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Abstract

We show theoretically and empirically that standard methods give downward biased estimates of productivity growth if technical change is factor-biased. We show how to correct for this bias and construct more reliable measures of the productivity gains from technical progress. We consider two empirical applications, one where the source of technical progress is unobserved, and a second where the source can be directly measured. In the first application, we use the frequently applied NBER-CES productivity database for the United States over the years 1958–2011. The bias is especially large in the last decade, making our finding relevant for the discussion on the slowdown in US productivity growth since 2000. In the second application, we study the adoption of broadband internet in Norwegian firms in the early 2000s. We have plausibly exogenous variation in the availability and adoption of broadband internet by firms. In both applications, we find that the factor-biased nature of technological progress, if ignored, leads to the erroneous conclusion of only modest productivity gains from adopting new technology when the actual gains are in fact considerable.

Keywords: Technical change; Skill bias; Total factor productivity.

JEL codes: E23; J24; L60; O11; O33; O47.

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1 Introduction

It is often argued that productivity growth – as typically measured – has been slow in many economies and sectors that have invested heavily in information technology (IT). This observation has often been referred to as the "productivity paradox", and an early, widely cited example is Solow (1987): "You can see the computer age everywhere but in the productivity statistics." Solow was referring to a slowdown in productivity growth in the United States in the 1970s and 80s despite rapid development in IT over the same period. More recently, there has been similar claims about later investments in IT, such as broadband internet (see e.g. Acemoglu et al., 2014; Syverson, 2017).

Broadly speaking, the existing literature has proposed two types of explanations. The first set of explanations argues that the productivity gains from IT are in fact considerable, but that researchers are not able to accurately measure these gains primarily due to measurement issues in output or inputs (Diewert and Fox, 1999; Collard-Wexler and Loecker, 2016; Feldstein, 2019). Standard methods may for example underestimate the quality of new products and services, partly because some of them are provided to consumers at little monetary cost. The second set of arguments claims that there is little, if any, productivity gains from IT. Proposed explanations include, mismanagement of IT or redistribution and dissipation of profits (see e.g. Brynjolfsson, 1993). Others point out that estimated productivity gains from historic inventions such as electrification and the internal combustion engine occurred in irregular patterns over a long time period (Syverson, 2013).

In this paper we argue, theoretically and empirically, that the "productivity paradox" may partly be due to a type of mismeasurement of productivity gains that the existing literature has not discussed. Concretely, we show that standard methods deliver downward biased estimates of productivity gains if there is a factor-biased technical change.[1] We show how to correct for this bias and construct more reliable measures of the productivity gains. We apply these methodological insights to two distinct empirical settings. In both settings we find that ignoring the factor-biased nature of IT leads to the erroneous conclusion of only modest productivity gains.

A technical change may in general affect output in two ways: by changing the production function parameters and by changing the levels and composition of inputs. The change in the production function parameters is a part of the change in total factor productivity (TFP), while the change in inputs is not. The typical approach to isolate the change in output that is due to productivity is to specify a production function and use this to control for changes in the quantity of inputs. Moreover, it has been common to allow

[1] As discussed in greater detail later, formally define factor-biased technical change as a change in the production function that affects the marginal rate of transformation between different input factors (Violante, 2016).

technical change to change the Hicks-neutral parameter, but not the other parameters of the production function. We argue that only allowing the Hicks-neutral parameter to change results in downward biased estimates of productivity growth if the new technology affects the relative productivity and utilization of factors; in other words, if technical change is factor-biased.[2]

To preview the intiution behind our results, it is useful to consider a simple example where the production technology is given by a Cobb-Douglas production function and where there are two states of the world: one state without a given technology and one state with this technology. Moreover, let us assume that the technology is skill-biased, that each firm uses skilled and unskilled workers as inputs, and that they produce a homogenous output. In this example, the technical change have two key consequences: the output elasticity of skilled workers increases, and firms hire more skilled workers. The skilled workers that are hired because of skill-biased technical change (SBTC) increase output for two reasons. They increase output by, first, the pre-SBTC output elasticity of skilled workers and, second, the increase in output elasticity of skilled workers caused by SBTC. Only the second component represents an increase in the productivity of skilled workers. The common approach to calculate the effect of the technical change on TFP is to estimate the production function on a sample that includes both states of the world and to only allow the technology to affect TFP through a Hicks-neutral parameter. We show that this method will give an estimated output elasticity of skilled workers that is higher than their *true* pre-SBTC output elasticity. In this case, the researcher will falsely overestimate the productivity of skilled workers pre-SBTC and hence adjust the contribution of newly hired skilled workers to output post-SBTC by too much. As a result, the estimated impact of the technical change on TFP does not capture the full factor-biased component and will be lower than the actual expansion in the overall productive capacity.

Section 2 develops a framework which allows us to demonstrate theoretically that using a production function that does not take factor-biased technical change into account leads to a bias in the estimated effect on TFP. We demonstrate that the bias is negative as long as input levels adjust endogenously to the technical change in a profit-maximizing way. We show that this result holds for the Constant Elasticity of Substitution (CES) production function, including of course frequently used specific cases such as Cobb-Douglas. Given the importance of CES and in particular the Cobb-Douglas production function in TFP measurement, this finding means that many commonly used estimates of TFP are likely too low.

[2]A growing body of evidence suggests that important technical innovations are factor-biased (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Akerman et al., 2015). New technologies such as computers and the internet have been argued to favor skilled workers relatively more than unskilled workers. Doraszelski and Jaumandreu (2018) estimate that around half of aggregate growth in TFP in Spain is factor-biased.

We propose two methods to address this issue depending on the data on hand. Common for both methods is that, instead of using average output elasticities based on the entire sample when controlling for changes in use of inputs, one should use the output elasticities that do not contain the factor-biased technical change. When studying the evolution of productivity over time, estimating the production function on data from before the period of interest ensures that all subsequent factor-biased shocks are included in the productivity term. When studying the differences in productivity between, for example, firms or cities which for exogenous reasons differ in technology adoption, using the production function that applies to those that have not adopted the new technology means that all effects on productivity, also the factor-biased effects, are included in the estimated effect on productivity.

In Section 3 and 4 we examine the practical implications of our finding for two settings which both relate to important empirical methodologies in economics. The first concerns the estimation of how aggregate productivity evolves over time when underlying technology shocks are unobserved. The second concerns estimating the causal effect on productivity of observed technological changes.

In the first example we focus on estimating the evolution of aggregate productivity when potentially factor-biased unobserved shocks affect the evolution of the production function over time. A common method in the literature is to use annual moving averages of aggregate cost shares as proxies for the production function's evolving output elasticities. These estimates are often averages of current and lagged output elasticities, so any factor-biased shocks are therefore partly included in the estimated production function parameters and will produce a downward bias in the estimated evolution of TFP over time. We assess the quantitative importance of the misspecification bias using one of the most commonly used sources for aggregate productivity analysis of the US economy: the NBER-CES productivity database. It covers all US manufacturing sectors from 1958 to 2011. The TFP measure provided in the data set builds on Cobb-Douglas production functions where input shares are based on averages over current and lagged annual expenditure shares. When we adjust these estimates by only using lagged annual expenditure shares and therefore ensuring that all factor-biased technology shocks are captured in the estimate of TFP growth, we find that the NBER-CES estimates underreport true growth in TFP by between a tenth to a fifth over the entire period. The difference is larger the longer the time period we analyze.

Our findings are relevant for analysis of productivity growth for two reasons. First, this database and its estimates are widely used in this type of analysis. Moreover, many other databases, such as the Penn World Tables, are based on similar methodology. Second, the magnitude of the bias is quantitatively important. In particular it is related to the discussion about the slowdown in US productivity growth since 2000 (Adler et al., 2017; Fernald, 2015; Jones, 2017; Syverson, 2017).[3] We find that the difference between our corrected measures of TFP growth and the measures provided in the NBER-CES database is almost twice as high in the period after 2000 compared to earlier periods. This suggests that productivity growth during this period has been more factor-biased than usual, and that it has caused conventional measures of productivity growth to be particularly downward biased. It is therefore our conjecture that the estimated productivity slowdown may have been partly due to mismeasurement rather than a real downturn in productivity growth. Syverson (2017) discusses and largely rejects several potential sources of mismeasurement as explanations of the productivity slowdown, but our source of misspecification is to the best of our knowledge new in this context.

Analyzing the evolution of aggregate productivity over time abstracts from the specific effects of different technologies and instead only calculates the aggregate effect as a net result of potentially many different shocks and their interactions with each other. Increasingly, researchers gain access to more detailed data where one can observe the adoption of particular technologies, regulation or other potential sources of changes in productivity. In our second example we demonstrate that our argument also applies in a setting where both the new technology is observable and we have exogenous variation in the adoption of the technology. As in the setting above, we will fail to capture the entire factor-biased productivity effect if we (i) use the the average production function parameters obtained from using the entire sample in estimation to adjust for changes in the levels of observable inputs, or (ii) assume that the new technology is Hicks-neutral. Since technology adoption is observable we can estimate the effect of technology on the production function itself in a flexible manner and allow for the new technology to be factor-biased. We can then use the pre-adoption production function to accurately adjust for changes in the levels of observable inputs and allow all of the factor-biased effects to be captured in the estimated effect of technology on productivity.

In Section 4 we demonstrate this by analyzing the impact of a specific technology for which we can identify the causal effect of adoption on the output elasticity of specific input factors, namely broadband internet. As a source of plausible exogenous variation in broadband availability we use a public program in Norway where broadband internet was progressively rolled out during the years 2001–2007. Using the same natural experiment, Akerman et al. (2015) document that adoption of broadband internet changes the production function of firms in a way that complements skilled workers and, to a lesser extent, substitutes unskilled workers. In the current paper we extend this analysis by exploring

[3]The extent to which the productivity slowdown is real has received much attention. One reason is that productivity growth is often viewed as the most important contributor to overall output growth (e.g. Jones, 2016, finds that around 80% of US output per capita growth since 1948 is due to growth in TFP).

the consequences of broadband internet on TFP. We find that ignoring the role played by factor-biased technical change makes it difficult to detect any effect of broadband internet on firm productivity. When we appropriately adjust for how the new technology affects the production function we find that the expansion of broadband internet increases TFP among Norwegian firms by around 3.5 percent.

This finding has implications for the related empirical literature on how policy and technology affect firm-level productivity. Regressions that treat technical changes as factor-neutral and add it as another input in the production function will typically yield estimates that are too low. This is important because this type of regression design is arguably the most common way of exploring the effect of important economic events on productivity (see for example Draca et al., 2007, or the literature overview by Syverson, 2011). Important examples in recent years include for example Bloom et al. (2019) who estimate the effect of management quality on productivity, Balasubramanian and Sivadasan (2011) who estimate the effect of patenting on US firm-level TFP, Greenstone et al. (2012) who analyze the effect of environmental regulation on US manufacturing productivity, Atalay et al. (2012) who investigate the relationship between vertical integration and firm performance, and Moretti (2004) who investigate human capital spillovers across plants in the same city. Our findings indicate that if such studies were to take take factor-biased effects into account they would find even larger effects on productivity.

2 Framework

In this section we demonstrate theoretically how standard methods for estimating productivity gains from technical change are likely to deliver downward biased estimates when the technical change is factor-biased.

2.1 Measuring TFP with and without factor-biased technical change

Suppose we have a firm that in a given period produces an output Y_i by using a vector of inputs X_i. The mapping of inputs to output depends on the factor-neutral shifter A_i and the parameters of the production function denoted by the vector η_i. Economic theory typically defines productivity gains from a technical change as a shift in the isoquant of the production technology, or equivalently as a change in output for given inputs (see e.g. Caves et al., 1982, and Syverson, 2011).[4]

Suppose that the firm chooses between two types of production technologies, $i \in \{0,1\}$,

[4] We exclude the presence of nonrival contributors to production and endogenous growth, such as ideas, in this context. See for example Jones (2005) for an overview.

so that in every given period the production technology can be represented by

$$Y_i = A_i F\left(X_i; \eta_i\right). \tag{1}$$

We define the percentage change in TFP from the technical change as

$$\begin{aligned} \frac{\Delta TFP}{TFP} &\equiv \frac{TFP_1 - TFP_0}{TFP_0} \\ &\equiv \frac{Y_1/F\left(X_1;\eta_0\right)}{Y_0/F\left(X_0;\eta_0\right)} - 1 \\ &= \frac{A_1 F\left(X_1;\eta_1\right)}{A_0 F\left(X_1;\eta_0\right)} - 1 \end{aligned} \tag{2}$$

where we in the second equality use the production technology in state 0 to adjust for the change in input levels. This ensures that we include the effect of changing η from η_0 to η_1 in the measure of the change in TFP. In the third equality we use the expression of Y_i in equation (1).

Equation (2) shows that the change in TFP consists of two components. The first component, A_1/A_0, captures the change in the Hicks neutral productivity, while the second component, $F\left(X_1;\eta_1\right)/F\left(X_1;\eta_0\right)$, captures the change in output that is driven by a change in input parameters η_i. As in Violante (2016) we define a factor-biased technical change as a change in the marginal rates of transformation between inputs at a given input ratio. This implies that the factor-biased technical change is captured by changes in η, not by changes in A_i.

In empirical research a common assumption is that a technical change affects A_i, but not the parameters η.[5] In other words, the underlying assumption is that technical changes are factor-neutral and that firms are producing according to a production technology given by

$$Y_i = \tilde{A}_i F\left(X_i; \tilde{\eta}\right). \tag{3}$$

In equation (3) the technical change potentially changes the Hicks neutral parameter $\tilde{A}_i$ and the use of inputs X_i, but the other parameters of the production technology, $\tilde{\eta}$, are assumed to be the same for firms that use the old production technology ($i = 0$) and the new production technology ($i = 1$). Under this assumption the percentage change in TFP from the technical change is given by

$$\frac{\Delta \widetilde{TFP}}{\widetilde{TFP}} \equiv \frac{\widetilde{TFP}_1 - \widetilde{TFP}_0}{\widetilde{TFP}_0} = \frac{\tilde{A}_1}{\tilde{A}_0} - 1 \tag{4}$$

[5] See e.g. Bloom et al. (2019), Balasubramanian and Sivadasan (2011), Greenstone et al. (2012), Atalay et al. (2012), and Moretti (2004).

where the change is entirely driven by the change in the Hicks neutral parameter $\tilde{A}_i$.

2.2 Definition of misspecification bias

To define the misspecification bias, the difference between the measure of TFP that does not include the factor-biased component and the one that does, suppose the researcher uses the production function in equation (3) when the true production function is given by equation (1). Due to this misspecification, she will erroneously infer that the input parameters are given by $\tilde{\eta}$ and that they are invariant to which production technology is used. If the full sample of data is used to estimate $\tilde{\eta}$, these parameters are a function of the input parameters under both the old technology η_0 and the new technology η_1. For example, if $\tilde{\eta}$ is estimated by OLS or linear IV, the estimates will be weighted averages of η_0 and η_1, where the weights depends on the relative importance of the associated input factors (see Angrist and Imbens, 1995; Angrist, 1998). We therefore view $\tilde{\eta}$ as a convex combination of η_0 and η_1 for the remainder of the paper.[6] The misspecification will lead to the following bias in the measure of TFP growth:[7]

$$\frac{\Delta\widetilde{TFP}}{\widetilde{TFP}}-\frac{\Delta TFP}{TFP} = \frac{A_1F\left(X_1;\eta_1\right)}{A_0F\left(X_1;\eta_0\right)}\left[\frac{F\left(X_1;\eta_0\right)F\left(X_0;\tilde{\eta}\right)}{F\left(X_0;\eta_0\right)F\left(X_1;\tilde{\eta}\right)}-1\right]. \tag{5}$$

From equation (5) we can draw several conclusions about the misspecification bias:

Proposition 1.

a) There is no misspecification bias if there is no factor-biased technical change. In this case, $\eta_0=\eta_1=\tilde{\eta}$ and the bias is equal to zero.

b) There is no misspecification bias if factor inputs do not change in response to the change in input parameters η_i. In this case, $X_0=X_1$ and the bias is equal to zero.

c) There is a misspecification bias if there is factor-biased technical change and if factor inputs change in response to the change in input parameters η_i. In this case, $F\left(X_1;\eta_0\right)/F\left(X_0;\eta_0\right)\neq F\left(X_1;\tilde{\eta}\right)/F\left(X_0;\tilde{\eta}\right)$ and the bias is not equal to zero.

d) The misspecification bias is negative if

$$\frac{F\left(X_1;\eta_0\right)}{F\left(X_0;\eta_0\right)}<\frac{F\left(X_1;\tilde{\eta}\right)}{F\left(X_0;\tilde{\eta}\right)}. \tag{6}$$

Proposition 1 summarizes the key properties for the existence and nature of the misspecification bias. It also states the necessary conditions for such a bias to exist: the presence

[6] Some weights can in theory occasionally be negative, see for example the recent discussion by de Chaisemartin and D'Haultfœuille (2020) and others, but for the vast majority of cases $\tilde{\eta}$ is likely to be a convex combination of η_0 and η_1.

[7] We obtain equation (5) by using the definition of $\Delta TFP/TFP$ in equation (2), that equation (3) can be rewritten as $\tilde{A}=Y_i/F\left(X_i;\tilde{\eta}\right)$, and that the true production function is given by equation (1).

of a factor-biased technical change and a change in use of factor inputs in response to the technical change.

The economic intuition behind the results in Proposition 1 is as follows. Technical change gives rise to two events, a change in the production function parameters and a change in input levels. The change in the production function parameters is part of the change in TFP while the change in input levels is not. The production function is used to control for the effect of changes in input levels on output since such changes are not part of the change in TFP. If the misspecified production function parameters, $\tilde{\eta}$, which are based on both the pre- and post-technical change production function, are used and input levels change, the contribution of the change in input levels is discounted by $\tilde{\eta}$ instead of η_0. This gives rise to a misspecified estimate of the change in TFP because the change in input levels is not discounted by the correct parameter. If, in addition, the change in input levels is systematically correlated with the change in the production function parameters, the misspecification term is negative. The estimated change in TFP is in this case smaller than the actual change because some of the factor-biased technical change is omitted from the estimated change.

Proposition 1 and the inequality in equation (6) hold, as we will show, for a vast set of the most commonly used models in economics. It holds, for example, by construction for the important case when factor shares are used as estimates of the exponents in a Cobb-Douglas production function. This is the methodology typically followed in the growth accounting literature. It is also the methodology used in the NBER-CES database for creating measures of TFP. The inequality in equation (6) holds for the case when a Cobb-Douglas production function is used and η is estimated using contemporaneous or moving averages of factor shares. This is because the components of X and η are based on the same variable and must therefore by construction move in the same direction.

Equation (5) indicates how to correct the standard method of measuring changes in TFP so that it obtains correct estimates of the change in TFP. By replacing $\tilde{\eta}$ with η_0 in equation (3) it is clear from equation (5) that the estimator will not suffer from the misspecification bias. Forcing the production function parameters to remain at their pre-technical change levels ensures that all changes in input levels are appropriately accounted for.

Proposition 2. *Standard methods of measuring changes in TFP generate unbiased estimates of the change in TFP if production function parameters that prevailed before the change in technology, i.e. η_0, are used.*

Proof. When one replaces $\tilde{\eta}$ with η_0 in the expression for the misspecification term in equation (5) the terms in the brackets cancel out and the misspecification term becomes zero. □

To further develop these results, we next consider a few canonical production functions.

2.3 *Misspecification bias in canonical production functions*

We now consider the existence and nature of the misspecification bias in several common specifications of the production function $F(X_i;\eta_i)$. We begin with the Cobb-Douglas production function before we generalize our results to the broader Constant Elasticity of Substitution (CES) setting. We assume that firms use different types of labor in production and that the labor market is fully competitive such that every firm is faced with a perfectly elastic supply curve for each type of labor. Wages are assumed to be unaffected by technical change, which makes our analysis more suitable to a situation where several small sectors are affected in different ways and workers can move across sectors, or where some firms adopt new technologies while others do not.[8] Alternatively, one can view it as applicable to an analysis of short-run changes in productivity.

2.3.1 Cobb-Douglas production functions Suppose that the production technology is given by a Cobb-Douglas production function with two input factors, skilled (S) and unskilled (U) labor:

$$Y_i \;=\; A_i S_i^{\alpha_i} U_i^{\beta_i}, \tag{7}$$

where $i=1$ if the firm has adopted the new technology, and 0 otherwise. To fix ideas, assume that the technical change is strongly skill-biased, increasing the output elasticity of skilled workers ($\alpha_1 > \alpha_0$) and decreasing the output elasticity of unskilled workers ($\beta_1 < \beta_0$).[9]

The misspecification bias in equation (5) is equal to

$$\frac{\Delta\widetilde{TFP}_{CD}}{\widetilde{TFP}_{CD}} - \frac{\Delta TFP_{CD}}{TFP_{CD}} = \frac{A_1}{A_0} S_1^{\alpha_1-\alpha_0} U_1^{\beta_1-\beta_0}\left[\left(\frac{S_1}{S_0}\right)^{\alpha_0-\tilde{\alpha}}\left(\frac{U_1}{U_0}\right)^{\beta_0-\tilde{\beta}} - 1\right]. \tag{8}$$

To further simplify the expression, we assume constant returns to scale ($\beta_i = 1-\alpha_i$) and homogenous firms, each with an output of unity. This implies that the conditional factor demands are $S_i = \frac{1}{A_i}\left(\frac{w_U}{w_S}\frac{\alpha_i}{1-\alpha_i}\right)^{1-\alpha_i}$ and $U_i = \frac{1}{A_i}\left(\frac{w_S}{w_U}\frac{1-\alpha_i}{\alpha_i}\right)^{\alpha_i}$ where w_j represents the wage

[8] See for example Beaudry et al. (2010) for an analysis where different technologies co-exist and the effect on factor prices.

[9] With constant returns to scale, these changes would be equally large in absolute terms.

of labor category $j \in \{S,U\}$. The misspecification bias in equation (8) is equal to

$$\frac{\Delta \widetilde{TFP}_{CD}}{\widetilde{TFP}_{CD}} - \frac{\Delta TFP_{CD}}{TFP_{CD}} \quad = \quad \frac{A_1}{A_0}\left(\frac{1}{A_1}\frac{w_S}{w_U}\frac{\alpha_1}{1-\alpha_1}\right)^{\alpha_1-\alpha_0}\left[\left(\frac{\frac{\alpha_1}{1-\alpha_1}}{\frac{\alpha_0}{1-\alpha_0}}\right)^{(\alpha_0-\tilde{\alpha})} - 1\right]$$

which is negative since $\alpha_1 > \alpha_0$ and $\alpha_0 < \tilde{\alpha}$. This example illustrates that methods of measuring TFP as purely Hicks neutral underestimate the total growth in TFP in a Cobb-Douglas production function.

The intuition is the following. The rise in the output elasticity of skilled workers ($\alpha_1 > \alpha_0$) increases the marginal product of skilled workers and makes firms employ relatively more skilled workers. Since $\alpha_1 > \alpha_0$ a production function estimated on the entire sample of firms will contain an output elasticity for skilled workers, $\tilde{\alpha}$, that is higher than the level before technical change occurred, α_0. Applying this production function means that the contribution of skilled workers to output is adjusted for by too much. A similar argument, but in the opposite direction, holds for unskilled workers. Since inputs which is used more (less) after the technical change is systematically adjusted for by too much (little), the measured change in TFP is too low.

2.3.2 CES production functions The most commonly used production functions when calculating TFP are encompassed within the CES production function:

$$Y_i \quad = \quad \left(\alpha_i S_i^{\rho} + (1-\alpha_i)\, U_i^{\rho}\right)^{\frac{1}{\rho}}. \tag{9}$$

The elasticity of substitution between the two input factors is $1/(1-\rho)$ and α_i is a factor augmenting parameter for skilled and unskilled workers. The CES production function nests several commonly used functions such as (i) the Leontief production function when $\rho \to -\infty$ and the elasticity of substitution between factors is zero, (ii) the Cobb-Douglas production function when $\rho \to 0$ and the elasticity of substitution between factors is unity, and (iii) a linear production function where inputs are perfect substitutes when $\rho \to 1$ and the elasticity of substitution approaches infinity.

While it is challenging to show analytically that the misspecification bias is always negative for this more general functional form, it is easy to solve for the expression numerically. As an example, we set $\rho = 0.35$ and consider an incremental increase from when unskilled and skilled workers are of equal importance in production ($\alpha_0 = 0.5$) to a setting where skilled workers are marginally more important ($\alpha_1 = 0.6$).[10] We assume

[10] $\rho = 0.35$ is motivated by for example Johnson (1970), Freeman (1986), and Heckman et al. (1998) who all place ρ somewhere between 0.25 and 0.5. Also see Acemoglu and Autor, 2011, for a discussion on the substitution between workers with college vs. high-school degree.

that the researcher uses $\tilde{\alpha} = 0.55$, an average of the two underlying values for α, as a proxy for α when estimating the rise in TFP. Under these assumptions we find that the misspecification bias in equation (5) is around -3.2 percent. This means that estimated TFP growth will be 3.2 percent lower than actual TFP growth under parameter values commonly found in the empirical literature on unskilled versus skilled workers.

In Appendix A we consider the misspecification bias more generally and solve for the misspecification bias numerically for a wide range of values that encompass the three settings above. More specifically we let ρ range from -10,000 to 0.99 and α_i range from close to 0 to close to 1. We find that the misspecification bias is negative for all configurations of the CES production function with the exception being the perfectly linear production function where the misspecification bias is zero.[11]

2.4 When could the misspecification bias matter?

In the remainder of the paper, we apply the results in Proposition 1 to two distinct settings, and find evidence that the usual measures of productivity gains are far from accurate because they ignore the factor-biased nature of the technical change. In Section 3, we study a setting where technological progress is unobserved and the reasearcher wants to estimate the change in TFP over time. This would, for example, be the case in many empirical assessments of the evolution of aggregate TFP at the national or sectoral level. In Section 4, we study a setting with direct measures of technical change and the researcher wants to estimate the change in TFP from this observed change. This would, for example, be the case in recent empirical work that has access to data on adoption of new technologies at the firm level.

3 Addressing the bias when technology shocks are unobservable

We now consider how to estimate TFP growth when the timing of the technical change is unobserved. We illustrate the quantitative importance of the misspecification bias in equation (5) by applying the methodology described in Section 2 to one of the most commonly used sources of macroeconomic productivity statistics: the NBER-CES productivity database and its methodology of estimating aggregate TFP in the US manufacturing industry. We will focus on quantifying the mismeasurement term by calculating the difference

[11] It is trivial to show that for $\rho = 1$, i. e. perfectly linear production, the misspecification bias is zero if the change in the production function does not affect which factor is used in production. The reason is that only one factor is typically used under perfectly linear production, and the problem therefore becomes similar to when the production function is a function of only one factor. A setting with only one production factor is one where factor-biased technical change by definition cannot occur, and since our misspecification bias is a consequence of factor-biased technical change the misspecification bias is therefore zero under perfectly linear production.

between estimates of TFP that do and do not include all of the factor-biased component. We will also analyze whether this difference has been particularly large since 2000 and during the slowdown in US productivity growth during this period.

3.1 Data

We use the NBER-CES Productivity database which is jointly produced by the NBER and the U.S. Census Bureau's Center for Economic Studies. It covers 450 4-digit manufacturing industries in the United States for the period 1958 through 2011 and contains measures of output and factor inputs as well as deflators. The data set is often used to compute estimates of the evolution of TFP over time in the US manufacturing sector.[12]

The database contains measures of changes in TFP since 1958. We refer to these estimates as $\hat{\hat{\theta}}_t$. As outlined by Bartelsman and Gray (1996) and Becker et al. (2016), the NBER methodology for calculating TFP growth uses a five-factor Cobb-Douglas production function with the following inputs: capital, production worker hours, non-production workers, non-energy materials, and energy. The exponents in the Cobb-Douglas production function are computed based on averages of current and previous period expenditure shares for the five different inputs.

The cumulative growth in TFP from 1958 to year t when using the NBER methodology is measured as

$$\hat{\hat{\theta}}_t = \sum_{s=1959}^{t} \left(\frac{Y_s / \prod_j x_{j,s}^{\frac{\hat{\eta}_{j,s-1}+\hat{\eta}_{j,s}}{2}}}{Y_{s-1} / \prod_j x_{j,s-1}^{\frac{\hat{\eta}_{j,s-1}+\hat{\eta}_{j,s}}{2}}} - 1 \right), \tag{10}$$

where Y_t is output in year t, and $x_{j,t}$ and $\hat{\eta}_{j,t}$ denote input levels and expenditure shares, respectively, for input j in year t.

The measure in equation (10) potentially suffers from the misspecification bias outlined in Section 2. The production function parameters used when computing the change in TFP from year $s-1$ to year s are averages over the two years. Using such a moving average when computing the change in TFP over time is common but rarely theoretically motivated, except that it smoothens the production function estimates over time. Since the production function parameters are not allowed to change between $s-1$ and s one implicitly assumes that the entire change in TFP is Hicks-neutral. Proposition 1 demonstrates that restricting the estimated production function parameters to be time-invariant as in equation (10) is likely to bias our estimate of the change in TFP over time downwards.

[12] Some examples of applications include Acemoglu et al. (2014), Chang and Hong (2006), and Mallick and Sousa (2017).

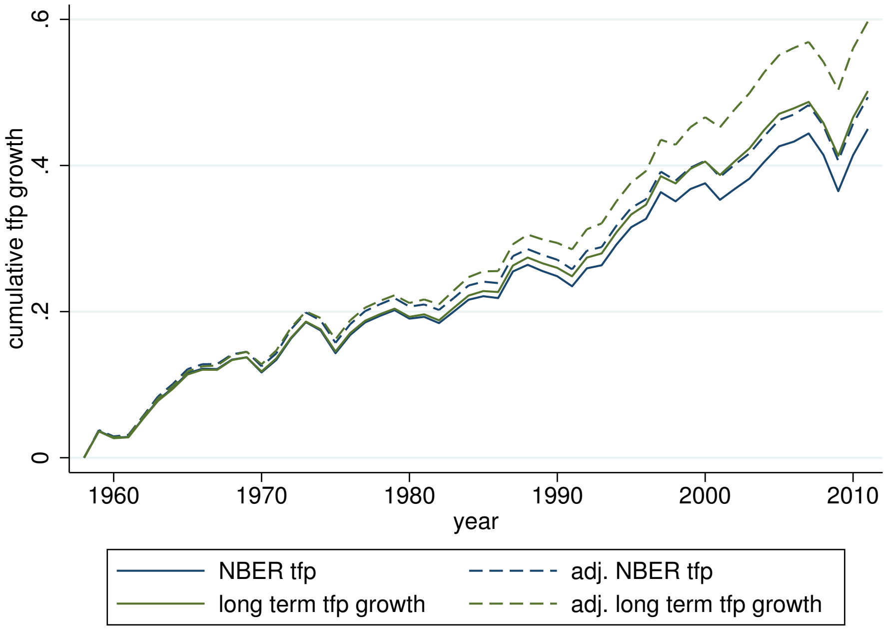


Figure 1. Unadjusted and adjusted evolution of TFP in NBER Productivity database 1958-2011.

Note: All data are from the NBER Productivity database and cover 459 1987 Standard Industrial Classification (SIC) 4-digit sectors. The four lines show the evolution of total factor productivity (TFP) over time. The difference between the lines depend on how we calculate expenditure shares in the five-factor production function. The solid blue line uses the methodology used to calculate the TFP variable included in the original data set and which is explained in Bartelsman and Gray (1996). It uses the average of current and lagged expenditure shares for each input factor. The dashed blue line uses instead lagged expenditure shares for each input factor. The solid green line uses the average of current and initial (year 1958) expenditure shares for each input, while the dashed green line uses only initial (year 1958) expenditure shares. Sectors are weighted by their contemporaneous value added. See Appendix Figure D.1 for the equivalent graph but with sector weights based on initial (1958) value added instead.

3.2 Measuring misspecification bias in yearly productivity growth

Proposition 2 shows that applying the pre-shock production function parameters addresses the misspecification bias. A simple way in this context is to use the parameters in year $s-1$ instead of the average parameters based on years $s-1$ and s. We adjust the measure in equation (10) and obtain

$$\hat{\theta}_t = \sum_{s=1959}^{t} \left(\frac{Y_s / \prod_j x_{j,s}^{\hat{\eta}_{j,s-1}}}{Y_{s-1} / \prod_j x_{j,s-1}^{\hat{\eta}_{j,s-1}}} - 1 \right), \tag{11}$$

where the cumulative growth in TFP is measured by using only lagged levels of expenditure shares as measures of the exponents in the Cobb-Douglas production function. This implies that we allow annual factor-biased shocks to be fully captured in the measure of TFP growth.

The cumulative growth in TFP from 1958 to 2011 is displayed in Figure 1. The solid blue line displays the measure that uses the NBER-CES methodology as described by equation (10) and the dashed blue line is our adjusted measure given in equation (11). The difference between $\hat{\hat{\theta}}_t$ and $\hat{\theta}_t$ is due to the misspecification term and, as predicted by the fact that this term is negative under fairly general assumptions, $\hat{\hat{\theta}}_t$ is lower than $\hat{\theta}_t$. The adjusted measure shows an overall increase of 49.3 percent while the NBER-CES measure shows an increase of 45.0 percent, i.e. the true effect is almost a tenth (or 4.3 percentage points) larger than the commonly estimated effect.[13]

We can also consider shocks that occur over longer periods. To this end we calculate the following measures

$$\hat{\hat{\theta}}_t^{LR} = \frac{Y_t / \prod_j x_{j,t}^{\frac{\hat{\eta}_{j,1958}+\hat{\eta}_{j,t}}{2}}}{Y_{1958} / \prod_j x_{j,1958}^{\frac{\hat{\eta}_{j,1958}+\hat{\eta}_{j,t}}{2}}} - 1 \tag{12}$$

and

$$\hat{\theta}_t^{LR} = \frac{Y_t / \prod_j x_{j,t}^{\hat{\eta}_{j,1958}}}{Y_{1958} / \prod_j x_{j,1958}^{\hat{\eta}_{j,1958}}} - 1. \tag{13}$$

In equations (12) and (13) we compare each year t to the initial year 1958. These estimates are likely to be larger than the sum of annual shocks since the latter methodology adjusts the production technology in each period and therefore captures only a smaller share of the long-term factor-biased component. Comparing each year t to 1958 would instead include much larger factor-biased effects since we do not update the production function each year. Applying the NBER-CES methodology would mean that the estimate of long-run productivity growth would be based on using the average of current and 1958 expenditure shares as a measure of the underlying production function. This would yield the estimate $\hat{\hat{\theta}}_t^{LR}$ of the long-run productivity growth between 1958 and year t. The solid green line in Figure 1 shows how this estimate evolves over time. As expected, it is larger than the short run estimate $\hat{\hat{\theta}}_t$.

In addition, $\hat{\hat{\theta}}_t^{LR}$ is misspecified according to Proposition 1. The estimate in $\hat{\hat{\theta}}_t^{LR}$ is based on averages of $\hat{\eta}_{j,1958}$ and $\hat{\eta}_{j,t}$, and not only on $\hat{\eta}_{j,1958}$, i.e. the production function parameters before the shocks occurred. The measure does therefore not capture the full factor-biased component. Adjusting for misspecification term yields instead an estimate $\hat{\theta}_t^{LR}$, which uses only the 1958 expenditure shares as a measure of production function parameters. This measure is displayed in the dashed green line. Since the full factor-biased component of the technical change is included in the adjusted estimate, while only some of it is included in the unadjusted estimate, the dashed line increases faster than solid line. The adjusted measure of long-run TFP growth is 59.7 as opposed to 50.2 percent, implying that the true productivity increase is about a fifth larger than the estimate that standard

[13] Sectors are weighted by their contemporaneous value added. See Appendix Figure D.1 for the equivalent graph but with sector weights based on initial (1958) value added instead.

measures yield. Interestingly, the difference between $\hat{\hat{\theta}}_t^{LR}$ and $\hat{\theta}_t^{LR}$ continues to widen over time, indicating that differences in utilization across inputs continue to evolve during the time period and do not revert back to the original levels from 1958. In other words, any factor-biased shocks appear permanent rather than transitory in nature.

Taken together the misspecification of the TFP estimator creates a quantitatively relevant downward bias. Adjusting for the bias implies that actual TFP growth over this period might have been between a tenth or a fifth higher than measures one obtains with more standard estimators of TFP growth.

3.3 The evolution of the mismeasurement term over time

Figure 2 shows how the annual differences between the adjusted and unadjusted measures of TFP growth evolves over time. There is a positive and economically meaningful difference throughout the sample. The highest average level is reached in the decade 2000–2010, which is potentially also the decade with the highest rate of investment in skill-biased technology. This time period also coincides with the era of the "great productivity slowdown", the period when the US economy experienced a slowdown in measured labor productivity growth as discussed above. The fact that the estimated mismeasurement term is especially large during this period suggests that this type of mismeasurement may be part of the explanation for the slowdown in measured productivity growth.

4 Addressing the bias when technical change is observable

We now turn to the case of estimating changes in TFP of observable technical change. In order to apply our method we need to address three measurement challenges: First, we need a setting where we observe adoption of the new technology at the firm level. Second, to analyze whether the technical change is factor-biased, for example skill-biased, we need to observe the skill level of employees. Finally, we need exogenous variation in adoption of the new technology in order to identify the causal effect on the productivity of different factor inputs.

To address these challenges, we turn our attention to a specific natural experiment that involves the expansion of broadband internet in the early 2000s in Norway. To generate exogenous variation in the availability of broadband internet over time and space, we consider a public program with limited funding which rolled out broadband access points. Moreover, we have detailed knowledge of firm inputs and output, including the level of education of each worker. We base our identification strategy and data on the work by Bhuller et al. (2013) and Akerman et al. (2015).

In this empirical setting we are able to measure the misspecification bias introduced

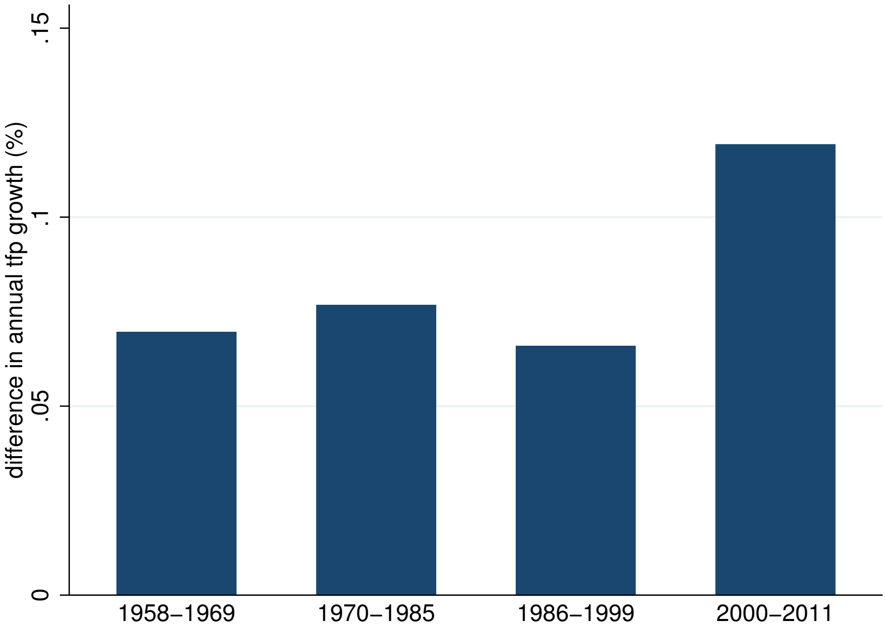


Figure 2. Difference between adjusted and unadjusted estimates of TFP growth in NBER Productivity database 1958-2011.

Note: All data are from the NBER Productivity database and cover 459 1987 Standard Industrial Classification (SIC) 4-digit sectors. The bars show the evolution of the annual difference between the adjusted ($\hat{\theta}_t$) and unadjusted ($\hat{\hat{\theta}}_t$) measures of total factor productivity (TFP) over time. These measures are defined in equations (10) and (11). The difference thus depends on how we calculate expenditure shares in the five-factor production function. Sectors are weighted by their contemporaneous value added.

in Section 2 when common methods of estimating the productivity effects of technical change are used. We will also show how making the estimation more flexible, by allowing the production function parameters to change with adoption of broadband internet, can eliminate the misspecification bias and allow the researcher to capture the full productivity effects of the new technology. In fact we find that adjusting for factor-biased changes is necessary to detect a productivity enhancing effect of broadband internet.

We first describe the data, before we describe the expansion of broadband internet and how broadband internet changed the production function in Norwegian firms.

4.1 Data

Our data are collected from several sources and it allows us to link workers and firms as well as municipalities.

Firms and workers Our firm-level data come from Statistics Norway. It is collected from administrative registers, verified by the Norwegian Tax Authority, and likely to be highly accurate (Atkinson et al., 1995). The data include the universe of non-financial joint-stock firms during 2000-2008.[14] We use balance sheet data on revenues and production inputs (such as capital, labor, and intermediates), 4-digit industry identifiers as well as information about which municipality the firm is located in.

We combine our firm data with a linked registry on employees where we have complete records on all firms and workers for the years 2000–2008. We know the length of education and annual labor income for all workers. We define individuals as skilled if they have a college or university degree in our baseline specification, while individuals with less schooling are defined as unskilled.

Internet For the years 2001–2008 we have two types of internet data. The first data set contains information on broadband adoption for a stratified random sample of firms. The second data set contains municipality-level information on availability of broadband internet to households (independently of whether they take it up). As we will explain in detail, we use the former as a measure of firm-level broadband adoption, while the latter will be our instrumental variable, i.e. the measure of broadband availability rates.[15] We define broadband internet as internet connections where download speeds exceed 256 kbit/s.[16]

The data on firm-level broadband adoption comes from the annual Community Survey on ICT Usage of Firms and is conducted by Statistics Norway. Among other things, the survey reports usage of broadband internet in firms. The survey samples in each year from the universe of joint-stock firms, and it is stratified by industry and the number of employees. We use the joint stock firms in the internet survey (20,966 firm-year observations), for which we observe broadband internet adoption, to calculate municipality-level broadband adoption rates. The sampling weights from the stratified randomization are used to calculate representative estimates for the corresponding population of joint-stock firms. We show the distribution of firms by industry in Appendix Figure C.1, and compare the industry composition in our survey sample and in the corresponding population of firms. We can see that the distributions in our sample (with sampling weights) closely mirror the distributions for the population of firms. Appendix Figures C.2 and C.3 also confirm the ability of our sampling weights to produce representative estimates: The figures display the distributions of output and inputs across firms, and the time trends in these variables, respectively.

[14] Joint-stock firms account for the vast majority of revenues and workers in the private sector. They covered 81% of revenues and 71% of workers in 2001.

[15] We do not observe the availability rates of broadband internet to firms, and therefore use the availability rates to households as an instrument for broadband adoption in firms. If the availability of broadband to households were a noisy proxy for the availability to firms, this could generate a weak first stage for our instrument (which we do not have) but it would not be a violation of exclusion or independence conditions.

[16] Before the expansion of broadband internet, all firms with a telephone connection would have dial-up access to internet, but limited to a bitrate of less than 56 kbit/s. Broadband internet facilitated internet use without excessive waiting times.

Information on municipality-level broadband availability comes from the Norwegian Ministry of Government Administration. The ministry monitors the availability of broadband internet to households, and all suppliers of broadband internet are required to report availability rates to the Norwegian Telecommunications Authority. These rates are calculated from information on each local access point's signal range, and the place of residence of households. This allows us to measure the fraction of households for which broadband internet is available in each year and municipality, independently of whether they take it up.

4.1.1 Sample selection We use our data on joint-stock firms to estimate the effect of broadband internet on TFP and production function parameters.[17] We focus on firms with at least one employee in each of the two levels of skill to make the sample appropriate for our estimation of production functions and TFP. For the intention-to-treat (ITT) effects of the increased availability of broadband internet, we use the population of firms (149,676 unique firms). The analysis of broadband adoption in firms and the structural production function estimation, however, uses a two-sample instrumental variables estimator. The first stage is based on the sample of joint stock firms recorded in the internet survey (16,744 firms) for which we observe broadband adoption, while the second stage is based on the full population of firms. In the first stage, we use sampling weights to produce representative estimates for the corresponding population of joint-stock firms.

[17]We exclude firms that are carrying out extraction of natural resources (including oil, gas and fish) in the interest of external validity. The production function estimates hardly change at all if we include firms carrying out extraction of natural resources.

Table 1. Summary statistics of firm variables

	2001	2004	2007	Overall
Log inputs and output (USD, thousands)				
Revenues	7.63	7.63	7.74	7.65
	(1.31)	(1.31)	(1.38)	(1.33)
Value added	6.83	6.86	6.97	6.88
	(1.20)	(1.20)	(1.28)	(1.22)
Intermediates	6.61	6.59	6.68	6.61
	(1.93)	(1.93)	(1.98)	(1.94)
Capital	4.68	4.45	4.48	4.49
	(1.89)	(1.98)	(2.02)	(1.97)
Log wage bills (USD, thousands)	(log)	(log)	(log)	(log)
Total	5.90	5.98	6.19	6.01
	(1.15)	(1.16)	(1.20)	(1.17)
Unskilled	5.52	5.60	5.80	5.63
	(1.26)	(1.25)	(1.29)	(1.26)
Skilled	4.08	4.17	4.36	4.19
	(1.64)	(1.69)	(1.77)	(1.70)
Number of firms				
Population	19,598	21,441	23,282	149,676
Survey	2,118	2,270	3,093	16,744

Note: This table shows summary statistics for the population of joint-stock firms over the years 2001-2007, consisting of all joint-stock firms with at least one unskilled and one skilled employee. (Un)Skilled comprises workers with(out) a college degree. Detailed descriptions of the variables are given in Appendix Table C.1.

4.1.2 Descriptive statistics Summary statistics for the most important firm-related variables are displayed in Table 1. The first panel shows means of output and non-labor inputs over time, with standard deviations in parentheses. In our estimations of TFP and the production functions we use value added as our measure of output, and we define it as revenues minus intermediates (materials and intermediate inputs). The value of total stock of fixed assets is used as our measure of capital. Table 1 shows that these variables are fairly stable over time, possibly with a weakly increasing trend in revenues, value added and intermediates.

In the second panel of Table 1 we display the means and standard deviations of wage bills, separate by skill levels. Wage bills increase over time, especially for the high skilled. We follow Fox and Smeets (2011) in measuring labor inputs by wage bills instead of the number of workers.[18] This makes it easier to compare the measures of physical capital and human capital: physical capital is measured in terms of monetary units to reflect the quality of the machinery employed, while the wage bill measures labor in terms of its expense in order to better reflect its quality.

We report estimates from a standard Cobb-Douglas production function based on the

[18]Our findings of SBTC from broadband adoption in firms are robust to measuring labor inputs by the number of workers instead of the wage bill.

survey sample (with sampling weights) and the population of firms in Appendix Table E.1. The first two columns report OLS estimates, while the last two columns use the method for estimating production functions proposed by Levinsohn and Petrin (2003). Whether we use the survey sample or the population of firms matters little for the estimated output elasticities. It is also noteworthy that, as predicted by theory, OLS overstates the labor coefficients because the level of inputs chosen is positively correlated with unobserved productivity. The magnitudes of the output elasticities of capital and labor are comparable to what is found in previous studies using micro data (see e.g. Olley and Pakes, 1996; Pavcnik, 2002; Fox and Smeets, 2011).

4.2 Expansion of broadband internet

In the late 1990s and early 2000s many countries were planning the expansion of internet-related infrastructure. In Norway, an important moment came when the National Broadband Policy was accepted by the Norwegian Parliament in the late 1990s. We provide details about this program and describe the expansion of broadband internet in more detail in Appendix B. The discussion draws on Bhuller et al. (2013) and Akerman et al. (2015).

4.3 Empirical strategy and identification

In this section we specify two types of production functions where one is more flexible than the other. In the more flexible specification we follow Akerman et al. (2015) and assume that the production function is a Cobb-Douglas production function where the exponents on the input factors potentially change with the availability of broadband internet.

The main challenge in the estimation is to address the potential endogeneity of broadband adoption. Randomizing broadband adoption is not feasible: We cannot in practice force firms to adopt a new technology. One can, however, think of a field experiment which randomizes broadband availability at the municipality level. The randomization would break the correlation between availability rates, unobserved determinants of productivity and worker outcomes. The intention of our identification strategy is to mimic this hypothetical experiment. Our source of exogenous variation comes from the staged installation of broadband infrastructure, generating spatial and temporal variation in broadband availability and adoption (conditional on year and municipality fixed effects).

4.3.1 Broadband adoption and TFP To take our framework introduced in Section 2 to data, we specify the following two ITT regressions:

$$y_{ijmt} = x'_{ijmt}\tilde{\beta}^0 + z_{mt}\tilde{\beta}^I + \tilde{\pi}_t + \tilde{\rho}_m + \tilde{\xi}_j + \tilde{\varepsilon}_{ijmt} \quad (14)$$

and

$$y_{ijmt} = x'_{ijmt}\beta^0 + z_{mt}x'_{it}\beta^I + \pi_t + \rho_m + \xi_j + \varepsilon_{ijmt}, \tag{15}$$

where y_{ijmt} indicates log value added of firm i in sector j in year t located in municipality m, z_{mt} is the availability of broadband internet at the municipality level in year t, x_{ijmt} is a vector containing the inputs in the production function, $x_{ijmt} \equiv \{1, k_{ijmt}, u_{ijmt}, s_{ijmt}\}$, where the terms include a constant term, the log of capital (total fixed assets) and log of the wage bill paid to unskilled and skilled workers, respectively. Unobservable determinants of production that are fixed at the municipality level are controlled for through the municipality fixed effects (ρ_m), just like common time shocks are absorbed by the year indicators (π_t). In addition, we control for (4-digit) industry fixed effects (ξ_j).

The regression in equation (14) corresponds to the methodology of treating broadband technology as factor-neutral only – internet availability is treated as simply another input. The coefficients on production inputs, $\tilde{\beta}^0$, are likely to be a convex combination of pre- and post-internet output elasticities.[19] If the internet is skill-biased, $\tilde{\beta}^0$ will have a coefficient for skilled workers that is higher than the pre-internet output elasticity and the contribution of adding skilled workers to production will be adjusted for by too much. The coefficient on internet availability, $\tilde{\beta}^I$, which captures the effect of internet availability on productivity, will be biased towards zero as noted in equation (6).

The regression given by equation (15) allows for factor-biased effects of internet availability since z_{mt} is interacted with all production factors. The vector β^0 consists of the pre-internet output elasticities (η_0) and the sum of the vectors β^0 and β^I is equal to the post-internet output elasticities (η_1). The change in TFP when going from no availability ($z_{it} = 0$) to full availability is equal to $x'_{ijmt}\beta^I$, which can be further decomposed into a factor-neutral component (β^I_0, the coefficient on the interaction term between internet availability and the constant) and a factor-biased component ($\beta^I_k k_{ijmt} + \beta^I_u u_{ijmt} + \beta^I_s s_{ijmt}$). This means that we are able to estimate the full effect of internet availability on TFP. The effect for an average firm is given by $\beta^I_0 + \beta^I_k \bar{k} + \beta^I_u \bar{u} + \beta^I_s \bar{s}$ where $\bar{x}$ denotes the sample average across firms of the input factor x. To make the interpretation easier we subtract the sample average from each input factor k_{ijmt}, u_{ijmt} and s_{ijmt}. By doing this we can interpret β^I_0 as the effect of internet availability on TFP evaluated at the sample average of input factor levels, i. e. the effect of internet availability when $k_{ijmt} = \bar{k}$, $u_{ijmt} = \bar{u}$ and $s_{ijmt} = \bar{s}$.

We also use our data on firm-level adoption rates to conduct an instrumental variables analysis and estimate the following regression equations:

$$y_{ijmt} = x'_{ijmt}\tilde{\beta}^0 + d_{ijmt}\tilde{\beta}^I + \tilde{\pi}_t + \tilde{\rho}_m + \tilde{\xi}_j + \tilde{\varepsilon}_{ijmt} \tag{16}$$

[19] See the discussion in Section (2.2).

and

$$y_{ijmt} = x'_{ijmt}\beta^0 + d_{ijmt}x'_{it}\beta^I + \pi_t + \rho_m + \xi_j + \varepsilon_{ijmt}, \tag{17}$$

where $d_{ijmt} = 1$ if firm i has adopted internet in period t and zero otherwise. In these specifications we study the effect of actual internet adoption on productivity. The first stage for equation (16) is given by

$$d_{ijmt} = x'_{ijmt}\tilde{\delta} + z_{mt}\tilde{\phi} + \tilde{\gamma}_m + \tilde{\theta}_t + \tilde{\zeta}_j + \tilde{v}_{ijmt} \tag{18}$$

while the first stage regressions for equation (17) are given by

$$\begin{aligned} d_{ijmt} &= x'_{ijmt}\delta + z_{mt}x'_{ijmt}\phi_0 + \gamma_m + \theta_t + \zeta_j + v_{ijmt} \\ d_{ijmt}x_{1,ijmt} &= x'_{ijmt}\delta_1 + z_{mt}x'_{ijmt}\phi_1 + \gamma_{1,m} + \theta_{1,t} + \zeta_{1,j} + v_{1,ijmt} \\ \vdots &= \vdots \\ d_{ijmt}x_{n,ijmt} &= x'_{ijmt}\delta_n + z_{mt}x'_{ijmt}\phi_n + \gamma_{n,m} + \theta_{n,t} + \zeta_{n,j} + v_{n,ijmt}. \end{aligned} \tag{19}$$

The availability rate z_{mt} serves as an instrument for broadband adoption in firms. While exogeneity of the instrument is sufficient for a causal interpretation of the ITT effects from equations (14) and (15), IV estimation requires stronger assumptions. In particular, a necessary assumption is that increased availability affects productivity and wages only through broadband adoption in firms, and not directly in any other way. In Akerman et al. (2015) we take several steps to challenge this exclusion restriction, finding suggestive evidence in favor of the assumption.[20]

While we can estimate equations (14) and (15) on the full estimation sample of firms, we rely on information on broadband adoption from survey data to estimate equations (18) and (19). This means that we estimate the first stages using only a subsample of the full estimation sample of firms that we use in the reduced form. It is well known that in such cases we need to adjust the estimated standard errors. We cannot use existing results by for example Angrist and Krueger (1995) or Inoue and Solon (2010) because our first stages are estimated on a subsample of the full sample used in the reduced form estimation, and not in a separate (split) sample as in existing work. We therefore follow a recently developed method by Akerman et al. (forthcoming) that allows to compute valid standard errors while making use of the full data set in our analysis and not unnecessarily restrict

[20]Another concern is that the factor inputs in x_{it} could be correlated with broadband adoption and unobserved productivity. Following Levinsohn and Petrin (2003, hereafter LP), we take a more structural approach to address this threat to identification of the production function (see also Olley and Pakes, 1996, and Ackerberg et al., 2015). LP uses a structural model of an optimizing firm to derive the conditions under which intermediate inputs can be used to proxy for unobserved productivity in the production function.

both stages in the IV methodology to the sample dictated by the first stage.[21]

4.4 *Empirical results*

4.4.1 Production function parameters and average effect on TFP We start by reporting the results of a standard Cobb-Douglas production function where broadband internet is assumed to only affect output in a factor-neutral way as specified in equation (14). In this specification, broadband internet is allowed to change the intercept term, but the output elasticities are assumed to be the same for firms with and without internet. Column (1) in Table 2 reports the estimates from the ITT regression in equation (14). We do not see any effect of broadband internet on output, indicating that the Hicks neutral TFP effect of broadband internet is close to zero in this specification. Column (3) reveals that this is also true for the IV model in equation (16) where we instrument actual broadband adoption in firms. The coefficients on the input factors in these specifications are, however, likely to include some of the factor-biased effect. The intercept, which is an estimate of the overall impact of internet on TFP, is likely to be downward biased since it will not include the full factor-biased effect of internet on productivity.

We proceed by estimating pre- and post-internet output elasticities separately to be able to include the internet induced change in output elasticities in the estimate of how internet affects TFP. In column (2) we report estimates for equation (15) where we allow output elasticities to vary with internet availability. We note that the output elasticity of skilled labor increases substantially with the internet (as noted by Akerman et al., 2015). Moreover, the estimated output elasticity of skilled labor in column (1) lies in-between the estimates for when $z_{it} = 0$ and $z_{it} = 1$ in column (2). The same relationship holds when we compare the IV estimates in columns (3) and (4). This illustrates that the standard approach is likely to generate estimates that are a convex combination of the production functions for firms with and without the new technology. Since the input factors x_{ijmt} are in deviations from the mean, we can interpret the coefficients on availability $\times$ intercept (adoption $\times$ intercept) as the mean overall effect of internet availability (adoption) on log value added, i.e. the effect of broadband availability (adoption) on TFP when all inputs are at their sample means. Interestingly, we see that a ten percentage point increase in internet availability increases productivity by 0.4 percent whilea ten percentage point increase in internet adoption increases productivity by 1.4 percent.[22]

[21] In Appendix Table E.2 we report estimates for the first stage regressions.

[22] We view using wage bills as a superior alternative to using the number of workers as a measure of labor inputs. One important reason is that wage bills account for heterogeneity in the quality of the workforce, see for example Fox and Smeets (2011). Nevertheless, we report the results for when we use the number of workers instead of total wage bills in Appendix Table E.4. Our precision is a little weaker, possibly because we ignore any human capital heterogeneity in addition to college completion, but our estimates are quantitatively similar.

Table 2. Effects on output elasticities using wage bills

Dependent variable: Log value added				
	ITT		Sub-sample IV	
	(1)	(2)	(3)	(4)
Log capital	0.099	0.100	0.099	0.098
	(0.004)	(0.005)	(0.004)	(0.007)
Log unskilled	0.558	0.576	0.558	0.561
	(0.014)	(0.012)	(0.014)	(0.018)
Log skilled	0.198	0.136	0.198	0.106
	(0.012)	(0.007)	(0.011)	(0.015)
Broadband $\times$Intercept	-0.001	0.035	-0.003	0.139
	(0.010)	(0.012)	(0.043)	(0.070)
Broadband $\times$Log capital		-0.002		-0.003
		(0.007)		(0.012)
Broadband $\times$Log unskilled		-0.023		-0.021
		(0.023)		(0.037)
Broadband $\times$Log skilled		0.076		0.132
		(0.017)		(0.031)
Firm-year observations	149,676	149,676	149,676	149,676

Note: Estimates are based on the models in equations (14) to (17), using the population of joint-stock firms over the period 2001-2007. Column 1 reports ITT estimates for a production function where output elasticities do not change with the internet, see equation (14). Column 2 reports ITT effects where output elasticities can change with the internet, as in equation (17). Columns 3 and 4 report instrumental variable estimates for the equivalent configurations, as in equations (16) and (17), respectively. The dependent variable is the log value added in a given year. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The standard errors are clustered at the municipality level and robust to heteroskedasticity. Inputs are deviations from sample means and the coefficients for availability $\times$ intercept (adoption $\times$ intercept) therefore show the mean effect of internet availability (adoption) on log value added.

In Appendix Table E.5 we follow Levinsohn and Petrin (2003) and use intermediate inputs to proxy for unobserved productivity in the production function. LP uses a structural model of an optimizing firm to derive the conditions under which intermediate inputs can be used to proxy for unobserved productivity in the production function.[23] While we lose some precision, it is reassuring to note that the differences between the two methods remain the same.

The results are in line with our main prediction, namely that allowing for factor-biased effects when estimating the productivity impact of a factor-biased technology, yields larger estimates than falsely assuming that the technology is factor-neutral. In columns (1) and (3) we use the same production technology for both pre- and post-adoption, the equivalent of using $\tilde{\eta}$ in Proposition 1, while in columns (2) and (4) we use the equivalent of η_0 to calculate TFP and thus include the factor-biased effect in the measure of how internet affects TFP (see Proposition 2). In our specific setting, we cannot reject a null hypothesis of

[23] Levinsohn and Petrin (2003) extend on Olley and Pakes (1996) by using intermediate inputs instead of investments as a proxy for unobserved productivity. This addresses the problem that investment is zero in a nontrivial number of cases.

internet having no impact on TFP if we do not account for factor-biased effects. However, when we include factor-biased effects we do indeed find statistically and economically significant effects of internet on TFP.

4.4.2 Aggregate TFP gain from broadband internet Our results indicate that the estimate of the effect of broadband internet on TFP depends on whether we take factor-biased effects into account. We now turn our attention to the implications for aggregate TFP. Since we know availability rates for the population of firms and the actual adoption rate for a sample of firms we can compute the change in the aggregate TFP in our sample. Moreover, we can calculate aggregate TFP using the standard, but misspecified, empirical model and compare these findings to those that we achieve when using the correctly specified model.

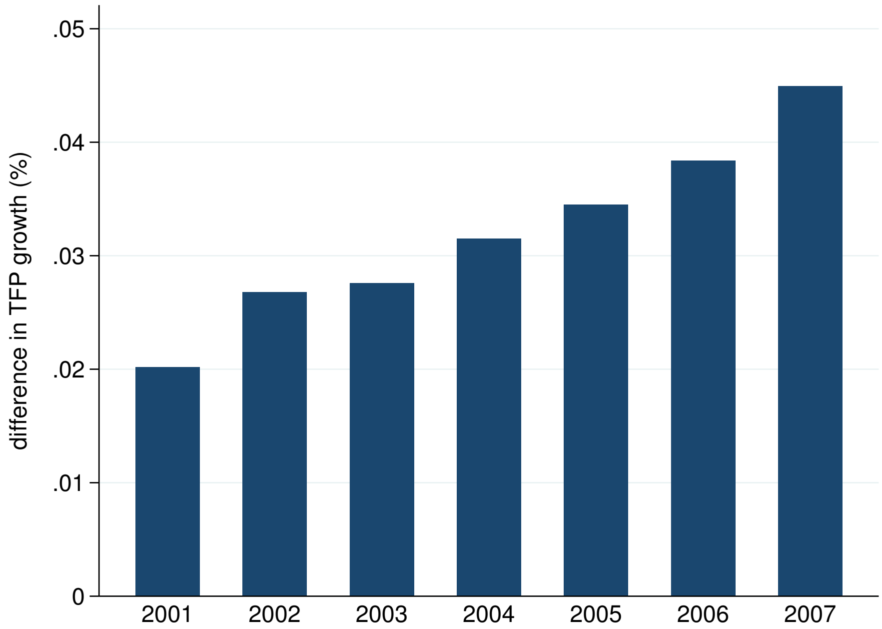
In Figure 3 we calculate the average increase in TFP across firms for each year from a baseline with no internet, and plot the difference between the estimates from the correctly specified model and the misspecified model. We note that the differences in the effect of internet availability on aggregate TFP are quantitatively important. By 2007 the difference is 4.3 percent. Our estimates of how actual adoption of broadband internet in a firm affects the firm's TFP are reported in our instrumental variables estimates. The difference between the estimates in the two models are larger than for the ITT estimates as can be seen in Figure 4. Appendix Figures F.1 and F.2 show that the difference is around 2.1 percent (11 percent) if we use the number of workers instead of wage bills in the estimation in the reduced form model (IV model). Taken together, these results mean that standard methods of estimating the evolution of TFP in Norway over this period omit some of the contribution from the factor-biased component in how the internet affects productivity.

5 Conclusions

Productivity growth is arguably the most important engine of growth in developed economies and most of the new technologies in recent decades are argued to be strongly factor-biased. In this paper we show, theoretically and empirically, that standard methods give downward biased estimates of growth in aggregate TFP in the presence of factor-biased technical change. We propose estimating production function parameters which are allowed to shift when technical change occurs. We show that using production function parameters that apply to the time before a shock occurs, or to a setting before a new technology is adopted, to construct TFP estimates allows the factor-biased component of the shock's effect on productivity to be fully included in the TFP estimate.

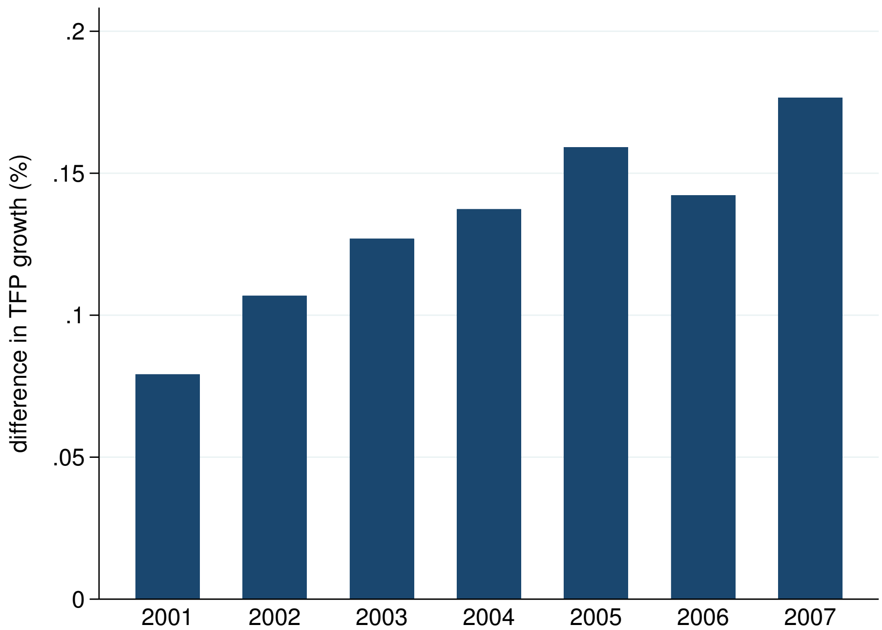
We studied two empirical applications, one where the source of technical progress is unobserved, and a second where the source can be directly measured. In the first

Figure 3. Intention-to-treat estimates for the TFP gain from internet availability.



Note: Estimates are based on the models in equations (14) to (15), using the population of joint-stock firms over the period 2001-2007. The height of the bars show the difference in the estimates of TFP growth that one finds from using the correctly specified model in (15) and the misspecified model in (14). Labor inputs are measured using wage bills.

Figure 4. Instrumental variable estimates for the TFP gain from broadband internet adoption.



Note: Estimates are based on the models in equations (16) to (17), using the population of joint-stock firms over the period 2001-2007. The height of the bars show the difference in the estimates of TFP growth that one finds from using the correctly specified model in (17) and the misspecified model in (16). Labor inputs are measured using wage bills.

application, we used the frequently applied NBER-CES productivity database for the United States over the years 1958–2011. Our results indicate that allowing for factor-biased technical change substantially increases the estimated TFP growth. The difference is especially large after 2000 indicating that mismeasurement can potentially explain part of the estimated slowdown in US productivity growth in the decade 2000–2010.

In the second application, we studied the adoption of broadband internet in Norwegian firms in the early 2000s where we have plausibly exogenous variation in the availability and adoption of broadband internet by firms. In both applications, we find that the factor-biased nature of technological progress, if ignored, leads to the erroneous conclusion of only modest productivity gains from adopting new technology when the actual gains are in fact considerable.

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Appendix A: Simulation of the sign of the misspecification term for CES production functions

We simulate the misspecification term in equation (5) for the following CES production function

$$F(S,U;\eta_i) \;=\; \left(\beta_i S_i^{\rho} + (1-\beta_i)\,U_i^{\rho}\right)^{\frac{1}{\rho}},$$

for all values of ρ from -10000 to 0.99. Recall that the Leontief production function is represented by ρ approaching minus infinity, Cobb-Douglas by $\rho = 0$ and a perfectly linear production system by $\rho = 1$. Similarly, we use all combinations of labor costs (w_S and w_U) from 1 to 20.[24] For all combinations of ρ, w_S and w_U, we study what happens when we shift β from β_0 to β_1. We include all combinations of β_0 ranging from 0 to 1 and β_1 ranging from 0 to 1. This means that we study factor-biased effects that are both skill- and unskilled-biased. When calculating the values of $F(S,U;\eta_i)$, we use the fact that under CES the following conditional factor demands apply if firms are homogenous and output is unity:

$$S(w_S,w_U,\eta_i) = \left(\frac{\beta}{w_S}\right)^{\sigma}\left(\beta^{\sigma} w_S^{1-\sigma} + (1-\beta)^{\sigma} w_U^{1-\sigma}\right)^{\frac{\sigma}{1-\sigma}}$$

and

$$U(w_S,w_U,\eta_i) = \left(\frac{1-\beta}{w_U}\right)^{\sigma}\left(\beta^{\sigma} w_S^{1-\sigma} + (1-\beta)^{\sigma} w_U^{1-\sigma}\right)^{\frac{\sigma}{1-\sigma}},$$

where $\rho = \frac{\sigma-1}{\sigma}$.

In all of the simulations we find that the misspecification term in equation (5) is weakly negative. Furthermore, it is trivial to show that for $\rho = 1$, i. e. when production is perfectly linear, the misspecification bias is zero if the change in the production function does not affect which factor is used in production. The reason is that only one factor is typically used under perfectly linear production, and the problem therefore becomes similar to when the production function is a function of only one factor. A setting with only one production factor is one where factor-biased technical change by definition cannot occur, and since our misspecification bias is a consequence of factor-biased technical change the misspecification bias is zero.

[24] We assume in this analysis that wages are unaffected by the change in technology

Appendix B: Expansion of broadband internet

The program. The two main goals of the National Broadband Policy were the following: (i) to ensure that every area of the country could access broadband internet at a uniform price, (ii) make sure rapid public sector adoption of broadband internet. Several steps were taken to reach these goals. Most importantly, the government invested heavily in the required infrastructure. The investment was mainly channeled through the (state-owned) telecom company Telenor. This company was the only supplier of broadband access to end-users in the early 2000s and is still the main supplier today with around 33 percent of the market. Also,virtually all broadband infrastructure was, and still is, owned and operated by Telenor.

Local governments had to ensure supply of broadband internet by 2005 to public institutions in their areas, such as administrations, schools, and hospitals (St.meld.nr. 49, 2002–2003). The federal government provided financial support to rural municipalities through a funding program known as *Høykom*. Local governments could through the program receive funds upon submitting a project plan. The aim was to ensure broadband availability in all parts of the country. Financial support was provided in the initial years, thereby making it possible for most public institutions to cover high initial costs.

Supply and demand factors. Local access points had to be installed to allow for the transmission of broadband signals through fiber-optic cables. Such access points were progressively rolled out starting in year 2000 which created substantial variation in broadband availability across time and regions. The staged expansion of access points was due to both limited public funding and because Norway is a large and sparsely populated country.[25] Populated areas are mostly far apart or partitioned by mountains or the rugged and fjord-broken coastline.

The reports describing the National Broadband Policy and the roll-out of broadband access points (see St.meld.nr. 38 (1997-1998); St.meld.nr. 49 (2002-2003)), suggest that topographical features and existing infrastructure (such as roads, tunnels, and railway routes) are the main *supply factors* determining the timing of roll-out.[26] Based on the program accounts, we expect the potential *demand factors* to be related to public service provision, income level, educational attainment, and the degree of urbanization in the municipality.

[25]The Norwegian territory covers about 149,400 square miles, an area about the size of California or Germany, with around 13 percent and 6 percent of those regions' populations (in 2008), respectively.

[26]The reason is that the transmission of broadband signals through fiber-optic cables required installation of local access points. In areas with challenging topography and landscapes, it was more difficult and expensive to install the local access points and the fiber-optic cables. Furthermore, the existing infrastructure mattered for the marginal costs of installing cables to extend the availability of broadband within a municipality and to neighboring areas.

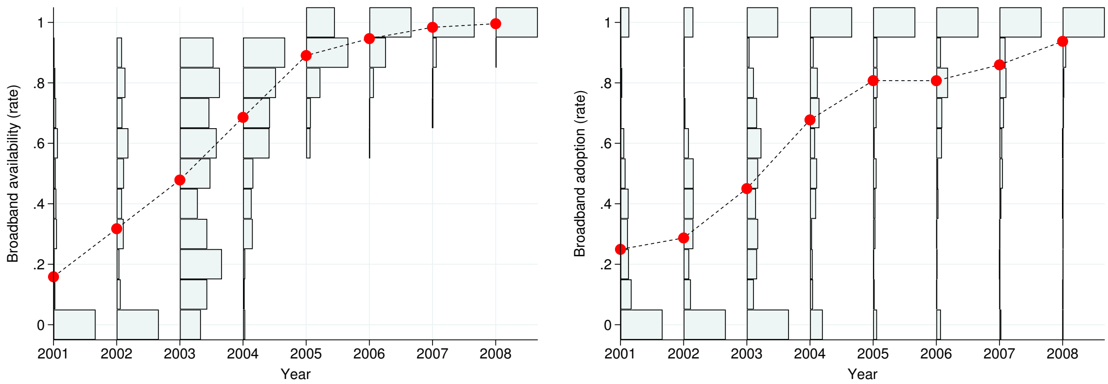


Figure B.1. Availability and adoption of broadband internet across municipalities and time.

Note: The left panel shows yearly histograms of broadband availability across municipalities (wighted by firms in the sample). The right panel shows the same for broadband adoption rates. *Source:* Akerman et al. (2022).

Evolution of broadband availability Figures B.1 and B.2 shows how the measure of broadband availability to households varies over time and across municipalities. The figures illustrate that for a large number of municipalities there was no broadband availability in the first few years, whereas most municipalities had achieved fairly high availability rates in 2005.[27] In addition, there is considerable variation in availability rates within the municipalities in these years and few municipalities experience a complete shift from no availability to full availability in a given year. The general pattern is that access points were progressively rolled out within and across municipalities, generating a continuous measure of availability rates that display considerable temporal and spatial variation (even conditional on year and municipality fixed effects).

Broadband adoption in firms In order to illustrate our identification strategy it is useful to look at the pattern of how broadband was adopted in firms. To this end, we start by specifying the following regression:

$$d_{imt} = \delta z_{mt} + \gamma_m + \eta_t + \nu_{imt}, \tag{20}$$

where d_{imt} equals one if firm i in municipality m in year t has adopted broadband internet and is zero otherwise. The instrument z_{mt} is the broadband coverage rate in municipality m in year t (the share of households for which broadband internet is available, independently of whether they adopt). To exploit the quasi-randomization provided by the broadband internet roll-out documented above we need to condition on municipality fixed effects γ_m

[27] By 2000, broadband transmission centrals were installed in the cities of Oslo, Stavanger, and Trondheim, as well as in a few neighboring municipalities of Oslo and Trondheim. But because of limited area signal range, broadband internet was available for fewer than one-third of the households in these municipalities.

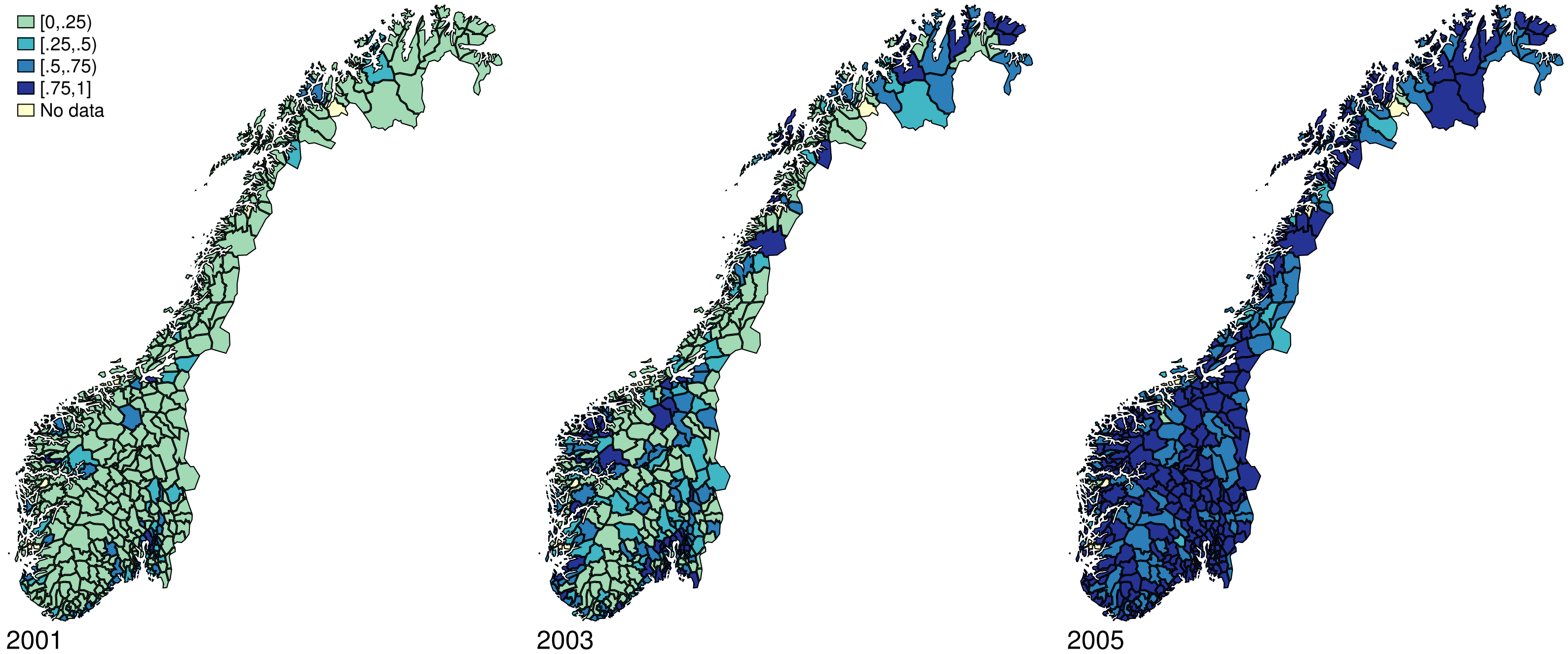


Figure B.2. Geographical distribution of broadband availability rates.
Note: The graphs show the geographical distribution of broadband availability rates of households in 2001, 2003 and 2005. *Source:* Akerman et al. (2015).

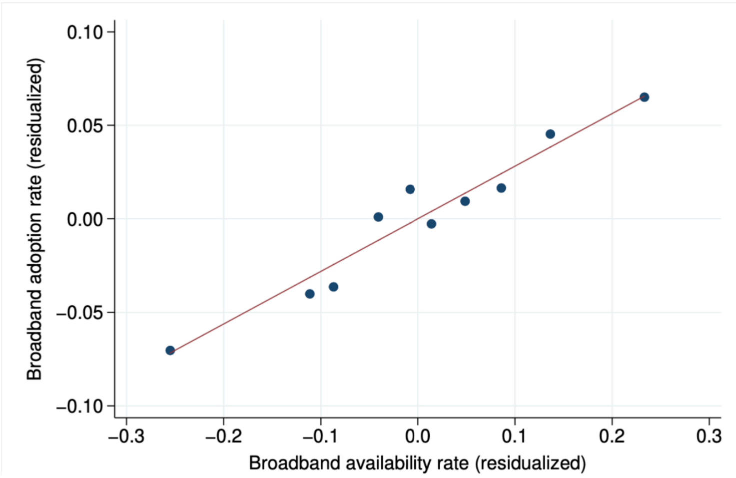
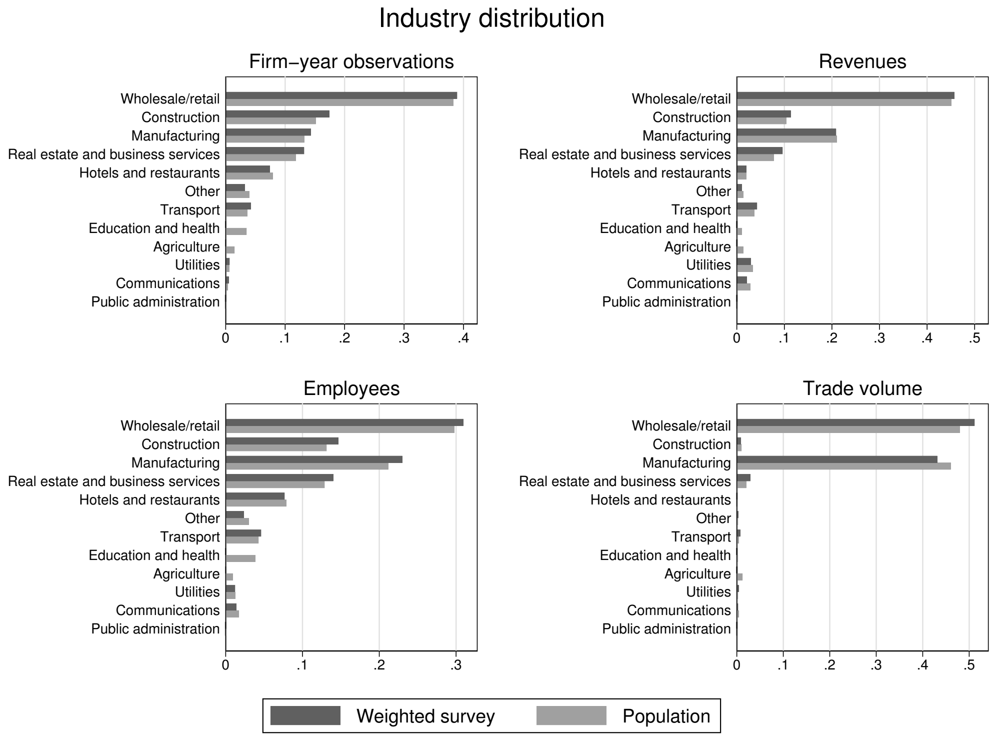


Figure B.3. First stage regression.
Note: The scatter plot shows average (residual) adoption at (residual) availability deciles. The estimated slope equals 0.28 (0.02). *Source:* Akerman et al. (2022).

and time dummies η_t.

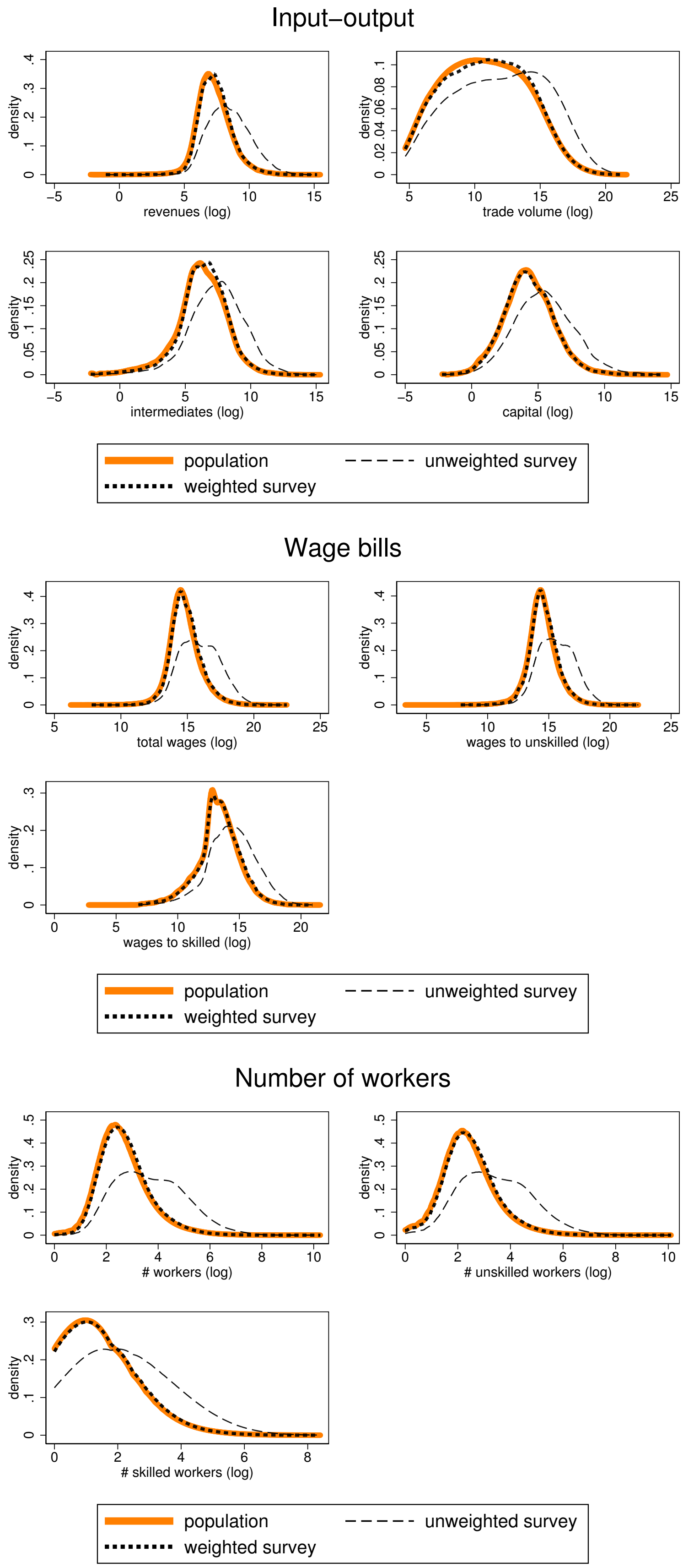
We display our results from equation (20) in Figure B.3. It shows a scatter plot of the broadband adoption rate of firms against the broadband availability rate in the municipality, after taking out municipality and year fixed effects. It is clear that there is a strong linear association between broadband availability and firm adoption rates. The vertical axis reports residuals from a regression of broadband adoption rates of firms on municipality and year fixed effects. The horizontal axis reports residuals from a regression of broadband availability rates of households on municipality and year fixed effects. We estimate the coefficient on the availability rate δ to be about 0.28 with a standard error of 0.02 implying that a 10 percentage point increase in broadband availability induces (an additional) 2.8 percent of the firms to adopt broadband internet.

Appendix C: Data



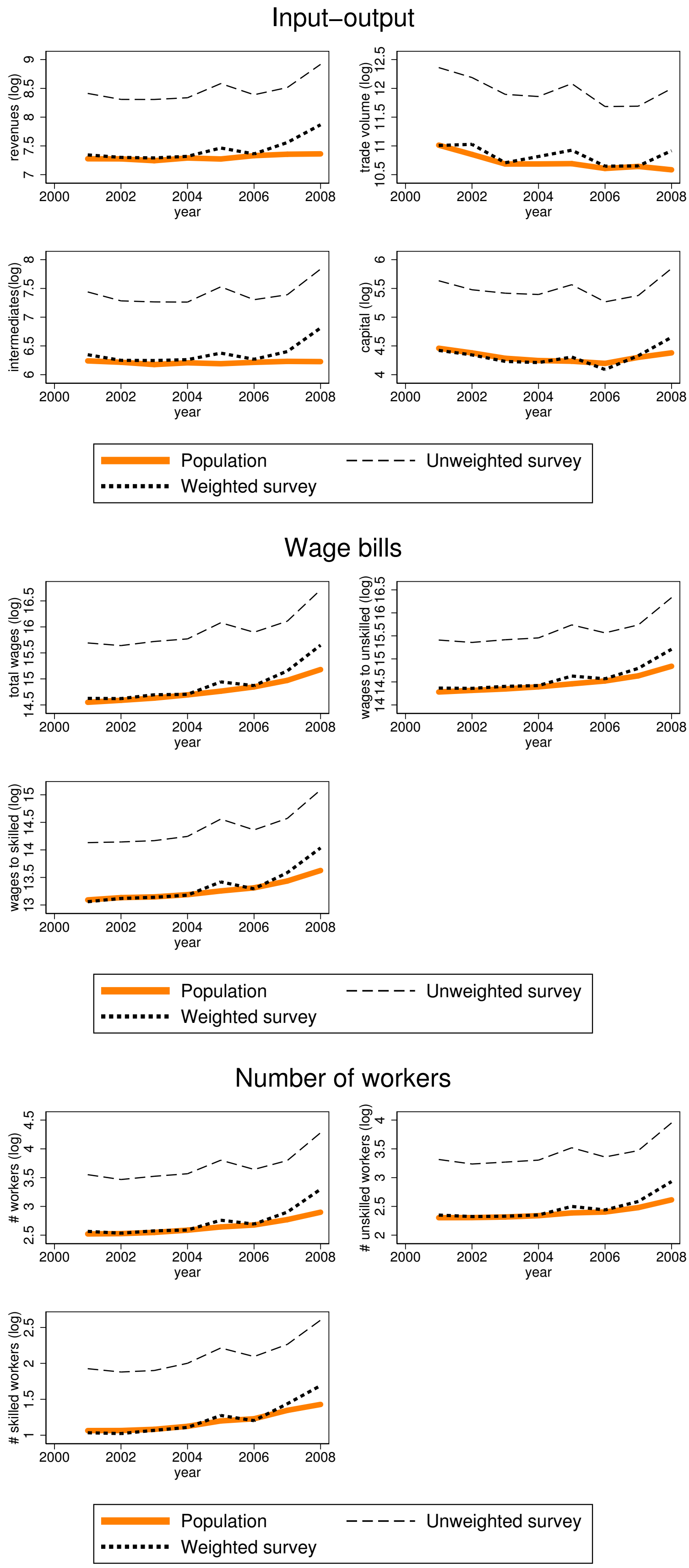
Note: The figure compares the weighted survey sample of joint-stock firms to the population of joint-stock firms. *Source:* Akerman et al. (2015).

Figure C.1. Distribution of firms by industry



Note: The figures compare the weighted survey sample of joint-stock firms to the population of joint-stock firms. Detailed descriptions of the variables are given in Appendix Table C.1. *Source:* Akerman et al. (2015).

Figure C.2. Cross-sectional distribution of key firm variables



Note: The figures compare the weighted survey sample of joint-stock firms to the population of joint-stock firms. Detailed descriptions of the variables are given in Appendix Table C.1. *Source:* Akerman et al. (2015).

Figure C.3. Time trends in key firm variables

Table C.1. Variable definitions

Variable	Description
Firm accounts	Source: The Account Statistics.
Revenues	Total sales by a firm in year t.
Intermediates	Procurement of materials and intermediate inputs of a firm in year t.
Capital	Value of total fixed assets of a firm in year t.
Value added	Sales minus intermediates of a firm in year t.
Industry	4-digit code classifying a firm's main activity in year t according to the Nomenclature of Economic Activities (NACE2002) system.
Municipality	4-digit code for the municipality in which a firm is located in year t.
Internet	Source: The community survey on ICT in firms.
Broadband	Dummy variable for whether a firm has adopted broadband internet (speed at or above 256 kilobits per second) in year t.
Employees	Source: Register of Employers and Employees and the Wage Statistics Survey.
Annual wages	Annual pre-tax wages in year t
Employment status	Dummy variable for whether annual wages exceed the substantial gainful activity threshold in year t (USD 6,850 in 2001), which defines employment in the Social Security System.
Individual characteristics	Source: National Education Database and Central Population Register.
Education level	Years of schooling.
Internet availability	Source: Norwegian Ministry of Government Administration.
Availability rate	Fraction of households in year t in a given municipality for which broadband internet is available, independently of whether they take it up.

Appendix D: Additional figures

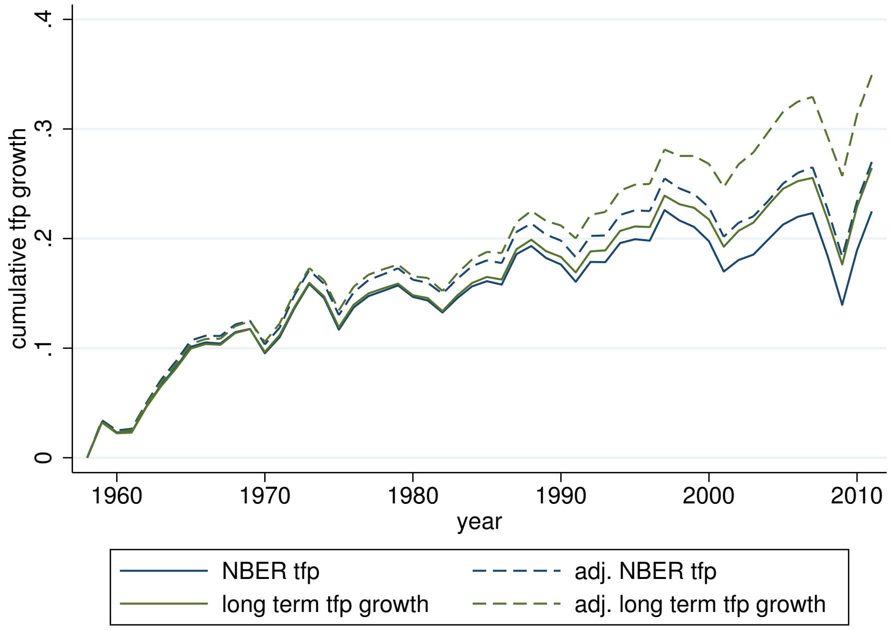


Figure D.1. Unadjusted and adjusted evolution of TFP in NBER Productivity database 1958-2011. Industry weights are based on initial (year 1958) value added.

Note: All data are from the NBER Productivity database and covers 459 1987 Standard Industrial Classification (SIC) 4-digit sectors. The four lines show the evolution of total factor productivity (TFP) over time. The difference between the lines depend on how we calculate expenditure shares in the five-factor production function. The solid blue line uses the methodology used to calculate the TFP variable included in the original data set and which is explained in Bartelsman and Gray (1996). It uses the average of current and lagged expenditure shares for each input factor. The dashed blue line uses instead lagged expenditure shares for each input factor. The solid green line uses the average of current and initial (year 1958) expenditure shares for each input, while the dashed green line uses only initial (year 1958) expenditure shares. Sectors are weighted by their initial (year 1958) value added.

Appendix E: Additional tables

Table E.1. Production function estimates.

Dependent variable:	Log value added			
	OLS		LP	
	Population	Weighted Survey	Population	Weighted Survey
	(1)	(2)	(3)	(4)
Panel A: 1 skill category				
Intercept	1.971	1.841	4.172	3.187
	(0.0408)	(0.0851)	(0.0932)	(0.193)
Log capital	0.0780	0.0821	0.104	0.164
	(0.00297)	(0.00497)	(0.019)	(0.019)
Log labor	0.845	0.856	0.652	0.676
	(0.00351)	(0.00733)	(0.00480)	(0.00934)
Panel B: 2 skill categories				
Intercept	3.461	3.380	5.887	4.695
	(0.0455)	(0.0984)	(0.110)	(0.207)
Log capital	0.0990	0.106	0.107	0.194
	(0.00399)	(0.00599)	(0.022)	(0.019)
Log unskilled	0.558	0.570	0.410	0.429
	(0.0136)	(0.0141)	(0.0108)	(0.0143)
Log skilled	0.198	0.194	0.138	0.135
	(0.0115)	(0.0127)	(0.00913)	(0.0105)
Firm-year observations	149,676	16,744	149,676	16,744

Note: The table reports estimates of Cobb-Douglas production functions, using the population of joint-stock firms over the period 2001-2007. The dependent variable is the log value added in a given year. Columns 2 and 4 restrict the sample to the survey sample. Sampling weights are used in columns 2 and 4 to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The standard errors are clustered at the municipality level and robust to heteroskedasticity. *Source:* Akerman et al. (2015).

Table E.2. First stage regressions using wage bills

Dependent variable:	Internet	Internet × Log capital	Internet × Log unskilled	Internet × Log skilled
	(1)	(2)	(3)	(4)
Log capital	0.014	0.192	0.003	0.005
	(0.010)	(0.033)	(0.014)	(0.016)
Log unskilled	0.043	0.157	0.321	0.121
	(0.022)	(0.042)	(0.047)	(0.033)
Log skilled	0.066	0.088	0.025	0.164
	(0.015)	(0.022)	(0.018)	(0.037)
Availability ×				
Intercept	0.208	0.075	0.100	0.074
	(0.041)	(0.053)	(0.037)	(0.084)
Log capital	-0.004	0.648	-0.002	0.004
	(0.011)	(0.036)	(0.016)	(0.019)
Log unskilled	-0.020	-0.118	0.547	-0.063
	(0.024)	(0.045)	(0.049)	(0.037)
Log skilled	-0.037	-0.087	-0.020	0.607
	(0.017)	(0.023)	(0.019)	(0.043)
Firm-year observations	16,744	16,744	16,744	16,744
F-value (excl. instruments)	30.6	406.5	200.2	102.0

Note: Estimates are based on the first stage regressions in equation (4), using the survey sample of joint-stock firms over the period 2001-2007. Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The table reports the Sanderson-Windmeijer F-statistic. All reported standard errors are clustered at the municipality level. *Source:* Akerman et al. (2015).

Table E.3. First stage regressions using headcount

Dependent variable:	Internet	Internet × Log capital	Internet × Log unskilled	Internet × Log skilled
	(1)	(2)	(3)	(4)
Log capital	0.01	0.187	-0.001	0.001
	(0.010)	(0.030)	(0.011)	(0.008)
Log unskilled	0.022	0.097	0.310	0.048
	(0.022)	(0.042)	(0.038)	(0.018)
Log skilled	0.154	0.282	0.102	0.322
	(0.019)	(0.039)	(0.022)	(0.028)
Availability ×				
Intercept	0.182	0.023	0.026	0.034
	(0.039)	(0.059)	(0.034)	(0.051)
Log capital	0.003	0.648	0.005	0.004
	(0.010)	(0.034)	(0.012)	(0.009)
Log unskilled	-0.006	-0.061	0.569	-0.034
	(0.025)	(0.045)	(0.040)	(0.020)
Log skilled	-0.121	-0.260	-0.088	0.546
	(0.020)	(0.043)	(0.023)	(0.026)
Firm-year observations	16,744	16,744	16,744	16,744
F-value (excl. instruments)	28.8	330.0	270.3	40.4

Note: Estimates are based on the first stage regressions in equation (4), using the survey sample of joint-stock firms over the period 2001-2007. Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The table reports the Sanderson-Windmeijer F-statistic. All reported standard errors are clustered at the municipality level. *Source:* Akerman et al. (2015).

Table E.4. ITT effects on output elasticities using the number of workers.

Dependent variable: Log value added				
	ITT		Sub-sample IV	
	(1)	(2)	(3)	(4)
Log capital	0.115	0.094	0.115	0.085
	(0.004)	(0.005)	(0.004)	(0.008)
Log unskilled	0.523	0.616	0.523	0.657
	(0.020)	(0.013)	(0.021)	(0.026)
Log skilled	0.323	0.253	0.321	0.184
	(0.012)	(0.012)	(0.011)	(0.037)
Broadband ×Intercept	0.009	0.029	0.039	0.139
	(0.011)	(0.016)	(0.050)	(0.091)
Broadband ×Log capital		0.026		0.039
		(0.008)		(0.012)
Broadband ×Log unskilled		-0.112		-0.181
		(0.031)		(0.053)
Broadband ×Log skilled		0.083		0.173
		(0.020)		(0.050)
Firm-year observations	149,676	149,676	149,676	149,676

Note: Estimates are based on the models in equations (14) to (16), using the population of joint-stock firms over the period 2001-2007. Column 1 reports ITT estimates for a production function where output elasticities do not change with the internet, see equation (14). Column 2 reports ITT effects as in equation (17). Columns 3 and 4 report instrumental variable estimates as in equations (16) and (17), respectively. The dependent variable is the log value added in a given year. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The standard errors are clustered at the municipality level and robust to heteroskedasticity. Inputs are deviations from sample means and the coefficients for availability × intercept (adoption × intercept) therefore show the mean effect of internet availability (adoption) on log value added.

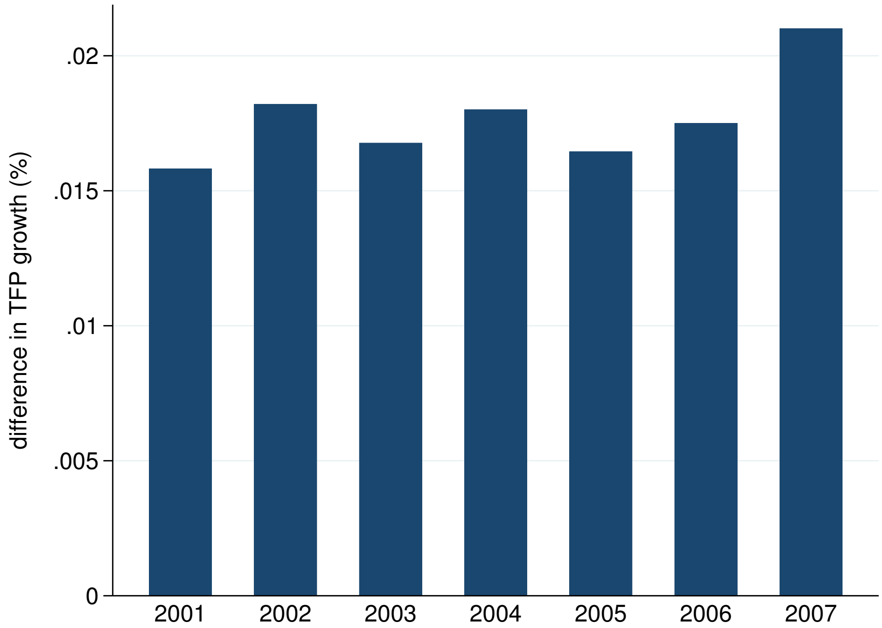
Table E.5. Effects on output elasticities using wage bills, with Levinsohn-Petrin adjustment.

Dependent variable: Log value added				
	ITT (LP)		Sub-sample IV (LP)	
	(1)	(2)	(3)	(4)
Log capital	0.299	0.304	0.298	0.290
	(0.084)	(0.085)	(0.083)	(0.090)
Log unskilled	0.410	0.444	0.410	0.452
	(0.011)	(0.011)	(0.011)	(0.017)
Log skilled	0.138	0.095	0.138	0.077
	(0.009)	(0.005)	(0.009)	(0.010)
Broadband $\times$Intercept	-0.003	0.017	-0.015	0.082
	(0.009)	(0.009)	(0.038)	(0.050)
Broadband $\times$Log capital		-0.002		-0.003
		(0.006)		(0.009)
Broadband $\times$Log unskilled		-0.041		-0.061
		(0.020)		(0.032)
Broadband $\times$Log skilled		0.053		0.091
		(0.013)		(0.023)
Firm-year observations	149,676	149,676	149,676	149,676

Note: Estimates are based on the models in equations (14) to (16), using the population of joint-stock firms over the period 2001-2007. Column 1 reports ITT estimates for a production function where output elasticities do not change with the internet, see equation (14). Column 2 reports ITT effects as in equation (15). Columns 3 and 4 report instrumental variable estimates as in equations (16) and (17). In Column 3 output elasticities do not change with the internet while they do in Column 4. The dependent variable is the log value added in a given year. (Un)Skilled comprises workers with(out) a college degree. All regressions include fixed effects for year, municipality and industry. The standard errors are clustered at the municipality level and robust to heteroskedasticity. Inputs are deviations from sample means and the coefficients for availability $\times$ intercept (adoption $\times$ intercept) therefore show the mean effect of internet availability (adoption) on log value added. We apply the Levinsohn Petrin method in all specifications.

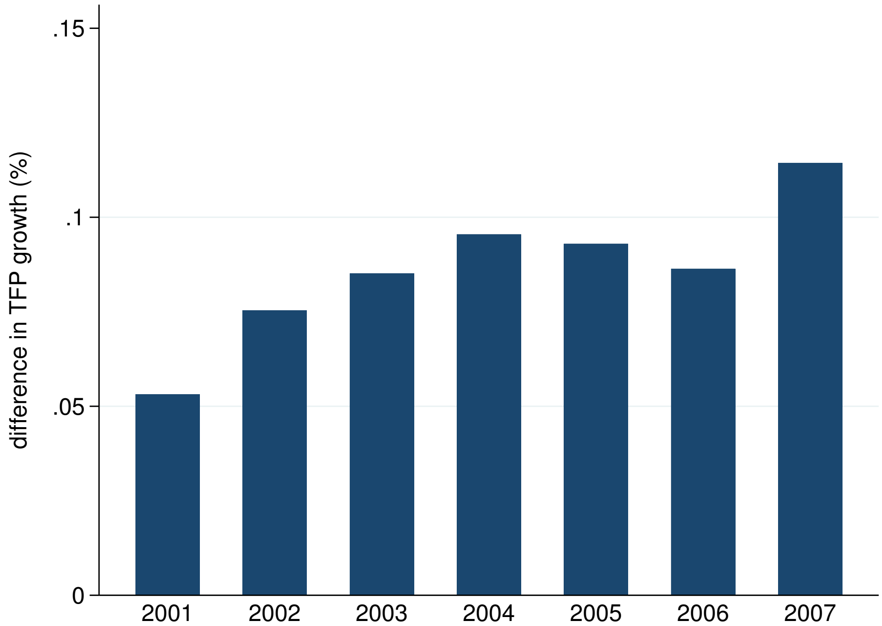
Appendix F: Additional figures

Figure F.1. ITT estimates for the TFP gain from internet availability using the number of workers instead of wage bills.



Note: All data are from the NBER Productivity database and cover 459 1987 Standard Industrial Classification (SIC) 4-digit sectors. The bars show the evolution of the annual difference between the adjusted ($\hat{\theta}_t$) and unadjusted ($\hat{\hat{\theta}}_t$) measures of total factor productivity (TFP) over time. These measures are defined in equations (10) and (11). The difference thus depends on how we calculate expenditure shares in the five-factor production function. Sectors are weighted by their contemporaneous value added. Labor inputs are measured using the number of workers.

Figure F.2. Instrumental variable estimates for the TFP gain from broadband internet adoption using the number of workers instead of wage bills.



Note: All data are from the NBER Productivity database and cover 459 1987 Standard Industrial Classification (SIC) 4-digit sectors. The bars show the evolution of the annual difference between the adjusted ($\hat{\theta}_t$) and unadjusted ($\hat{\hat{\theta}}_t$) measures of total factor productivity (TFP) over time. These measures are defined in equations (10) and (11). The difference thus depends on how we calculate expenditure shares in the five-factor production function. Sectors are weighted by their contemporaneous value added. Labor inputs are measured using the number of workers.