill biased technological change. Rather, the drivers of the observed polarization patterns differ compared to those in the US and other countries. While they document some occupations shrinking, they argue that these are more likely to be driven by the resource boom in Canada, rather than by technological change.

4.3 Reinstatement effect

Table 7: Studies by findings on reinstatement

	(1) support	(2) depends	(3) weak	(4) no support
share	0.81	0.09	0.08	0.03
#	64	7	6	2

Notes: Columns (1)-(4) present the share and number (#) of studies with empirical results that support, depend (on various characteristics, e.g. technology type, analysis level, etc.), are weak, and do not support the presence of a reinstatement effect, respectively. The total # of studies in the sample is 127 of which 79 examine the reinstatement effect.

4.3.1 Overview, methods and technical issues

Does the introduction of new technologies create new jobs? In total, seventy-nine studies in our sample report empirical insights on the reinstatement effect. Among those studies that report empirical evidence on the reinstatement effect, roughly 80% support the existence of this effect, while 17% report ambiguous findings and only two studies (3%) find insignificant effects (see Table 7).

The reinstatement effect is operationalized as a change in the absolute and relative labor demand, often distinguishing between different types of labor such as high- and low skilled, manufacturing and non-manufacturing, and different occupations and tasks. Some of the studies additionally document changes in wages or the expansion of industrial or firm output which may be associated with the creation of new jobs. A few micro level studies look at job transition rates and the characteristics of new jobs. Almost all of the reinstatement studies (82%) simultaneously report findings on the replacement effect and seventeen studies (22%) on the real income effect.

Table 8: Studies by findings on reinstatement effect for each technology group considered

	(1)	(2)	(3)	(4)	(5)
		by finding			
	total	support	depends	weak	no support
ICT					
share	0.38	0.77	0.07	0.13	0.03
#	30	23	2	4	1
Robots					
share	0.13	0.90	0	0	0.10
#	10	9	0	0	1
Innovation					
share	0.18	0.57	0.29	0.14	0
#	14	8	4	2	0
TFP-style					
share	0.14	0.91	0.09	0	0
#	11	10	1	0	0
Other					
share	0.28	0.91	0.05	0.05	0
#	22	20	1	1	0

Notes: Column (1) presents the share and number (#) of studies by the technology group considered in each row panel relative to the total number of studies examining the reinstatement effect. The row-sum of shares in column (1) does not add up to one since there are studies considering more than one technology group. Columns (2)-(4) present the share and # of studies by the set of findings reported on the reinstatement effect for each type of technology considered in each row panel. For findings, a study is classified as 'support' if it finds a significant empirical effect that supports the reinstatement effect examined. 'Depends' refers to the set of studies that find varying effects depending on the type of technology or the (sub)sample analyzed (e.g. type of sector or labor). Studies reporting effects that are negligible in terms of the magnitude were classified as 'weak'. Studies were labeled as 'no support' if they investigate the effect of interest, but documented insignificant or opposite effects. The technology types reported include ICT, robots, innovation, TFP-style and Other types of technologies (e.g. indirectly measured through prices, automation risks), respectively. Note that there is no overlap in findings reported, i.e. more than one primary finding in each study, and thus the shares across columns add up to one, up to rounding. The total # of studies in the sample is 127 of which seventy-nine examine the reinstatement effect.

In column (1) of Table 8, we find that the largest fraction of studies looking at reinstatement focus on the impact of ICT (38%) and innovation (18%). This is followed by ten studies on robots and eleven on TFP-style technologies reporting reinstatement results. The remaining twenty-two studies use technology measures that fall in our residual category "other/indirect". In columns (2)-(5) Table 8, we find that across all technology categories, with the exception of one robot and ICT study, there is high support or at least no strong opposition against the reinstatement effect. Out of these studies, and similarly to the replacement effect, the highest ambiguity about the existence of the reinstatement effect is observed in the innovation (43%) and ICT studies (20%). However, even in these cases the support rates remain high. Generally, these statistics are based on a small number of studies, and thus should be considered with caution in terms of their relative importance.

The vast majority of studies (n=63) uses regression analysis, while thirteen of the studies rely on descriptive empirical analysis. Only three are based on simulation methods (see Table 4). Most of these studies are at the macro and meso level with 33% and 34%, respectively, followed by 28% of the studies at the micro level and 14% at the regional level (see Appendix Table A.2).

4.3.2 Studies supporting the reinstatement effect

Among those studies that support the reinstatement effect, twenty-three look at the impact of ICT (Atasoy, 2013; Aubert-Tarby et al., 2018; Autor et al., 2003; Autor and Dorn, 2013; Baddeley, 2008; Balsmeier and Woerter, 2019; Fossen and Sorgner, 2021; Fung, 2006; Morrison Paul and Siegel, 2001; Behaghel and Moschion, 2016; Autor, 2015; Berman et al., 1994; Luker and Lyons, 1997; Autor et al., 2015; Blanas et al., 2019; Gaggl and Wright, 2017; Gallipoli and Makridis, 2018; Ivus and Boland, 2015; Kristal, 2013; Kaiser, 2001; Jerbashian, 2019; Maurin and Thesmar, 2004; Morrison, 1997). The majority of them (fifteen) simultaneously support the replacement effect, while five studies do not find significant support for it (Aubert-Tarby et al., 2018; Fung, 2006; Behaghel and Moschion, 2016; Gaggl and Wright, 2017; Ivus and Boland, 2015). This does not necessarily imply that these studies find overall positive employment effects. Only Fung (2006) and Aubert-Tarby et al. (2018) show at the firm level that ICT adoption has created but not destroyed jobs.

At the city level, Behaghel and Moschion (2016) study the impact of ICT on skill upgrading and job-to-job transitions. They show that the adoption of ICT is associated with an increased demand for skilled labor and does not coincide with higher dismissal rates. Nevertheless, their results do not allow to draw conclusions about the net impact of ICT on labor demand. Gaggl and Wright (2017) and Ivus and Boland (2015) argue that the impact of ICT on net employment depends on various dimensions. Gaggl and Wright (2017) find a positive relationship between ICT adoption and the demand for non-routine cognitive labor, but do not observe effects on job replacement. However, they find that the positive effect diminishes over time which may indicate that it is only a transitory phenomenon. The detailed descriptive analysis of industrial job creation and destruction dynamics by Borland and Coelli (2017) provides evidence that the positive employment effects in Canada are heterogeneous across regions. Specifically, ICT diffusion only exhibits significant positive interactions with labor in rural regions and these effects are more pronounced in ICT intensive industries.

Only two studies that support the reinstatement effect report ambiguous findings for an ICT-induced replacement effect (Gallipoli and Makridis, 2018; Maurin and Thesmar, 2004). Gallipoli and Makridis (2018) report numerous empirical stylized facts for the US between 1980-2013 using micro level census data and detailed occupational employment statistics. They document the emergence of new and well-paid IT occupations, mostly in services. They show that productivity growth during this period can be mostly attributed to services while the employment share in manufacturing declined. However, their findings do not allow to draw conclusions about the definite existence of replacement or net employment effects. Maurin and Thesmar (2004) explore employee level data on different types of computer technologies used at work. They find a positive correlation between the diffusion of computers and the share of high skilled labor. This may indicate a replacement effect, but it does not necessarily need to hold. However, the authors also show that the impact of ICTs on labor demand is conditional on the type of ICT and also on the occupations and their task content.

Only the study by Atasoy (2013) reports findings exclusively for the reinstatement effect, but not on any of the other two effects. The authors study the impact of broadband deployment on county level labor markets in the US between 1999-2007. They find a positive effect of broadband access on employment and wages and that the positive wage effects are larger in counties with relatively more skilled labor, which brings support to theories of skill biased technological change.

The majority of ICT studies (65%) supports both, replacement and reinstatement. Most of them are regression-based analyses except for the economic history essay by Autor (2015) and the detailed descriptive empirical analyses on employment shifts across industries and occupations during 1988-1996 by Luker and Lyons (1997). Autor (2015) documents in detail how the demand for labor for certain occupations in services, such as managers and professionals, personal care, food services and others, continuously increased since the 1980s until the financial crisis when the patterns of growth slowed down. Further, he documents patterns of skill polarization reflected in the highest growth rates in the lowest and highest skill percentile. Similarly, Luker and Lyons (1997) document shifts from manufacturing to services. They show that a net increase in high-tech industries can be mostly attributed to services. Generally, high-tech service employment appears to grow faster than employment in the rest of the economy.

The remaining thirteen ICT studies that simultaneously support the replacement and reinstatement of labor rely on regression analyses (Autor et al., 2003; Autor and Dorn, 2013; Baddeley, 2008; Balsmeier and Woerter, 2019; Fossen and Sorgner, 2021; Morrison Paul and Siegel, 2001; Berman et al., 1994; Autor et al., 2015; Blanas et al., 2019; Kristal, 2013; Kaiser, 2001; Jerbashian, 2019; Morrison, 1997). Among these, the two studies by Autor et al. (2015) and Autor and Dorn (2013) use region level data. They find support for theories on routine biased technological change and observe increasing employment in abstract and manual tasks which neutralizes the negative employment effects of routine-task replacement. Autor and Dorn (2013) also document a rise in polarization, i.e. both a rise in low skill service jobs and a differential wage growth across occupations. The study by Baddeley (2008) offers a macro level analysis and confirms that computerization, next to financialization, was associated with a shift in labor from manufacturing to services in the UK between 1979-2005.

At the meso level of analysis, Autor et al. (2003), Morrison Paul and Siegel (2001), Berman et al. (1994), Blanas et al. (2019), Kristal (2013), Jerbashian (2019), and Morrison (1997) observe that ICT adoption is associated with the creation of new jobs. Autor et al. (2003) find an increase in non-routine jobs. Morrison (1997) finds that investments in computers and R&D are associated with skill polarization patterns, i.e. an increased demand for high and low skill workers. Berman et al. (1994) document a rise in non-production labor which coincides with a skill upgrading process. A similar skill bias is confirmed by Blanas et al. (2019) who show that robots and ICT are associated with higher employment in high and medium skill jobs and in services. Relatedly, Jerbashian (2019) shows a positive correlation between falling IT prices and employment in high-wage occupations.

Three studies document simultaneous replacement and reinstatement effects at the micro level, whereby Balsmeier and Woerter (2019) and Kaiser (2001) provide evidence at the firm level and Fossen and Sorgner (2021) at the level of individual employees. The two firm level studies find that increased investment in IT is associated with the creation of high skill jobs. Fossen and Sorgner (2021) find evidence for the creation of another class of jobs showing that digitalization significantly increases the probability that high skill workers engage in entrepreneurial activity.

Nine studies among those supporting the reinstatement effect use robots as a measure of technological change (de Vries et al., 2020; Dekle, 2020; Edler and Ribakova, 1994; Acemoglu and Restrepo, 2019; Blanas et al., 2019; Graetz and Michaels, 2018; Leigh et al., 2019; Gentili et al., 2020; Labaj and Vitaloš, 2020). Two thirds of the reinstatement-supporting robot studies report ambiguous effects of robots on net employment and the remaining three (Leigh et al., 2019; Gentili et al., 2020; Dekle, 2020) report positive effects. None of these studies reports a clear negative impact of robots on net employment. This suggests that whenever evidence for robot-driven reinstatement is found, it tends to overcompensate the replacement of labor.

All, except for Edler and Ribakova (1994) and Gentili et al. (2020), are regression-based analyses, mostly at the industry or regional level. Edler and Ribakova (1994) build on an empirical input output model and find a higher demand for skilled labor in response to robot diffusion. Gentili et al. (2020) perform a descriptive clustering analysis and attribute changes in the robot intensity to changes in employment measured by hours worked. They find that those industries with the highest robot intensity experienced the highest productivity and employment gains. However, these effects are clustered in high-tech industries which account for a small share of total employment.

Among the regression-based studies, only Labaj and Vitaloš (2020) focus at the macro level by exploring the extent to which variations in the economy wide wage bill and labor share are explained by robot diffusion rates in the US and European countries. They decompose aggregate changes in the task content of production into a reinstatement and replacement effect and find evidence for both. However, the authors emphasize that whether reinstatement or replacement dominates varies across countries (especially between the US and EU) and that this variation cannot be explained by robot diffusion.

Next, for the six remaining meso level regression-based analyses (de Vries et al., 2020; Dekle, 2020; Acemoglu and Restrepo, 2019; Blanas et al., 2019; Graetz and Michaels, 2018; Leigh et al., 2019) we observe that they mostly report increases in high skill and in services jobs. Dekle (2020) observes similar effects but instead for total employment, i.e. not only for high skill and service jobs. Leigh et al. (2019) also shows that in US manufacturing the impact of robots tends to be positive.

Ten studies that provide supporting evidence for the reinstatement effect rely on TFP-style measures of technological change. Two of them are descriptive analyses (Angelini et al., 2020; Fort et al., 2018) and the other eight rely on regressions (Ho, 2008; Baltagi and Rich, 2005; Boyle and McCormack, 2002; Autor and Salomons, 2018; Bessen, 2020; Graham and Spence, 2000; Kim and Kim, 2020; Sala and Trivin, 2018). In their descriptive study, Angelini et al. (2020) infer technological change from shifts in the skill content of production and provide evidence for the reinstatement of service jobs reflected in employment shifts from manufacturing to services. Fort et al. (2018) conduct a detailed descriptive analysis of the impact of labor productivity changes on employment shifts at the industry and plant level. They emphasize that labor displacement and net employment effects depend on the industry considered.

The other eight regression studies are mostly at the industry or macro level. They rely on different proxies of productivity changes, mostly captured by TFP or labor productivity, and study labor demand in absolute and relative terms. Bessen (2020) investigates the role of the elasticity of demand with respect to productivity for three industries since the 19$^{\text{th}}$ century. The author highlights that final demand was historically a key driver of the reinstatement of labor in the steel, textiles and automobile industry. The studies by Ho (2008), Baltagi and Rich (2005), Kim and Kim (2020), and Sala and Trivin (2018) show that the reinstatement of labor may be biased, as reflected in an increasing demand for skilled and non-production labor. The other three studies provide similar findings in different settings. Boyle and McCormack (2002) finds that capital accumulation and technological change are key drivers of employment growth. Autor and Salomons (2018) investigate TFP shocks in upstream industries and show that this is positively associated with hours worked and employment in downstream industries. Graham and Spence (2000) show that regional employment increases can be attributed to technology.

Continuing, eight studies that rely on innovation as a measure of technological change find support for the reinstatement effect. Five of them report positive net employment effects (Fung, 2006; Vivarelli et al., 1996; Calvino and Virgillito, 2018; Dachs et al., 2017; Tether and Massini, 1998; Xiang, 2005) and two emphasize that the net outcome depends on external circumstances and the type of innovation, i.e. process or product (Capello and Lenzi, 2013; Cirillo, 2017). The remaining one is the critical meta-analysis by Vivarelli et al., 1996 which is inconclusive about potential net employment effects.

In terms of the empirical approach used, two studies (Calvino and Virgillito, 2018; Tether and Massini, 1998) are based on descriptive analyses (including a literature review) and the other six rely on regression analyses. The analysis by Calvino and Virgillito (2018) offers a literature review on the impact of innovation, captured by different indicators (R&D intensity, CIS, patents) on employment at the firm and sector level. They document that the employment effect is mostly positive, but also depends on the sector and the type of innovation (i.e. process or product). They also confirm a mostly positive effect of product innovation and a negative effect of process innovation. Tether and Massini (1998) descriptively explore employment creation by small innovative firms at the micro level, where innovative firms are defined as inventor award winning firms. The authors show that these firms have faster than average employment growth patterns, but the extent to which the observation of a positive relationship between innovativeness and employment can be generalized beyond this specific setting remains limited.

Three of the six regression analyses are studies at the micro level using firm level data (Fung, 2006; Vivarelli et al., 1996; Dachs et al., 2017). Fung (2006) studies labor saving product and process innovation in the banking sector and finds positive spillovers from patented process innovations on labor demand in non-innovating banks. Both Vivarelli et al. (1996) and Dachs et al. (2017) observe that product innovation is positively associated with sales and labor demand, but Vivarelli et al. (1996) finds this pattern only for a subset of sectors which are characterized by higher design and engineering intensities and higher percentages of product innovations.

Another two studies are at the industry level (Cirillo, 2017; Xiang, 2005). Cirillo (2017) finds a positive relationship between the industry level share of firms introducing product innovations, industry level demand, and employment growth. Similarly, Xiang (2005) shows that the introduction of new goods is positively associated with the relative demand for skilled labor in the US manufacturing industry.

Capello and Lenzi (2013) confirm the positive association of product innovation with employment using regional level data for the EU. Applying spatial regressions, they show a positive relationship between the share of firms that introduce product innovations and regional employment and wage growth in sub-national regions (NUTS2) that are characterized by a high share of blue collar workers. The authors also highlight that the effect in regions with low shares of blue collar workers may be negative and that these relationships have changed over time.

Twenty studies that find support for the reinstatement effect rely on technology measures that fall into the residual category "other/indirect". Among these, Morrison Paul and Siegel (2001), Feldmann (2013), Vainiomaki and Laaksonen (1999), Van Roy et al. (2018), Yildirim et al. (2020), Kim and Kim (2020), and Fagerberg et al. (1997) use R&D expenditures or patents as a measure of technological change. Morrison Paul and Siegel (2001) and Kim and Kim (2020) observe a positive relationship between R&D expenditures and employment of high skilled labor. Yildirim et al. (2020) and Fagerberg et al. (1997) and Van Roy et al. (2018) all document a positive relationship between R&D and labor, whereas Van Roy et al. (2018) find that this only holds in high- but not in low-tech industries. Vainiomaki and Laaksonen (1999) find that high technology sectors, measured by R&D intensity, have the highest job creation rates. Feldmann (2013) finds only indirect support for the reinstatement effect. Specifically, in the short term, increased innovation reflected in patent applications had a negative employment effect, but this effect diminishes after some time which indicates that employment was reinstated after a technology shock with an initially negative impact.

Three studies use different indicators of specific types of capital investment as proxies of technological change. Ho (2008) uses a price index-based approach to capture quality improvements in equipment and finds that these enhancements are associated with an increase in demand for non-production labor in US manufacturing. Morrison (1997) considers investments in specific high-tech equipment and Raval (2019) uses the evolution of the capital stock as a technology measure. They all report a positive relationship between labor demand and the capital indicators, suggesting a complementarity between these factors. The results by Morrison (1997), similar to Ho (2008), suggest that this relation is particularly strong for non-production labor.

Two studies with support for the reinstatement effect use an indirect automation risk-based approach (Gardberg et al., 2020; Oesch and Rodriguez Menes, 2010). Both confirm at the country, and Gardberg et al. (2020) additionally at the individual employee level, that displacement is less likely in occupational groups with low automation risk. In contrast, employment has even increased in these jobs.

Padalino and Vivarelli (1997), Hoskins (2000), Madariaga (2018), Reijnders and J. (2018), and Jiang et al. (2019) are macro level studies using indirect approaches to capture technological change, such as decomposition analyses and substitution elasticities. Padalino and Vivarelli (1997) and Jiang et al. (2019) find a positive relationship between technological change and employment, while the other two find it only for certain sectors and jobs. However, also Padalino and Vivarelli (1997) observe that the employment-GDP relationship is opposite in manufacturing, suggesting the simultaneous existence of replacement in manufacturing and reinstatement in non-manufacturing industries in recent decades.

Finally, four non-regression analyses in the sample of studies relying on the residual technology category find support for the reinstatement effect. Reshef (2013) relies on an empirically estimated simulation model calibrated on US data. The results confirm the hypothesis of skill biased technological change in the US during 1963-2005 and find an increasing demand for skilled labor at the expense of unskilled. For Canada, Green and Sand (2015) cannot confirm the skill bias hypothesis in their detailed descriptive analysis. The analyses by Buyst et al. (2018) and Oesch and Rodriguez Menes (2010) also suggest a bias of technological change being associated with increases in high paid occupations. Both studies also provide evidence to rises in the demand for labor in the lowest skill group, but Oesch and Rodriguez Menes (2010) show that this effect is heterogeneous across countries.

4.3.3 Studies not supporting the reinstatement effect

The two non-supporting studies are the studies by Acemoglu and Restrepo (2020) and Goaied and Sassi (2019). While they do not find support for the reinstatement effect, they offer support for the replacement and real income effect. Both studies rely on regression analyses and report an overall negative impact of technology on net employment. Acemoglu and Restrepo (2019) cover the time period from 1990-2007 and study the impact of robots on the regional employment to population ratio. The authors find that robot diffusion is associated with an increase in unemployment which appears to be particularly driven by employment losses in manufacturing industries and routine manual, blue collar occupations. The effects are larger for men than women. Simultaneously, they report positive productivity effects and increases in capital income.

Goaied and Sassi (2019) study the long term impact of ICT diffusion in 167 countries grouped into five regions using the number of mobile phone and internet users as a technology indicator. Distinguishing between long and short term effects, the authors report not only a negative short term replacement effect, but also long term negative associations between both technology indicators and employment. They report a positive relationship between GDP and employment, but cannot attribute this to technology.

4.3.4 Studies with ambiguous findings and indirect evidence

Fifteen studies report ambiguous or only indirect evidence for the reinstatement effect. Six of these studies examine the impact of innovation, six of ICT, one uses TFP-style measures and two more look, next to ICT capital, into the role of R&D intensity.

The TFP-style study by Dupaigne and Patrick (2009) estimates the macroeconomic employment effect of positive labor productivity shocks using a vector auto-regressive model. The authors find that the impact, whether positive or negative, is heterogeneous across countries and also depends on how technology shocks are measured.

Among the ICT studies, four of them rely on regression analyses (Autor et al., 1998; Fonseca et al., 2018; Breemersch et al., 2019; O'Mahony et al., 2021), one study conducts a simulation excercise (Charalampidis, 2020) and another one relies on descriptive statistics (Borland and Coelli, 2017). Charalampidis (2020) studies automation technology shocks (while not providing much detail about the measurement of these shocks) and analyzes their interaction with aggregate fluctuations of the labor share. While this study finds that technology shocks explain a large share of the fluctuations, it remains inconclusive with regards to the longer term impact of these shocks. However, the author argues that labor reinstatement may be insufficient to offset job losses. The analysis by Borland and Coelli (2017) relies on a detailed descriptive analysis of those industries in Australia that reported the largest changes in employment during the past few decades. They link these observations to ICT diffusion curves, but fail to identify any clear impact of technology on labor. The aggregate demand for labor was roughly constant over the considered period, but they also observe an increase in non-routine intensive occupations.

Two of the four regression analyses in this sample investigate job polarization. Fonseca et al. (2018) find support for technology as a driver of job polarization, which may be indicative for the reinstatement of certain types of jobs. Breemersch et al. (2019) observe country-level employment growth and cross-industrial shifts, but fail to attribute this to technological change. Autor et al. (1998) document skill upgrading processes and higher wage premia, but do not show any clear impact on the demand for labor. The study by O'Mahony et al. (2021) investigates the relationship between ICT diffusion and the labor share. They find a negative relationship between ICT capital investments and the labor share which may indicate lack of reinstatement. Interestingly, the authors also study the impact of R&D investments and observe the opposite effect.

The six innovation studies (Evangelista and Vezzani, 2012; Pellegrino et al., 2019; Piva and Vivarelli, 2005; Piva and Vivarelli, 2004; Van Reenen, 1997; Kwon et al., 2015) report ambiguous or only weak support for the reinstatement effect. All of them are regression analyses at the firm level and confirm a positive effect of product innovation on employment, but a negative one of process innovation. Further, all of them, except for Piva and Vivarelli (2004) and Piva and Vivarelli (2005), simultaneously report ambiguous findings for the replacement effect.

4.4 Real income effect

Table 9: Studies by findings on real income

	(1) support	(2) depends	(3) weak	(4) no support
share	0.70	0.12	0.06	0.12
#	23	4	2	4

Notes: Columns (1)-(4) present the share and number (#) of studies with empirical results that support, depend (on various characteristics, e.g. technology type, analysis level, etc.), are weak, and do not support the presence of a real income effect, respectively. The total # of studies in the sample is 127 of which 33 examine the real income effect.

4.4.1 Overview, methods and technical issues

With thirty-three studies in total, the number of papers that provide empirical insights on the real income effect is much smaller compared to the other two effects. In Table 9, we see that among these, twenty-three papers find support, six report ambiguous (weak or depends) results, and four find no support.

The majority of studies investigate the impact of ICT (36%), followed by robots (27%), TFP-style (18%) and other/indirect measures of technological change (15%). Only two papers (6%) rely on innovation as a technology measure (see column (1) from Table 10).

Table 10: Studies by findings on real income effect for each technology group considered

	(1)	(2)	(3)	(4)	(5)
		by finding			
	total	support	depends	weak	no support
ICT					
share	0.36	0.83	0	0	0.17
#	12	10	0	0	2
Robots					
share	0.27	0.67	0.22	0.11	0
#	9	6	2	1	0
Innovation					
share	0.06	0.50	0.50	0	0
#	2	1	1	0	0
TFP-style					
share	0.18	0.83	0	0	0.17
#	6	5	0	0	1
Other					
share	0.15	0.40	0.20	0.20	0.20
#	5	2	1	1	1

Notes: Column (1) presents the share and number (#) of studies by the technology group considered in each row panel relative to the total number of studies examining the real income effect. The row-sum of shares in column (1) does not add up to one since there are studies considering more than one technology group. Columns (2)-(4) present the share and # of studies by the set of findings reported on the real income effect for each type of technology considered in each row panel. For findings, a study is classified as 'support' if it finds a significant empirical effect that supports the real income effect examined. 'Depends' refers to the set of studies that find varying effects depending on the type of technology or the (sub)sample analyzed (e.g. type of sector or labor). Studies reporting effects that are negligible in terms of the magnitude were classified as 'weak'. Studies were labeled as 'no support' if they investigate the effect of interest, but documented insignificant or opposite effects. The technology types reported include ICT, robots, innovation, TFP-style and Other types of technologies (e.g. indirectly measured through prices, automation risks), respectively. Note that there is no overlap in findings reported, i.e. more than one primary finding in each study, and thus the shares across columns add up to one, up to rounding. The total # of studies in the sample is 127 of which thirty-three examine the real income effect.

The existence of the real income effect is empirically supported if studies find empirical support for the existence of different channels, such as productivity and prices, income, and final demand or output. In our sample, the majority of papers (68%) provides empirical evidence about the productivity channel, followed by income (29%), and output (18%) (see Table 11). Despite the high number of papers reporting results on the productivity effects of technological change, only 9% are informative about the impact on prices, which is a relevant indicator to evaluate whether or not consumers benefit from the productivity gains of technological change.

Table 11: Studies by type of real income effect examined

	(1) productivity	(2) prices	(3) income	(4) output	(5) other
share	0.68	0.09	0.29	0.18	0.06
#	23	3	10	6	2

Notes: Columns (1)-(5) present the share and number (#) of studies focusing on productivity, prices, income, output, and other real income effects, respectively. The total # of studies in the sample is 127 of which 33 examine the real income effect.

Note that support for one of these channels is not sufficient to draw conclusions about the impact on employment. For example, productivity gains are not necessarily forwarded to consumers in the form of lower prices, and lower prices do not necessarily imply an increase in the demand and expansion of output, and an expansion of output does not necessarily imply a higher demand for labor.

4.4.2 Studies supporting the effect

From the twenty-three studies that empirically support the real income effect, sixteen report a positive effect of technological change on productivity (Autor et al., 2002; Baddeley, 2008; Chun et al., 2015; Dekle, 2020; Jung and Lim, 2020; Oulton, 2002; Strohmaier and Rainer, 2016; Vu, 2013; Boyle and McCormack, 2002; Chen and Yu, 2014; Acemoglu and Restrepo, 2019; Autor and Salomons, 2018; Autor, 2015; Acemoglu and Restrepo, 2020; Bessen, 2020; Graetz and Michaels, 2018). Among these studies only Bessen (2020) and Graetz and Michaels (2018) simultaneously report a decrease in prices where Graetz and Michaels (2018) also document a rising wage income. Also, Boyle and McCormack (2002), Autor and Salomons (2018), and Autor (2015) observe next to the productivity effect, a rise in income. Vu (2013) additionally find evidence for an expansion of output at the industry level using data on Singapore. Berman et al. (1994) and Blanas et al. (2019) document a positive effect of technological change on wage income, which holds in Blanas et al. (2019) only for certain occupations. Cirillo (2017), Fagerberg et al. (1997), Padalino and Vivarelli (1997), Goaied and Sassi (2019), and Graham and Spence (2000) find support for the last order mechanism of the real income effect showing that the expansion of output associated with technological change shows a positive relationship with the demand for labor. Cirillo (2017) indicates that this holds only for a certain type of occupations.

Among those studies that find support for the real income effect, ten study the impact of ICT (Autor et al., 2002; Baddeley, 2008; Chun et al., 2015; Oulton, 2002; Strohmaier and Rainer, 2016; Vu, 2013; Autor, 2015; Berman et al., 1994; Blanas et al., 2019; Goaied and Sassi, 2019). Seven of them report a positive impact of ICT on productivity, three report positive income effects, and two provide evidence of a positive relationship between output growth and labor demand. The three studies by Autor et al. (2002), Oulton (2002), and Autor (2015) rely on descriptive analyses using industry level case studies, macro level growth accounting methods, and descriptive evidence on macroeconomic history. The other seven regression analyses are macro or meso level studies, except for one firm level study by Chun et al. (2015).

Another six studies that support the real income effect examine the impact of robot diffusion (Dekle, 2020; Jung and Lim, 2020; Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2020; Blanas et al., 2019; Graetz and Michaels, 2018). All these studies are regression analyses at the meso or regional level. They all provide evidence of the productivity increasing effect of robots except for Blanas et al. (2019) who document a positive effect of robots on the wage bill of high skilled, old and middle aged men which may indicate an increase in the demand for certain types of jobs like engineers and managers.

Five papers rely on production function-based measures of technological change (TFP-style) (Boyle and McCormack, 2002; Chen and Yu, 2014; Autor and Salomons, 2018; Bessen, 2020; Graham and Spence, 2000). These studies use different types of decomposition analyses to isolate the impact of technological change. All of them are quantitative analyses using regression techniques, mostly at the macro level except for the study by Bessen (2020) who performs a detailed analysis of the steel, auto and textile industry at a historical scale, and the region-industry level study by Graham and Spence (2000). Four of these studies report positive productivity effects. Specifically, Boyle and McCormack (2002) and Autor and Salomons (2018) document a positive impact on wage income, Bessen (2020) additionally documents decreasing prices in response to labor productivity growth, and Graham and Spence (2000) confirm that higher output is positively associated with the demand for labor.

One study by Cirillo (2017) examines the impact of innovation and finds at the industry level that an innovation-induced expansion of output and sales is positively associated with labor demand, especially for clerk and manual workers.

The studies by Fagerberg et al. (1997) and Padalino and Vivarelli (1997) use technology measure that fall into our residual category "other/indirect". Fagerberg et al. (1997) rely on R&D as a technology indicator and Padalino and Vivarelli (1997) use changing growth-employment elasticities as indirect proxy of technological change. They both document a positive relationship between aggregate output and employment.

4.4.3 Studies not supporting this effect

Only four studies do not find supporting evidence for the existence of the real income effect (Badescu and Garces-Ayerbe, 2009; Colombo et al., 2013; Samaniego, 2006; Dixon and Lim, 2020). All four studies evaluate the productivity mechanism, i.e. the relationship between technological change and productivity. Furthermore, Dixon and Lim (2020) provide additional explorations on income effects. Badescu and Garces-Ayerbe (2009) and Colombo et al. (2013) study the impact of ICT diffusion at the micro level. Dixon and Lim (2020) use a production function-based approach (TFP-style) to measure technological change, and Samaniego (2006) relies on indirect measures of technological change to study the impact on TFP growth at the macro level. Badescu and Garces-Ayerbe (2009) and Colombo et al. (2013) find no significant relationship between productivity and ICT diffusion, while Dixon and Lim (2020) and Samaniego (2006) report even negative effects. Dixon and Lim (2020) additionally find that the impact of technology on income is negative. Based on an empirically estimated general equilibrium simulation model, Samaniego (2006) studies the impact of productivity shocks. The author argues that the negative productivity effect of a new technology can be explained by the incompatibility of an existing with a new technology. However, they also argue that this may be only a temporary phenomenon.

4.4.4 Studies with ambiguous findings and indirect evidence

Six studies in our sample report ambiguous findings or only indirect evidence for the real income effect (Camina et al., 2020; Fu et al., 2021; Blien et al., 2021; Compagnucci et al., 2019; Cozzarin, 2016; Oesch and Rodriguez Menes, 2010). The studies by Camina et al. (2020), Fu et al. (2021), and Compagnucci et al. (2019) study the impact of robot diffusion. Camina et al. (2020) show that whether robots are productivity enhancing depends on the exact type of robot-based technology; for example, some subsets of these technologies like data-driven control can even exhibit a negative effect. Fu et al. (2021) report cross country differences: while robots show a positive effect on labor productivity in developed economies, no significant effects are found for developing countries. Compagnucci et al. (2019) finds ambiguous results related to the real income effect: they find a negative effect of robots on wages, but a negative one on prices.

Blien et al. (2021) and Oesch and Rodriguez Menes (2010) rely on indirect measures of technological change. In particular, Blien et al. (2021) look at the routine intensity of occupations and evaluate its interaction with the income of certain occupations. Using this indirect measurement of technological change, they observe that the effects on employees' income are heterogeneous across occupations: employees in jobs with high routine intensity experience income losses after a job layoff. The authors also document that routine intensity was a less significant predictor of income losses during the 80s compared to more recent periods. In a descriptive macro level analysis, Oesch and Rodriguez Menes (2010) use the changes in the wage growth of various occupation groups that vary in their task content. They examine the evolution of wages for different occupations but find only weak effects.

Finally, Cozzarin (2016) studies the impact of innovation on wages and productivity in manufacturing and only finds weak aggregate effects. In tendency, Cozzarin (2016) observes a positive association between process innovation, wages and productivity, but a negative association between product innovation and productivity.

5 Discussion

What is the net employment effect of technological change? The total effect on employment depends on whether the labor saving or the labor creating effect of technological change dominates. Using a systematic review, we distinguished between three channels through which technological change affects the demand for labor: 1) the replacement effect; 2) the reinstatement effect; and 3) the real income effect. The first mechanism is labor saving, while the latter two lead to the creation of labor. In this section, we compare and critically discuss the evidence supporting the labor saving and labor creating effect of technological change. We also discuss the impact of each type of technology on net employment.

5.1 Evidence for net employment effect

In total, 103 (81%) of the 127 studies in our sample investigate the labor saving effect of technology, while seventy-nine (62%) of the studies look at the reinstatement effect and thirty-three (26%) studies examine the real income effect. In absolute terms, sixty-nine studies find support for the replacement effect, while sixty-four and twenty-three studies find support for the reinstatement and real income effect, respectively. Hence, our review suggests that at least as many studies find support for the labor creating effect of technological change as the number of studies providing evidence for the replacement effect. Although our study does not comprehensively analyze and compare the sizes of the effects reported in the selected studies, our findings do suggest that technological progress has not resulted in a negative net effect on employment in the past decades.

Table 12: Studies by findings on total employment

	(1) positive	(2) depends	(3) weak	(4) negative
share	0.29	0.35	0.18	0.18
#	26	31	16	16

Notes: Columns (1)-(4) present the share and number (#) of studies with empirical results reporting positive, depends (on various characteristics, e.g. technology type, analysis level, etc.), weak, and negative effects on total employment, respectively. The total # of studies is 127.

It is also relevant to note that out of the studies that report findings related to one of the three mechanisms through which technology can affect labor, roughly comparable shares of studies find support for the employment effect of interest, i.e. 67% of the studies find support for the replacement effect, while 81% and 70% find support for the reinstatement and real income effect, respectively. These numbers suggest that if there were a publication bias, the bias would not be more prevalent among studies reporting on one of the three mechanisms. Moreover, Table 12 shows that out of the studies that provide evidence over the total employment effect of technological change, a larger share finds support for an overall positive employment effect (29%) than a negative employment effect (18%).

5.1.1 Evidence for the net employment effect of robots

Table 13: Each type of technology by findings on total employment effect

	(1)	(2)	(3)	(4)	(5)
		by finding			
	total	positive	depends	weak	negative
ICT					
share	0.29	0.27	0.42	0.23	0.08
#	26	7	11	6	2
Robots					
share	0.16	0.36	0.14	0.29	0.21
#	14	5	2	4	3
Innovation					
share	0.15	0.46	0.38	0.15	0
#	13	6	5	2	0
TFP-style					
share	0.15	0.08	0.38	0.15	0.38
#	13	1	5	2	5
Other					
share	0.33	0.28	0.41	0.10	0.21
#	29	8	12	3	6

Notes: Column (1) presents the share and number (#) of studies by the technology group considered in each row panel relative to the total number of studies examining the total employment effect. The row-sum of shares in column (1) does not add up to one since there are studies considering more than one technology group. Columns (2)-(4) present the share and # of studies by the set of findings reported on the total employment effect for each type of technology considered in each row panel. For findings, a study is classified as 'positive' if it finds a significant positive empirical effect that supports the total employment effect examined. 'Depends' refers to the set of studies that find varying effects depending on the type of technology or the (sub)sample analyzed (e.g. type of sector or labor). Studies reporting effects that are negligible in terms of the magnitude were classified as 'weak'. Studies were labeled as 'negative' if they investigate the effect of interest, but documented negative effects. The technology types reported include ICT, robots, innovation, TFP-style and Other types of technologies (e.g. indirectly measured through prices, automation risks), respectively. Note that there is no overlap in findings reported, i.e. more than one primary finding in each study, and thus the shares across columns add up to one, up to rounding. The total # of studies is 127 of which seventy-five examine the total employment effect.

Zooming in on the different types of technology, we find that the highest relative support for the replacement effect is found for studies analyzing the impact of robots. Out of the studies investigating the replacement effect of robots, thirteen (87%, Table 6) find support for this mechanism. Most evidence comes from meso (i.e. industry) level studies, but support for the replacement effect is also found in firm and worker level studies. In total, nine studies find support for the reinstatement effect of robots. Interestingly, a large share of the studies examining the reinstatement effect also investigate the effect on net employment. None of these studies find clear evidence for a negative effect of robots on net employment.

Table 13 also illustrates that among the studies examining the total employment effect, a larger share of robot studies find support for a positive employment effect (36%) than for a negative employment effect (21%). Moreover, a substantial share of robot studies studying the total employment effect report negligible effects in terms of the magnitude. Finally, six studies find positive productivity and income effects in response to robot diffusion. Although not all productivity gains are translated into employment gains (Acemoglu and Restrepo, 2019), our findings overall suggest that the labor saving impact of robots is generally compensated by robot-driven reinstatement of labor.

5.1.2 Evidence for the net employment effect from TFP-style studies

Another set of studies that mostly support the existence of the replacement effect are those grouped as "TFP-style". TFP-style studies rely on production function-based indicators (e.g. labor productivity, TFP, substitution elasticities) as a measure of technological change and are used in micro, meso as well as macro level studies.

In line with other measures of technology, thirteen (76%, Table 6) TFP-style studies find support for the replacement effect and report shifts in labor demand, particularly from production to non-production labor across industries, and from low skilled workers to high skilled workers. Likewise, ten studies (91%, Table 8) which find support for the reinstatement effect document employment shifts from manufacturing to services and employment increases for skilled non-production labor. Moreover, one reinstatement study shows that TFP shocks in upstream industries are associated with employment increases in downstream industries.

In addition to the reinstatement effect of productivity improvements, five studies supporting the real income effect report positive effects on wage income and decreasing prices. One study illustrates that the real income effect is also associated with positive employment effects. Similar to the robot studies, the number of TFP-style studies finding support for the replacement effect is roughly balanced compared to the number of studies findings support for one of two labor creating mechanisms.

5.1.3 Indirect evidence for the net employment effect

Simultaneous support for the labor saving and enhancing effects of technology also comes from studies using measures that fall into the residual category "other/indirect". In total, twenty-two studies find support for the replacement effect (73%, Table 6), while twenty studies (91%, Table 8) support the reinstatement effect, and two studies (40%, Table 10) provide evidence for the real income effect.

A first set of studies relates employment to automation risks. Studies on the replacement effect find that occupations with a high automation risk are associated with larger employment declines. Instead, studies investigating the reinstatement effect report that a low automation risk is related to employment increases. Similarly, studies using measures related to capital and high-tech equipment investments find support for both the replacement and reinstatement effect. The same holds for studies looking at the impact of R&D expenditures and patents. One study on the real income effect also reports a positive relation between R&D, aggregate output and employment. The reinstatement effect of capital and R&D investments is particularly strong for high skilled labor, non-production labor and high-tech industries.

In line with these findings, the studies on the replacement effect also report evidence for skill biased technological change and document that especially low skilled labor is negatively affected by technological progress. However, some descriptive studies also provide evidence that technology can have a positive effect on the demand for low skilled labor, especially in service jobs. Further, we found that a number of indirect measures of technology only provide evidence for one of the three employment mechanisms. One replacement effect study reports a negative association between GDP growth and employment in manufacturing while a number of decomposition-like and substitution elasticity-based studies find support for the reinstatement effect. Finally, one study on the real income effect uses growth-employment elasticities as an indirect measure for technology and reports a positive relationship between aggregate output and employment. Again, we conclude that indirect measures of technological change provide a roughly equal amount of evidence for the labor saving on the one hand and labor creating effect of technology on the other hand.

These indirect measures of technological change also have a number of disadvantages. For instance, the downside of using automation risk indicators is that they implicitly assume that tasks that can be performed by machines will automatically substitute for human labor. To that end, these automation risk indicators do not take into account that firms' decision to adopt technologies also depends on many factors such as the price of different inputs (i.e. labor and machines), legislation, or the availability of training data in the case of intelligent automation. Moreover, occupation level automation risk indicators are likely to overestimate the share of automatable jobs as they disregard task heterogeneity within occupations as well as the adaptability of jobs in response to technological change (Arntz et al., 2017). Consequently, these studies most likely underestimate the true labor saving impact of technologies.

A subset of studies also analyzes the reallocation of employment across occupations or sectors. Labor market patterns such as polarization are in line with the idea that technology is mostly suitable for replacing workers in the middle of the skill distribution whose jobs are relatively intensive in routine tasks. However, it is also important to recognize that next to technology, there are also other potential explanations for these shifts, such as trade or changes in wages (e.g. induced by shifts in the supply of specific groups of labor).

5.1.4 Evidence for the net employment effect of ICT

The most ambiguous evidence comes from studies on ICT. Relative to other types of technologies, a substantial number of studies find no or only indirect support for the replacement effect of ICT. Nevertheless, twenty-three (62%, Table 6) of the studies examining the replacement effect of ICT find evidence for it. The findings come from mostly meso level, but also micro and regional level studies and illustrate that mainly low skilled and routine task intensive occupations are adversely affected by ICT. Similar to the number of studies finding support for the replacement effect, twenty-three (77%, Table 8) studies find support for the reinstatement effect. These studies confirm that ICT reinstates labor as it induces the emergence of new ICT occupations. Moreover, the findings also suggest that ICT complements workers in the performance of non-routine tasks. In particular, the dissemination of ICT technologies is related to an employment increase for high skilled workers and non-routine cognitive labor.

In addition, a number of studies have established the link between the upsurge of ICT and employment growth in the service sector. Seven studies on the real income effect report a positive effect of ICT on productivity. A few other studies also report positive income effects, and a positive relationship between output growth and labor demand. The majority of studies support both the replacement and reinstatement effect at the same time. In line with these findings, eleven studies (42%, Table 13) that examine the impact of ICT on total employment find that the impact depends on other factors. The most important factor determining whether the effect of ICT is labor saving or creating is the type of labor. We conclude that ICT does not appear to induce an overall net negative effect. This is also supported by the observation that a larger share of ICT studies looking at the total employment effect reports a positive effect (27%) than a negative effect (8%).

5.1.5 Evidence for the net employment effect of innovation

The least support for the replacement effect is found by studies examining the impact of innovation. Only three studies find support for the replacement effect (25%, Table 6). Most of these studies are conducted at the firm level. The innovation studies showing support for the replacement effect find that the labor saving effect is mostly driven by process innovation. Similarly, studies that do not support the replacement effect or find ambiguous evidence show that specifically product innovation tends to have a positive effect on employment, while the available evidence is not strong enough to conclude that the impact of process innovation is labor saving. In fact, a large number of studies find no significant or only a weak effect of product, organizational or process innovation on employment. In total, eight (57%, Table 8) studies on innovation find support for the reinstatement effect. Another four studies (29%) indicate that the reinstatement effect depends on other factors. The papers analyzing the reinstatement effect confirm that the employment effect depends on the type of innovation. In general, studies seem to find a positive employment in the case of product innovation and a negative or ambiguous effect of process innovation.

6 Conclusions

This study systematically reviewed the available evidence on the impact of technological change on employment. Overall, we find that a substantially larger number of studies provide evidence for the labor creating impact of technological change than for the labor saving impact. Several studies providing support for the labor creating impact of technology report positive effects on productivity and prices, income, and final demand or output. Through these channels, technological change is expected to indirectly increase the demand for labor. However, only a few studies measure the actual employment implications of these mechanisms.

Although we are careful in concluding that, if anything, technological change appears to have a positive net effect on employment, we do conclude that the replacement effect is more than offset by the labor creating effect of technology. Hence, there does not appear to be an empirical foundation for the fear of technological unemployment. We also investigated whether different types of technology have a differential effect on total employment. For almost all technology measures (i.e. robots, ICT, TFP-style, other/indirect measures) we find a comparable number of studies finding support for the labor saving as well as labor creating effect of technology. Only for innovation measures, the empirical evidence suggests that product innovation is mostly labor creating, while the evidence concerning process innovation remains inconclusive.

Despite the fact that we find no evidence for a negative net employment effect in quantitative terms, the qualitative impact of technological change on employment cannot be neglected. As our systematic review has pointed out, different types of technology have predominantly adverse effects on low skilled and production labor, manufacturing jobs, and workers performing routine tasks. Given the considerable labor saving potential of technology, reskilling or retraining workers whose jobs are susceptible to automation is essential. However, not only individuals whose jobs have disappeared due to automation would benefit from (re-)training. Research shows that technological change also has induced within-occupational changes in skill requirements. In fact, according to estimates of the OECD (Arntz et al., 2017), the share of jobs that will face changes in the task content due to automation is higher than the share of jobs that is of high risk of being automated. Hence, upskilling is also of utmost importance for workers whose jobs are not directly threatened by technological change. Nevertheless, not all workers might be able to make the transition to new jobs after experiencing job loss. These workers might increasingly have to rely on social support systems.

Our systematic review is also subject to a number of limitations. First, the performance of tasks that have been considered beyond the potential of technologies are now within the scope of what machines can do (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). However, empirical evidence on the impact of intelligent automation – in particular the combination of robotics, machine learning, and quantum computing – remains limited. In fact, none of the studies in our review assesses the impact of this new wave of technological innovation. Therefore, our findings cannot be extrapolated into the future and more research is needed to examine and understand the likelihood of various emerging views on what the future of work will look like (Baldwin, 2019).

Second, our study also faces an inherent methodological challenge. Generally, it should be noted that it is not surprising to observe high support rates for each of the effects as studies with insignificant results are rarely published. Hence, these results are subject to a reporting bias, similar to the publication selection bias discussed in Ugur (2019). This appears to be a more general problem of published empirical studies which also exists in other disciplines such as medicine, psychology, and experimental economics research. In these fields, pre-registrations were introduced with a detailed protocol of the empirical approach that has to be approved before the experimental study is conducted. While similar procedures are more difficult to establish in statistical analyses that often need to be adapted during the workflow, it should be kept in mind that the results reported are likely to suffer from a reporting bias in favor of the analyzed theory. Nevertheless, there is no reason to assume that the size of the bias differs across the three employment effects that we analyze in our study.

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A.1 Search strings for Web of Science

TS=((automation OR technolog* OR digiti$ation OR robot* OR “artificial intelligence”) AND (labo$r OR *employment)) AND WC=(ECONOMICS OR MANAGEMENT OR BUSINESS OR BUSINESS, FINANCE OR SOCIOLOGY OR INDUSTRIAL RELATIONS LABOR OR DEVELOPMENT STUDIES OR SOCIAL SCIENCES INTERDISCIPLINARY OR HISTORY OR SOCIAL ISSUES OR URBAN STUDIES OR GEOGRAPHY) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article OR Book Chapter OR Early Access OR Proceedings Paper OR Review) Indexes=SSCI Timespan=1988-now

A.2 Additional Tables and Figures

Table A.1: Findings for each effect, including na/nr

	(1)	(2)	(3)	(4)	(5)
	Replacement				
	support	depends	weak	no support	na/nr
share	0.54	0.10	0.04	0.13	0.19
#	69	13	5	16	24
	Reinstatement				
	support	depends	weak	no support	na/nr
share	0.50	0.06	0.05	0.02	0.38
#	64	7	6	2	48
	Real income				
	support	depends	weak	no support	na/nr
share	0.18	0.03	0.02	0.03	0.74
#	23	4	2	4	94
	Total employment				
	positive	depends	weak	negative	na/nr
share	0.20	0.24	0.13	0.13	0.30
#	26	31	16	16	38

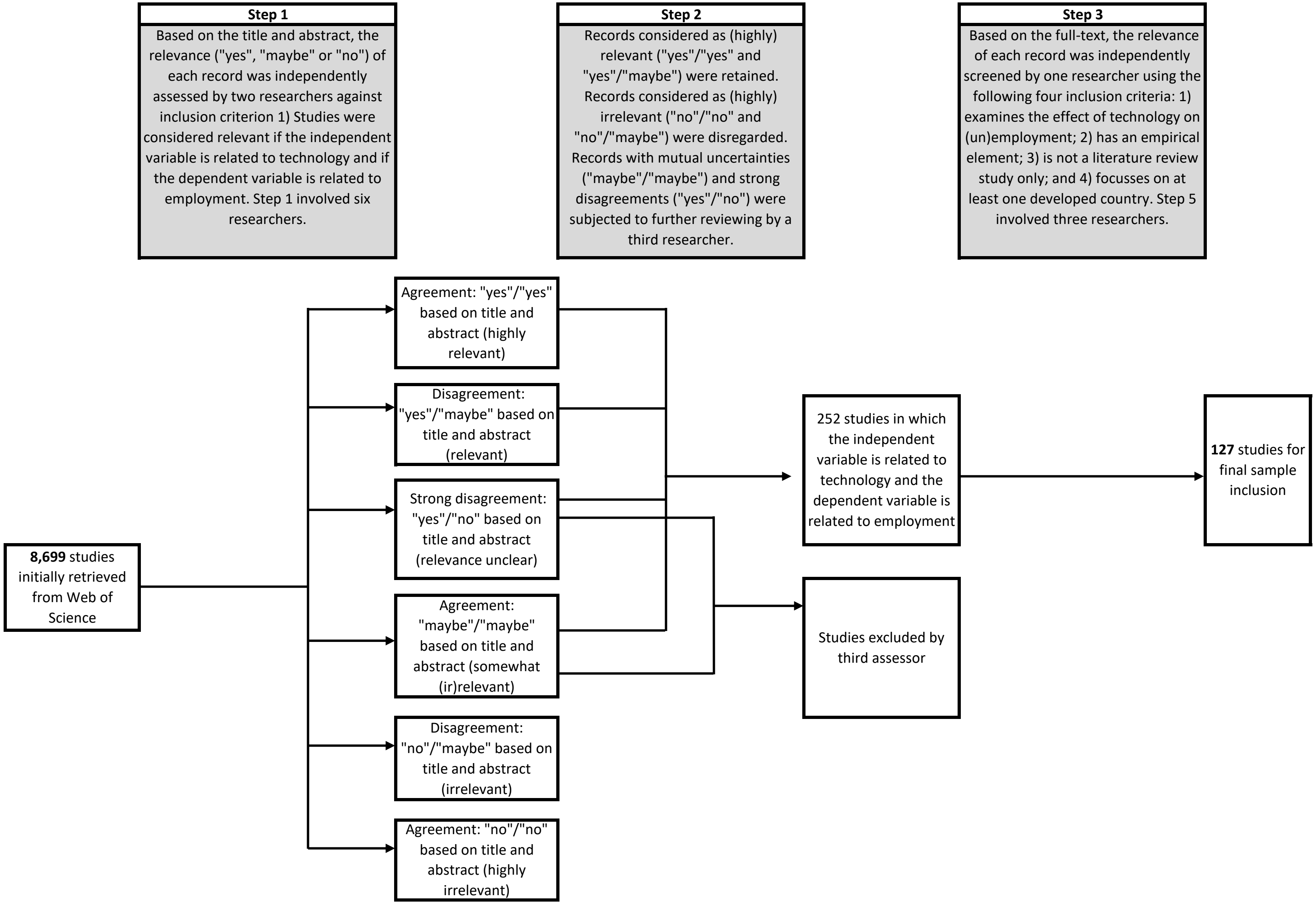
Notes: Columns (1)-(4) present the share and number (#) of studies with empirical results that support, depend (on various characteristics, e.g. type of technology or level of analysis), are weak, and do not support the presence of the effect considered in each row panel. Column (5) presents the share and number of studies out of the total sample of studies which do not examine the effect of interest. The row row-panels present results for the replacement, reinstatement, real income and total employment effect. The total # of studies is 127.

Table A.2: Reinstatement effect by level of analysis

	(1) macro	(2) meso	(3) micro	(4) regional
share	0.33	0.34	0.28	0.14
#	26	27	22	11

Notes: Columns (1)-(4) present the share and number (#) of studies employing macro, meso, micro, and regional level of analysis, respectively when reporting any type of finding on the reinstatement effect.

Figure A.1: Overview of the selection procedure of studies



Source: Author's illustration.