Creative Disruption –
Technology innovation, labour demand and the pandemic

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Abstract

We utilize a new survey on Norwegian firms' digitalization and technology investments, linked to population-wide register data and show that the pandemic massively disrupted the technology investment plans of firms, not only postponing investments, but also introducing new technologies. More productive firms innovated, while less productive firms postponed investments. In the short-term, both firm productivities and worker wages increase on average, but this is driven by wage growth for skilled workers. New technologies are associated with increased long-term expected labour demand for skilled workers, and reduced demand for unskilled workers, particularly for the more productive firms.

Keywords: Technology investments, Digitalization, Labour demand, Pandemic, COVID-19

JEL-codes: D22, D24, F14, L11, L60

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1. Introduction

The Covid-19 pandemic created major disruptions to the world economy amidst a period of large technological transformations. This paper studies how these disruptions interfered with technology transformations across firms and furthermore how they affected the labour demand for different types of workers. We investigate the extent to which the crisis accelerated or postponed ongoing investments in digitalization and automation within firms, and whether these technology responses lead to a widening or narrowing of the productivity distribution across firms. Finally, we explore the effects on the demand for high- and low-skilled workers.

We provide novel evidence on firms' technology responses to the pandemic, utilizing a brand new large-scale Norwegian questionnaire survey of firms conducted in November 2020. The survey data is linked to register data on the firms' inputs and outputs, enabling us to estimate measures of TFP, and to administrative records on workers and their levels of education, enabling us to track the firms' demand for different types of workers.

A major crisis such as the pandemic hurts firms' incomes and increases their uncertainty regarding the future, discouraging new investments (Bloom et al., 2007; Christiano et al, 2014), partly by increasing the user cost of capital. Financing may become more difficult and leave the firms even more reliant on own available funds (Stein, 2003; Fee et al., 2009). On the other hand, a crisis may lead to innovation because the opportunity cost of reallocation is lower (Caballero and Hammour, 1996) and the marginal value of time declines due to lower congestion costs (Hall, 2009). It is unclear, a priori, what impact a recession may have on new investments. Previous empirical evidence suggests recessions can induce shifts of an episodic nature strongly reinforcing ongoing processes (Hershbein and Kahn, 2018; Jainovic and Siu, 2020).

Whether the COVID-induced recession has had a similar impact is of interest since it differed fundamentally in some respects from previous recessions. The pandemic created a "perfect storm", both dampening demand and hampering supply at the same time, disrupting people-to-people contact and those reliant on travel and transport across borders. The pandemic was also a reallocation shock (Barrero et al. ,2020) and had a devastating impact on firms' international supply chains (Meier and Pinto, 2020; Chowdhury et al., 2021). The extent to which the negative influence of uncertainty and interruptions in supply-chains dominate over the positive influence from the freeing up of resources and possible creativity stimulated by the novelty of the situation is still an open question.[1]

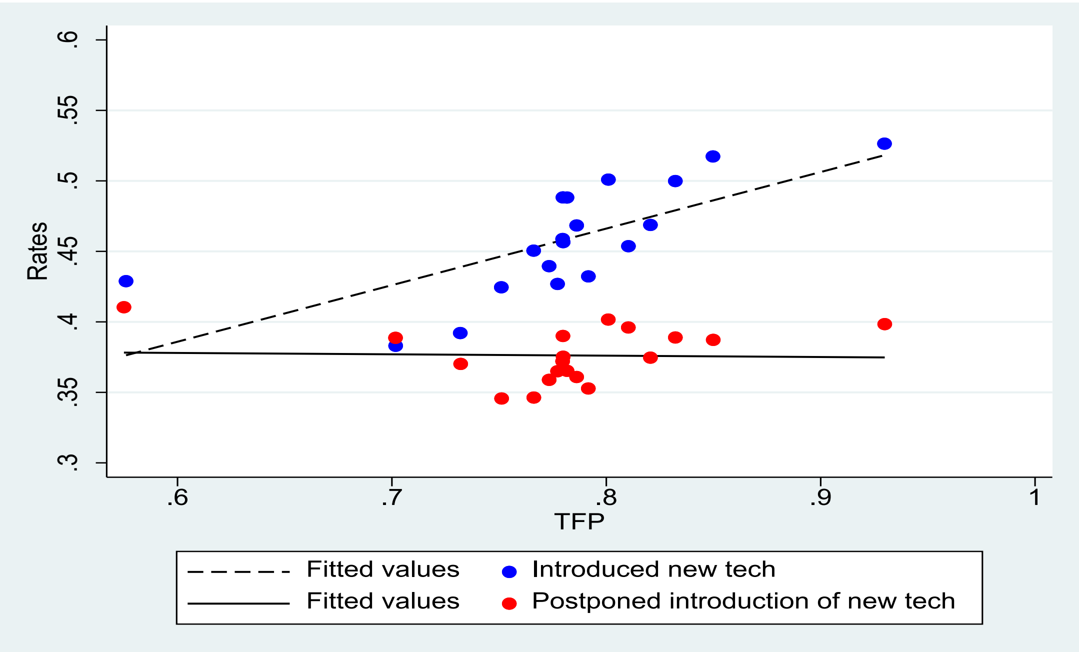
The Digitalization, Organization and Technology 2020 (DoT2020) survey comprises 35 percent of all Norwegian private sector firms with over 10 employees. As we report below, the pandemic massively disrupted the technology investment schedules of Norwegian firms. Thirty-nine percent of all private sector firms report that they postponed scheduled investments in new technology. At the same time, 41 percent of firms, employing half of the private sector workforce – including firms who had postponed investments - reported that they adopted new technology due to the pandemic. Eighty-five percent of the new technology adoption involved new digital tools beyond the obvious introduction of Zoom and Teams and the like. The firms that were the hardest hit by the pandemic were also the ones with the most vigorous technology response.

The process of creative destruction (Schumpeter, 1942) tends to increase productivity dispersion across firms (Klette and Kortum, 2004; Aghion and Howitt, 1992; Moene and Wallerstein, 1997). For innovations and technology adoption to generate productivity dispersion there must be some frictions affecting adoption costs which affect the marginal returns to innovation, and they need to be sufficient to prevent the new technology from immediately taking over the whole market (Klette and Kortum, 2004). We investigate such barriers to technology adoption by directly asking firms if their pre-pandemic technology adoption was constrained by limited access to necessary financial, human capital, or other resources, and study how these constraints affected the response during the crisis. It turns out that firms that reported constraints before the pandemic, were more likely to change their technology adoption during the crisis, indicating that the pandemic actually also lifted some of these constraints, possibly by reducing aggregate demand for investments and congestions.

[1] See the literature review below for a discussion of recent empirical results.

It is a stylized fact that the productivity distribution within industry has been widening over recent decades (Barth et al., 2014). Technological change is a prime suspect behind this development (Acemoglu and Autor, 2011). We contribute to this literature by linking firms' technology responses to their pre-pandemic levels of total factor productivity (TFP). Figure 1 provides a descriptive illustration of this relationship in our data.

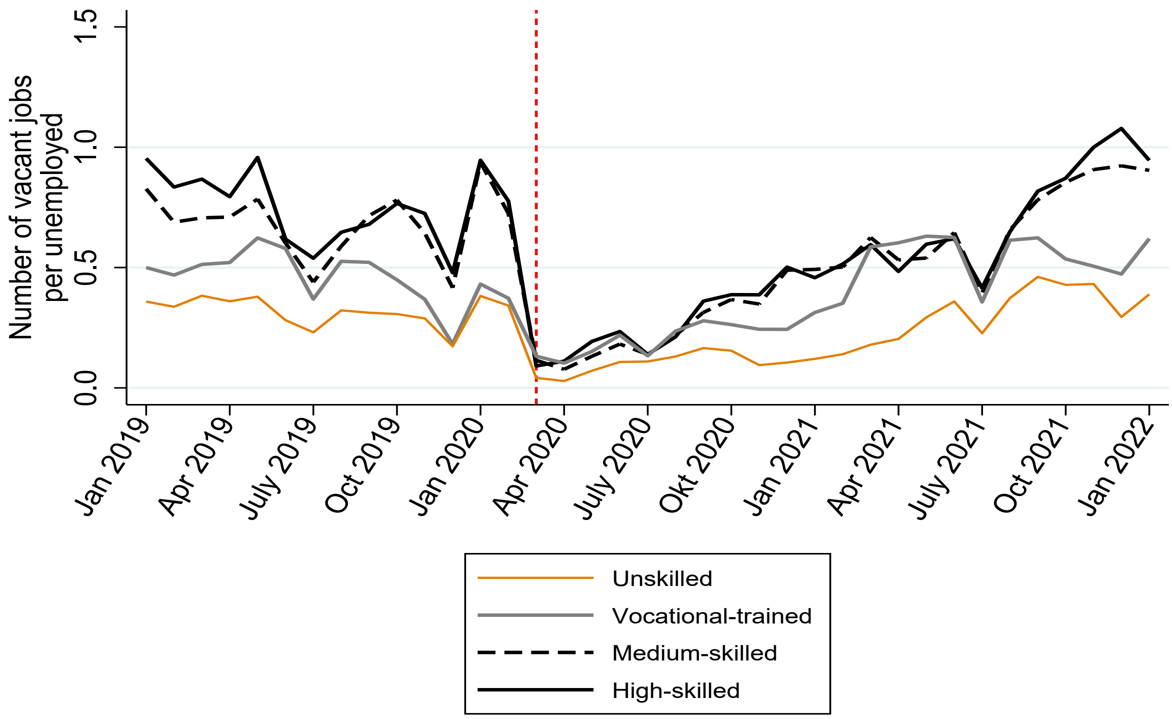
Figure 1 Technology adoption and postponement due to the pandemic by vigintiles of pre-pandemic TFP



Note: The figure shows the share of firms who report introducing new technology (blue dots, dashed line) and postpone the introduction of new technology (red dots, solid line) due to the pandemic, by vigintiles (20 bins) of firms' pre-pandemic TFP. The binscatter incorporates controls for industry and a dummy for missing TFP in 2019. The observations are weighted by the inverse of the sampling probability and correct for non-response. See Section 4 for details on data.

We show below that the pattern in Figure 1 holds in a bivariate Probit model including a host of covariates. The more productive firms are more likely to introduce new technology due to the pandemic, and slightly less likely to postpone the introduction of planned investments. Therefore, provided that new technology improves firms' productivity, the technology responses to the crisis could accelerate the widening of the productivity distribution.

Figure 2 Labour demand for skills before and under the pandemic.



Note: Figures on labour demand are based on data (own calculations) from the Norwegian Labour and Welfare Administration (NAV) on vacancies and unemployment by private sector occupations.

Increasing productivity dispersion is likely to increase earnings inequality both through the level effect of productivity on wages and through assortative matching of workers across firms (Barth et al., 2014). We address this in Section 8. Still, how new technology, such as automation and digitalization, affects the relative demand for different skills at the level of the firm remains an open question[2]. What we do know, as seen from Figure 2, is that the relative demand for high- and medium-skilled workers in Norway increases quite dramatically during the pandemic and in 2022 surpasses pre-pandemic levels, while the demand for unskilled labour grows more slowly back to pre-pandemic levels. We contribute to this literature by studying the relationship between firms' technology adoption and their expected future change in demand for high-skilled and low-skilled

[2] Technological change over recent decades has affected labour demand and thus labour market outcomes such as employment, wage levels and dispersion (Schönberg et al., 2009; Michaels et al., 2014). Inter alia, the extent to which technological change has been skill biased, or has led to a polarization in demand for high and low skilled labour, is still an open question (see eg. Autor et al., 2006; Autor et al. 2003; Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2014)

workers. Firms who introduce new technology are also more likely to anticipate greater demand for high skilled workers compared to low skilled workers, implying a skill-biased technology response to the crisis. Furthermore, we demonstrate that this skills-bias is even larger in high productivity firms, implying an even stronger assortative matching of workers across firms. Firms at the top of the productivity distribution are both more likely to adopt new technology and more likely to change the skill mix of their workers once they do.

The remainder of the paper is structured as follows: Section 2 briefly recapitulate the pandemic in Norway. Section 3 reviews the literature on technological change, automation and digitalization. Data is described in Section 4. Our econometric strategy is described in Section 5. Section 6 presents our results regarding technology innovation and postponement of technology implementation, while Section 7 focuses on how these technological innovations in the short-run alter worker wages and firm productivities. In Section 8 we study the consequences of innovations for long-term expected labour demand. Section 9 briefly concludes.

2. The Pandemic in Norway

The first case of COVID-19 in Norway was confirmed on February 26th 2020 in the city of Tromsø.[3] The first case of community spread was detected on March 10th. The government immediately ordered businesses to facilitate remote work and the population to maintain social distance. On March 12th the Norwegian government announced drastic social distancing requirements and administrative closings of establishments. Schools and universities closed, cultural and sporting events were prohibited, gyms and pools, hairdressers and other personal services such as beauty salons closed. Bars, cafes and restaurants were ordered to close unless they were able to maintain the required distance between their customers. The pandemic and the policy

[3] Chinese authorities reported a cluster of cases in Wuhan, Hubei Province, related to pneumonia of an unknown origin in December 31th, 2019 (https://www.who.int/news/item/27-04-2020-who-timeline---covid-19)

response to it strongly affected the Norwegian labour market in Spring 2020 but, as documented by Barth et al. (2021), the economy mostly recovered as the pandemic continued despite on-going infection control measures. Some sectors continued to be more severely affected than others. Clubs, pubs and restaurants remained closed for long periods. In other parts of the economy where it was possible for employees to work from home they did so for all or part of the week. This process of closing down the economy and enforcing social distance was by no means unique to Norway (Castex et al., 2021)

3. Technological Change, Robots, Digitalization, and the Pandemic

Digitalisation and the introduction of robots might reduce the set of tasks where labour adds significant value (Brynjolfsson and McAfee, 2011, 2014; Frey and Osborne, 2017). Technology-induced unemployment may follow if new technology substitutes for labour, reducing net employment where job destruction exceeds any impact on job creation. Declining demand for labour may also result in falling real wages. Robots and AI could thus make workers redundant and re-shape society in a fundamental way (Ford, 2015). Others take a more positive view, by allowing for endogenous task formation and general equilibrium effects (e.g., Acemoglu and Restrepro, 2017, 2020), but even Acemoglu and Restrepro (2020) conclude that one more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42 percent. In Germany, Dauth et al. (2021) find that every robot destroys two manufacturing jobs, but aggregate employment is left unchanged.[4] However, while labour productivity rises, wages do not. Not all jobs are at risk of being automated. For instance, Arntz et al. (2020) estimate that only 9-10% of all jobs in the UK and US were "automatable" through

[4] Findings show that 'more robot exposed workers are even more likely to remain employed in their original workplace' (Dauth et al., 2021). However, there are trade-offs: these workers do not necessarily perform the same tasks as before, there are fewer manufacturing jobs for young labour market entrants, medium-skilled workers face earnings losses, and migrant and female workers are more prone to be employed on contingent contracts (Wagner, 2018; Dauth et al., 2021). Similarly, Arntz et al. (2020) find that cutting-edge digital technologies have little effect on aggregate employment but do induce large flows between occupations and industries.

"automatisation and digitalisation". Overall, in our view (and others, e.g., Autor (2022)), the final judgement on this issue is yet to be made.

The process of automation and digitalisation was an on-going process pre-Pandemic, but previous research indicates that ongoing processes of technological change can be amplified in economic downturns (Hershbein and Kahn, 2018; Jainovic and Siu, 2020). For example, the negative demand shock of the Great Recession in the U.S. accelerated routine-biased technological change (Hershbein and Kahn, 2018). However, the Great Depression of 1929 shifted innovation behavior expressed through patenting of younger and smaller inventors towards larger, more productive, firms and thereby increasing their importance and power (Babina et al, 2021). So it is uncertain, a priori, what might have happened during COVID. COVID also disrupted global value chains thus impacting supply, as was seen following the Great East Japanese Earthquake of 2011 (Carvalho et al, 2021).

Certain aspects of digitalization are particularly relevant under the current pandemic, which in most countries introduced the concept of social distancing. Thus, electronic communication devices allowing working at home have grown in importance. Previous research has shown that teleworking might have positive productivity impacts (Bloom et al., 2015) and that quite a considerable number of jobs can be done at home (Dingel and Neiman, 2020). Autor and Reynolds (2020) predict that a rapidly automating post-COVID-19 economy will entail more teleworking, city de-densification, large-firm consolidation, increased inequality and adverse consequences for low wage workers.

Early in the pandemic, based on a small UK-sample of firms, Riom and Valero (2020) observe increased digital innovations for firms already involved in digitalization. Similarly, based on 600 respondents from a survey among U.S. CFOs (nine percent response rate), Barry et al. (2021) report that CFOs expect lasting effects for years to come: high workplace flexibility firms foresee a continuation of remote work, employment recovery, and shifting away from traditional capital investment, whereas low workplace flexibility firms rely on automation to replace labour. Finally, an most related to our study, on large-scale representative IAB-panel, Gahtmann et al. (2023) found that pandemic in Germany caused two in three firms to invest in digital technologies (three quarters of which because of the pandemic), in particular in hardware and software to enable decentralized communication, management and coordination, and encouraged additional firm-sponsored training in addition providing an insurance effect, particularly benefitting males, younger and medium-skilled workers .

Still, the evidence on how Covid-19 affects firms' adoption of technologies is limited. In our analyses and data, we focus on technological innovations other than electronic communication platforms such as zoom and teams (which became widespread during the pandemic), and focus on other new digital tools in excess of zoom and teams.

4. Data

The DoT 2020-survey was conducted in November 2020, nine months after the outbreak of the pandemic. It is a large survey comprising close to 10,000 Norwegian firms with more than 10 employees. This probability sample of firms constitutes around 30 percent of all private sector Norwegian firms with more than 10 employees, but all firms with above 200 employees were included in the sample. This sampling strategy make data represent over 77% of the private sector employees. With a response rate of over 65 percent, the final data comprise responses from nearly 7,000 firms. In all our analyses, we weight the observations by weights that denote the inverse of the probability that the observation is included because of the sampling design and corrected for non-response. Thus, our results are representative for the population of firms with 10 or more employees.

This paper utilizes questions on the introduction of new technology due to the pandemic, the kinds of innovations adopted, their permanency, whether they are postponed (and why), barriers to and promotors of innovation, and the impact of innovations on labour demand for different skills. We are particularly interested in modern digital technology and equipment, which in our questionnaire is defined as e.g. computer integrated production, advanced robots, automatic electronic communication, smart-systems, process-control systems, automatic pilot-systems, remote control and surveillance of units over internet, software, algorithms and internet-based operations that utilize Big Data, cloud-based operations and systems, and online platforms (e.g., Amazon). The survey also addresses wage formation and unions. Unweighted descriptive statistics are presented in Table A4 in the appendix. Other key questions in the questionnaire are described in detail in the appendix.

Our key focus is to understand how the pandemic changes the Norwegian private sector technology innovation behaviour, with particular emphasise on productivity (total factor productivity). However, other factors might also influence productivity, thus we also study factors such as financial limitations, skill limitation, disruption and trade union agreements. Most of these key explanatory variables must be derived, and thus they need to be described more in detail.

First, DoT2020 is linked to Norwegian population-wide register data on firms and workers. To derive our key measure, a firm-specific measure of productivity, *total factor productivity*, we utilise information from the Accounting Registers and Statistics Norway's Firm Register and Structural Statistics from 2005-2019, thus yielding information on industry, value added (operating income less operating costs, wage costs, depreciation and rental costs), capital assets (total capital) and employment for most firms in Norway. We estimate firm-specific total factor productivities, by applying standard value-added production function regression techniques (Ackerberg et al., 2015; Gandi et al., 2020). This is described in detail in the appendix.[5] As one of the key explanatory variables in our analyses, we focus on the total factor productivity from the latest pre-pandemic year, i.e., firm-specific total factor productivity 2019 will be our measure of pre-pandemic productivity.

Second, we assume that the more a firm's business was disrupted due to the pandemic, the more likely this firm's technology innovation behaviour would be affected. One measure capturing

[5] Note that for new firms (established in 2020) and firms operating in certain industries (e.g., finance sector) the information needed to estimate TFP do not exist. For these firms, we impute a value of zero, but in all regressions, we add a dummy taking the value of 1 if this value is imputed.

such disruption is the occurrence of temporary layoffs or furloughs, on the assumption that a product demand shock results in a decline in labour demand. Thus, we estimate the average rate of temporary layoffs for a firm during the period March-October 2019 (before the pandemic), and then the rate for the same months in 2020. The growth in the rate from 2019 to 2020 expresses how disrupted the firm's business was by the pandemic.

Third, the Norwegian government created support schemes, e.g., for apprentices, offering wage support for unemployed workers, together with founding support, but more importantly, investment support and R&D tax incentive schemes.[6] From the accounting data for 2020, we measure the total public support received by each firm in our data. Close to 80 percent of the firms do not receive public support, while 10 percent of firms receive at least 1000k Norwegian Krones (99 percentile implies a support of 33000k NOK). To capture the importance of public support, we create a dummy variable taking the value of 1 if the amount of public support exceeds 1000k NOK (otherwise 0).

Fourthly, since the empirical evidence on how unions affect innovations and productivity is mixed (Addison et al., 2017; Barth et al., 2020; Hirsch, 2007; Doucouliagos and Laroche, 2013) and trade union agreements are dominant in the Norwegian economy, we include a measure of collective bargaining in our analysis, simply a dummy taking the value of 1 if a trade union agreement is present at the firm (0 otherwise). Information on trade union agreements is taken directly from a question in the DoT2020-questionnaire:

Q7 Is employees' pay determined by collective agreements, or is it determined individually?

[6] Under the pandemic, the government introduced several generous financial support schemes (certain industries exempted) to compensate for the sales loss induced by the pandemic and the public strategies to battle spreading of the disease. The first of these schemes compensated firms with a sales loss of 30 percent compared to the previous month. From September 2020, the second scheme worked on a bi-monthly basis, but still entailed a 30 percent sales loss compared to these months the previous year. Our measure of public support does not comprise sales-loss support.

Fifth, to capture barriers to innovation we include a variable for *financial limitations* based on the responses to the question (see appendix for more details):

Q1 To which extent have the following factors the last two years acted as barriers to the firm's innovation activities (Response: 4 categories: to a large extent, some, not much, not at all):

a)Lack of internal financial resources

b)Lack of external financial resources

c)Lack of success in public support schemes

d)Lack of collaborators

e) Uncertain demand for the firm's innovation ideas applying the graded response model and estimate empirical Bayes predictions of the latent variable to this question:

Finally, a measure of *skill limitations* is constructed by transforming a 4-point Likert scale into 5 values based on the question:

Q1 To which extent have the following factor the last two years acted as barriers to the firm's innovation activities (Response: 4 categories: to a large extent, some, not much, not at all):

f) Lack of workforce skills.

5. Econometric strategy

The econometric strategies applied in this paper are quite simple. First, we apply standard Bivariate Probit regressions to reveal how different explanatory factors affect a firm's decision to introduce new technology due to the pandemic and/or postponing an investment decision due to the pandemic. Firms may choose to both postpone some investments and bring forward others, so the decisions are clearly related to one another at the level of the firm. Let us assume that there is an underlying unobserved continuous variable Y_{1i}^{*}, determining the choice to invest in new technology, and that this is a function of several observed variables and an error term, $Y_{1i}^{*} = \beta_0 + \beta_X X_i + \beta_Z Z_i + \varepsilon_{1i}$, where X expresses a control vector comprising industry dummies, dummy for being a service provider and a dummy for utilizing machines, while Z comprises our key explanatory variables. Similarly, let us assume that there is an underlying unobserved continuous variable Y_{1i}^{*}, determining the choice to postpone investments in new technology, and that this is a function of several observed variables and an error term, $Y_{2i}^{*} = \beta_0 + \beta_X X_i + \beta_Z Z_i + \varepsilon_{2i}$, where X expresses a control vector comprising industry dummies, dummy for being a service provider, a dummy for utilizing machines and pre-pandemic employment (February 2020), while Z comprises our key explanatory variables. For firm i, we only observe y_{ji} =1, j∈1,2 when Y_{ji}^{*}>0, j∈1,2. We assume that the error terms are bivariate normal distributed, i.e., (ε_{1i},ε_{2i}) ~Φ((0,0)(1,1), ρ), ρ∈[-1,1]. The bivariate regressions are estimated by maximum likelihood.

Next, we utilize a similar set-up to study how the joint probabilities of different types of technology investments and the decision to postpone investments (for different reasons) in new technology are related to our key variables. However, in this case we face 4-variate and 3-variate Probit regressions. Since there are no closed analytical expression for higher dimensional Normal integrals in the likelihood-function, these regressions are estimated by simulated maximum likelihood using the Geweke-Hajivassiliou-Keane (GHK) simulator (see Greene (2003: 931-933); Roodman, 2011).

Next, we study the short-term outcomes of technology innovations due to the pandemic on workers' log hourly wage growth and on firms' TFP-growth. For workers, we utilize information from 2019-2021, and estimate the linear fixed job effects-regression in first-difference form: $dlnW_{ift} = lnW_{ift} - lnW_{ift-1} = \beta_0 + \beta_X(X_{ift} - X_{ift-1}) + \beta_Z Z_f + \xi_{1ift}$, t∈2020-2021, where W expresses hourly wages, X is a control vector, while ξ_1 expresses a standard error term. Note by taking first-difference, we eliminate the fixed job effect. Z expresses innovations introduced due to the pandemic so is constructed to measure change from 2019 (i.e., pre-pandemic). We estimate this regression for all workers, and separately for four different skill groups: unskilled, vocational-trained, skilled(intermediate) and high-skilled as defined in the questionnaire. The unskilled are defined as those who require no training. The vocationally-trained require the completion of vocational training to perform their job. Those with intermediate skills are those whose jobs require some higher education or extended training such as expert craftspeople and technicians. The high-skilled are those whose jobs require university-level education.

For firms, we utilize information on TFP from 2019 and 2020 in the estimation of the following equation: $d\omega_{ift} = \omega_{ift} - \omega_{ift-1} = \beta_0 + \beta_\omega \omega_{ift-1} + \beta_Z Z_f + \beta_{\omega Z} \omega_{ift-1} X Z_f + \Phi_{in} + \xi_{2ift}$, t∈2020, where ω expresses total factor productivity (TFP), Z expresses innovations introduced due to the pandemic, Φ_{in} expresses a vector of industry dummies, while ξ_2 expresses a standard error term. In the equation above, we treat Z as exogenous, but ω_{ift-1} and $\omega_{ift-1} X Z_f$ are endogenous, and will be instrumented by the firm-FE (and this interacted with Z) from a linear regression of ω_{ift} on year dummies utilizing data from 2009-2018.

Finally, to reveal how the implementation of new technology affects the long-term labour demand for skills, we estimate a set of Generalized Ordered Probit models, i.e., for each firm i we assume there exist an unobserved continuous variable truly measuring future labour demand, $Y_{3i}^* = \beta_0 + \beta_X X_i + \beta_Z Z_i + \varepsilon_{3i}$, which can be expressed as a function of our control variables and a normal distributed error term ($\varepsilon_{3i} \sim \Phi(0,1)$). However, we do not observe Y_{3i}^*, only y_{ji}, j∈ 1,3 distinguishing between three alternative states, namely decline, no change and growth. These are defined on separate intervals on the distribution of Y_{3i}^*. These regressions are similar to ordinary Ordered Probit regressions, except that the Generalized Ordered Probit relaxes the parallel lines assumption.[7] To simplify the interpretation of our results, we present all our results in terms of the average marginal effects of changing our key variables on the predicted probabilities.

[7] Except for the constant, which varies between the ordered outcomes in the Ordered Probit model, the generalized Ordered Probit allows also the parameter estimates to vary across the outcomes (Williams, 2006; Greene et al., 2010).

6. Results on technology innovation and postponement of technology implementation

6.1 Technology innovations and postponement due to the pandemic

How did the pandemic affect Norwegian firms' investments in new technology? We begin with Table 1 which presents the simple descriptive relationship between the introduction and the postponement of new technology due to the pandemic based on yes/no responses to the two questions (numbers in parentheses refer to the questionnaire presented in the appendix): "In addition to programs/platforms for digital meetings (e.g., zoom, teams), has the pandemic caused the firm to adopt new technology, such as e.g., new digital tools, robots and automation" (Q4) and "Has the pandemic caused the implementation of new technology to be postponed?" (Q6).

Table 1 The introduction and postponement of new technology due to the pandemic (cell proportions).

	The postponement of new technology due to the pandemic					
The introduction of new technology due	Not postponed		Postponed		*Total*	
to the pandemic	Firms	Workers	Firms	Workers	Firms	Workers
Not introduced new technology	0.42	0.33	0.17	0.14	0.59	0.47
Introduced new technology	0.20	0.28	0.21	0.25	0.41	0.53
Total	0.62	0.61	0.38	0.39	1.00	1.00

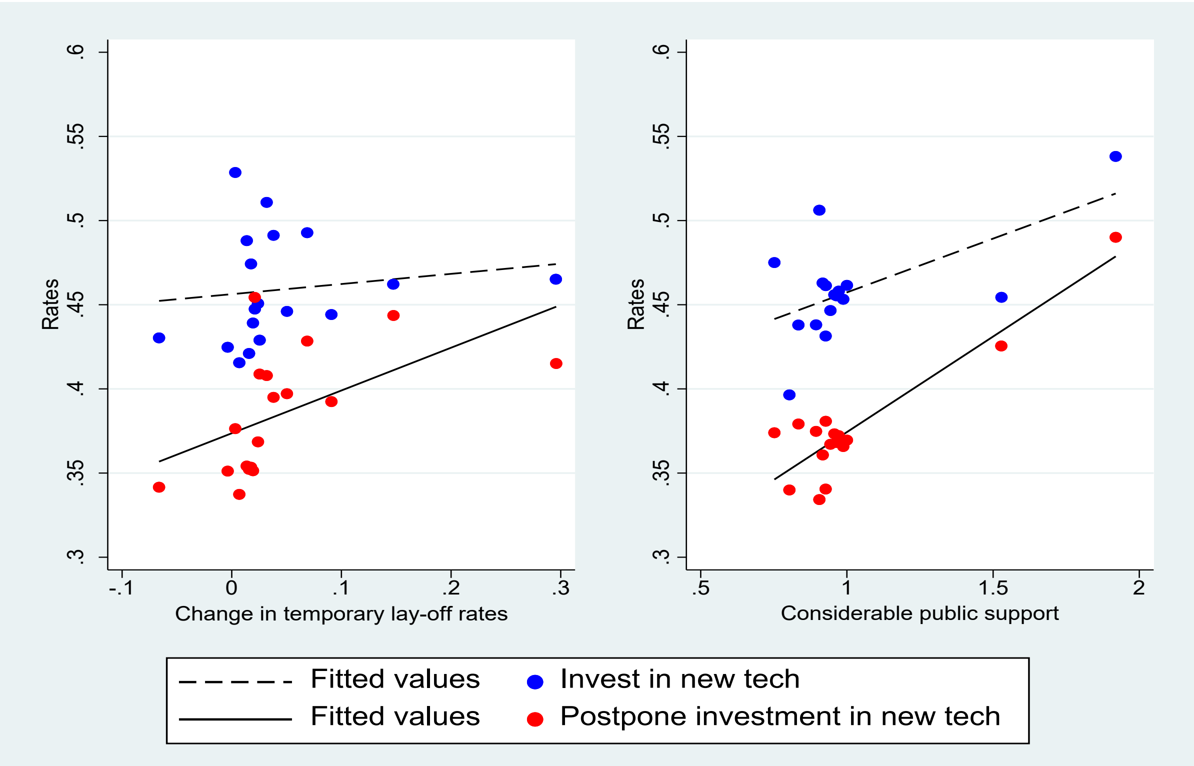
Note: Population: 6708 private sector firms in DoT2020. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response, and in addition the worker figures are employment weighted, thus the table provide population-representative figures for firms and workers (in parentheses). Based on yes/no responses to the questions "In addition to eventual programs for digital meetings (e.g., zoom, teams), has the pandemic caused the firm to adopt new technology, such as e.g., new digital tools, robots and automation" (Q4) and "Has the pandemic caused the implementation of new technology to be postponed?" (Q6). See appendix for more details on questions.

In Table 1 we see the average impact of the pandemic on technology investments in excess of digital meeting platforms among Norwegian firms.[8] The striking observation is that the pandemic massively disrupted the technology investment schedules of Norwegian firms. Thirty-eight percent

[8] Responses to question Q3 in the questionnaire on digital meeting platforms such as zoom and team indicate that close to 85 percent of the Norwegian firms employing over 90 percent of the workers implemented such digital tools due to the pandemic.

of all private sector firms employing 39 percent of employees experienced postponements in scheduled technology investments. Yet, at the same time, 41 percent of private sector firms, employing 53 percent of all workers, experienced the introduction of new technology due to the pandemic.

Figure 3 Technology adoption and postponement due to the pandemic by disruption (change in temporary lay-off rates) and by public support



Note: The figures show the share of firms who report to have introduced new technology (blue dots, dashed line) and postponed the introduction of new technology (red dots, solid line) due to the pandemic, by vigintiles (20 bins) of change in firms' temporary lay-off rates (from pre-pandemic to 2020) (left-side-figure) and by whether they received considerable public support in 2020 (right-hand-side figure). The binscatters incorporate controls for industry and a dummy missing TFP 2019. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. See Section 4 on detail on data.

Figure 3 shows the bivariate relationship between technology adoption and postponement against the severity of the crisis, measured by the share of workers who were laid off (furloughed), and the amount of public support received during 2020.[9] We see that both adoption and

[9] Our public support measure does not comprise sales-loss pandemic support, but primarily innovation and tax credits.

postponement of new technology are positively related to change in temporary lay-off rates and public support. The gradient is steepest for postponement in both cases. These indicators are clearly correlated, and we study their impact in a multivariate framework below. The firms that are the hardest hit by the crisis are also the firms that respond most vigorously to the pandemic. In a similar vein, the firms that receive the most public support during the crisis are also the ones who respond the most.

Postponement of new technology adoption and its reasons

In Table 2, we look closer at why postponement occurred. Postponement means deciding to delay a previously planned investment. Table 2 presents responses (yes/no) to the question "Has the pandemic resulted in the implementation of new technology being postponed?" (see Q6 in the appendix): a) Due to increased uncertainty; b) Due to the pandemic making the implementation of changes more difficult; c) Due to delivery difficulties; and d) Due to any other circumstances? Since the responses are not mutually exclusive, they do not sum to unity.

Table 2 The reasons for postponement of new technology due to the pandemic (cell proportions).

	Uncertainty	**Implementation difficulties**	**Delivery difficulties**	**Other circumstances**
Firms	0.55	0.63	0.55	0.37
Workers	0.49	0.67	0.54	0.36

Sample: All private sector firms in DoT2020 which had postponed investment. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Response to the question "Has the pandemic caused that the implementation of new technology has been postponed?" (see Q6 in the appendix) with the not mutually exclusive alternatives: a) Due to increased uncertainty? b) Due to the pandemic making the implementation of changes more difficult; c) Due to delivery difficulties; and d) Due to any other circumstances. Since the responses are not mutually exclusive, they do not sum to unity.

A majority of firms who postponed the introduction of new technology due to the pandemic report *uncertainty* as a reason (55 percent). This is consistent with studies establishing the importance of recession-induced uncertainty on the postponement of capital investments (Bloom et al., 2007).

Table A1 in the appendix provides some descriptive statistics for postponement and for the different reasons for postponement. Larger and more productive firms were more likely to postpone adoption, mainly because of implementation and delivery difficulties. Firms that were constrained before the pandemic further postponed adoption during the crisis, and firms that were the hardest hit had higher postponement rates, for all reasons. There is no clear association between reasons for postponement and levels of public support during the crisis year.

Introduction of new technology due to the pandemic; what and when

We asked the firms who report introducing new technology due to the pandemic about the type of technology they introduced and the permanency of this technology. Forty-one percent of the firms said the pandemic had caused them to introduce new technology. Panel A) of Table 3 reports responses to the follow-up question for those firms who had introduced new technology, namely "What kind of technology is this (If yes to Q4 a-d) (Q5): a) Robot-technology; b) Automation; c) New digital tools; and d) Something else. These questions/responses are mutually exclusive.

The table shows clearly that digital tools were the dominant form of new technology adoption following the pandemic (remember this is in excess of communication platforms like Zoom and Teams). Conditional on introducing new technology due to the pandemic, we find that eighty-five percent of the firms, employing close to 90 percent of the private sector workforce experienced new investments in digitalization due to the pandemic. Robots and automation were much less common. In the later regressions we group robots and automation into one category (to increase precision in estimates). Table A2 in the appendix reports some descriptive statistics showing that larger firms are more likely to introduce new digital tools and robots, a positive correlation between adoption and TFP, and that firms that were constrained pre-pandemic, actually were more likely to implement new technology during the pandemic. There appears to be a concave relationship between business disruptions and adoption, and a positive relation between public support and technology adoption, in particular for digital tools.

Table 3 Share of new technology adopters by type and timing of adoption (row percentages among innovators)

	Robots	Automation	New digital tools	Something else
A) *Type of technology*				
Firms	0.01	0.05	0.85	0.10
Workers	0.02	0.04	0.89	0.06
	Temporarily introduced	**Accelerated already planned permanent**	**Permanent implemented**	**Due to be implemented permanent soon**
B) *Permanency*				
Firms	0.34	0.29	0.32	0.05
Workers	0.23	0.42	0.32	0.04

Sample: All private sector firms in DoT2020. Note: Share of all firms that introduce new technology due to the pandemic. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Panel A) probes those that have responded yes to "In addition to eventual programs for digital meetings (e.g., zoom, teams), has the pandemic caused the firm to adopt new technology, such as e.g., digitalisation and automation " (Q4) and report the response (yes/no) to the question "What kinds of technology is this (if yes to Q4 a-d)(Q5): a)Robot-technology; b)Automation; c)New digital tools; and d)Something else. Panel B) also probes those responded yes to Q4, but reports the response (yes/no) to timing and permanency dimension: "In addition to eventual programs for digital meetings (e.g., zoom, teams), has the pandemic caused the firm to adopt new technology, such as e.g., digitalisation and automation (Q4): a)Yes, we have temporarily implemented new technology; b)Yes, we have accelerated planned permanent implementation of new technology; c)Yes, we have permanent implemented new technology due to changed product demand and production environment; d)Yes, we are just about to implement new technology due to changed product demand and production environment.

Innovation, as a process in general, however, is characterised by path dependency (Klette and Kortum, 2004; Acemoglu et al., 2012; Aghion et al., 2016). The scant previous literature (Riom and Valero, 2020) on how the pandemic influences technology investments of firms reveals that most firms investing in technology under the pandemic had invested in this technology previously. Panel B) reports the technology adopters' response to (Q4): a) Yes, we have temporarily implemented new technology; b) Yes, we have accelerated planned permanent implementation of new technology; c)Yes, we have permanently implemented new technology due to changed product demand and production environment; d) Yes, we are just about to implement new technology due to changed product demand and production environment. These responses are mutually exclusive.

Two-thirds of the firms that introduce new technology report that the technology change is permanent (given by the sum of columns 2-4), and only one third that they are temporarily introduced. These changes are thus likely to affect a majority of firms for a long time. Furthermore, although 29 percent respond that they accelerated already planned investments, thus partly reflecting an on-going process, for the rest (71 percent) this was not something they had been planning to do before the pandemic. Thus, the pandemic strongly influenced these firms and workers in new directions. Table A3 in the appendix shows that this is particularly true for smaller firms. Really large firms are more likely to accelerate existing investment plans.

6.2 How did firms' pre-pandemic traits impact investments during COVID?

How did firms' pre-pandemic traits influence their investment decisions during COVID? Our previous Figures 1 and 2 provided only bivariate relationships, begging the question of how investments and postponement of new technology relate to our key explanatory variables in a multivariate setting. As argued in Section 4, the decision to innovate and to postpone are related so we model them jointly using Bivariate Probit regressions. Throughout we condition on pre-pandemic TFP (2019), as well as a control vector comprising industry dummies (19), a dummy for being a service provider, a dummy for utilizing machines and a dummy for missing information on TFP. We also conduct analyses with an extended control vector containing barriers and promotors of innovation which includes information on financial difficulties limiting previous investments, skill limitations, the change in temporary layoff rate, public support, and trade union agreements.

The Bivariate Probit yields four outcomes for innovate/postpone due to the pandemic: (No innovation, No postponement), (No innovation, Postponement), (Innovation, No postponement), and (Innovation, Postponement). We present our results in Table 4 as marginal effects on the predicted probabilities for the four outcomes. Table A5 in the appendix presents the parameter estimates of the two probit-regressions. In both Models 1 and 2 the estimated joint correlations of the error terms are highly positive and significant (hovering around 0.30-0.35), which provides a strong argument for modelling this process jointly.

Model 1 of Table 4 indicates that firms with higher pre-pandemic TFP are more likely to introduce new technology and not postpone investment (column 3) and are marginally less likely to postpone the introduction of new technology. Our measure of TFP has a standard deviation of 0.5 so a one standard deviation increase in TFP implies a 4.2 percentage point reduced probability of postponement without innovation, and a 5.5 percentage points higher probability of innovation without postponement. In other words, high productivity firms innovate but do not postpone, while low productivity firms postpone but do not innovate.[10]

Table 4 Technology adoption and technology postponement under the pandemic and the relationship to barriers to and promotors of new technology adoption before the pandemic. Bivariate Probits. Marginal effects on the four outcomes.

Outcomes:	Model 1				Model 2			
New technology	No	No	Yes	Yes	No	No	Yes	Yes
Postponement of technology	No	Yes	No	Yes	No	Yes	No	Yes
TFP	-0.061	**-0.083***	**0.110****	0.035	-0.052	-0.077	**0.099***	0.025
	(0.063)	(0.039)	(0.046)	(0.046)	(0.068)	(0.049)	(0.047)	(0.050)
Lacking skills(index)					**-0.029****	-0.007	**0.016****	**0.020****
					(0.006)	(0.004)	(0.003)	(0.005)
Lacking financial resources (index)					**-0.110****	**0.038****	**-0.011***	**0.083****
					(0.009)	(0.008)	(0.005)	(0.004)
Change in temp. lay off rate					**-0.148****	0.014	0.027	**0.107****
					(0.052)	(0.063)	(0.080)	(0.035)
Considerable public support					-0.024	**0.027****	**-0.023***	0.020
					(0.022)	(0.010)	(0.009)	(0.016)
Trade union agreement					**-0.049****	-0.006	**0.020***	**0.034****
					(0.017)	(0.007)	(0.010)	(0.012)
Workforce size/100					**-0.013****	**-0.007****	**0.013****	**0.008****
					(0.004)	(0.002)	(0.004)	(0.002)
Controls								
Additional controls in all regressions: industry dummies (17), dummies for service provider and machine users.								
N	6548				6548			

Note: Population: All private sector firms in DoT2020. Bivariate Probit regressions. Dependent variables: dummies for technology adoption and technology postponement. The table reports marginal effects of the explanatory variables presented in left column on the probabilities of new technology adoption and postponement of new technology (given by column head). Standard errors are clustered on stratum. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response, thus the table provide population-representative figures for the population of firms. ^{x}, * and ** denote 10, 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on the estimation available upon request.

[10] Note that one could worry that this correlation picks up firm productivity trend differentials. Using our complete pre-period tfp-data (2005-2019), we have derived firm-specific linear productivity trends and added this to our models in this section and in Section 7. Unfortunately, our measure is associated with noise, particularly in the regressions in Section 7. It does not change our results qualitatively.

In Model 2 of Table 4, we extend the control vector. The correlations between TFP and investment decisions remain qualitatively similar to those in Model 1. High productivity implies innovation without postponement, while low productivity implies postponement.[11] The next two variables capture previous constraints with respect to innovation. The first is an index reflecting lack of skills. The index has a standard deviation of 1.15. The second is an index reflecting lack of finances with a standard deviation of .866. Firms who reported lacking necessary skills for pre-pandemic innovation were more likely to introduce new technology during the pandemic, while firms who reported financial constraints were more likely to both introduce new technology *and* to postpone the introduction of planned investments. Both types of constraints implied a lower probability of doing nothing (No, No) during the pandemic.

We have two indicators of how hard the firm was hit by the pandemic. The first is a measure of temporary layoffs during the pandemic, and the other is a measure of public financial support during 2020. Both indicators are associated with a higher probability of postponing planned investments. Firms who had to lay off a large fraction of the workforce during the pandemic were more likely both to postpone the introduction of planned investments *and* to introduce new technology (final column). They were also less likely to do nothing (No, No). Firms who received public support were more likely to postpone planned investments without introducing new technology, and less likely to introduce new technology without postponement.

In the Appendix Table A7 we report results from an analysis of the reasons for postponement. Firms who had to lay off more workers are more likely to report uncertainty as the main reason hampering innovations, while firms who received public support are more likely to report implementation difficulties as an important reason hampering innovations during the pandemic.

[11] A more detailed investigation on the nature and type of innovation, reported in Appendix Table A6, reveals that high productivity firms were more likely to accelerate already planned innovations, and to invest in robots and automation.

Unions and the response to the pandemic

Table 4 also reveals that trade union agreements stimulated rather than hampered innovation during the crisis. This result is consistent with our earlier research which indicated that unions in Norway were associated with a higher probability of firms investing in technology (Bryson and Dale-Olsen, 2021). In earlier research we showed that one reason for this union effect is that unions are able to ameliorate workers' anxiety in the face of workplace innovation when the union is involved in implementing change (Bryson et al., 2013). Firms with collective agreements were 5.4 percentage points more likely to introduce new technology in response to the pandemic than firms without a collective agreement and were significantly less likely to do nothing (No, No). A more detailed analysis on the nature and type of innovation, reported in Appendix table A6, shows that firms with collective agreements were more likely both to introduce temporary innovations and to accelerate already planned investments during the pandemic, and had a 14 percentage points higher probability of investing in new digital tools.

Discussion

The key findings from Table 4 are twofold. Firstly, the pandemic caused creative disruptions, both postponing and accelerating innovations, and that the direction of the responses tends to increase the inequality between high and low productivity firms. High productivity firms innovate, low productivity firms postpone. Second, the firms who were hit the hardest by the pandemic, were the ones with the most vigorous response. Even firms that report being previously constrained responded to the pandemic by introducing new technology, but also to postpone planned innovations. Furthermore, these results are not driven by firm size since pre-pandemic employment is controlled for in all regressions.[12]

[12] Otherwise, one would easily suspect that size differentials were crucial for our results, since large firms could be more productive and innovative.

7. The short-term impact of technology innovation on worker wages and firm productivities

In this section, we study the short-term outcomes for workers and firms. In the previous section we showed that innovations induced by the pandemic are widening the productivity distribution, since it is the firms that were the most productive pre-pandemic who innovate while the least productivity firms postpone their innovations. The first question we ask is simply do workers benefit from these innovations, and if so, which worker groups? To answer this, we study within-job log hourly wage growth for two periods, from 2019-2020 and from 2020-2021. By analysing this wage growth within jobs, we eliminate job fixed effects. We then stack our data and run within-industry fixed effects linear regressions of log hourly wage growth on our innovation measures. By adding the industry-fixed effects we effectively control for differential industry wage time trends. Table 5 presents our results.

In the first column of Panel A), we focus on all workers. This regression reveals that, on average, workers experience hourly wage growth that is 2.5 percent higher following technological innovations induced by the pandemic, as compared to being in the same job in the absence of pandemic-induced innovation.

The next four columns show the results for each of the four skill groups: unskilled, vocational skilled, skilled and high-skilled. The picture provided by these estimates is clear: it is only skilled and high-skilled workers who benefit from innovation-induced wage growth. Unskilled and vocational-skilled do not.

In Panel B) we differentiate between the different kinds of innovations a firm might introduce due to the pandemic. We see that the overall wage impact associated with robots and automation is much stronger than the introduction of new digital tools, but both yield significantly higher wage growth than not innovating. Once again, we see that it is the skilled and high-skilled workers who benefit from these innovations. The point estimates associated with unskilled workers are actually negative (and strongly so in the case of robots and automation). The evidence suggests that pandemic induced innovations fueled increasing wage inequality.

Table 5 The impact on log hourly wage growth within jobs following the introduction of new technology due to the pandemic.

	All	**Unskilled**	**Vocational**	**Skilled**	**High skilled**
Panel A) All innovations					
Introduced new tech	**0.025****	-0.009	0.007	**0.026****	**0.014**^{x}
	(0.006)	(0.013)	(0.008)	(0.008)	(0.008)
Panel B) Tech types					
Robots & automation	**0.061****	-0.081	-0.005	**0.071***	**0.029**^{x}
	(0.023)	(0.052)	(0.024)	(0.029)	(0.015)
New digital tech	**0.024****	-0.007	0.007	**0.022****	0.012
	(0.006)	(0.014)	(0.019)	(0.007)	(0.008)
Other tech	0.011	-0.008	0.009	**0.028**^{x}	-0.004
	(0.013)	(0.026)	(0.027)	(0.015)	(0.042)
Additional controls in all regressions: year dummy and industry FE.					
For all:					
Workers	716571	45121	186542	353275	154447
Firms	6690	3247	3595	6302	6206
N	1240856	71431	313796	589553	265613

Note: Population: All workers employed by private sector firms in DoT2020. Population is denoted by column head. Dependent variable: growth in log hourly wage within a job. Table elements thus express linear FE regression estimates of parameters denoted by row heading on growth in log hourly wages. Panel A)-B) present estimates from separate regressions. The observations are weighted by the inverse of the sampling probability and corrected for non-response. Standard errors are clustered on worker and firms. ^{x}, * and ** denote 10, 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on the estimation available upon request.

We end this section by examining the effects of innovations on short-term productivity growth. To do so we estimate simple linear IV-regressions of log TFP-growth on pre-pandemic TFP, innovations, innovationsXTFP, and controls (industry-dummies and background). In all these regressions, we instrument pre-pandemic TFP (2019) with historical TFP values (2009-2018). Table 6 presents our results from these regressions. Models 1 and 2 focus on all kinds of technical innovations, while Models 3 and 4 focus on the introduction of specific technologies. In Models 2 and 4 we add a control vector containing firm-specific background characteristics such as a trade union agreement, changes in temporary layoff-rates, an index for whether a lack of skills hindered pre-pandemic innovations, an index for whether lack of financial resources hindered pre-pandemic innovations, and whether the firm receiveed considerable public support, e.g., for innovations and R&D.

Regardless of model, we see that our control vector has a minor impact on the estimates. All models also reveal positive correlations between pre-pandemic TFP (2019) and TFP in 2020. These correlations are expressed by the estimates associated with pre-pandemic TFP as seen in Table 6 added 1 (eg, in Model 1 for non-innovators: corr(Pre-pandemic tfp, tfp2020)= -0.076+1**)**.

Table 6 The impact on (log) total factor productivity growth following the introduction of new technology due to the pandemic.

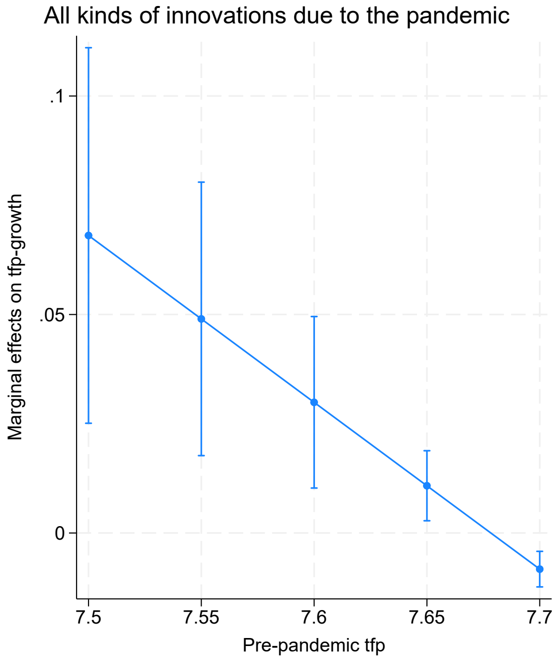
	All kinds of innovations		Specific kinds of innovations	
	Model 1	Model 2	Model 3	Model 4
Introduced new tech	**2.935****	**2.931****		
	(0.926)	(0.916)		
Pre-pandemic tfp	**-0.076****	**-0.077****	**-**0.056	**-0.075****
	(0.024)	(0.023)	(0.032)	(0.024)
Introduced new techXPre-pandemic tfp	**-0.382****	**-0.382****		
	(0.121)	(0.119)		
Robots & automation			1.017	0.863
			(2.268)	(2.297)
New digital tech			**3.150****	**3.001****
			(0.987)	(0.966)
Other tech innovation			**1.531**^{x}	1.482
			(0.848)	(0.863)
Robots & automationXPre-pandemic tfp			-0.134	-0.114
			(0.297)	(0.300)
New digital techXPre-pandemic tfp			**-0.410****	**-0.391****
			(0.129)	(0.126)
Other tech innovationXPre-pandemic tfp			**-0.199**^{x}	-0.193
			(0.110)	(0.112)
Additional controls:				
5-digit industry dummies, dummies for service provider and machine users	Yes	Yes	Yes	Yes
Lacking skills(index), lacking financial resources (index), change in temp. lay off rate, considerable public support, trade union agreement		Yes		Yes
First stage strength of instruments				
Kleibergen-Paap F-value	151.7	153.91	58.99	62.03
N	4200	4200	4168	4168

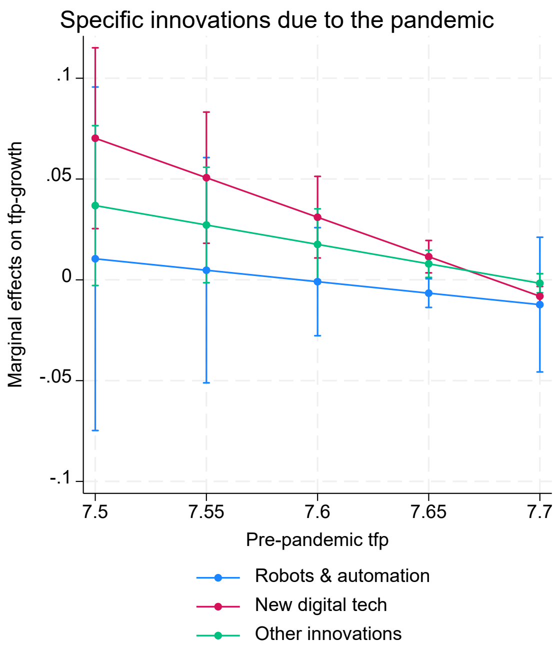
Note: Population: All private sector limited liability firms in DoT2020 (reporting to the Norwegian Accounting register) observed 2019 and 2020. Linear IV regressions. Dependent variables: Growth in TFP (log) from 2019 to 2020. The table reports the estimates associated with the explanatory variables presented in left column. Standard errors are clustered on stratum. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response, thus the table provide population-representative figures for the population of firms.· ^{x}, ·* and ** denote 10, 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on the estimation available upon request.

Table 6 also reveals that the introduction of new technology due to the pandemic is generally associated with higher productivity growth, but that these positive correlations diminish for more productive firms. This pattern is also seen for the specific technologies, but as we see, the short-term productivity growth following the introduction of robots and automation is highly insignificant.

Figure 4 presents the marginal effects on (log) productivity growth from these innovations across the pre-pandemic productivity distribution. On the left-hand side of Figure 4 we see the marginal effects from the introduction of new technology on the productivity growth. For most firms, the impact on growth is positive, but as we get closer to the top of the productivity distribution, the effect dwindles and becomes negative.

Figure 4 The impact on (log) total factor productivity growth following the introduction of new technology due to the pandemic across the pre-pandemic productivity distribution.





Note: Population: All private sector limited liability firms in DoT2020 (reporting to the Norwegian Accounting register) observed 2019 and 2020. The figures are based on the estimates from Model 2 (figure to the left) and Model 4 (figure to the right) of Table 6. The figures show the marginal effects for 1-99 percentiles of the pre-pandemic total factor productivity distribution.

On the right-hand side of Figure 4, we see the marginal effects from the introduction of the specific technologies on the productivity growth. We see the same pattern here, i.e., for most firms, the impact on growth is positive, but as we get closer to the top of the productivity distribution, the effect dwindles and becomes negative. However, we see that it is only in the case of the introduction of new digital technologies that this pattern is strongly significant.

8. Long-term expected labour demand and technology innovations

In this final section, we consider how innovations caused or brought forward by the pandemic affect expected long-term future expected labour demand (by 2025). In doing so, we differentiate between four types of labour: unskilled, vocational training, high school/intermediate skills, and university/high-skilled (Q2). Respondents are asked whether they expect growth, decline or no-change in their demand for different skills (Q9, see the questionnaire in the appendix and the data section for details). We also conduct analyses to see what impact innovations have on overall labour demand (Q8). We estimate three different Generalised Ordered Probit models, where we first focus on (a) the introduction of new technology overall, and (b) the type of technology. Our results are presented in Table 7, in the form of marginal effects. Parameter estimates are presented in Table A8 in the appendix.

The introduction of new technology is associated with both expected reductions and increases in labour demand for all skill groups. Our study encompasses many different technologies, of course, and it is not surprising that the introduction of new technology may work in different ways in different firms. The reference category, no-change, is the one that becomes less likely relative to all other outcomes, confirming the role the pandemic played in a process of creative destruction. On average the positive effect of the introduction of new technology is 8 percentage points stronger than the decline in labour demand (0.091-0.011), but we must keep in mind that the respondents do not report the size of the expected effect and only the direction. The difference between the numbers should thus be interpreted as a share of firms with positive or negative effects, and not in terms of the size of changes in labour demand.

Table 7 Future long-term demand for skills and the introduction of new technology due to the pandemic. Ordered Probit. Marginal effects. Dependent variable: Expected Future Labor Demand

	All types of labour		Unskilled labour		Vocational training		High school / intermediate skills		University/ high-skilled individuals	
	Reduc- tion	Growth	Reduc- tion	Growth	Reduc- tion	Growth	Reduc- tion	Growth	Reduc- tion	Growth
a)General										
Introduction of new technology	**0.011****	**0.091****	**0.107****	**0.012****	**0.024****	**0.109****	**0.015****	**0.126****	**0.012****	**0.100****
	(0.004)	(0.006)	(0.014)	(0.003)	(0.005)	(0.011)	(0.003)	(0.007)	(0.004)	(0.009)
b)Type of technology										
Robots & Automation	0.036	**0.047****	**0.148****	0.006	**0.065****	**0.076****	**0.047****	**0.084****	**0.026***	**0.170****
	(0.0031)	(0.018)	(0.054)	(0.026)	(0.012)	(0.047)	(0.012)	(0.039)	(0.011)	(0.034)
New digital tools	**0.013****	**0.102***	**0.114****	**0.012***	**0.019****	**0.125****	**0.012****	**0.141****	**0.011***	**0.106****
	(0.004)	(0.008)	(0.016)	(0.005)	(0.004)	(0.015)	(0.004)	(0.009)	(0.005)	(0.013)
N	5638		5638		5949		5852		5299	

Note: Population: All private sector firms in DoT2020. a)-b) denote separate identical regressions, except for additional variables denoted by leftmost-column. Ordered Probit regressions. Dependent variable: variable indicating, growing demand, no change, or reduced demand for total labour demand or the 4 types of labour denoted by column head (based on question Q2 or Q8 (overall demand) in the questionnaire). Additional control variables in all regressions: pre-pandemic TFP, industry dummies (19) and dummies for trade union agreement, service provider and machine users. In the table, the marginal effect on the probability of no change in labour demand equals the negative of the sum of the two outcomes presented. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Standard errors are clustered on strata.· * and ** denote 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on parameter estimates and their standard errors available upon request.

The nature of the impact varies across skill groups. The relative size of the impacts flips from a negative effect for unskilled workers of 9.8 percentage points (-10.7+1.2) to positive effects on the remaining skill groups. Overall, the pandemic induced innovations imply increased demand for all but the unskilled workers.

With respect to the results for the different types of technology, both robots & automation and new digital tools are associated with diminishing demand for unskilled labour in many firms but increasing labour demand growth for the higher skill groups. To explore the relationship between labor demand and productivity for these two types of technology adoption, we repeat the analyses of Panel b) in Table 7, adding interaction-terms between a dummy for high pre-pandemic

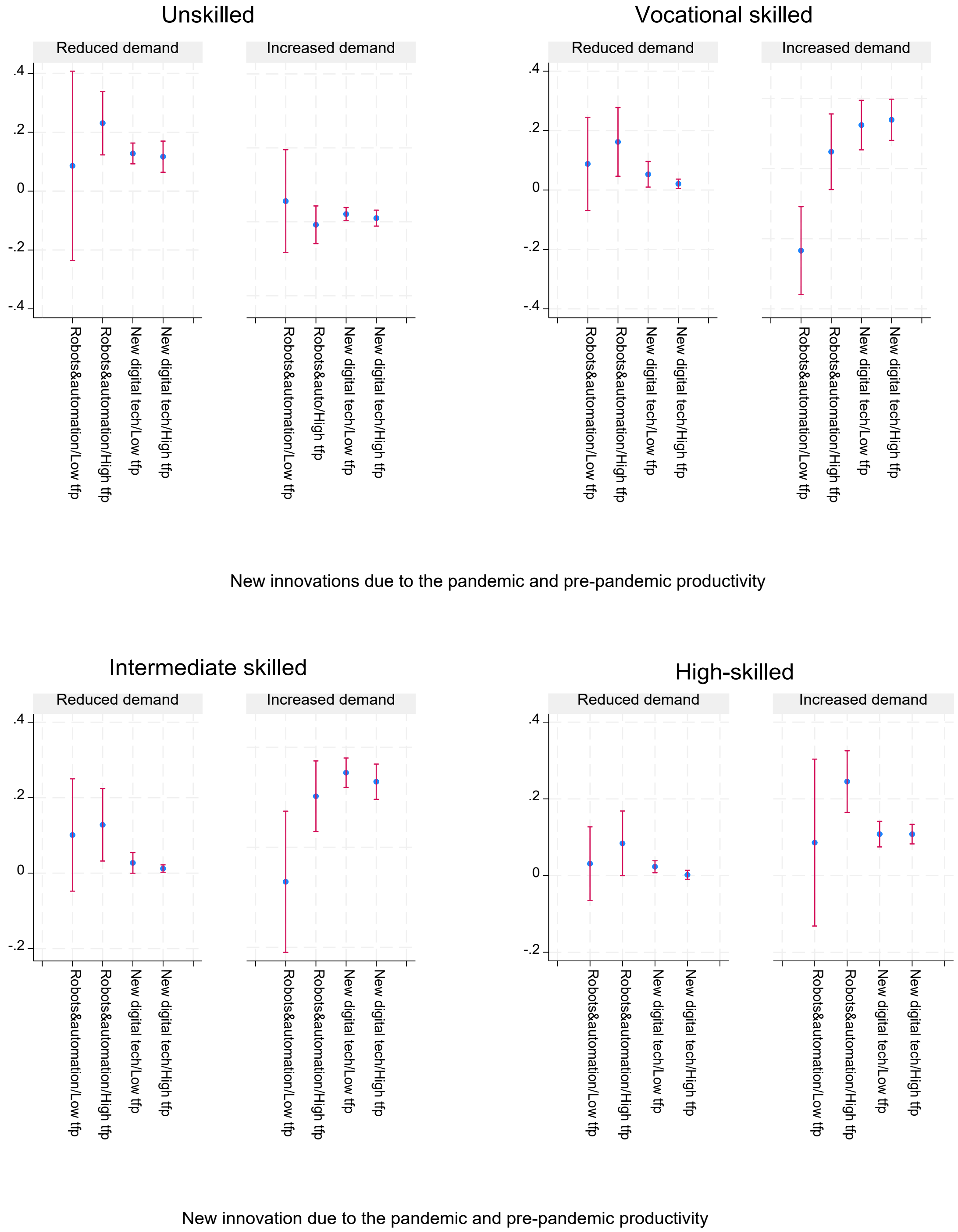
TFP (=1 if above median) and the variables for Robots and automation and New digital tools. We estimate the average marginal effects associated with the innovation, at different points across the pre-pandemic productivity distribution (low/high). Figures 5 presents our results.

In the upper half of Figure 5 we see how the labour demand for the unskilled and vocationally skilled are affected by introduction of Robots and automation or new digital technologies due to the pandemic across the productivity distribution. This is expressed in terms of the predicted probabilities for reduced demand and increased demand. For unskilled workers, we see that new innovations are strongly significantly associated with an increased probability of reduced demand, except for low-productivity firms introducing robots due to large uncertainty. At the same time, the introduction of these technologies implies a reduced probability of increased demand, except for low productivity robot-introducing firms. For vocationally-trained workers, we see a similar but slightly weaker effect when it comes to the probability of reduced demand. However, once again we see that pre-pandemic productivity matters for the way in which the introduction of robots and automation affects labour demand.

In the lower half of Figure 5 we see the impact of innovations due to the pandemic on the labour demand for intermediate and high-skilled workers. The introduction of these innovations tends to be associated with minor impacts on the probability of reduced demand, but they are strongly associated with increased demand for labour. Once again, we see that the expected long-term demand for skilled workers following the introduction of robots and automation is much stronger for high productivity firms than for low-productivity firms.

Overall, the picture is clear: introduction of Robots and automation increases the gap between the demand for unskilled and low skilled and the demand for skilled workers as productivity grows, thus if pay reflects productivity, it will enforce pay inequality between these two groups of workers.

Figure 5 Labour demand and technology adoption for low- and high productivity firms



Note: Population: All private sector firms in DoT2020. Generalised Ordered Probit regressions. Dependent variable: variable indicating, growing demand, no change, or reduced demand for the types of labour (based on question Q2 in the questionnaire). Technology innovations: robots & automation, new digital tools. Additional control variables in all regressions: dummy for total factor productivity(above median=1) interacted with the two types of technology innovations induced by the pandemic, interaction between missing info on TFT the two types of technology innovations, and industry dummies (19) and dummies for service provider and machine users. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. The figure shows the marginal effects on the predicted probability associated with the introduction of robots & automation (upper figure) and new digital tools (lower figure) across the productivity distribution for those with no-missing on TFP. The figure also indicates 95-confidence interval. Further details on the regression results are available from the authors upon request.

9. Conclusion

Technological progress, as an engine for economic growth, is at the core of every modern economy. This process is often gradual and path-dependent, but sometimes shocks occur that disrupt this process. In the winter of 2020, the world was hit by the COVID-19 pandemic, causing a strong negative health shock to people around the world and disrupting markets. A key question is thus whether firms' technological adoption will intensify or face a set-back during the COVID-crisis. In this paper, we utilize a brand new large-scale Norwegian questionnaire survey, the Digitalization, Organisation and Technology 2020 (DoT2020) survey, conducted November-December 2020, to show how firms' technological adoption is affected by COVID-crisis.

Our key findings are that the pandemic massively disrupted the technology investment schedules and plans of Norwegian firms. Nearly half the firms and workers experienced postponement of investment plans. However, nearly equally common was the experience of being induced to introduce new technologies during the pandemic. The vast majority of the innovations involved the introduction of new digital tools over and above the obvious use of communication platforms such as Zoom and Teams, but also robots and automation were introduced due to the pandemic. These technologies were mostly implemented permanently and will affect firms for a long time. Although some firms accelerated already planned investments, the majority did not, which suggests that the pandemic strongly influenced these firms and workers in new directions.

The pandemic appeared to have increased inequality between high and low productivity firms, since high productivity firms grabbed the opportunity and pushed forward already planned innovation, while low productivity firms postponed innovations. A majority of firms innovating, experience short-term productivity growth. All in all, the pandemic thus appears to have widened the productivity distribution across firms.

While on average firms receiving considerable tech public support were less likely to innovate and more likely to postpone than firms not receiving public support, we see that they also found the opportunity to conduct certain permanent technology innovations under the pandemic.

Firms that had previously experienced barriers to investments, such as financial barriers and scarcity of skills were more likely to introduce new technologies. Firms with collective agreements were also more likely to introduce new technologies during the pandemic, and generally less likely to do nothing during the crisis, suggesting that unions were conducive to firms' responsiveness to the crisis rather than the opposite.

The introduction of new technology due to the pandemic is mainly associated with increased long-term labour demand for all skill groups, except for unskilled workers. Particularly high productivity firms are expected to lower their demand for unskilled workers due to innovations induced by the pandemic. Still, to a certain degree this depends on the type of technology. On one hand, the introduction of robots and automation appears to have detrimental impact on the labour demand for the unskilled workers and positive impact on the demand for high-skilled workers as the productivity of the firm increases. On the other hand, the introduction of new digital tools usually implies higher demand for all skill groups except unskilled workers, but this diminishes as productivity grows.

Finally, we see that it is the skilled and high-skilled workers that benefit from these innovations by experiencing high log hourly wage growth. Thus, the innovations induced by the pandemic enforce the process of increasing wage inequality in the labour market.

Our study does not capture all aspects of creative destruction; we do not consider growth, exit, and entry of firms. Still, we may conclude that the pandemic has clearly been a device for technological progress. Firms report enduring technological shifts that will affect productivity and labour markets for years to come. At the same time, the pandemic has influenced ongoing processes, which have been strongly magnified and reinforced. Digitalization, automation, and falling demand for unskilled labour were not created by or under the pandemic but has been ongoing for decades. These processes were magnified, accelerated, but also hampered by the pandemic. How these disruptions finally affect overall productivity and labour markets in the longer term remains to be seen.

Appendix

Tables

Table A1 The postponement of new technology due to the pandemic.

	Postponement of technology due to pandemic	**Uncertainty**	**Implementation difficulties**	**Delivery difficulties**	**Other circumstances**
All	0.37	0.21	0.24	0.21	0.14
Unions					
Union agreement	0.37	0.20	0.23	0.21	0.14
No agreement	0.37	0.21	0.25	0.21	0.14
Size					
11-25 employees	0.36	0.21	0.23	0.21	0.14
26-50 employees	0.36	0.20	0.23	0.21	0.13
51-100 employees	0.37	0.19	0.25	0.21	0.13
101-500 employees	0.41	0.19	0.29	0.22	0.15
>500 employees	0.47	0.21	0.34	0.25	0.13
Productivity					
TFP low	0.33	0.19	0.23	0.18	0.14
TFP medium	0.37	0.21	0.22	0.21	0.14
TFP high	0.40	0.22	0.27	0.25	0.14
Financial difficulties affecting previous technology investments					
Index low	0.24	0.11	0.13	0.13	0.08
Index medium	0.36	0.19	0.23	0.22	0.13
Index high	0.51	0.33	0.37	0.29	0.22
Skill limitation affecting previous technology investments					
Index low	0.32	0.18	0.20	0.19	0.12
Index medium	0.45	0.26	0.31	0.26	0.17
Index high	0.47	0.24	0.32	0.25	0.21
Business disruption – Change in temporary layoff rate					
Δrate low	0.33	0.17	0.21	0.19	0.12
Δrate medium	0.42	0.23	0.30	0.17	0.10
Δrate high	0.43	0.28	0.30	0.25	0.18
Public firm support					
No support	0.34	0.20	0.23	0.22	0.13
Little support	0.44	0.28	0.28	0.24	0.19
Considerable support	0.31	0.18	0.23	0.15	0.13

Note: Population: All private sector firms in DoT2020. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Figures are rates of all firms. Note that the different reasons for postponing technology investments are not mutually exclusive, i.e., aggregating across reasons for postponement does not add up to the average postponement rate.

Table A2 The introduction of new technology due to the pandemic. Type of technology.

	New technology due to pandemic	**Robots**	**Automation**	**New digital tools**	**Something else**
All	0.41	0.004	0.02	0.35	0.04
Unions					
Union agreement	0.44	0.004	0.02	0.38	0.04
No agreement	0.38	0.005	0.02	0.32	0.03
Size					
11-25 employees	0.37	0.003	0.02	0.31	0.04
26-50 employees	0.47	0.005	0.02	0.41	0.04
51-100 employees	0.49	0.005	0.03	0.43	0.03
101-500 employees	0.52	0.013	0.02	0.47	0.02
>500 employees	0.68	0.010	0.03	0.61	0.03
Productivity					
TFP low	0.34	0.001	0.01	0.28	0.04
TFP medium	0.37	0.006	0.02	0.32	0.03
TFP high	0.42	0.004	0.02	0.37	0.03
Financial difficulties affecting previous technology investments					
Index low	0.30	0.002	0.01	0.24	0.04
Index medium	0.44	0.005	0.02	0.38	0.03
Index high	0.52	0.006	0.03	0.45	0.04
Skill limitation affecting previous technology investments					
Index low	0.37	0.003	0.01	0.31	0.04
Index medium	0.50	0.006	0.02	0.44	0.03
Index high	0.58	0.024	0.03	0.49	0.03
Business disruption – Change in temporary layoff rate					
Δrate low	0.40	0.004	0.02	0.34	0.03
Δrate medium	0.59	0.011	0.07	0.48	0.22
Δrate high	0.43	0.004	0.02	0.36	0.05
Public firm support					
No support	0.37	0.005	0.02	0.32	0.03
Little support	0.41	0.001	0.02	0.33	0.06
Considerable support	0.53	0.006	0.01	0.47	0.04

Note: Population: All private sector firms in DoT2020. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Figures are rates of all firms.

Table A3 The introduction of new technology due to the pandemic. Temporary versus permanent.

	New technology due to pandemic	**Temporarily introduced**	**Accelerated already planned permanent**	**Permanent implemented**	**Due to be implemented permanent soon**
All	0.41	0.14	0.11	0.13	0.02
Unions					
Union agreement	0.44	0.16	0.12	0.13	0.02
No agreement	0.38	0.12	0.10	0.13	0.02
Size					
11-25 employees	0.37	0.15	0.08	0.11	0.02
26-50 employees	0.47	0.15	0.13	0.16	0.03
51-100 employees	0.49	0.13	0.17	0.16	0.03
101-500 employees	0.52	0.10	0.22	0.17	0.03
>500 employees	0.68	0.13	0.29	0.21	0.03
Productivity					
TFP low	0.34	0.12	0.08	0.10	0.02
TFP medium	0.37	0.12	0.10	0.13	0.02
TFP high	0.42	0.12	0.14	0.14	0.02
Financial difficulties affecting previous technology investments					
Index low	0.30	0.12	0.07	0.09	0.01
Index medium	0.44	0.14	0.13	0.14	0.02
Index high	0.52	0.17	0.14	0.17	0.03
Skill limitation affecting previous technology investments					
Index low	0.37	0.14	0.09	0.12	0.01
Index medium	0.50	0.14	0.16	0.15	0.04
Index high	0.58	0.20	0.16	0.18	0.03
Business disruption – Change in temporary layoff rate					
Δrate low	0.40	0.14	0.10	0.13	0.02
Δrate medium	0.59	0.05	0.24	0.26	0.02
Δrate high	0.43	0.15	0.13	0.12	0.03
Public firm support					
No support	0.37	0.12	0.10	0.12	0.02
Little support	0.41	0.17	0.12	0.10	0.02
Considerable support	0.53	0.18	0.14	0.17	0.02

Note: Population: All private sector firms in DoT2020. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. Figures are rates of all firms.

Table A4 Descriptive statistics

Variable	Mean	Std. deviation	Variable	Mean	Std. deviation
Postponement of technology due to pandemic	0.375	0.484	Union agreement	0.660	0.474
Uncertainty	0.201	0.401	Pre-pandemic workforce size	101.3	333.2
Implementation difficulties	0.251	0.434	Unskilled labour growth	0.112	0.316
Delivery difficulties	0.212	0.409	Unskilled labour decline	0.281	0.449
Other circumstances	0.129	0.346	Vocational training growth	0.478	0.499
Introduced new technology due to pandemic	0.457	0.498	Vocational training decline	0.045	0.209
Robots	0.006	0.075	Intermediate skills growth	0.459	0.498
Automation	0.021	0.142	Intermediate skills decline	0.025	0.155
New digital tools	0.396	0.489	High-skilled growth	0.299	0.457
Something else	0.034	0.181	High-skilled decline	0.023	0.150
Temporarily introduced	0.137	0.344	Service-providing firm	0.551	0.497
Accelerated already planned permanent	0.143	0.350	Public support (1000NOK)	3960.8	81209.3
Permanent implemented	0.147	0.354	Considerable public support	0.082	0.274
Due to be implemented permanent soon	0.024	0.154			
Financial limitations (index)	0.025	0.866			
Lacking skills (index)	2.480	1.149			
Change in temp.layoff rate	0.039	0.090			
Total factor productivity	0.779	0.551			

Note: Population: All 6709 private sector firms in DoT2020. Unweighted descriptive statistics.

Table A5 Technology innovation and technology postponement under the pandemic and the relationship to barriers to and promotors of new technology adoption before the pandemic. Parameter estimates.

	Model 1		Model 2	
Outcome:	Innovate	Postpone	Innovate	Postpone
TFP	**0.384***	-0.130	**0.355***	-0.135
	(0.184)	(0.178)	(0.158)	(0.254)
Lacking skills(index)			**0.097****	0.037
			(0.008)	(0.025)
Lacking financial resources (index)			**0.200****	**0.347****
			(0.019)	(0.034)
Change in temp. lay off rate			0.372	**0.346x**
			(0.279)	(0.177)
Considerable public support			-0.008	**0.136***
			(0.055)	(0.065)
Trade union agreement			**0.151****	**0.082****
			(0.058)	(0.032)
Workforce size/100	**0.060****	0.006	**0.054****	0.005
	(0.018)	(0.004)	(0.016)	(0.004)
Controls				
Additional controls in all regressions: industry dummies (17), dummies for service provider and machine users, and pre-pandemic employment				
ρ	**0.358**(0.036)**		**0.303**(0.033)**	
N	6548		6548	

Note: Population: All private sector firms in DoT2020. Bivariate Probit regressions. Dependent variables: dummies for technology adoption and technology postponement. The table reports parameter estimates of the explanatory variables presented in left column on the outcomes of new technology adoption and postponement of new technology (given by column head). ρ expresses cross-equation correlation. Standard errors are clustered on stratum. These parameter estimates yield the marginal effects presented in Table 3. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. x, * and ** denote 10, 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on parameter estimates and their standard errors available upon request.

Table A6 Types of technology adoption and technology postponement under the pandemic and the relationship to barriers to and promotors of new technology adoption before the pandemic. Parameter estimates.

	4-variate Probit				3-Probit		
	Temporary innovation	Permanent innovation	Accelerated planned innovation	Postponed innovation	Robots & automation	New digital tools	Postponed innovation
TFP	-0.146	-0.044	**1.178****	-0.106	**0.787***	**0.259**^{x}	-0.100
	(0.217)	(0.134)	(0.181)	(0.260)	(0.340)	(0.154)	(0.282)
Lacking skills	**-0.046***	**0.077****	**0.143****	0.039	**0.109****	**0.095****	**0.039**^{x}
	(0.022)	(0.017)	(0.017)	(0.025)	(0.025)	(0.010)	(0.023)
Lacking financial resources	**0.167****	**0.115****	**0.061****	**0.345****	**0.084****	**0.206****	**0.342****
	(0.030)	(0.018)	(0.016)	(0.033)	(0.021)	(0.025)	(0.033)
Change in temp. lay off rate	0.221	-0.228	**0.558***	**0.437****	0.463	-0.089	**0.422***
	(0.293)	(0.150)	(0.261)	(0.126)	(0.331)	(0.199)	(0.174)
Considerable public support	-0.045	**0.132****	**-0.115**^{x}	**0.111***	-0.120	0.037	**0.115***
	(0.069)	(0.035)	(0.070)	(0.047)	(0.165)	(0.039)	(0.055)
Trade union agreement	**0.114**^{x}	0.026	**0.104****	**0.068****	-0.013	**0.142****	**0.066**^{x}
	(0.061)	(0.039)	(0.029)	(0.033)	(0.120)	(0.054)	(0.034)
Workforce size/100	**-0.014****	**0.017****	**0.047****	0.006	0.001	**0.050****	0.006
	(0.003)	(0.006)	(0.009)	(0.004)	(0.008)	(0.015)	(0.004)
ρ12	**-0.514**** (0.020)		-	-	**-0.886**** (0.015)		-
ρ23	-	**-0.475**** (0.030)			-	**0.256**** (0.030)	
ρ34	-	-	**0.115**** (0.044)			-	
ρ13	**-0.395****	-	(0.028)	-	**0.137****		(0.033)
ρ14	**0.184****	-	-	(0.040)			
ρ24	-	**0.151****	-	(0.023)			
Controls							
Additional controls in all regressions: industry dummies (10), dummies for service provider and machine users, and pre-pandemic employment							

Note: Population: 6548 observations of private sector firms in DoT2020. 4-variate and 3-variate Probit regressions. Dependent variables: dummies for type of technology adoption and technology postponement. The table presents the parameter estimates of the explanatory variables presented in left column on the outcomes of type of new technology adoption and postponement of new technology (given by column head). These parameter estimates yield the marginal effects presented in Table 4. Standard errors are clustered on stratum. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. * and ** denote 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on parameter estimates and their standard errors available upon request.

Table A7 Technology postponement under the pandemic and the relationship to barriers to and promotors of new technology adoption before the pandemic. 4-variate Probit. Parameter estimates

	4-variate Probit			
	Uncertainty	Implementation difficulties	Delivery problems	Introduced new technology
TFP	0.112	-0.011	-0.059	**0.339***
	(0.112)	(0.151)	(0.194)	(0.151)
Lacking skills	-0.009	0.016	0.022	**0.096****
	(0.018)	(0.011)	(0.048)	(0.009)
Lacking financial resources	**0.389****	**0.368****	**0.315****	**0.201****
	(0.016)	(0.032)	(0.053)	(0.018)
Change in temp. lay off rate	**0.944****	**0.373***	0.321	0.361
	(0.073)	(0.174)	(0.227)	(0.302)
Considerable public support	0.084	**0.165****	0.108	-0.001
	(0.109)	(0.039)	(0.067)	(0.046)
Trade union agreement	**0.092****	**0.091****	0.039	**0.152****
	(0.035)	(0.030)	(0.033)	(0.057)
Workforce size/100	-0.003	0.007	-0.002	**0.053****
	(0.002)	(0.005)	(0.003)	(0.017)
$\rho12$	**0.822**** ((0.011))		-	-
$\rho23$	-	**0.718**** (0.005)		
$\rho34$	-	-	**0.248**** (0.026)	
$\rho13$	**0.671****	-	(0.016)	-
$\rho14$	**0.297****	-	-	(0.028)
$\rho24$	**-**	**0.290****	-	(0.027)
Controls				
Additional controls in all regressions: industry dummies (10), dummies for service provider and machine users, and pre-pandemic employment				

Note: Population: 6548 observations of private sector firms in DoT2020. 4-variate Probit regressions. Dependent variables: dummies for type of technology adoption and reason for technology postponement. The table presents the parameter estimates of the explanatory variables presented in left column on the outcomes of reasons for new technology postponement and on new technology adoption due to the pandemic (given by column head). These parameter estimates yield the marginal effects presented in Table 5. Standard errors are clustered on stratum. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. * and ** denote 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on parameter estimates and their standard errors available upon request.

Table A8 Future demand for skills and the introduction of new technology due to the pandemic. Generalised Ordered Probit. Parameter estimates

	All types of labour		Unskilled labour		Vocational training		High school / intermediate skills		University/ high-skilled individuals	
	Reduc-tion	Growth	Reduc-tion	Growth	Reduc-tion	Growth	Reduc-tion	Growth	Reduc-tion	Growth
a)General										
Introduction of new technology	**-0.076****	**-0.272****	**-0.341****	**-0.314****	**-0.253****	**-0.350****	**-0.242****	**-0.379****	**-0.184****	**-0.332****
	(0.026)	(0.014)	(0.053)	(0.041)	(0.041)	(0.044)	(0.062)	(0.029)	(0.046)	(0.044)
b)Type of technology										
Robots & Automation	**-0.256**	**-0.224****	**-0.475****	**-0.411****	**-0.686****	**-0.789****	**-0.789****	**-0.357****	**-0.397****	**-0.582****
	(0.232)	(0.08)	(0.168)	(0.125)	(0.127)	(0.181)	(0.181)	(0.097)	(0.154)	(0.114)
New digital tools	**-0.096****	**-0.312****	**-0.364****	**-0.334****	**-0.206****	**-0.202****	**-0.202****	**-0.414****	**-0.165***	**-0.348****
	(0.029)	(0.028)	(0.051)	(0.039)	(0.042)	(0.061)	(0.061)	(0.026)	(0.074)	(0.047)
N	5638		5638		5949		5852		5299	

Note: Population: All private sector firms in DoT2020. a)-b) denote separate identical regressions, except for additional variables denoted by leftmost-column. Ordered Probit regressions. Dependent variable: variable indicating, growing demand, no change, or reduced demand for all workers or the 4 types of labour denoted by column head. Additional control variables in all regressions: total factor productivity, industry dummies (17) and dummies for trade union agreement, service provider and machine users. Standard errors are clustered on strata. The observations are weighted by weights that denote the inverse of the sampling probability and corrected for non-response. * and ** denote 5 and 1 percent level of significance, respectively. Significant parameters presented in bold. Full set of regression details on parameter estimates and their standard errors available upon request.

Questionnaire

Key questions

Q1 To which extent have the following factors the last two years acted as barriers to the firm's innovation activities:

fs1)Lack of internal financial resources
fs2)Lack of external financial resources
fs3)Lack of workforce skills
fs4)Lack of success in public support schemes
fs5)Lack of collaborators
fs6) Lack of demand for the firm's innovation ideas
Response: 4 categories: to a large extent, some, not much, not at all.

Q2 Do you in next 5 year expect increased or reduced labour demand in your firm for the following skills:

a)Simple jobs/activities that require no training
b)Qualified jobs/activities that require completed vocational training
c)Qualified jobs/activities that require higher education/extended training (expert craftsman, technician, high school)
d)Highly qualified jobs/activities that require education at the university level
Response: 5 categories, strong growth, some growth, no change, some decline, strong decline.
We construct a variable taking 3 values based on the responses: growth, no change, decline

Q3 Has the pandemic caused the firm to adopt new programs/platforms for conducting digital meetings such as zoom and team or similar programs?

Response: Yes/No,

Q4 In addition to eventual programs for digital meetings (e.g., zoom, teams), has the pandemic caused the firm to adopt new technology, such as e.g., new digital tools, robots and automation:

a)Yes, we have temporarily implemented new technology
b)Yes, we have accelerated planned permanent implementation of new technology
c)Yes, we have permanent implemented new technology due to changed product demand and production environment
d)Yes, we are just about to implement new technology due to changed product demand and production environment
e) the pandemic has not changed our technology use
Response: Yes/No

Q5 What kinds of technology is this (if yes to Q4 a-d)

a)Robot-technology
b)Automation
c)New digital tools
d)Something else
Response: Yes/No

Q6 Has the pandemic resulted in the implementation of new technology being postponed?

a)Due to increased uncertainty?
b)Due to the pandemic has made the implementation of changes more difficult
c)Due to delivery difficulties
d)Due to any other circumstances
Response: Yes/No

Q7 Is the pay to employees determined by collective agreements, or is it determined individually?

a)Collective agreements
b)Only determined individually with each employee
Response: Yes/No

Q8 Do you in next 5 year expect increased or reduced overall employment your firm regardless of skills:

Response: 5 categories, strong growth, some growth, no change, some decline, strong decline. We construct a variable taking 3 values based on the responses: growth, no change, decline

Q9 Do you in next 5 year expect increased or reduced overall employment your firm for these four skill groups: a)unskilled, b)vocationally-trained, c)skilled(intermediate) and d)high-skilled. The unskilled are defined as those who require no training. The vocationally-trained require the completion of vocational training to perform their job. Those with intermediate skills are those whose jobs require some higher education or extended training such as expert craftspeople and technicians. The high-skilled are those whose jobs require university-level education.

Response: 5 categories, strong growth, some growth, no change, some decline, strong decline. We construct a variable taking 3 values based on the responses: growth, no change, decline

Construction of firm-specific index of financial limitations regarding previous innovation

```
Graded response model                          Number of obs = 6,743
Log pseudolikelihood = -136954.96
------------------------------------------------------------------------------
             |               Robust
             | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
fs1          |
     Discrim |    3.71405   .1665355    22.30   0.000     3.387646    4.040453
        Diff |
         >=1 |   -.258035    .021813                     -.3007876   -.2152824
         >=2 |   .6439489   .0203307                      .6041015    .6837963
          =3 |   1.482328   .0332417                      1.417175    1.547481
-------------+----------------------------------------------------------------
fs2          |
     Discrim |   4.011905   .2058834    19.49   0.000     3.608381    4.415429
        Diff |
         >=1 |   .1351325   .0193407                      .0972255    .1730396
         >=2 |   .9905435   .0249251                      .9416913    1.039396
          =3 |   1.704894   .0402952                      1.625917    1.783871
-------------+----------------------------------------------------------------
fs4          |
     Discrim |   2.249175   .0780189    28.83   0.000     2.096261     2.40209
        Diff |
         >=1 |  -.0748245   .0236814                     -.1212392   -.0284097
         >=2 |   .9540346   .0265906                      .9019179    1.006151
          =3 |   1.851807   .0460027                      1.761644    1.941971
-------------+----------------------------------------------------------------
fs5          |
     Discrim |    1.90077   .0750213    25.34   0.000     1.753731    2.047809
        Diff |
         >=1 |  -.1445979   .0257311                       -.19503   -.0941659
         >=2 |   1.290491   .0365611                      1.218832    1.362149
          =3 |   2.691491   .0887298                      2.517584    2.865398
-------------+----------------------------------------------------------------
fs6          |
     Discrim |   1.623262   .0635761    25.53   0.000     1.498655    1.747869
        Diff |
         >=1 |  -.3678014    .030539                     -.4276568   -.3079461
         >=2 |   .8980176   .0300118                      .8391956    .9568395
          =3 |   2.421321   .0713991                      2.281381     2.56126
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Construction of firm-specific total factor productivity

Using the accounting data for all Norwegians firms during the period 2005-2019, our starting point is a simple Cobb-Douglas production function expressed as Equation A1):

A1) $lnY_{it} = lnA + \beta^L lnL_{it} + \beta^k lnK_{it} + \gamma_t + \omega_{it} + \varepsilon_{it}$,

Y is value added for firm i at time t, ω_{it} is a firm-specific productivity level known to the firm as they choose the level of transitory inputs and make decisions depending union density, but not observed by us, γ_t represents technological change, u_{it} is union density at workplace i+ at time t, L expresses labour, K is capital, and ε is a stochastic term representing idiosyncratic shocks that are unknown to the firm when it makes its decisions.

The classical estimation problem associated with A1) is the *endogeneity of transitory inputs*. We address this issue using the control function approach of Ackerberg et al. (2015) and Gandi et al. (2020), where we include a proxy for time varying productivity, ω_{it} , using lagged values of capital and materials and their interactions (third order polynomial) directly in the production function. We follow Ackerberg et al. (2015) as described by Rovigatti and Mollisi (2018). This approach consistently estimates A1) even if labour and materials are allocated simultaneously at time t, after the productivity shock. Implicitly we assume that firms observe their productivity shock and adjust intermediate inputs such as materials according to optimal demand conditional on the productivity shock and the state variable(s). We treat capital as the state variable, where capital evolves following an investment policy, determined at time t-1. Time varying productivity, ω_{it}, evolves following a first-order Markov process: ω_{it} = E(ω_{it} |Ω_{it-1}) + ξ_{it} = E(ω_{it}, |ω_{it-1}, u_{it-1}) + ξ_{it} = g(ω_{it-1}, u_{it-1}) + ξ_{it}. This implies that we let labour be determined before intermediate inputs and the realization of the productivity shock. We assume that neither labour, unions nor materials affect future profits. Estimation of A1) is fairly standard and well-established, and also yields an estimate of ω_{it}.We estimate A1) for all firms.

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