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Firm-Level Technological Change and Skill Demand

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Abstract

We quantify the contribution of firm-level technological change to skill demand and aggregate inequality in the presence of imperfect competition in the labor market. We show that skill-biased technological change increases both the firm-level skill ratio and the skill premium, while other shocks (e.g. firm-specific output demand shocks) cannot explain the increase in both outcomes. We exploit administrative data and a large survey measuring a broad class of firm-level technological changes from Hungary and Norway. We estimate that the aggregate college premium increases by 3.4% in Norway and by 4.9% in Hungary as a result of the skill bias in technological change.

JEL classification

J31, J24, O30, O33

Keywords

skill-biased technological change, innovation, skill premiums, imperfect competition

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1 Introduction

While technological change is the main driver of economic growth, it can also contribute to rising inequality (Acemoglu 2002, Goldin & Katz 2010). In this paper, we study the consequences of technological change on inequality by focusing on the role of firms. Firms play a crucial role in the diffusion of new technologies through the process of innovation (Griliches 1957, Mansfield 1961, Mokyr 2003, Bloom et al. 2016). At the same time, a growing number of studies document that changes in firm-level wage premiums contribute to rising aggregate inequality (Card et al. 2013, Barth et al. 2016, Song et al. 2018). Consequently, it is important to understand how firm-level innovation activities and inequality are interlinked.

Direct evidence on the impact of *firm-level* technological change on skill demand is still scarce, and somewhat inconclusive. For instance, Aghion et al. (2017) find that more R&D-intensive firms pay a lower college premium, while Bøler (2015) finds that higher R&D intensity is associated with an increase in the skill ratio. Moreover, the empirical evidence documenting the relationship between innovation and inequality is nearly exclusively based on easily measurable proxies of innovation, such as R&D and patents, which are unlikely to capture a large part of firm- or economy-level technological change. For instance, in France, one of the most innovative countries in Europe, 34% of innovative firms reported no R&D spending, and 88% innovated without applying for a patent. These numbers are even higher in less innovative countries, where technology adoption plays a larger role, such as Hungary (Appendix Figure B.3). This paper complements the existing literature by utilizing a large-scale panel survey on firms' innovation activities that allows us to observe when firms significantly alter their production functions. We identify changes in production functions from survey questions about the introduction of production processes, products or management methods that are new to the firm, but not necessarily new to the market or the world. The relevance of this measure of technological change, for the European countries, is demonstrated by its strong correlation with country-level college premiums (see Figure 1).[1]

We study the impact of firm-level technological change on skill demand in a framework that combines the standard CES production function with imperfect competition in the labor market (see e.g. Card et al. 2018, Manning 2013). In our framework, firms do not take wages as given. Instead, they actively set them, taking into account that higher wages are needed to attract more workers. In response to a skill-biased technological change of the production function, firms want to increase their skill ratio, and so they need to raise the relative wage of their skilled workers. The result is an increase in both the firm-level skill ratio and the skill premium.

We also show that firm's optimization implies that the skill ratio and skill premium will move in opposite directions following other shocks to the firm, such as firm-specific output demand shocks or labor supply shocks (e.g. due to changes in amenities or local labor supply). Intuitively, these shocks do not shift the firm-level relative skill demand curve, but affect which point is chosen on the curve. A downward-sloping relative skill demand curve implies that these shocks either increase the

[1] In Appendix Section A.1 we provide further details about this relationship, and show that the positive correlation is robust to controlling for the share of R&D conducting firms, the college ratio or GDP/capita. In Appendix Section A.2, we also provide some additional evidence by exploiting country-industry level variation in innovation activities.

skill ratio and decrease the skill premium or *vice versa*, but they cannot lead to an increase in both outcomes. Skill-biased technological change, on the other hand, shifts out the firm-level relative skill demand curve, and leads to an increase in both outcomes. Therefore, studying the changes both in the skill ratio and the skill premium of firms following a technological change allows us to identify whether the change is skill biased. This result holds even if the event of applying a new technology coincides with favorable output demand shocks or changing labor market conditions. This insight is similar to the one provided by Katz & Murphy (1992) in relation to the U.S. wage structure over the 80s, where they argued that a positive relationship between relative skill prices and quantities suggests that technological change is skill biased. In this paper, we show that the same reasoning can be applied at the firm-level, when there is imperfect competition in the labor markets. Furthermore, we demonstrate that our results hold under various wage setting protocols such as union bargaining (e.g. Van Reenen 1996) and rent sharing (e.g. Kline et al. 2019).

We apply our framework to quantify the extent to which technological change is skill biased. Using the FOCs derived from the firm's problem, we can infer the change in the skill bias term in the production function from the sum of the percentage changes in the skill ratio and the skill premium.[2] Furthermore, as we discussed before, shocks coinciding with the technological change will move the skill premium and the skill ratio in opposite directions, implying that their effects will be cancelled out when taking the sum. Therefore, the assumptions required to identify the extent to which a technological change is skill biased are weaker than the assumptions needed to identify the impact of innovation on firm-level productivity. For instance, a key concern for identifying the latter is that innovative firms might foresee–and start innovating in response to–some positive demand shocks. This would bias the estimates of the impact of innovation on firm productivity, since the increase in firm output might simply reflect the demand shocks and not the increase in productivity *per se*. In contrast, our estimates of the degree to which technological change is skill biased are identified from the changes in relative input demand, which is not affected by the changes in output caused by positive demand shocks. This is a key insight, which allows us to identify skill bias for various forms of technological change. Nevertheless, in Section 5.4 we also corroborate our key findings by documenting the changes in skill demand in response to innovation activities induced by a quasi-exogenous change in an R&D tax credit policy in Norway.

Guided by our framework, we investigate empirically whether innovation activities lead to an increase in the skill premium and the skill ratio at the firm level. We use exceptionally rich micro data from Norway combined with the information available from the European Community Innovation Survey (CIS), which allows us to study comprehensive measures of firm-level technological changes. We interpret innovation reported in the survey as a change in the firm's production function, and, therefore, we use innovation and technological change interchangeably. Similarly to Caroli & Van Reenen (2001), who study the effect of innovation on skill demand in French and British firms, we implement a difference-in-differences identification strategy. Our richer data, however, allows us to exploit within-firm changes in innovation and control for changes in firms' worker composition.

[2] More precisely, the skill bias parameter is the sum of the percentage change in the skill premium and the percentage change in the skill ratio divided by the parameter of the CES production function capturing the elasticity of substitution between high- and low-skilled workers. While we do not directly estimate the elasticity of substitution in our empirical implementation, we show that our results are robust to applying a wide range of existing estimates in the literature.

We start our analysis by studying the changes in the college ratio and college premium at firms implementing new technologies relative to firms that do not implement new technologies during the same period. The empirical strategy, therefore, controls for unobserved (time-invariant) firm differences in college premium and ratio, focusing solely on changes in these outcomes. In our benchmark firm-level analysis we find that the skill ratio increases by 1.8% (s.e. 0.8%) and the skill premium by 0.5% (s.e. 0.4%) following innovation. The increase in the skill premium is larger for incumbent workers (0.7%, s.e. 0.4%), suggesting that the firms' composition of workers also changes. To control for this compositional change, we also study the change in the firm-level skill premium in worker-level regressions, where, we look at changes in workers' wages at firms that change their technologies (relative to firms that do not). By focusing on wage changes we filter out unobserved worker skills. We find that once we control for changes in workers' skill composition, the college premium increases by 1.1% (s.e. 0.5%). The joint increase in college ratio and college premium indicates that technological change is associated with an increase in skill demand.

Our estimates of the impact of innovation on the skill premium are robust to including a variety of controls for market-specific shocks that could potentially be correlated with firm-level innovation. In particular, we include local labor market-specific time effects and industry-specific time effects in our regressions. Furthermore, the estimates are not sensitive to alternative timing assumptions, and they are also robust to controlling for domestic or international outsourcing, and to including firm fixed effects in the regressions.

We also show that the increase in the skill premium persists in the medium term, and is not driven by an increase in amenities (proxied by non-cash benefits) or longer contracted hours. Moreover, the wage change arises for both new entrants and incumbent workers, which is consistent with the wage-setting protocol assumed in our benchmark framework.[3] Our results, therefore, do not just reflect a short-term rent sharing benefiting incumbent college workers more than non-college workers, but a longer-term shift in wages affecting both incumbent and new entrant college workers.

Interestingly, higher-intensity innovation, measured by higher R&D expenditure per worker, leads to a larger increase in the college premium compared to lower innovation spending. We also find that the increase in the skill premium emerges after innovation, and is not driven by pre-innovation wage premium differences. We also study the impact of the implementing new technologies among firms that had not innovated in the past. We implement an event study analysis for these firms and show that following innovation we see an increase in both the college premium and the college ratio while we do not find an evidence for pre-existing trends in these outcomes.

A key testable prediction of our model is that the relative magnitude of the increase in the college premium and the college ratio depends on firms' wage-setting power. In labor markets with limited wage setting power, firm-level wages should be less responsive, and employment more responsive, to skill-biased technological changes. Our model also suggests that firms' wage-setting power should be more limited in areas with high firm density compared to in areas with low firm density.[4] We assess

[3] In our benchmark framework firms post wages. Lachowska et al. (2021) shows that wage posting is the primary determinant of wage setting in the US context.

[4] This comes from the observation that a firm's wage-setting power depends on the dispersion of workers' idiosyncratic preferences for working at particular firms, and this dispersion is likely to be larger if commuting times between firms

this prediction empirically, and show that the skill ratio is relatively more responsive in local areas with higher firm density (more limited wage-setting power) compared to areas with low firm density.

In addition to the evidence from Norway, we also study the impact of technological change in Hungary. However, due to data limitations, we there focus solely on firm-level specifications. Comparing the results from these economies is interesting as Norway is an R&D-based economy where high-novelty innovation dominates, while in Hungary relatively few firms innovate, and if they do, they often adopt technologies developed elsewhere. This allows us to compare two very different innovation systems. In Hungary we find a larger change in skill demand: the college ratio increases by 3.7% (s.e. 1.6%) and the college premium by 1.4% (s.e. 0.7%) following technological change.

Overall, our findings show that technological change tends to be skill biased both in Norway and Hungary. We also quantify the contribution of technological progress to the change in the aggregate college premium. First, we perform an accounting exercise: we decompose the economy-wide skill premium into two components, one coming from the skill premium paid by innovative firms, and one coming from non-innovative firms. Next, we show that firm-level innovation activities contribute to aggregate inequality through two channels: 1) skilled workers moving to innovative firms (which may pay higher wages), and 2) innovative firms raising the skill premium following innovation. We quantify both of these terms using our estimates and find that the firm-level application of new technologies increased the aggregate college premium by 3.4 percent in Norway and 4.9 percent in Hungary over a 10-year period.

Our estimates on the contribution of technological change to the aggregate college premium shed new light on the recent decline in the college-to-non-college wage premium observed in many developed countries.[5] The drop in college premium might reflect that technological change, which was favoring college-educated workers from the 80s to the early 2000s (Katz & Murphy 1992), altered its character, and is now favoring other groups in the economy. At the same time, the recent fall in the aggregate college premium has coincided with a significant expansion in higher education in these countries, potentially obscuring a substantial contribution of technology to inequality. Our estimates imply that technological change remains a key driver of aggregate trends in inequality, despite the stagnation of the aggregate college premium.

Finally, we assess whether there is heterogeneity in the contribution of different types of innovation to inequality. A common pattern in both countries is that both innovation with technical aspects (product or process innovation) and organizational changes are skill biased. Nevertheless, the bulk of the contribution to aggregate inequality comes from firms combining technical with organizational changes and conducting R&D. A difference between the two countries is that the relative importance of R&D-based innovation is larger in Norway, reflecting that it is closer to the technology frontier compared to Hungary, where technology adoption plays a larger role.

Our paper relates to several strands of the literature. First, we contribute to the large literature

are longer due to geographical dispersion.

[5] For instance, the college premium decreased by 11 percentage points in Norway between 2005 and 2015, and by 15 percentage points in Hungary between 2000 and 2015. The college wage premium also flattened out in the United Kingdom (see Blundell et al. 2022) and in the United States (see e.g. Autor 2019, Goldin et al. 2020)

that links the evolution of wage inequality to skill-biased technological change for the US (e.g. Katz & Murphy 1992, Juhn et al. 1993, Autor et al. 1998, Acemoglu 2002, Goldin & Katz 2010, Acemoglu & Autor 2011a) and for a broader set of countries (e.g. Machin & Van Reenen 1998, Michaels et al. 2014). Instead of inferring the change in skill bias from aggregate trends in the relative skill ratio and skill premium, we exploit the fact that most technologies diffuse slowly and that firms play a crucial role in this process (Griliches 1957). We directly capture firm-level technological change, providing a more comprehensive measure that extends beyond the traditional reliance on R&D and patents commonly used in the literature.

By focusing on firm-level changes in technology and applying a difference-in-differences strategy we can net out the effect of changes in institutions (Bound & Johnson 1992, DiNardo et al. 1996, Stansbury & Summers 2020) and market power (De Loecker et al. 2020), and focus solely on the contribution of technological change. Our strategy also differs from Haanwinckel (2018) who, similarly to us, recognizes the crucial role of firms, but instead of directly studying changes in skill demand at the firm level, builds a model of tasks within firms and infers technological change from aggregate changes in worker-firm sorting and in the distribution of firm-level skill premiums.[6] Another insight we add to the literature is that in the presence of imperfect competition in the labor market, skill-biased technological change will increase the within-skill, across-firm inequality, providing an alternative channel to explain the increasing within skill-inequality documented in the literature (see e.g. Juhn et al. 1993, DiNardo et al. 1996, Acemoglu 2002).

Our paper also contributes to the literature that directly studies technological change (or innovation) and skill demand. Many papers in the literature focus on specific technologies, such as the steam engine (Chin et al. 2006), computers (see, e.g. Krueger 1993, DiNardo & Pischke 1997, Dunne et al. 2004, Beaudry et al. 2010), broadband internet (e.g. Akerman et al. 2015, Hjort & Poulsen 2019), robots (e.g. Graetz & Michaels 2018), artificial intelligence (e.g. Frank et al. 2019), automation (Doms et al. 1997, Acemoglu et al. 2020) or high-novelty innovation, such as R&D (Bøler 2015, Aghion et al. 2017) and patents (Kline et al. 2019). In this paper, we consider a much wider range of innovation activities that is likely to capture most forms of technological change taking place in the economy, including adoption of technologies by firms far from the technology frontier. Moreover, we take a step further and also quantify the contribution of firm-level technological changes to aggregate inequality. Inferring macro-level labor demand shifts from specific micro-level technological changes captures how technological advancements spread throughout the economy. This direct assessment of aggregate changes in labor demand improves upon the standard Katz & Murphy (1992) framework by eliminating the treatment of technological changes as residuals.

Focusing on a wider range of innovation activities is not unprecedented in the literature (Caroli & Van Reenen 2001, Bresnahan et al. 2002, Abowd et al. 2007). Nevertheless, these studies usually rely on relatively small cross-sectional surveys that measure specific innovation activities, and assume perfect competition in the labor market. In contrast, our data includes five waves of a large-scale innovation survey, where each wave covers a large number of firms (around 5,000), and provides

[6] Haanwinckel (2018) introduces imperfect competition in the labor market into a task-based framework, while here we apply the standard CES production function. In principle it is possible to derive estimable reduced form equations between changes in task content and firm-level technological change, but such an analysis is beyond the scope of our paper. Nevertheless, in Section 5 we empirically assess the change in task content.

consistent measures for various types of innovation activities over time (and across countries). The panel dimension of our survey also allows us to account for compositional changes following innovation, which leaves us with more credible estimates of the effect of innovation on the skill premium. Finally, our paper also makes a methodological advancement relative to these papers by highlighting that simply focusing on the skill ratio to assess the skill-bias of technological change is insufficient in the presence of imperfect competition in the labor market. The changes in the skill ratio can be confounded by shocks to labor supply, or even by output demand shocks, if firms' wage-setting power differs between low- and high-skilled workers. These issues are not resolved with implementing instrumental variable strategies.[7] Our approach instead infers the skill bias of new technologies from the firms' first order conditions, combined with estimates on the changes in firm-level skill premium and skill ratio. While this approach applies the canonical CES production function and imposes some structure on firm behavior, it allows us to infer the skill bias of technological change both in the presence of imperfect competition in the labor market, as well as if the technological change coincides with other shocks, such as changes in the output demand or changes in local labor supply.

Our paper also relates to a growing number of papers studying responses to firm-level shocks with imperfect competition in the labor markets (e.g. Card et al. 2018, Garin & Silvério 2018, Kroft et al. 2020, Lamadon et al. 2022, Carbonnier et al. 2022). The fact that we find an increase in the firm-level skill premium following innovation is consistent with some wage-setting power of firms. The implied firm-specific labor supply elasticity is between two to three, which is consistent with recent quasi-experimental estimates from the literature (e.g. Dube et al. 2017, Caldwell & Oehlsen 2018, Cho 2018, Kroft et al. 2020, Bassier et al. 2020). We also demonstrate that, consistent with the predictions of the model, the implied firm-specific elasticity is tightly linked to firm density in the local labor market. These geographic differences also suggest that technological change can affect rural and urban labor markets differently.

Finally, we contribute to the literature on the heterogeneity of innovation. One strand of this literature quantifies and compares innovation with technological aspects and organizational changes. The seminal paper of Caroli & Van Reenen (2001) shows that both types of innovations are skill biased, while Evangelista & Vezzani (2010) focus on productivity and show that firms that conduct a broader range of innovation activities—for example, combining technological with organizational innovation—have a higher performance. Another dimension, the distinction between R&D and non-R&D innovation, was emphasized by Lopez-Rodriguez & Martinez-Lopez (2017), who show that non-R&D innovation also contributes to productivity. Our contribution is that we compare the skill bias of all these different types of innovation and quantify their aggregate effect on the skill premium. Our results show that all these different types of innovation are skill biased to a certain extent, but their absolute and relative contribution depend on the environments in which firms operate.

In what follows, Section 2 outlines the relationship between technological change, skill demand and relative wages of skilled and non-skilled workers when there is imperfect competition in the labor markets, and shows how to infer skill bias using the firm's first order conditions. Section 3 describes our data sources and the institutional context in Norway. Section 4 discusses our empirical strategy to

[7] If firms' wage-setting power differs between skilled and unskilled workers, even a quasi-exogenous increase in Hicks-neutral productivity can increase the skill ratio even if there is no skill bias (see Proposition 1).

estimate the change in college ratio and college premium following innovation. The results for Norway are shown in Section 5, while we present the results for Hungary in Section 6. We quantify the aggregate implication of changes in firm-level skill demand in Section 7. Finally, Section 8 concludes.

2 Conceptual framework

We study the impact of firm-level technological change on the skill premium and the skill ratio. Motivated by our empirical findings showing that firm-level technological change has an impact on firm-level wages, we endow firms with some wage-setting power. This wage-setting power arises from worker heterogeneity in their valuation of jobs due to non-wage related characteristics, as in Card et al. (2018). We start by describing the firm's problem before we examine how firm-level technological change affects employment and wages.

We assume that there are J firms, each using two inputs in production at time t: high-skilled labor (H_{jt}) and low-skilled labor (L_{jt}).[8] We use the terms skills and education interchangeably, as we proxy skills by education in the empirical section. Firms produce output (Q_{jt}) with the following CES technology in every period:

$$Q_{jt} = A_{jt}\left[\theta_{jt}H_{jt}^{\frac{\sigma-1}{\sigma}} + (1-\theta_{jt})L_{jt}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \quad \sigma \geq 0 \tag{1}$$

where A_{jt} is the Hicks-neutral productivity term, while θ_{jt} is the skill bias productivity term measuring the extent to which the technology used by the firm is skill biased.[9] Importantly, technological change affects one or both of these productivity terms. Extending this production function to allow for capital or other intermediate inputs is a relatively straightforward exercise, as we demonstrate in Appendix D.[10]

Following Violante (2008), we define skill-biased technological change as an increase in the marginal rate of transformation (MRT) between skilled and unskilled workers. In our production function, an increase in θ will always increase the MRT, and therefore it represents skill-biased

[8] In our conceptual framework, we abstract away from worker heterogeneity within a skill group. However, while it would complicate the discussion, it can be shown that our results would hold in the presence of worker heterogeneity, conditional on netting out changes in firms' worker composition. We carefully deal with worker heterogeneity within skill groups in our empirical implementation (see Section 4 for more details).

[9] Given the wide range of technological changes captured by our measures, we remain agnostic about the exact mechanisms driving the skill bias. The increase in skill demand can come from capital-skill complementary (see e.g. Krusell et al. 2000), from better ability of skilled workers to deal with new technologies (see e.g. Nelson & Phelps 1966), or from "flatter" organizations (see e.g. Milgrom & Roberts 1990).

[10] We add capital by applying a nested CES structure. However, the results can be generalized to any production function of the following structure: $F(Q_{jt}, K_{jt})$, where Q_{jt} comes from equation (1) and K_{jt} denotes capital. Note that such a production function rules out that capital is more complementary to high-skilled than to low-skilled workers (see e.g. Krusell et al. 2000). We consider such complementarity between capital and skills as one formalization of skill-biased technological change (Violante 2008), which we approximate with a change in θ_{jt}.

technological change.[11] Firms maximize profit given their production functions:

$$\pi_{jt}(A_{jt}, \theta_{jt}) = \max_{w_{L_{jt}}, w_{H_{jt}}, p_{jt}} p_{jt}Q_{jt} - H_{jt}(w_{H_{jt}})w_{H_{jt}} - L_{jt}(w_{L_{jt}})w_{L_{jt}}, \tag{2}$$

and the following constraints:

$$Q_{jt} = A_{jt}\left[\theta_{jt}H_{jt}^{\frac{\sigma-1}{\sigma}} + (1-\theta_{jt})L_{jt}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{3a}$$

$$\ln p_{jt} = \frac{1}{\rho}\ln\kappa_{jt} - \frac{1}{\rho}\ln Q_{jt} + \frac{\rho-1}{\rho}\ln p_t + \frac{1}{\rho}\ln I_t, \tag{3b}$$

$$\ln L_{jt}(w_{Ljt}) = \ln(L_t\mathit{\Lambda}_{Lt}) + \beta\ln w_{Ljt} + \ln a_{Ljt}, \tag{3c}$$

$$\ln H_{jt}(w_{Hjt}) = \ln(H_t\mathit{\Lambda}_{Ht}) + \beta\ln w_{Hjt} + \ln a_{Hjt}. \tag{3d}$$

Constraint (3a) simply restates the production function defined above. Constraint (3b) represents a downward-sloping output demand function that can be micro founded using a monopolistic competition framework (see Appendix D). In this constraint, p_{jt} is the price of the firm's product, ρ is the elasticity of demand, κ_{jt} captures firm-specific demand shifters, p_t denotes the price index in firm j's market at time t, while I_t is the income spent on total consumption in firm j's market in period t.[12]

The third (3c) and fourth (3d) constraints represent the upward-sloping labor supply functions firms face. These firm-level labor supply curves can be micro founded using a discrete choice framework as in Card et al. (2018). In this framework, each firm posts a pair of skill-specific wages, $\{w_{Ljt}, w_{Hjt}\}$, that all workers costlessly observe. For workers in skill group $S \in \{L, H\}$, the indirect utility of working at firm j is:

$$u_{iSjt} = \ln(\tau w_{Sjt}^{\lambda}) + \ln a_{Sjt} + \epsilon_{iSjt}, \tag{4}$$

where τ and λ approximate the income tax system (see Lamadon et al. 2022), $\ln a_{Sjt}$ is a firm-specific amenity that is common to all workers in group S, while ϵ_{iSjt} captures idiosyncratic preferences of worker i for working at firm j, arising from commuting distance, work flexibility and so on. We assume that the ϵ_{iSjt} are independent draws from a type-I Extreme Value distribution with a dispersion parameter ϕ. As demonstrated by Card et al. (2018), under these assumptions, the approximate firm-specific upward-sloping labor supply functions lead to equations (3c) and (3d), where the terms $\ln(L_t\mathit{\Lambda}_{Lt})$ and $\ln(H_t\mathit{\Lambda}_{Ht})$ represent local labor market conditions. Importantly, the firm-specific labor supply elasticity, $\beta = \lambda/\phi$, is decreasing in the dispersion of worker preferences: the more heterogeneous the workers' preferences, the more firms need to raise wages to attract more workers. A special case of this model is a perfectly competitive labor market, where the dispersion of

[11] An alternative way to write the production function is as follows:

$$Q_{jt} = \left[(A_{Hjt}H_{jt})^{\frac{\sigma-1}{\sigma}} + (A_{Ljt}L_{jt})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

In our case, $A_{jt} = \left(A_{Hjt}^{\frac{\sigma-1}{\sigma}} + A_{Ljt}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ and $\theta = (A_{Hjt}/A_{jt})^{\frac{\sigma-1}{\sigma}}$. Note that an increase in A_{Hjt}/A_{Ljt} in this formulation only favors skilled workers if $\sigma > 1$. When $\sigma < 1$, a decrease in A_{Hjt}/A_{Ljt} leads to skill-biased technological change. In our formulation of the production function, θ will increase in both these cases.

[12] When different firms serve different markets, p_t and I_t are market-specific. However, to make the notation simpler, we suppress this index in our derivations.

workers' idiosyncratic preferences converges to zero—meaning that all workplaces are homogeneous from the workers' perspectives. In this case, β is infinite and so firms face a perfectly elastic labor supply function.

In this framework equilibrium is defined as workers' decision of which firm to choose, given firm characteristics, the share of high-skilled workers and preference parameters. In equilibrium, workers maximize their utility when choosing firms, firms maximize profits when setting wages for low- and high-skilled workers, and market-level prices and wages reflect the equality of supply and demand on the two labor markets and the product markets. We discuss the equilibrium definition more formally in Definition 1 of Appendix Appendix D.

The first order conditions from the firm's profit maximization problem lead to the following relationship between the relative wages and skill ratio at the firm level:

$$\ln \frac{w_{H_{jt}}}{w_{L_{jt}}} = \ln \frac{\theta_{jt}}{1-\theta_{jt}} - \frac{1}{\sigma} \ln \frac{H_{jt}}{L_{jt}}, \tag{5}$$

where $\frac{\theta_{jt}}{1-\theta_{jt}}$ measures the extent to which technology is tilted toward high-skilled labor. This equation resembles the key equation describing the relationship between relative demand and relative wages of college and non-college workers in the skill-biased technological change literature (see e.g. Katz & Murphy 1992, Violante 2008, Goldin & Katz 2010). In our framework, however, the relationship emerges at the firm level: linking the firm-specific skill premium and ratio.

Since $\sigma \geq 0$, equation (5) highlights that relative wages and relative skill ratios are negatively related in absence of changes in skill bias, θ_{jt}. Intuitively, the negative relationship is driven by a firm-level "law of demand": if the relative price of an input increases, firms will substitute away from that input. Even though firm-level relative wages and employment both change endogenously in a setting where labor markets are non-competitive, they still remain negatively related in the absence of skill-biased change. Consequently, if we observe that relative skill ratios and relative wages are both positively affected by technological change, we can infer that the technological change is skill biased.

The derived equation (5) together with the constraints given by equations (3a)-(3d) imply that

$$\ln \frac{w_{Hjt}}{w_{Ljt}} = \frac{\sigma}{\sigma+\beta} \ln \frac{\theta_{jt}}{1-\theta_{jt}} - \frac{1}{\sigma+\beta} \ln \frac{H_t \mathit{\Lambda}_{Ht}}{L_t \mathit{\Lambda}_{Lt}} - \frac{1}{\sigma+\beta} \ln \frac{a_{Hjt}}{a_{Ljt}}, \tag{6a}$$

$$\ln \frac{H_{jt}}{L_{jt}} = \frac{\beta\sigma}{\sigma+\beta} \ln \frac{\theta_{jt}}{1-\theta_{jt}} + \frac{\sigma}{\sigma+\beta} \ln \frac{H_t \mathit{\Lambda}_{Ht}}{L_t \mathit{\Lambda}_{Lt}} + \frac{\sigma}{\sigma+\beta} \ln \frac{a_{Hjt}}{a_{Ljt}}. \tag{6b}$$

These equations highlight that the relative skill and wage ratios do not depend on the Hicks-neutral part of the production function (A_{jt}) or the various (firm-specific) output demand shocks (e.g. κ_{jt}). Instead, these relative terms depend on the extent to which the technology relies on skilled workers (θ_{jt}), on the relative firm-level amenities (a_{Hjt}/a_{Ljt}), and on the market-level labor supply shocks in the two markets ($H_t \mathit{\Lambda}_{Ht}/L_t \mathit{\Lambda}_{Lt}$). In particular, the changes in the skill premium and the skill share depend on θ_{jt} in the following way:

$$\underbrace{\Delta \ln \frac{w_{Hjt}}{w_{Ljt}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \frac{\sigma}{\sigma+\beta} \underbrace{\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}}_{\substack{\text{Change in}\\ \text{skill bias}}} - \frac{1}{\sigma+\beta} \underbrace{\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}}_{\substack{\text{Change in}\\ \text{market-level}\\ \text{labor supply}}} - \frac{1}{\sigma+\beta} \underbrace{\Delta \ln \frac{a_{Hjt}}{a_{Ljt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{amenities}}}, \tag{7a}$$

$$\underbrace{\Delta \ln \frac{H_{jt}}{L_{jt}}}_{\substack{\text{Change in}\\ \text{skill ratio}}} = \frac{\beta\sigma}{\sigma+\beta} \underbrace{\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}}_{\substack{\text{Change in}\\ \text{skill bias}}} + \frac{\sigma}{\sigma+\beta} \underbrace{\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}}_{\substack{\text{Change in}\\ \text{market-level}\\ \text{labor supply}}} + \frac{\sigma}{\sigma+\beta} \underbrace{\Delta \ln \frac{a_{Hjt}}{a_{Ljt}}}_{\substack{\text{Change in}\\ \text{relative}\\ \text{amenities}}}, \tag{7b}$$

where Δ denotes the change between before and after innovation.

These equations motivate our difference-in-differences style regressions described in detail in Section 4. We study the changes in the skill premium and the skill ratio following innovation and compare it to the changes in non-innovative firms. According to these equations, skill-biased innovation—an increase in θ—positively (or non-negatively if $\beta = \infty$) affects both the skill ratio and the skill premium. At the same time, other firm- or market-specific shocks either have no effect on the skill ratio (e.g. a Hicks-neutral increase in the production function, A_{jt}, or a change in output demand, κ_{jt}) or have an opposite effect on the skill ratio and the skill premium (e.g. a relative change in labor supply, $H_t \Lambda_{Ht}/L_t \Lambda_{Lt}$, or a relative change in amenities, a_{Hjt}/a_{Ljt}).

It is worth emphasizing that even if technological change is initiated in response to some firm-specific demand shock (e.g. a change in κ_{jt}), such shocks do not affect the skill ratio and skill premium (as they do not appear in equations (7a) and (7b)). We hence avoid the well-known issue of separating the effect of innovation on TFP (or A_{jt}) from output demand shocks that coincide with it (see e.g. Crépon et al. 1998, Griffith et al. 2006). Still, to make sure that our results do not simply reflect the endogenous nature of firm-level innovation, we present evidence from Norway where we exploit an exogenous change in incentives to invest in innovation (see Section 5.4).

The equations also highlight the importance of identifying skill-biased technological change from changes in both the skill ratio and the skill premium. Inferring whether a technological change is skill biased solely from a change in the skill ratio requires dealing with potential changes in relative labor supply and changes in relative amenities.[13] For instance, an increase in the skill ratio might simply reflect that firms invest more in innovation if they expect a change in the relative supply of high- and low-skilled workers, or a change in relative amenities. To identify skill biasedness from the skill ratio alone, it is necessary to control for a number of hard-to-observe factors, or to exploit changes in innovation activities that are orthogonal to potential confounders. In fact, as we will see later, even when studying an exogenous technology shifter, focusing solely on skill ratio can be problematic whenever the firm-specific labor supply elasticities differ by skill groups (i.e. $\beta_H \neq \beta_L$). In this case Hicks-neutral shocks can increase the skill ratio, while they cannot simultaneously increase the skill

[13] As we discuss later (see Proposition 1), whenever the firm-specific labor supply elasticities differ by skill groups, even firm-specific demand shocks can generate an increase in skill ratio. Such shocks cannot, on the other hand, explain an increase in both the skill ratio and the skill premium.

ratio and the skill premium (see Proposition 1).

A special case in our model is when labor markets are competitive (where β is infinite). In this case, as equations (6a) and (6b) highlight, a skill-biased change, $\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}$, only affects the skill ratio, and not the skill premium. So in perfectly competitive labor markets it is indeed sufficient to study changes in the skill ratio. Nevertheless, even in this case, documenting the lack of change in the skill premium can be used to rule out the presence of other contaminating shocks that could potentially affect the skill ratio. For instance, as equations (6a) and (6b) show, the change in relative supply of skilled workers can lead to an increase in the skill ratio, only if there is a simultaneous decrease in the skill premium.[14]

Perfectly competitive market is an extreme case of our framework. Still, even if β is less than infinite, a more elastic firm-specific labor supply elasticity (β is higher), implies a smaller change in the skill premium, and a larger change in the skill ratio in response to changes in the skill bias (θ) (equations (7a) and (7b)). The firm-specific labor supply elasticity, β, depends on the dispersion in the idiosyncratic preferences of individuals working at a particular firm (see equation (4) and the subsequent discussion). This dispersion is likely to depend on the average distance between different workplaces within the labor market, as this gives rise to differences in commuting time. Firm density, à la Ciccone & Hall (1996), is therefore a good proxy for such dispersion. In line with this prediction, we show in Section 5.2 that in local areas with high firm density the increase in the skill premium is smaller, while the increase in the skill ratio is larger following innovation.

The above derivation assumes that workers' qualities are constant within skill groups. Yet, a potential reason why relative wages change following innovation is that firms may hire higher-quality workers within a given skill group. In the extreme case, innovation only affects worker sorting to firms, and not the wage premium paid to equally productive workers. As a result, it is crucial to make sure that results are not driven by firm-level changes in worker composition following innovation. To do this, we show in Section 5.2 that changes in the wage premium are also present for incumbent workers who worked at the firm before innovation (as well as for new entrants). Moreover, we exploit our particularly rich data from Norway to control for unobservable worker characteristics. We discuss this in more detail in Section 4.

Our framework can further be used to quantify the extent of the skill-biased technological change. Firms' optimal choice of skill ratio and skill premium implies equation (5). The change in skill bias is given by:

$$\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}} = \Delta \ln \frac{w_{H_{jt}}}{w_{L_{jt}}} + \frac{1}{\sigma} \Delta \ln \frac{H_{jt}}{L_{jt}}. \tag{8}$$

This equation implies that the change in the skill premium plus the change in skill ratio divided by

[14] Caroli & Van Reenen (2001) propose to apply a one-equation empirical strategy. They assume a translog production function, which is a second order approximation of our CES production function around $\sigma = 1$. Whenever $\sigma = 1$ (Cobb-Douglas production function), the change in the wage share, which can be calculated by adding up equations (7a) and (7b), will be equal to the change in skill bias:

$$\Delta \text{wage share of } \mathrm{H}_{jt} = \Delta \ln \frac{w_{H_{jt}}}{w_{L_{jt}}} + \Delta \ln \frac{H_{jt}}{L_{jt}} = \Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}.$$

However, the change in the share of high-skilled wages does not capture the change in skill bias whenever $\sigma \neq 1$.

σ gives us the change in skill bias. Notice that the changes in the skill premium and skill ratio in the formula contain the effects of all potential shocks that coincide with a technological change, such as output demand shocks, κ, local labor supply shocks, $H_t \Lambda_{Ht}/L_t \Lambda_{Lt}$, or relative change in amenities, a_{Hjt}/a_{Ljt}. These other shocks could increase the skill ratio and decrease the skill premium, or vice versa, but once we apply equation (8), the effect of these other shocks will offset each other, leaving only the change in the skill bias term in the production function.

Formally, suppose the following two equations are estimated:

$$\Delta \frac{w_{jt}^H}{w_{jt}^L} = \beta * innov_{jt} + \epsilon_{jt}^w$$

$$\Delta \frac{H_{jt}}{L_{jt}} = \beta * innov_{jt} + \epsilon_{jt}^e$$

The key insight of our model is that firm optimization (the FOC) implies that ϵ_{jt}^w and ϵ_{jt}^e will be related as they reflect different aspects of the same decision. For example, if the implementation of technology is driven by an increase in firm-level labor supply, we would see that $innov_{jt}$ correlates positively with ϵ_{jt}^w, but negatively with ϵ_{jt}^e. In the absence of skill-biased technological change, therefore, an increased supply of high-skilled workers will decrease their wages and increase hiring of such workers. Moreover, when we have a CES production function, we have that $\epsilon_{jt}^w = \nu_{jt} + \varepsilon_{jt}^w$ and $\epsilon_{jt}^e = -1/\sigma \times \nu_{jt} + \varepsilon_{jt}^e$, where ν_{jt} is the endogenous component of the error terms and ε_{jt}^w and ε_{jt}^e are pure random shocks. This implies that under the model assumptions we can assess the impact of innovation on the skill ratio and skill premium even in the presence of endogenous technology adoption.

2.1 Extensions

Below we present two extensions of the basic set-up that are discussed in more detail in Appendix D and Appendix E. First, we extend the framework to allow for skill-specific labor supply elasticities, and show that this accentuates the importance of identifying skill-biased technological changes through increases in both the skill ratio and the skill premium. Next, we extend our framework to account for strategic interactions between firms, and show how we can test for this in the data. We also discuss two alternative models of wage setting—bargaining and rent sharing—and how they matter for the prediction from our model on how to conclude that a technological change is skill biased.

Skill-Specific Labor Supply Elasticities. So far we have followed the literature, and assumed that the labor supply elasticities of low- and high-skilled workers are similar. In Appendix D.2, we relax this assumption by allowing the dispersion of the idiosyncratic error term, ϵ_{iSjt} in equation (4), to be skill specific. The upward-sloping labor supply curves (equations (3c) and (3d)) are then replaced by:

$$\ln L_{jt}(w_{Ljt}) = \ln(L_t \mathit{\Lambda}_{Lt}) + \beta_L \ln w_{Ljt} + \ln a_{Ljt}, \tag{3c$'$}$$

$$\ln H_{jt}(w_{Hjt}) = \ln(H_t \mathit{\Lambda}_{Ht}) + \beta_H \ln w_{Hjt} + \ln a_{Hjt}, \tag{3d$'$}$$

where $\beta_L = \frac{\lambda}{\theta_L}$ and $\beta_H = \frac{\lambda}{\theta_H}$ are firm-level labor supply elasticities of low- and high-skilled workers. When the firm-level labor supply elasticities differ, we cannot express the skill premium and the skill ratio in a closed form. Furthermore, it can be shown that even Hicks-neutral productivity shocks can affect both the skill premium and the skill ratio. Nevertheless, as stated in Proposition 1, such shocks will consistently move the skill ratio and premium in opposite directions.

Proposition 1. *Suppose that firms maximize profit given the constraints in equations (3a), (3b), (3c′) and (3d′). Changes in A_{jt} and κ_{jt} have the following effect on the firm-level skill ratio $\left(\ln \frac{H_{jt}}{L_{jt}}\right)$ and skill premium $\left(\ln \frac{w_{Hjt}}{w_{Ljt}}\right)$.*

1. *If $\beta_H = \beta_L$, then $\ln \frac{w_{Hjt}}{w_{Ljt}}$ and $\ln \frac{H_{jt}}{L_{jt}}$ are unaffected by A_{jt} and κ_{jt}.*
2. *If $\beta_H > \beta_L$, then $\ln \frac{w_{Hjt}}{w_{Ljt}}$ is decreasing and $\ln \frac{H_{jt}}{L_{jt}}$ is increasing in A_{jt} and in κ_{jt}.*
3. *If $\beta_H < \beta_L$, then $\ln \frac{w_{Hjt}}{w_{Ljt}}$ is increasing and $\ln \frac{H_{jt}}{L_{jt}}$ is decreasing in A_j and in κ_{jt}.*

Proof. See Appendix Section D.2. □

Proposition 1 states that Hicks-neutral changes (changes in A_{jt}) and firm specific demand shifters (changes in κ_{jt}) directly affect the skill ratio and the skill premium if the dispersion of idiosyncratic preferences differs across the two skill groups ($\beta_H \neq \beta_L$). Nevertheless, the effects of these shocks on $\ln \frac{w_{Hjt}}{w_{Ljt}}$ and $\ln \frac{H_{jt}}{L_{jt}}$ always have opposite signs. This implies that changes in demand shifters (κ_j) or Hicks-neutral shocks (A_j) cannot explain a joint increase of the skill premium and the skill ratio.

Why does even a Hicks-neutral change (A_{jt}) affect the skill ratio when $\beta_H \neq \beta_L$? When a firm experiences an increase in A_{jt}, it will expand and, therefore, increase its demand for both types of workers. Imagine, for example, that high-skilled workers are more responsive to changes in wages than low-skilled workers ($\beta_H > \beta_L$). In optimum, firms adjust both on the wage and quantity margins: they raise the wages of high-skilled workers less than the wages of low-skilled workers $\left(\Delta \ln \frac{w_{Hj}}{w_{Lj}} < 0\right)$, but hire relatively more of them $\left(\Delta \ln \frac{H_j}{L_j} > 0\right)$.

An important implication of Proposition 1 is that even if an innovation shock *per se* is exogenous, it is not sufficient to document an increase in the skill ratio following an innovation to conclude that the innovation has a skill-biased productivity term. In the presence of imperfect competition in the labor market, even a Hicks-neutral change in the production function can affect the skill ratio (for instance if $\beta_H > \beta_L$). It is still the case however, as equation (5) above demonstrates, that whenever both the skill premium and the skill ratio increase, technological change must be skill biased. Furthermore, the firm's first order conditions can be used in a similar way to quantify the extent of skill bias as for the benchmark model.

Labor Market Power. So far we have assumed that agents are atomistic in labor markets, and so they do not take into account how their behavior affects other agents' behavior. We relax this assumption and incorporate strategic interactions into our framework by following Berger et al. (2019a) and Deb et al. (2020). In particular, Deb et al. (2020) show that equation (5) has to be extended with an extra term capturing the change in market power in the presence of strategic interactions in the labor market (see more details in Appendix E)[15]:

$$\underbrace{\Delta \ln \frac{w_{Hjt}}{w_{Ljt}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \underbrace{\Delta \ln \frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}}_{\substack{\text{Change in}\\ \text{markdown}}} + \underbrace{\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}}_{\substack{\text{Change in}\\ \text{skill bias}}} - \frac{1}{\sigma} \underbrace{\Delta \ln \frac{H_{jt}}{L_{jt}}}_{\substack{\text{Change in}\\ \text{skill ratio}}}, \tag{9}$$

where $\Delta \ln \frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$ refers to the change in relative firm-specific markdowns for firm j operating in labor market m. In the presence of strategic interactions, the mark-downs are firm-specific and depend on the firm's market share of the particular skill group in the local labor market (Berger et al. 2019a). These market shares may themselves be affected both by skill-biased and Hicks-neutral technological change. Importantly, if Hicks-neutral innovation leads to a large increase in market shares (and so an increase in market power), this can introduce a positive correlation between the change in the college premium and the college ratio. Guided by equation (9), we investigate the importance of this empirically. We separate the change in skill bias from the change in labor market power following innovation by estimating the changes in market shares and relative markdowns. We find some evidence for changes in relative market power following innovation in Norway, but this has a negligible impact on our estimates of the impact of innovation on the skill premium (more details are given in Appendix E).

Alternative Wage Setting: Bargaining Model. We next describe the implications for identifying skill-biased technological change from alternative systems of wage setting (further details are given in Appendix Section F.1). We first consider the bargaining model of Van Reenen (1996) where wages and employment are determined through a Nash-bargaining process between a firm and a worker union. We extend the model to allow high- and low-skilled workers to be organized in different unions, and assume that the union of workers with skill S at firm j has the following objective function (see equation (1) in Van Reenen 1996):

$$U_{Sj} = S_j u(w_{Sj}) = S_j \frac{1}{1-m_S} w_{Sj}^{1-m_S}, \tag{10}$$

where $0 \leq m_S \leq 1$ measures risk aversion of the workers that can vary by skill group S. This formulation reflects that unions care about both the level of wages and employment. Similarly to Van Reenen (1996), we assume that wages and employment are determined through a Nash-bargaining process. The equilibrium solution maximizes Ω by optimally choosing the skill-specific wages (w_{Hj}

[15] This extension explicitly models labor markets, and therefore, we index the labor market-level variables with m.

and w_{Lj}) and the skill-specific employment (L_j and H_j) (see equation (3) in Van Reenen 1996):

$$\max_{w_{Lj},w_{Hj},L_j,H_j} \Omega = U_{Lj}^{\beta_L} U_{Hj}^{\beta_H} \Pi_j^{1-\beta_L-\beta_H}, \tag{11}$$

where Π_j is firm's profit and β_L and β_H are the bargaining powers of the two unions. It turns out that this problem leads to the same FOC as in our benchmark case. The change in the skill premium following innovation will take the following form:

$$\Delta \ln \frac{w_{Hj}}{w_{Lj}} = \Delta \ln \frac{\theta_j}{1-\theta_j} - \frac{1}{\sigma} \Delta \ln \frac{H_j}{L_j}. \tag{12}$$

We see that the relationship between the change in skill premium, skill demand and skill bias in a bargaining model is similar to the relationship derived in our main framework. Consequently, the same reasoning regarding inferring a skill-biased technological change applies.

Alternative Wage Setting: Rent Sharing. We also derive the relative skill ratio and wages in a dynamic optimal contracting model that leads to rent sharing (see further details in Appendix Section F.2). We follow Kline et al. (2019) and assume that there is imperfect substitutability between incumbent workers, I_{Sj}, and new hires, N_{Sj} because of training and recruitment costs involved in new hires. The firm can hire as many new workers as desired at the competitive market wage w_S^m. Each period they decide on the wages of the incumbent workers, w_{Sj}^I, by taking into account that higher wages increase the retention rate.

In the Appendix Section F.2 we derive the following relationship between changes in wages and employment:

$$\underbrace{\Delta \ln \frac{(1+\beta_H)\, w_{Hj}^I - w_H^m}{(1+\beta_L)\, w_{Lj}^I - w_L^m}}_{\substack{\text{Relative change in} \\ \text{incumbent wages}}} = \underbrace{\Delta \ln \frac{\theta_j}{1-\theta_j}}_{\substack{\text{Change in} \\ \text{skill bias}}} - \underbrace{\frac{1}{\sigma} \Delta \ln \frac{H_j}{L_j}}_{\substack{\text{Change in} \\ \text{skill ratio}}}, \tag{13}$$

where β_H and β_L determine the responsiveness of high- and low-skilled incumbent workers to changes in wages. This equation is similar to our benchmark equation (equation (5)) except for its left-hand side, which differs from the main model in two respects. First, although its functional form is slightly different, it still captures changes in the skill premium. Second, in this rent sharing model, the change in skill bias does not affect the wages of new workers, as firms can hire as many workers as they want at the prevailing competitive wage, w_S^m. Nevertheless, firms have stronger incentives to retain their high skilled workers when skill demand increases, which drives up incumbent wages. As a result, the relevant object for assessing skill bias is the wage growth of incumbent workers.

This derivation highlights that the main prediction of the main model also applies to rent sharing models: skill-biased technological change leads to a joint increase in the skill premium and the skill ratio. However, the model only predicts an increase in the skill premium for incumbent workers and not for new entrants.

3 Data and Institutional Setting

In our empirical application, we study the contribution of innovation activities and technological change to skill demand in Norway. We start by providing a brief description of innovation activities and the labor markets. Further details can be found in Appendix B. Next, we describe the data sources, and provide some descriptive statistics of the firms in our data.

3.1 Background

Norway is one of the richest and most developed countries in the world, with a GDP/capita level that is 20% larger than that of the US. In terms of innovation activities, Norway is classified as a "Strong innovator" (similar to France, ranked 10th in the EU out of 28) according to the European Innovation Scoreboard.[16] This suggests that Norway is much closer to, and might contribute to push, the technology frontier.

The Norwegian labor market is an example of the Nordic model with its three key features: (i) flexible hiring and firing, (ii) a generous social safety net, and (iii) active labor market policies. Union density is very high; more than 38% of workers in the private sector were organized in a union in 2014 (Nergaard 2014). Wages are typically determined through a two-step process involving industry-wide negotiations followed by local bargaining at the firm level. The industry-level negotiations results in proposed minimum wages, covering approximately half of private-sector workers (Blandhol et al. 2020). However, for these worker, subsequent firm-level wage-bargaining often results in substantially higher wage increases than those implied by the industry minimum wages, highlighting the firm's role in wage determination. Notably, for the majority of white-collar workers in the private sector, centrally negotiated collective agreements do not specify wages. As a result, wage formation mainly occurs at the firm-level, incorporating strong individual-level elements (Nergaard 2014).

3.2 Data and Descriptive Statistics

Innovation Survey. A key data source is the Norwegian version of the Community Innovation Survey (CIS), conducted in a harmonized way in the European Union member states and some other countries, including Norway. The richness of the CIS has been exploited in the recent literature to estimate the effect of various types of innovation on firm performance (Crépon et al. 1998, Griffith et al. 2006). However, to the best of our knowledge, no paper has so far used the CIS to assess the relationship between innovation and skill demand. The survey is biennial and covers a sample of manufacturing and service firms in the economy. All firms with at least 50 employees are present in every survey year, while a number of smaller firms are sampled. The survey asks questions on firm innovation activities in the survey year and the preceding two years. For example, the CIS 2014 refers to innovation activities in 2012, 2013 and 2014. In this paper we use seven waves of the CIS from

[16] https://ec.europa.eu/growth/industry/policy/innovation/scoreboards_en. This ranking is multi-dimensional, based strongly on the CIS. Norway is not an EU member state, but its score can be compared to the score of other member states. Based on data from 2018.

2001 to 2014. The sample sizes are increasing from about 3,500 firms in 2004 to more than 6,000 at the end of the period of study.[17]

The key idea of our empirical approach is to use the questions on innovation in the CIS to create a self-reported and direct measure on whether a firm experienced a technological change in a given period. The innovation measure in the CIS captures the introduction of products, services, processes and organizational solutions which are new or significantly modified from the viewpoint of the firm, but that are not necessarily new to the market (see the exact question in Appendix Table B.1). In terms of our conceptual framework, the CIS allows us to identify when firms experience a change in their production function. An advantage of the measures of innovation in the CIS is that they capture actual introductions of new technologies, i.e. changes in the production function. This is in contrast to innovation spending, such as R&D spending, that may not lead to technological change or may lead to it, but with some lag.

The broad definition of, and detailed questions about, innovation in the CIS allow us to capture a wide variety of technological changes. More details on this are found in Appendix Table B.1 that describes the survey questions used to define our variables, and Appendix Table B.2 that reports key summary statistics of these variables. Following the existing literature (see e.g. Caroli & Van Reenen 2001), we pay specific attention to whether innovation with technical aspects (product and/or process innovation) and organizational innovation have a differential impact.[18] We also study the degree to which "new" or R&D-based technological change is skill biased, compared to less novel or non-R&D based innovations. For the empirical implementation, we create an R&D dummy for whether the firm reports positive in-house R&D spending, and consider an innovation as new if the firm reports the innovation to be new to its market. When looking at R&D-intensity and conducting our study of an R&D tax credit, we complement the information from the CIS with information from the R&D survey which is conducted annually and for a larger set of firms. Finally, in most of the paper we use a binary indicator for whether innovation took place to measure technological change in firms.[19] In Appendix Section A.12, we extend our analysis to also look at whether R&D intensity, a proxy of innovation efforts, matters for whether the technological change is skill biased.

Employer-Employee Register. The employer-employee register, provided by Statistics Norway, contains annual records of all employment spells, as well as information on wages, days and hours worked.[20] We merge the employer-employee register to data on worker demographics that include

[17]With the exception of the introductory 2001 wave, the increase in the number of surveyed firms is driven by the fact that the number of firms in Norway increased over time (especially those in the sampling frame). The annual shares of firms surveyed are: 2001: 23% 2004: 29%; 2006: 35%, 2008: 33%; 2010: 35%; 2012: 33%; 2014: 31%. More details about the sample are provided in Appendix Table A.3.

[18]"Product innovation" is defined as "the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems." A "process innovation" is defined as "the implementation of a new or significantly improved production process, distribution method, or supporting activity." An "organizational innovation" is "a new organizational method in your enterprise's business practices (including knowledge management), workplace organization or external relations that has not been previously used by your enterprise". These carefully drafted definitions have been developed by extensive work after a number of pilot surveys by Eurostat, to make sure that the results are comparable across countries and time periods.

[19]In Table A.4 we show the number of CIS waves firm surveyed and the share of always, never innovators and those who switch innovation status across surveys.

[20]A more detailed description of this database is available at https://www.nav.no/en/home/employers/nav-state-register-of-employers-and-employees.

information on level of education and age. Finally, we link these data to data containing information from the balance sheets of limited liability firms.

To study the impact of innovation on skill demand, we start out with the employer-employee register for the years 1997-2014. We closely follow Blandhol et al. (2020) in preparing the employer-employee register and constructing a measure of workers' hourly wages. We keep the main (highest paid) employment spell ongoing on December 31st for each worker in each year. We keep the highest paid job among these spells to have one observation per worker. We further restrict the sample to workers aged 20-67. This data set is merged to six waves of the CIS for Norway, which were conducted in 2001 and biennially over the period 2004 to 2014. This leads to a dataset consisting of 3,369,587 workers employed in 39,175 firms. We create a firm-level data set by aggregating up from the worker level, and where part-time workers are given a reduced weight. Finally, we merge the employer-employee data to data from firms' balance sheets, and drop observations where the changes in value added or capital cannot be calculated.[21]

Descriptive Statistics. Table 1 compares innovative and non-innovative firms. Two types of differences are apparent. First, in line with much of the literature (see e.g. Griffith et al. 2006), innovative firms are larger. Second, innovation is associated with higher skill levels and skill premiums. In particular, both the average years of workers' education, and the share of college graduates are substantially higher in innovative firms. Innovative firms also pay substantially higher wages. In terms of age composition, innovative and non-innovative firms are very similar in both countries.

4 Empirical Approach

4.1 Firm-level Changes in the Skill Ratio and the Skill Premium

To estimate how technological change is related to changes in the skill ratio and the skill premium within firms, we start out with equation (7b) and estimate the link between innovation activities and long differences in outcomes à la Caroli & Van Reenen (2001):

$$\Delta \ln \frac{y^H_{jt}}{y^L_{jt}} = \delta \times innovation_{jt} + \xi_{s(j)t} + \varsigma_{l(j)t} + \epsilon_{jt}, \tag{14}$$

where $\Delta \ln \frac{y^H_{jt}}{y^L_{jt}}$ reflects the change in the outcome—the log ratio of college to non-college workers, or the college premium (the log ratio of the average wage of college and non-college workers)—at firm j between time $t-4$ and t in the main specification. We Winsorize Δy_{jt} at the 5th and 95th percentiles. We weight the firm-level regressions with the number of workers in year t. We cluster the standard errors at the firm-level.

The variable $innovation_{jt}$ is an indicator variable taking the value one if the firm reports an

[21] Appendix Table A.3 shows in detail the changes coming from the different sample size restrictions.

innovation in the current CIS wave. This variable hence captures a change in a firm's technology happening between $t-2$ and t.[22] In addition, we include district-year fixed effects ($\varsigma_{l(j)t}$), as well as industry-year fixed effects ($\xi_{s(j)t}$) to control for industry- and district-level labor supply shocks $\left(\Delta \ln \frac{H_t \Lambda_{Ht}}{L_t \Lambda_{Lt}}\right)$. Furthermore, by differentiating the outcome variable, we filter out inherent, unobserved differences between innovative and non-innovative firms. As a robustness check, we also include firm fixed effects in the regression. This implies using only within-firm variation in the change in innovation status – filtering out inherent differential growth rates of innovative and non-innovative firms.

One important concern with interpreting an increase in the firm-level skill premium (the log ratio of college and non-college workers' average wages) as evidence of an increase in the skill premium is that innovation might lead to a change in the composition of the firm's workforce. Higher productivity workers might select into more innovative firms or into firms that are about to start innovating. In this case, the estimated change in the skill premium simply reflects a change in the quality of the firm's high-skilled workers, and not an increase in the skill premium. To deal with this issue, we estimate the regression with the skill-premium change calculated only on the sample of incumbent workers—namely workers that were working in the firm both in years $t-4$ and t—in order to hold fixed the firm's workforce composition. An even better way to address this issue is looking at within-worker changes in wages—which we discuss next.

4.2 Worker-level Change in the Skill Premium

Our rich individual-level micro data allow us to go a step further and estimate the change in the skill premium at the worker level following firm technological change. To this end, we estimate a regression corresponding to Equation (14):

$$\Delta \ln wage_{it} = \delta^u innovation_{j(i,t)t} + \delta^s innovation_{j(i,t)t} \times college_i + \xi_{s(j(i,t))t} + \varsigma_{l(j(i,t))t} + \chi_{g(i)t} + \varepsilon_{it}, \quad (15)$$

where $\Delta \ln wage_{it} = \ln w_{it} - \ln w_{it-4}$, and captures the log change in worker i's wage between time $t-4$ and t.[23] The dummy $college_i$ indicates whether worker i has college education, and $innovation_{j(i,t)t}$ is the same key variable included in the firm regression equation (14), i.e. a dummy variable for whether firm j where worker i works at time t reports an innovation in time t CIS wave. Our main interest lies in δ^s, the coefficient of the interaction between $college_i$ and $innovation_{j(i,t)}$, which captures the

[22] In our benchmark specification, we focus on changes in outcomes between December 31 of year $t-4$ and December 31 of year t. While we do not have precise information about the timing of the innovation, we know that it occurred at some point during year t, $t-1$, or $t-2$. We chose $t-4$ as a baseline to make sure that we start from a pre-innovation observation. For example, if an innovation is implemented in January of year $t-2$, measuring baseline outcomes in December of year $t-3$ could potentially be problematic. Innovation requires some work before it is implemented, which could involve hiring new workers and adjusting wages. To allow some time between measuring baseline outcomes and the implementation of the innovation, we hence choose $t-4$ as the baseline year in the benchmark specification. We do however, assess the robustness of our results to varying the timing assumption, including starting the baseline from $t-3$; see further details in Appendix Table A.13.

[23] We Winsorize the changes at the 2nd and 98th percentiles. We apply a stricter Winsorization for firm-level outcomes as the distributions of the firm-level skill ratio and premium are more skewed than the distribution of individual wages in our data. The results are not sensitive to the specifics of Winsorization.

change in skill premium following a technological change in the firm. As in the firm-level regression, we include industry-time ($\xi_{s(j(i,t))t}$) and location-time ($\varsigma_{l(j(i,t))t}$) fixed effects. In addition, we add the interaction of four dummies representing the worker's education level (primary, secondary, vocational, college) with the year dummies ($\chi_{g(i)t}$). By including the interacted education group-year effects we effectively control for education-specific wage trends, as well as policy changes that might affect education groups differently. We cluster the standard errors at the firm level.

4.3 Specification Choice and Controls

Our theoretical framework highlights that innovation does not need to be exogenous to the firm in order for us to identify whether the resulting technological change is skill biased. We nevertheless go a long way in confirming that our conclusions are not driven by the endogenous nature of firm-level innovations. First, by focusing on the relationship between the change in the outcome (left-hand side) and the change in technology (right-hand side) we filter out time-invariant differences in the skill premium and the skill ratio between innovative and non-innovative firms. For example, we control for the fact that innovative firms might pay a larger premium even before innovation.

Second, we present evidence from including firm fixed effects in the firm-level regression and firm-college fixed effects in the worker-level regression. In these specification, we only compare the innovative to the non-innovative periods within the same firm. As we show later, the inclusion of these fixed effects yields very similar estimates.

In addition to that, we also assess the robustness of our results to controlling for changes in market-level labor supply in different ways. We explore multiple alternative control groups for innovative firms by including different combinations of district-time fixed effects and industry-year fixed effects in the regressions on the firm-level skill ratio and skill premium. In the worker-level regressions we can also include district-time-college and occupation-college-year fixed effects. Furthermore, we group firms into deciles based on their college premium and then include an additional interaction of firm premium-type deciles with the college dummy in the regression equation.

These sets of fixed effects filter out changes in the skill premium that arise at the labor market level. However, controlling for market-level changes at a very detailed level can be problematic if there are spillovers from innovative (treated) to non-innovative (untreated) firms within a narrowly defined market. Such spillovers would imply a violation of the Stable Unit Treatment Value Assumption (SUTVA) and bias our estimates. Reassuringly, our results are not sensitive to including a large number of combinations of location-occupation-industry-college year fixed effects, which suggests that the bias caused by such spillover effects must be limited in our context.

5 Empirical Results

5.1 Innovation and Changes in Skill Demand

Firm-Level Estimates. We assess the impact of technological change on the skill ratio by estimating regression equation (14). The main results are presented in Table 2. Columns (1) and (2) show the impact of innovation on the long difference in the share of college-educated workers in total employment. We find a positive and significant relationship: the college employment share increases by 0.4 (s.e. 0.1) percentage points. This corresponds to an increase of around 1.9 (s.e. 0.5) percent relative to the non-innovative firms' average college share (0.21; see Table 1). Column (2) shows the effect on the college to non-college ratio, which increases by around 1.8 (s.e. 0.8) percent. In column (5), we further find that innovation is associated with stronger employment growth.

Columns (3) and (4) show the impact on the skill premium. We find that following innovation, the skill premium increases by 0.5 (s.e. 0.4) percent. Nevertheless, the change in the firm-level skill premium could reflect both changes in the composition of the workforce and the genuine premium paid to skilled workers. To better understand the latter, we study the impact on the skill premium paid to incumbent workers who already worked at the firm before innovation. For this group, we find an even larger effect of 0.7 percent (s.e. 0.4). Below we provide further, more precise, evidence on the skill premium when studying the impact of innovation at the worker level.[24]

Appendix Section A.4 shows that the results are robust to different specification choices. Panel A of Appendix Table A.6 shows that the estimates do not change when we calculate the firm-level skill ratio and premium based only on full-time workers rather than both full- and part-time workers. In Panel B, we add additional controls for firm-level changes in value added and the capital stock. In Panel C, we include firm fixed effects in the regression, which implies that we use only within-firm variation in innovation and in the changes in the skill ratio and the premium. The within-firm estimates are similar to the benchmark estimate: the skill ratio changes by 1.8 percent (the same as in the benchmark) and the skill premium by 0.8 percent (versus 0.5 percent in the benchmark). Finally, in Panel D, we explore the possibility that a local labor market shock can have a differential impact depending on a firm's initial skill ratio.[25] Specifically, we classify firms into quartiles based on their initial skill ratio and include quartile-district-year fixed effects in the regression. Again, the results change little when including these more flexible location-year controls.

The main takeaway from the firm-level results is that innovation leads to an increase in both the share of skilled workers and their wage premium. Nevertheless, the change in the skill premium might reflect changes in the composition of the firm's workforce. To alleviate these concerns, we turn to the worker-level analysis that exploits within-worker variation.

[24] The increases in the firm-level skill ratio and skill premium come from an increased number of college workers. This is shown in Appendix Table A.5, where we study separately the effect of the policy on the (log) number of college and non-college workers and (log) average wage of workers. Following innovation, the number of college workers increases by 2.8 percent (s.e. 1.4), while there is a small, noisily estimated increase in the number of non-college workers (0.08 percent, s.e. 1.3).

[25] Proposition 2 in Appendix D highlights that whenever $\beta_H \neq \beta_L$, the very same labor supply shock might have a differential impact on firms operating in the same labor market, depending on the skill bias term of the firm (θ_{jt}).

Worker-Level Estimates. Table 3 shows worker-level estimates (Equation (15)). Column (1) reports results for the benchmark specification with industry-year fixed effects, schooling-year fixed effects and district-year fixed effects. The main estimates show that the post-innovation college premium increases by 1.1 percent (s.e. 0.5). These estimates are somewhat larger than the change in the incumbent skill premium estimated in the firm-level design (0.7 percent, s.e. 0.4 for incumbents), but the two estimates are not statistically different. Furthermore, Appendix Section A.6 offers additional insights, showing that firm-level changes in the college wage premium may underestimate the true shift due to changes in workforce composition. This effect stems from the positive selection of more productive low-skilled workers at innovative firms.[26] This positive selection results in higher average wages for low-skilled workers, not due to an increase in their wage premium, but rather because of their higher skills. Consequently, our estimates of firm-level college premium changes are somewhat downward biased.

Columns (2)-(8) of Table 3 provide a battery of robustness checks of the worker-level estimates. Column (2) includes college-district-year fixed effects in the regression, while Column (3) allows for even richer variation by allowing college-district-year effects varying by initial skill-share at the firm. Column (4) includes occupation-industry-district year fixed effects and so it controls for local labor supply and demand shocks. Column (5) includes firm fixed effects, while Column (6) includes firm-college fixed effects and so it only uses within-firm variation. Column (7) includes firm-year fixed effects, while Column (8) includes all the above mentioned controls. The estimated change on skill premium varies between 1.1 to 2.1 percent, all of them being highly significant at the conventional levels.

The worker-level results, therefore, confirm our main firm-level findings: following innovation, the skill-premium increases substantially, even after we control for the change in workforce composition at the firm.

5.2 Extensions

New Entrants vs. Incumbents. In Table 4, we investigate whether the change in the college wage premium differs for incumbent and new entrant workers. A key implication of our conceptual framework is that an increase in the wage premium results from firms having to pay higher wages to hire new workers following a skill-biased innovation. It follows that not only incumbent workers, but also new hires should experience a higher skill premium. This contrasts with some rent-sharing models, such as the framework laid out in Section 2 and Appendix Section F.2, where only incumbent workers obtain some rent following firm-level shocks. To test this prediction of the monopsonistic wage setting framework, we run the worker-level regression (equation (15)) separately for incumbents and new entrants. Column (1) shows that new entrants, who were at the firm at both in t and $t-4$, has a 1.1% (s.e. 0.5%) wage premium following innovation. A slightly higher change is observed for new entrants (column (2), who were at the firm in t, but not in $t-4$: their skill premium increased by

[26] In particular, we find that the wages of college incumbents, new entrants, and leavers are similar at both innovative and non-innovative firms, suggesting that compositional changes among college workers are limited. However, we observe positive selection among non-college workers: newly hired workers at innovative firms tend to have higher baseline wages, while leavers have lower ones.

1.4% (s.e. 0.8%). Furthermore, in Appendix Table A.11 we also demonstrate that the wage changes are not present for leavers, workers who were employed at the firm in year $t-4$ but not in year t. This demonstrates that the estimated wage changes at innovative firms pick up some firm-level changes in the wage premium and not only general trends in the labor markets (which would also be experienced by the leavers).

Columns (3) and (4) of Table 4 also explore the results when controlling for the skill premium at the previous firm of newly entering workers. In particular, we construct a proxy for firm-level wage premiums pre-innovation by calculating the firm AKM effects estimated preceding the baseline period (between $t-8$ and $t-4$). Next, for the new entrants, we control for the difference between the firm AKM effects of their previous ($t-4$) and present (t) employer. In Column 4, we present results by including skill-specific firm AKM effects in the same way. The estimates in Column (3) and Column (4) are very similar (1.2% and 1.0%) to the skill premium paid to incumbents (1.1%).

Firm-Level Labor Supply and Heterogeneity by Firm Density. So far, we have shown that firms raise both their skill premium and their skill ratio after innovation. The ratio of these two responses provides an estimate of the labor supply elasticity (β), under the assumption that elasticities are the same across the two skill groups (see Appendix A.7 for details). The estimated increase in the skill ratio is 1.8% (Column 2 in Table 2), while the estimates for the skill premium vary between 0.5% (Column 3 in Table 2) and 1.1% (Column 1 in Table 3). Consequently, the implied firm-level labor supply elasticity is between 1.6 and 3.6 depending on the specification. Reassuringly, these results fall within the range of existing estimates in the literature. For instance, Saez et al. (2019), studying payroll tax cuts in Sweden, find that the elasticity of firm-specific labor supply is between 1.8 and 2.4.[27]

Second, whenever firms have less wage setting power (face a more elastic firm-level labor supply), we expect a relatively larger impact on the skill ratio and a smaller impact on the skill premium. Remember that, in our model, the firm-level labor supply elasticity, β, is a function of ϕ, the dispersion of workers' idiosyncratic preferences for working at a particular firm. A key component of this dispersion is commuting distance, which is presumably smaller in local areas with higher firm density (or areas where the average distance between firms is smaller). In line with this in Appendix Table A.12 we show that in local areas with a high firm density (measured as the average number of firms per square kilometer), the skill ratio changes more, while the skill premium changes less. This is consistent with the idea that firms operating in these markets face a more elastic labor supply. In contrast, the estimates imply a quite inelastic labor supply in commuting zones with a low firm density. Overall, these findings corroborate a key prediction of our theoretical model: the relative changes in the skill ratio and the skill premium are related to our proxy of firm-specific labor supply elasticities. Furthermore, these geographic differences imply that rural and urban labor markets can be quite differently affected by technological change.

Labor Market Power. So far we have assumed that firms are atomistic and so they do not consider the impact of their actions on other firms' behavior. However, strategic interactions may be

[27] According to the meta-analysis by Sokolova & Sorensen (2018), the median firm-level labor supply elasticity is around 1.7. Recent quasi-experimental studies (e.g. Caldwell & Oehlsen 2018, Cho 2018, Kroft et al. 2020, Dube et al. 2017) find estimates between 2 and 5 (see more details in Bassier et al. 2020).

important for the skill demand of large firms, or for firms operating in labor markets with very low firm density. Moreover, innovation itself might affect the market power of firms, which could explain the change in the skill premium and the skill ratio even if the innovation itself is not skill biased (Berger et al. 2019a). In Appendix E we study the impact of innovation on subsequent college market share, non-college market share, and relative markdown (see Equation (9)). We find no changes in these proxies of market power following innovation. Importantly, when we apply the model of Deb et al. (2020) to calculate the impact of the changes in market power following innovation on the skill premium, we find that this impact is very limited (see the details in Appendix E).

Short and Medium-Term Effects. In Appendix Table A.13, we investigate how our estimates depend on the choice of timing window of our outcome variables. We explore extending the end of our time period from t to $t+3$ and looking at windows starting from $t-4$ and $t-3$, and so looking at the impact of innovation over a 3-6 years horizon. Allowing longer periods leads to larger point estimates in most specifications. For example, the change in college share increases from 0.4 percentage point to 0.6, the skill ratio from 1.8 percent to 2.1 percent, and the skill premium from 1.1 percent to 1.7 percent if we consider changes between $t-4$ and $t+2$.

Effect on Different Wage Measures and Hours Worked. In Appendix Section A.9, we investigate whether the estimated effects of innovation depend on the wage measure we use and whether it leads to a change in hours worked. The results from this extension are presented in Appendix Table A.14. In our baseline regressions, we use measures of hourly wages without non-cash benefits. First, we show that when we include non-cash benefits —which can be interpreted as a proxy for amenities—in workers' compensation, the estimated change in the college premium is very similar to the estimated change in the wage premium in the benchmark specification. Cash wages and amenities proxied by non-cash benefits increase to some extent following innovation. Second, we show that daily wages change in a similar way to hourly wages. We further find no indication of changes in hours worked. Innovation does not seem to affect the hours worked by college and non-college workers differently.

Polarization. So far, we have studied skill-biased technological change by classifying workers into two skill groups based on whether or not they have a college degree. Over the past three decades, however, the U.S. and several European countries have experienced job polarization. Employment shares have increased in both high- and low-skilled occupations, while those in the middle have declined. Acemoglu & Autor (2011b) explain this pattern by arguing that middle-skilled occupations, such as clerical, administrative, production and operative occupations, tend to be more negatively affected by technological change than either high- and low-skilled occupations. We explore the degree of wage polarization following innovation by studying the change in log number of workers separately for four schooling categories (primary schooling, secondary schooling, vocational education, and college) in Panel A of Appendix Table A.15. We find no decline in the number of workers with vocational training or secondary education (middle-skilled workers). In addition, when we estimate the impact on the skill premium of these workers (Panel B of Appendix Table A.15), we find that workers with vocational or secondary training experience a similar change in their wage premium following innovation to workers with only primary education. We therefore conclude that there is little support in the data for a more negative impact of innovation on middle education groups.

We also investigate whether the effect of innovation differs between routine and non-routine occupations (see e.g. Autor et al. 2003). In Appendix Table A.16 we estimate regression equation (15) by including routine intensity (based on Autor et al. 2003) and its interaction with the innovation dummy. We find no relative increase in the wage of workers in non-routine occupations that goes beyond the effect on the college premium. Moreover, the effect of innovation on the college premium remains largely unchanged in these regressions, which suggests that the increase in skill demand following innovation is not limited to non-routine occupations.

Outsourcing. Domestic outsourcing of less-skilled work to lower-wage contractors or international outsourcing to lower-wage countries can potentially lead to a joint increase in the skill premium and skill ratio. In our data we measure outsourcing behavior of firms (as outsourcing is considered a type of organizational innovation in the CIS). In Appendix Table A.17, we focus solely on non-outsourcing firms by interacting the key variables in the regression equations (15) and (14) with the outsourcing dummy. We find that both the college share, the college ratio and the college premiums are robust to the exclusion of outsourcing firms.

R&D Intensity. So far, we have explored skill bias resulting from innovation, which we have defined as a binary event. However, an equally significant aspect of technological change is the level of resources dedicated to the introduction of new technologies. In Appendix Section A.12, we investigate whether R&D intensity—total R&D expenditure per worker—matters for whether the resulting innovation is skill biased.[28] Our findings, reported in Table A.18, suggest that a greater per capita investment in R&D leads to a larger increase in the skill share, the skill ratio, as well as the skill premium. Specifically, doubling R&D expenditure is associated with a 5.4 percent (s.e. 1.9) greater increase in the skill ratio and a 1.6 percent (s.e. 0.9) higher growth in the skill premium.

Event study. We also study the impact of technological change in an event-study framework. We focus on firms that had not implemented any new technologies for two consecutive CIS waves, but start to innovate afterwards. The control group consists of firms that were surveyed at least three times by the CIS, and did not report innovation in any of those waves. We estimate the evolution of the skill ratio using the following firm-level regression:

$$\ln \frac{y_{jt}^H}{y_{jt}^L} = \sum_{k=-6}^{4} \delta_k \mathbf{1}\{t - E_j = k\} + \xi_{s(j)t} + \nu_j + u_{jt}, \tag{16}$$

where E_j denotes the year of the CIS wave when the firm j first reported innovation, and $E_j = \infty$ for never-innovating firms. The vector $\xi_{s(j)t}$ represents industry-year fixed effects, while ν_j represents firm fixed effects. By including firm fixed effects we are studying the evolution of the college ratio within firm.

For the skill premium, we estimate a corresponding event study regression equation at the worker

[28] We use the annual R&D survey to calculate the R&D expenditures more reliably, restricting our attention to innovative firms and including firm fixed effects into the regression to compare innovations with different R&D investments within firms.

level:

$$\ln wage_{it} = \sum_{k=-6}^{4} (\delta_k^u + \delta_k^s \times college_i) \times \mathbf{1}\{t - E_{j(i,t)} = k\} + \xi_{s(j(i,t))t} + \varsigma_{l(j(i,t))t} + \psi_i + \chi_{g(i)t} + \nu_{c(i)j(i,t)} + \varepsilon_{it}, \tag{17}$$

where the $\xi_{s(j(i,t))t}$ are industry-year fixed effects, the $\varsigma_{l(j(i,t)t}$ are location-year fixed effects, $\chi_{g(i)t}$ are schooling-year fixed effects, $\nu_{c(i)j(i,t)}$ are firm college-fixed effects and ψ_i are worker fixed effects. The inclusion of firm-college fixed effects in the regression implies that we are studying within firm evolution of college premium over time.

Figure 2 shows the main event study results. The lightly shaded area reflects the period during which no technological change was implemented. The darkly shaded area reflects the period when the first innovation took place (the CIS does not measure the exact year of innovation, so we cannot know the exact date). Panels A and B show the change in college share and ratio estimated based on regression equation (16). Prior to innovation, the skill demand in treated and control firms evolve similarly. Nevertheless, following technological change there is a divergence: by the fourth year following innovation the college share increased by around 1.4 (s.e. 1.01) percentage points, while the college ratio increased by 9.2 percent (s.e. 6.1).

Panels C and D show the effect on the skill premium estimated based on equation (17). Again we find no indication of pre-reform differences in the evolution of the skill premium. Nevertheless, following the reform a clear divergence emerges. In the specification with worker fixed effects (panel D), the skill ratio increases by 4.9 percent (s.e. 0.5). Overall the event study results underscore our benchmark result: following technological change there is a significant increase in skill demand. In Appendix Section A.13 we show further event study evidence where we extend the pre-reform years (Figure A.2) and where we apply the Sun & Abraham (2021) estimator to adjust for heterogeneous treatment effects (see Figure A.3).

5.3 Heterogeneity and Skill Bias

In this section we investigate the degree to which different forms of technological change are skill biased. This question adds to the debate regarding weather organizational changes, similarly to technical changes, are skill biased (Caroli & Van Reenen 2001). More concretely, we study whether only innovations involving R&D or high novelty value are skill biased, or whether firms' skill demand also changes after technology adoption. To this end, we estimate the effects of different types of innovation both on the skill premium and on the skill ratio.

For any set of innovators, we can calculate the extent of skill bias by applying Equation (8) from the first order conditions of the firm's problem:

$$\Delta \ln \frac{\theta}{1-\theta} \equiv \overline{\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}} = \overline{\Delta \ln \frac{w_{H_{jt}}}{w_{L_{jt}}}} + \frac{1}{\sigma} \overline{\Delta \ln \frac{H_{jt}}{L_{jt}}}, \tag{18}$$

where $\overline{\Delta \ln \frac{w_{H_{jt}}}{w_{L_{jt}}}}$ and $\overline{\Delta \ln \frac{H_{jt}}{L_{jt}}}$ are the average changes in the skill premium and the skill ratio following firm-level technological change. For the elasticity of substitution between high- and low-skilled labor, σ, we use $\sigma = 2.94$ from Acemoglu & Autor (2011b).[29]

The main findings are summarized in Table 5, while more detailed estimates are reported in Appendix Section A.14. Columns (1) and (3) show the changes in college share and skill ratio, while column (5) shows the change in skill premium estimated based on the worker-level regression. Finally, Column (7) shows the estimate of the skill bias (given by Equation (18)).

In Panel A, Row 1 repeats our benchmark estimates. Row 2 shows the estimated change for non-R&D-based innovation (i.e. technology adoption), while Rows 3 and 4 report the estimated change for R&D-based innovation. In Row 4 we show the combined effect of R&D-based innovation and the introduction of a product that is new to the market (as opposed to only new to the firm). R&D-based innovation shows a larger increase in the skill ratio compared to non-R&D-based innovation, though both lead to similar changes in the skill premium. This indicates that both types of innovation are skill-biased, but the bias from R&D-based innovation is nearly twice as large. The estimates suggest that, under a scenario of completely inelastic labor supply, non-R&D-based innovation could increase the skill premium by 10 percent, compared to 20 percent for R&D-based innovation. This underscores the importance of considering non-R&D activities when assessing the skill bias of technological change, as focusing solely on R&D overlooks a significant portion of the effect.

Panel B shows the effect of different forms of technological change. In Row 5, we report the extent of skill bias of innovations that directly involve technical aspects, while Rows 6 and 7 further distinguish between process and product innovation within that category (see footnote 18 and Table B.1 for the exact definitions). We find that technical innovation has a strong skill bias component (18 percent), which is present for both process and product innovation individually. In Row 8, we report the impact of organizational changes. Similarly to Caroli & Van Reenen (2001), we find that organizational innovation is skill biased. Nevertheless, organizational change is less skill biased than technical-based technological change. Furthermore, firms that combine technical and organizational change (Row 9) experience a similar skill-bias component than firms implementing technical changes individually. This suggests that the effects of different forms of skill biased changes are not additive. Finally, Row 10 shows the estimated effect for firms in the manufacturing sector that conduct R&D-based technical innovation. In the next section, we compare these estimates to the ones found in response to the R&D tax credit.

Panel C studies whether the extent of skill bias of innovations depends on the sector in which the firms operates, and whether the sector is technology intensive or knowledge intensive. We classify industries into four groups: high-tech manufacturing, low-tech manufacturing, knowledge-intensive

[29] As discussed above, calculating skill the bias does not require that the technological change is implemented independently from other, potentially confounding, shocks. Firm-level shocks (like output demand shocks or amenity shocks coinciding with the technological change) may cause a bias in the estimates of the skill premium or on the skill ratio, but such shocks will affect them in opposite directions. When we take the sum of the skill premium and $1/\sigma$ multiplied with the skill-ratio, the biases will cancel each other out, and so the skill bias parameter is identified. Nevertheless, we need to apply the correct σ. While we could estimate σ by exploiting firm-level labor supply shocks, we instead apply a standard value and then show robustness to a wide range of values σ (see Appendix Table **??**).

services, and less knowledge-intensive services.[30] The manufacturing sector, particularly the low-tech segment, exhibits the highest degree of skill bias. This finding underscores that skill-biased technological change is not confined to high-tech industries, but is prevalent across all parts of the economy. Interestingly, we observe little evidence of increased skill demand in the knowledge-intensive sectors, suggesting that technological change in that sector does not contribute to the aggregate college premium.

5.4 The Effects of an R&D Tax Credit Policy on Skill Demand

So far, we have documented that there is an increase both in the skill premium and the skill ratio following firm innovation. As described in detail in Section 2, an increase in both of these outcomes provides *prima facie* evidence that firm-level technological change is skill biased. Even if innovation is implemented in response to firm-level output demand shocks, market-level labor supply shocks, or changes in amenities, the increase in both the skill ratio and the skill premium cannot solely reflect those shocks. Still, to ensure that our results are not merely a consequence of the endogenous nature of firm-level innovation, we present evidence from Norway, where we exploit an exogenous change in incentives to invest in innovation.

In 2002 the government introduced a tax credit that lowered the marginal cost of investing in R&D for a subset of firms. In particular, firms were allowed to deduct up to 20% of their R&D expenses up to a threshold of NOK 4 million (approx 450,000 USD). This implied a reduction in the marginal cost of R&D investments for firms investing less than that threshold. We follow closely the empirical design of Bøler et al. (2015) and Bøler (2015) who studied the impact of this reform on the change in skill ratio (but not the change in skill premium) of manufacturing firms. In particular, in our benchmark analysis, we focus on firm with at least 50 employees in 2001 (the last pre-reform year) in the manufacturing sector. This is because our survey on R&D spending samples firms with fewer than 50 workers non-randomly, while it covers the full population of firms with at least 50 workers. Furthermore, as we will see below, the reform mainly affected R&D spending and technological change in the manufacturing sector.

Based on this, our treatment group consists of firms spending on R&D less than 4 million NOK on average between 1998 and 2001, prior to the policy change. We define our control group as firms with a pre-reform spending between 4 and 40 million NOK, excluding firms that spent more than 10 times the threshold pre-reform to make the control group more similar to the treated group. Note that this control group consists of highly innovative firms, while the treated group includes also quite dissimilar firms that had never invested in R&D. As a result, we also explore an alternative definition of the treatment group, where we only consider firms with a positive R&D spending for at least one year prior to the reform (but less than 4 million NOK on average over the pre-reform years 1998-2001).

[30] We use the Eurostat's categorization for this exercise. Manufacturing industries are classified based on the R&D intensities of industries. We consider Eurostat's "High-tech" and "Medium High-tech" industries to be High-tech. These are NACE rev. 2 categories 21, 26, 30.3, 20, 25.4, 27, 28, 29, 30 (exl. 30.1 and 30.3) and 32.5. We consider all other manufacturing as low-tech. Knowledge-intensive high-tech. services are defined based on the share of college educated workers, and the relevant NACE rev. 2 codes are: 59-63 and 70. We consider all other non-manufacturing industries sampled by the CIS as non-knowledge intensive services.

These firms are more comparable to the control group, and are also the firms that benefit most from the change in incentives. Consequently, for these firms, we expect large changes on the intensive margin (implementing more types of higher value innovations based on more R&D spending), but smaller effects on the the extensive margin (introducing a new product or process) as they are already spending on R&D before the reform.

We start our analysis by showing the evolution of R&D expenditures for treated and control firms. Panel A of Figure 3 shows total log R&D investments relative to the pre-reform (employment-weighted) average for treated (solid line) and control firms (dashed line). Treated and control firms follow parallel trends in R&D expenditures before the reform. However, the common trend diverges exactly in 2002, when the tax credit was introduced. The policy led to a 50-100 percent increase in R&D expenditure among treated firms. Panels B and C show the evolution of the college employment share and the skill ratio relative to the pre-reform average growth.[31] The graphs highlight that the skill ratio increases more at treated firms than at control firms (relative to the pre-reform trends), especially a few years after the policy. The somewhat sluggish divergence between treatment and control suggests that it takes time to translate the increased R&D expenditure into actual changes in technology. Finally, in Panel D we show the evolution of the college premium of workers at treated and control firms relative to their pre-reform trends in wages. Similar to the changes in skill ratio, we find that the skill premium grows more at treated firms compared to control firms.

Next, we employ a difference-in-differences strategy to estimate the effects of the R&D tax credit on the growth rates of college employment share and the college premium. We run the following regression to assess the impact on the growth rate of college share and college ratio:

$$\Delta \ln y_{jt} = \delta treat_j \times post_t + +\xi_{s(j)t} + \varsigma_{l(j)t} + \epsilon_{jt}, \tag{19}$$

where Δy_{jt} are the one-year changes in various firm-level outcomes (e.g. college ratio) of firm j at time t, $treat_j$ is a dummy variable for whether the firm is defined as treated according to the definition above, $post_t$ is an indicator variable taking the value one for the years following the introduction of the tax credit in 2002, $\xi_{s(j)t}$ reflect industry-year fixed effects and $\varsigma_{l(j)t}$ are district-year fixed effects. This specification is very similar to our baseline analysis. We estimate the regression equation using data for the years 1998-2008, but leaving out the two years immediately following the introduction of the policy.[32]

The δ coefficient in regression equation (19) identifies the change in growth rate following the introduction of the policy relative to the control group. In our case, control firms consist of highly innovative firms with high R&D spending. Therefore, we expect steady growth in both their skill

[31] We remove firm-level averages for the period 1998 to 2001, as well as the trends observed during this time for the treated and control groups. This allows us to focus on changes in the *growth rate* of the college ratio and college premium. It is worth noting that in Panel A, the trends were not removed since R&D spending proxies the *growth rate* of technology already, and so there is no further need to detrend the variable.

[32] These two years are omitted partly because the policy did not apply to all firms in 2002 (when it was extended), and also because it likely takes some time to turn the increase in R&D, an input of the innovation process, into an increase in innovation output, the actual technological change. Including these two years leads to somewhat less precise and slightly lower estimated coefficients, see Appendix Table A.25. We end the analysis in 2009 both because of the Global Financial Crisis, and because the thresholds of the Skattefunn program were modified in that year (Rybalka et al. 2018).

premium and skill ratio throughout the whole period. The treated firms, on the other hand, are less innovative, and their innovation activities were boosted by the R&D tax credit. Therefore, we expect an increase in the growth rates of their skill ratio and skill premium compared to pre-reform trends. This is exactly what the δ coefficient captures.

We present the key results in three panels in Table 6. Panel A shows the estimates for the full treatment group of firms with less than 4 million NOK pre-reform R&D expenditure, while Panels B and C restrict the treatment group to firms with positive or zero pre-reform spending, respectively. Columns (1)-(3) in Table 6 show the relationship between technological change and treatment status. Column (1) shows the impact on R&D expenditures, while columns (2) and (3) show the impact on the probability of introducing an innovation or a technical innovation—which is likely to be more directly associated with R&D compared to other types of innovation—, relative to the control group. When we consider all firms (panel A) we see a clear increase in R&D spending in the treated group (by 70 percent, s.e. 19).[33] The estimated change in the probability of implementing new technologies is also positive, but the changes are smaller (9 percentage point increase in the probability of innovation, 23 percentage point increase in the probability of technical innovation). These effects are nosily estimated, because we have to rely on only one CIS wave before the reform. Nevertheless, the point estimates point towards a sizable increase in the probability of introducing new technologies. Furthermore, some firms affected by the R&D tax credit had R&D spending before the reform. For those firms we expect more response on the intensity of innovation and not on the innovation decision itself (see Columns 2 and 3 in Panel B). For firms that did not have any R&D spending before the reform, we find a significant and large change in the probability of introducing new technologies. This effect is especially pronounced for innovation with technical aspects (44 percentage point), which may rely more on R&D than organizational innovation.

Columns (4) and (5) show the estimated change in the college share and the college ratio. In line with our benchmark estimates, we find that the growth rate of the skill ratio increased by 4.3 percent (s.e. 1.7). We find a somewhat larger change for firms that had positive R&D spending pre-reform (Panel B) relative to those that did not (Panel C).

In Column (6) we report the estimated change in the skill premium. To control for changes in worker composition, we estimate the change in the skill premium using the following worker-level regression:

$$\Delta \ln wage_{it} = \delta^u treat_{j(i,t)} \times post_t + \delta^s treat_{j(i,t)} \times post_t \times college_i + \psi_{g(i)t} + \xi_{s(j(i,t))t} + \varsigma_{l(j(i,t))t} + \chi_{g(i)t} + \varepsilon_{it}, \tag{20}$$

where $\Delta \ln wage_{it}$ is the one-year change in worker's i wage, $\psi_{g(i)t}$ denotes the interaction of the four education-group dummies with year dummies, $\xi_{s(j(i,t))t}$ are industry-year fixed effects and ($\varsigma_{l(j(i,t))t}$) location year fixed effects. We report δ^s, which captures the differential change in the growth of wages of college workers relative to non-college workers following the R&D tax credit implementation that

[33] The observed increase in R&D spending may partly reflect relabeling. Before the reform, firms had little incentive to report R&D expenditures, and some may have begun classifying existing activities as R&D only after the tax credit was introduced. This could lead to an overestimation of the true increase, but the large estimated increase cannot be just explained by relabeling. An evaluation commissioned by the Norwegian Ministry of Finance ((Rybalka et al. 2018), ch. 8) concluded that the reform did result in a genuine rise in R&D investment.

affected the treated group. Column (6) in Panel A shows that the growth rate of college workers' relative wages increased by 1 percent (s.e. 0.6). The estimated effects are larger for the group of treated firms that already had positive spending (Panel B; 1.6 percent, s.e. 0.8) compared to the firms with no pre-reform spending (Panel C; 0.5 percent, s.e. 0.6).

Together, these pieces of evidence suggest that, following the introduction of the R&D tax credit, treated firms increased both their skill demand and skill premium faster than firms in the control group. The estimated magnitudes are larger than the baseline estimates, but comparable to innovation based on high R&D spending. For example, as we demonstrate in Table A.18, a 100 percent increase in R&D spending increases the skill ratio by around 5.4 percent and the skill premium by around 1.6 percent. Taking into account that the R&D tax credit increased average spending by 70 percent, we re-scale these latter estimates and get and increase in the skill ratio of around $70\% \times 5.4\% = 3.8\%$ and in the skill premium by around $70\% \times 1.6\% = 1.3\%$. These estimates are very much comparable to our estimates for the effect of the tax credit (with 4.3 percent on skill the ratio and 1.1 percent on the skill premium).[34]

We can also compare the estimates on the firms that react on the extensive margin of innovation with our main results. Table 6 shows that in our baseline analysis, R&D-based technical innovation leads to an 0.6 percentage point increase in college share, 2.4 percent in the skill ratio, and 1.2 percent in the skill premium (Panel B, Row 10).Taking into account that the probability of technical innovation increased by 44 percentage point in Panel C of Table 6, the implied estimates from the R&D tax credit analysis are $0.6/0.44 = 1.36$ pecentage point for the college share, $4.6\%/0.44 = 10.5\%$ for the college ratio, and $0.5\%/0.44 = 1.1\%$ for the college premium.[35] This highlights that while the college-share and college-ratio estimates are somewhat higher in the R&D tax credit analysis, the college-premium estimates are very much in line with the baseline analysis. Overall, our baseline analysis, without an IV strategy, if anything, underestimates the true skill bias of technological change.

Table A.23 columns (1) and (2) report 2SLS results where we instrument technical innovation with $treat_j \times post_t$.[36] These are somewhat noisily estimated and larger than our main estimates.

The 2SLS estimates are reported in Table A.23 column (3). Besides instrumenting technical innovation with $treat_j \times post_t$, we also instrument $college_i \times innovation_j(i,t)$ with $treat_{j(it)} \times post_t \times college_i$. The estimated coefficient is similar to our main estimates.0

Robustness Checks. In Appendix Section A.15 we present several robustness checks. In Appendix Table A.24 we show the estimates with the inclusion of firm fixed effects in regression

[34]Another difference between our baseline results and the analysis of the tax credit is that in the baseline analysis, we apply a four-year change, while here we apply a one-year change. The motivation for applying a four-year change in the baseline analysis is that we are unsure about the exact timing of the innovation, and not because we study the long-term impact of innovation *per se*. In fact, the presence of measurement error in the timing of innovation in the baseline analyses likely implies that our main findings are underestimated.

[35]We present the corresponding two-sample 2SLS estimates in A.23, where we instrument technical innovation with $treat_j \times post_t$ in the firm-level regressions. In the worker-level regression we also instrument $college_i \times innovation_j(i,t)$ with $treat_{j(it)} \times post_t \times college_i$. The resulting point estimates closely align with those obtained by dividing the reduced-form estimates in columns 4–6 by the first-stage coefficient in column 3.

[36]The first stage of this regression is column (3) of Table 6. The first stage is run on a more restricted sample compared to the second stage, so we use a two-sample 2SLS estimator and booststrap the standard errors. This first stage only has a reasonable F-value for all firms and non-R&D firms, so we only reports results for these panels.

equation (19) and firm-college fixed effects in equation (20). Table A.25 shows the estimates with the inclusion of the years 2002 to 2004 in the regressions. Table A.26 shows the estimates when including firms with fewer than 50 employees. Finally, Table A.27 shows the estimates when we drop all workers in R&D occupations, and so we avoid a possible mechanical effect of R&D spending on the skill share and premium via a change in worker composition. In all cases, we find very similar estimates to our benchmark analysis. For example, when we exclude R&D workers from the analysis, we get a slightly smaller estimate for the skill ratio (3.4 vs. 4.3 percent in the benchmark) and a slightly larger change for the skill ratio (0.9 vs. 0.8 percent in the benchmark).

Placebo Analysis: Service Sector Firms. So far we have focused on firms in the manufacturing sector. Table A.28 studies the impact of the R&D tax credit on service sector firms. For the firms in the service sector, we find no significant change in R&D spending or in the probability of innovating in response to the R&D tax credit. Consistent with the absence of changes in innovation, we also find no significant shifts in the skill ratio or skill premium—if anything, skill demand slightly falls. This underscores that the observed change in skill demand of manufacturing firms is indeed driven by the increase in R&D investment.

6 Evidence From Hungary

So far we have studied the change in skill demand following technological change in Norway. Here we present some evidence for a less developed European country: Hungary. Hungary and Norway differ on many fronts. Norway is one of the richest and most developed countries in the world. Hungary is among the poorest European Union member states, with a GDP/capita slightly above 50% of the US level in PPP terms. In terms of innovation activities, Norway is a "Strong innovator" while Hungary is classified as a "Moderate innovator" (ranked 23rd) according to the European Innovation Scoreboard.

Labor market institutions also differ between Norway and Hungary. The Norwegian labor market is an example of the Nordic model with centralized collective bargaining. In strong contrast, Hungarian wage bargaining takes place mostly at the individual level. Union membership is very low and coverage of collective industry-level agreements is limited. These major differences between Norway and Hungary, both in terms of distance to the technological frontier and labor market institutions, are our main motivation for studying and comparing skill-biased technological change in these two countries in particular.

We have access to the CIS data for Hungary, which we can merge to administrative data at the firm level.[37] Table 7 presents the main results for Hungary where we replicate the firm-level analysis for Norway. The effects of innovation on skill demand and premium in Hungary are similar to the Norwegian results. According to Column (1), the share of college graduates increases by 0.2

[37] We have two shortcomings in Hungary compared to the Norwegian data. First, the Hungarian administrative data do not have information on educational level. To overcome this challenge we define a worker to have a college degree if more than 50 percent of workers in her occupation have a college degree. Second, we cannot merge worker-level data to the CIS. As a result, we compute the college wage premium, the college to non-college ratio and the skill premium for every firm-year observation. Then, we match the firm level data to the CIS following the strategy of Card et al. (2016). We explain the matching procedure in more detail in Appendix C.

percentage points (s.e. 0.2), while it increases by 0.4 percentage points in Norway. The effect of innovation growth on the skill ratio, on the other hand, is 3.7 percent, which is slightly larger than in Norway (1.8 percent). This can be explained by a lower average share of college graduates in Hungary, so that a one percentage point increase in the share of college graduates corresponds to a larger increase in the skill ratio in Hungary. Column (3) shows that innovation increases the skill premium in Hungary by 1.4 percent, which is also somewhat higher, but not statistically different from the Norwegian results. Finally, Column (4) shows that employment grows 1.2 percent faster in innovative firms compared to non-innovative firms in Hungary. This estimate is almost the same as in Norway (1.4 percent).

We examine the robustness of the Hungarian results in a similar way to the Norwegian estimates. Table C.3 shows that the results are robust to controlling for value added and capital growth (Panel A), firm fixed effects (Panel B), and the initial college wage share (Panel C).

Next, we examine the heterogeneity in the effects of innovation in Table C.6. First, innovation is more skill biased in Hungary than in Norway: in absence of a change in the college ratio, the change in skill bias would raise the college premium by 2.7 percent in Hungary and 1.7 percent in Norway. This can potentially result from Hungary being farther away from the technological frontier, but may also reflect differences in labor market institutions. Second, similar to Norway, Hungarian innovation is more skill-biased when it is carried out together with R&D activities, or when the firm has introduced a new product to the market. Third, similarly to Norway, each type of innovation is skill biased, but we find a larger effect of process and product innovation on the skill ratio in Hungary. Organizational change is less skill biased than technical innovation. Finally, similarly to Norway, we find that technological change is more skill biased in low-tech manufacturing and non-knowledge intensive sectors. Overall, even if technological change seems to be more skill biased in Hungary, the pattern of skill bias across different types of innovation is very similar in the two countries.

7 Quantitative Implications

7.1 The Contribution of Firm-level Technological Change to the Economy-wide Skill Premium

This section quantifies the contribution of skill-biased technological change in the evolution of the economy-wide skill premium. In our framework presented in Section 2, wages are modeled as a function of firm–skill–specific wage components. Extending this framework to incorporate individual-specific skill heterogeneity yields the following wage structure:

$$\ln w_{it} = \psi_i + \ln w_{Sj(i,t)}, \tag{21}$$

where ψ_i captures workers' skills that are portable across firms, and therefore are not affected by firm-level technological change (at least in the short term). The term $\ln w_{Sj(i,t)}$ represents the skill-group (S) specific firm-level wage premium of firm j.

In this economy, the aggregate or economy-wide college premium, the difference between the average wages of the college workers and the average wage of non-college workers, is the following:

$$\begin{aligned}\overline{\ln w_{H_t}} - \overline{\ln w_{L_t}} \quad &= \quad \tfrac{1}{H_t}\textstyle\sum_{i\in H}\psi_i + \tfrac{1}{H_t}\sum_{i\in H}\ln w_{Hj(i,t)} \\ &\quad - \left[\tfrac{1}{L_t}\textstyle\sum_{i\in L}\psi_i + \tfrac{1}{L_t}\sum_{i\in L}\ln w_{Lj(i,t)}\right].\end{aligned} \tag{22}$$

This equation shows that the economy-wide college premium could increase either because college workers become more skilled relative to non-college workers (ψ_i increases among college workers), or because the wage premium paid by firms changes. In the following analysis we focus on the latter, as this part is what is influenced by firm-level application of new technologies. Formally, we define the contribution of firms to the economy-wide skill premium as:[38]

$$\Theta \equiv \sum_{i\in H}\ln w_{Hj(i,t)} - \sum_{i\in L}\ln w_{Lj(i,t)}. \tag{23}$$

The change in the economy-wide skill premium, $\Delta\Theta$, can be decomposed into two parts (see Section **??** for the details):

$$\begin{aligned}\Delta\Theta \quad \equiv \quad & \underbrace{\sum_j\left(\frac{H_{jt+1}}{H_{t+1}} - \frac{H_{jt}}{H_t}\right)\ln w_{Hjt+1} - \sum_j\left(\frac{L_{jt+1}}{L_{t+1}} - \frac{L_{jt}}{L_t}\right)\ln w_{Ljt+1} +}_{\text{Reallocation Effect}} \\ & + \underbrace{\sum_j\frac{H_{jt}}{H_t}\left(\ln w_{Hjt+1} - \ln w_{Hjt}\right) - \sum_j\frac{L_{jt}}{L_t}\left(\ln w_{Ljt+1} - \ln w_{Ljt}\right).}_{\text{Wage premium effect}}\end{aligned} \tag{24}$$

The first part captures the reallocation of workers between firms paying different wages. When labor markets are imperfectly competitive, moving from lower to higher paying firms (or vice versa) contribute to chaning inequality. The second part of $\Delta\Theta$ captures the change in the skill premium at innovative and non-innovative firms. Again, as our empirical analysis demonstrated, firms adopting new technologies increase the college premium of their college workers, contributing to this term.

We assess the magnitudes in the equation above by calibrating the model introduced in Section 2. Specifically, we consider a two-sector version of the model: one sector consists of innovative firms, and the other of non-innovative firms. Firms in each sector face upward-sloping labor supply curves. We set $\beta = 3$, consistent with the elasticity implied by our estimates (see the discussion of firm-level labor supply in Section 5.2). We assume aggregate labor supply is fixed, so any increase in the share of one type of firm must come at the expense of the other.

Panels A and B in Table 8 present our chosen parameter values. We set $\sigma = 1.6$, following the literature (see Acemoglu (2002)). The share of college-educated workers is taken from the data

[38] It is important to note that the level of Θ cannot be identified from the data alone without further normalization of the average person effects, ψ_i. However, the change in Θ, which is the focus of our analysis below, can be identified.

and equals 35%. We then calibrate the skill bias parameter θ, the amenity level a, and total factor productivity A in the pre-reform period to match the observed skill ratio, the skill premium, the share of innovative firms in the high-skill market, and the wage gap among non-college workers.

We then apply the estimated change in skill bias to simulate the impact of technological change on the skill premium, as reported in Table 5.[39] We also allow for Hicks-neutral technological change as a consequence of innovation, calibrating its magnitude using the relative change in the employment of college and non-college workers at innovative firms. Panel C of Table 8 shows that our model closely matches the observed changes in the skill premium and skill ratio in the data. EXTEND FURTHER¡ BUT IT IS UNCLEAR WHY THOSE PARAMETERS ARE CHOOSEN.

Panel D presents the estimated contribution of firm-level technological change to the aggregate college wage premium. Our model indicates that the college premium increased by 2.31% as a result of skill-biased technological change. This effect can be decomposed into two components. First, approximately 90% of the increase is attributable to the wage premium effect, suggesting that innovation raises the economy-wide skill premium primarily through higher wages in innovative firms. Second, the remaining 10% reflects a reallocation effect: innovation induces workers to move from less innovative to more innovative firms, which already offer higher wage premia.

Perfectly Competitive Labor Markets. It is an interesting thought experiment to study what would happen if labour markets become more competitive, implying higher upward sloping labor supply elasticity. The final Panel of Table 8 assess the implication of skill bias technological change under various values of *beta*.[40]

When we increase β, making labor markets more competitive, the effect on the skill premium becomes larger. This occurs because innovative firms are able to expand more when they are less constrained by imperfect worker mobility, amplifying the direct impact of skill-biased technological change. However, with easier worker movement between sectors, the differential skill premium between innovative and non-innovative firms disappears, reducing the scope for reallocation effects. Empirically, the direct effect dominates, so even as reallocation effects diminish, the aggregate impact of technological change increases. Overall, the change in the wage premium would have been 3.33% (instead of 2.31%), approximately 45% larger.

Therefore, a key difference in our framework, relative to the standard competitive model is that skill-biased technological change affects not only between-skill group inequality, but also within-skill group inequality can also change. This follows from our model where similarly skilled workers are paid different firm-specific wage premiums, which creates within-skill inequality. Given that innovative firms pay a higher college premium to begin with, the estimated increase in the firm-specific college premium following innovation contributes to an increase in wage inequality within education groups.

[39] The estimates in Table 5 reflect a four-year effect of innovation. To approximate a long-run (ten-year) effect, we multiply these values by 2.5.

[40] It is worth emphasizing that the labor market structure itself can affect the share of innovative firms and the size of skill-biased technological change. In the following analysis, we keep these factors fixed, meaning that we present only a partial equilibrium analysis that serves as an initial benchmark. To understand the full implications of the labor market structure, we would need a fully developed structural estimation, which would allow us to do general equilibrium counterfactuals far from the current labor market structure. This analysis is beyond the scope of this paper.

The within-skill group increase in inequality (or the residuum) is a common finding in the empirical literature (see e.g. DiNardo et al. 1996, Acemoglu 2002) and it is often interpreted as evidence for an increase in the return to the components of skills other than years of schooling (see e.g. Juhn et al. 1993). Our imperfect competition framework and the empirical evidence provided in this paper offer a complementary explanation relying on the heterogeneous return of schooling across firms: technological change amplifies differences in the return to schooling across firms and, as a result, contributes to rising inequality within education groups.

Explaining aggregate trends in wage inequality. These quantitative results also help in explaining why the college premium fell both in Norway and Hungary[41] even though substantial technological change took place according to our findings. In particular, we can combine our estimate for the contribution of the change in skill bias with the economy-wide change in the skill ratio to estimate the economy-wide elasticity.[42] Using the aggregate-level production function of Katz & Murphy (1992), $\Delta \ln \frac{w_{H_t}}{w_{L_t}} = \Delta\Theta - \frac{1}{\sigma^{agg}} \Delta \ln \frac{H_t}{L_t}$, we can infer the implied (aggregate) substitution (σ^{agg}) between college and non-college workers.

The implied substitution elasticity σ^{agg} without skill-biased technological change is 4.9 for Norway and 9.4 for Hungary implied by earlier periods (see Acemoglu & Autor 2011a). These elasticities are considerably larger than the estimates in the existing literature. However, once we substitute our estimated contribution of technological change to the change in college premium, the implied elasticities of substitution are 3.5 in Norway and 4.8 in Hungary (see the second rows of Table **??**). These numbers are close to the elasticity of substitution found in Acemoglu & Autor (2011a). This demonstrates that our micro-based approach to estimating the skill-biased content of aggregate technological change aligns closely with the evolution of skills and wages in both countries.

8 Conclusion

This paper documents that innovation activities and technological change are associated with an increase in skill demand in Norway and Hungary. Our approach directly infers skill bias from firm-level technological change. We exploit an exceptionally rich survey, the CIS, which provides self-reported measures of firm-level technological change. We identify and quantify the extent to which firm-level technological change is skill biased by estimating the change in both the skill ratio and skill premium following innovation. We find that innovation is a key force behind the recent trends in inequality. This finding might be surprising given the considerable fall in the college premium observed in many countries in recent years. However, we demonstrate that the fall in the college premium likely reflects that in recent periods, the race between education and technology (as coined by Goldin & Katz 2010) was won by education. Our estimates imply that technological change still plays a prominent role in the evolution of the college premium.

Comparing the two countries, interestingly, we find that the increase in skill demand is larger in

[41] In particular, the skill premium in the period studied in this paper declined from 31 to 20% in Norway, and from 110 to 95% in Hungary.

[42] The skill ratio increased from 0.49 to 0.75 in Norway, and from 0.16 to 0.32 in Hungary during our study period.

Hungary, the country farther away from the technological frontier. Our findings hence demonstrate that technology adoption can be a very important source of rising inequality in countries far from the technological frontier. These results highlight that the nature of technological progress matters for shaping inequality. Finally, our findings underscore the importance of taking into account the presence of imperfect competition in the labor market when assessing how firm-level technological change shapes within- and between-skill group inequality.

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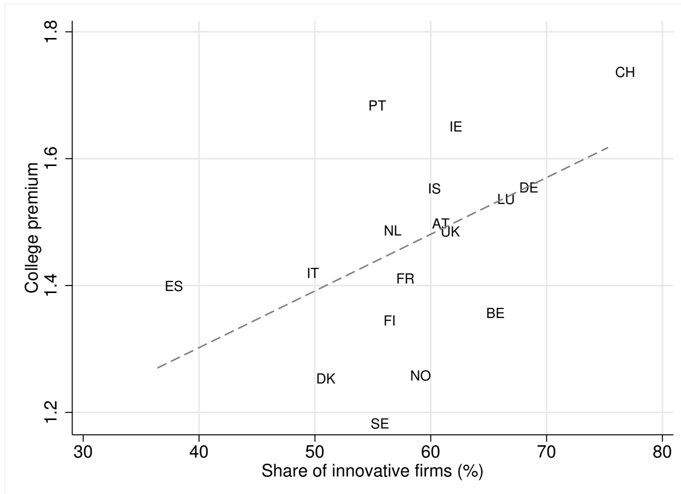
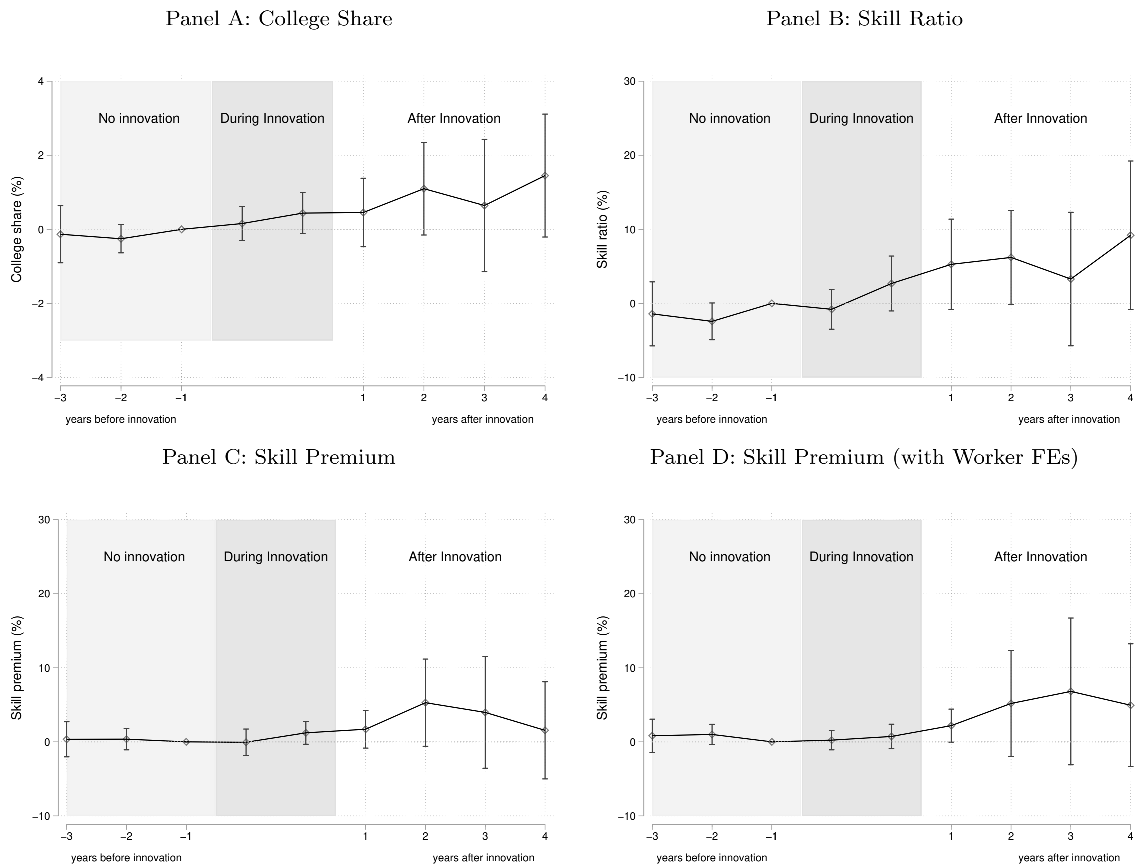
Figures

Figure 1: Share of Innovative Firms and the College Premium: Cross-Country Evidence



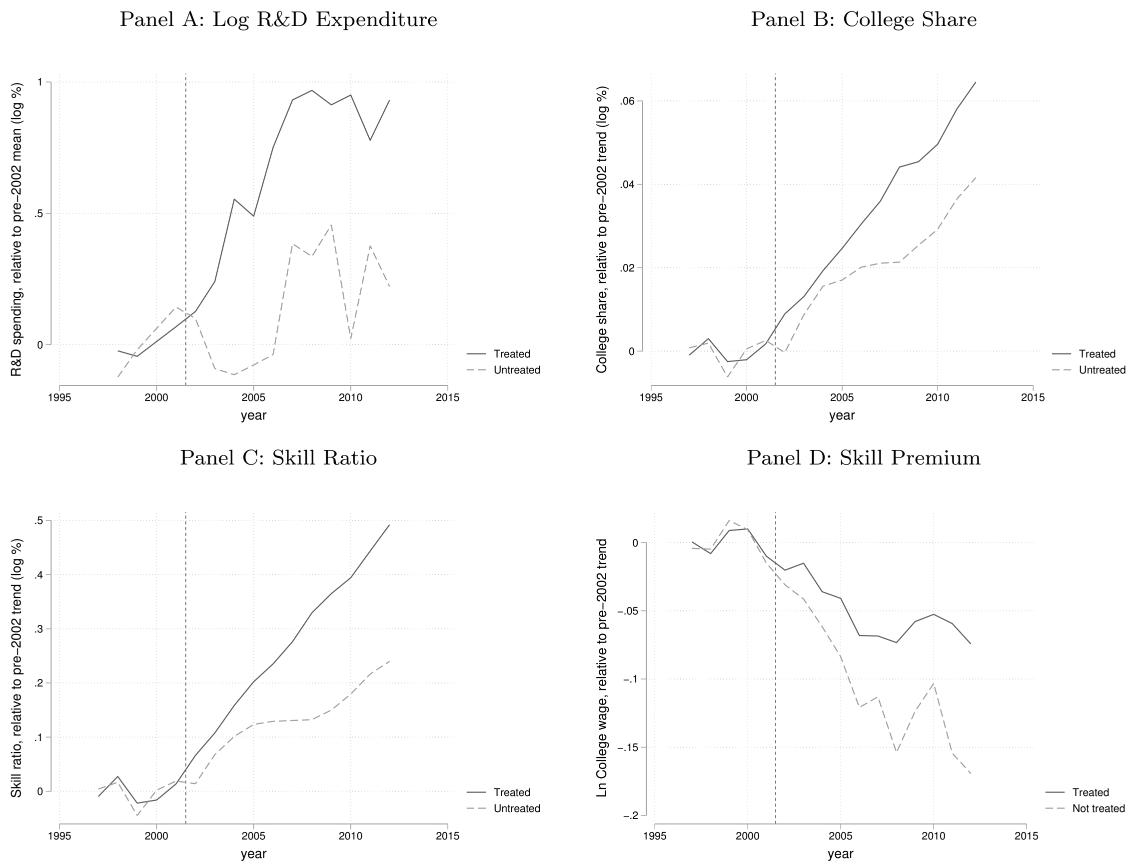
Notes: This figure shows the cross-country relationship between the college premium and the share of innovative firms in 2014. Innovative firms are those firms changing their technology between 2012 and 2014 by introducing any new or significantly modified product/service/process/organizational change. The data comes from Eurostat. The innovation variable is from the 2014 Community Innovation Survey, while the college premium comes from the Structure of Earnings Survey.

Figure 2: Event Study



Notes: This figure shows event study results for the evolution of the college share (panel A), the skill ratio (panel B) and the skill premium (panels C and D) around the time of starting innovation. An innovation "event" occurs if a firm does not report innovation in two consecutive CIS waves before reporting innovation in the next wave. The control group includes 'never innovators', defined as firms never reporting innovation while participating at least three times in the CIS. The figure plots the coefficients β_k and γ_k from equations (16) (panels A-B) and (17) (panels C-D) with their 95% confidence intervals. The lightly shaded area reflects the period where no technological change was implemented. The darkly shaded area reflects the period when the first innovation took place. The CIS does not measure the exact year of innovation, so we cannot know the exact date, however, the last year in this area corresponds to the year of the CIS when the firm reported innovation for the first time. Firm-level regressions (panels A and B) are weighted by the number of workers in the firm in the year before the fist innovation (t=-1), and include industry-year, district-year and firm fixed effects. Worker-level regressions include year-schooling, firm-college, firm-year and district-year fixed effects. Panel D also includes worker fixed effects. Standard errors are clustered at the firm level in both regressions.

Figure 3: Change in R&D Investments and in Skill Demand Following the Introduction of an R&D Tax Credit Policy



Notes: This figure shows the evolution of R&D investments, the college share and the college premium following the 2002 introduction of an R&D tax credit in Norway. The tax credit allowed firms to deduct up to 20% of their R&D expenses up to a threshold of NOK 4 million (approx 450,000 USD). This implied a reduction in the marginal cost of R&D investments for firms investing less than the threshold. We assign firms to the treated group if they spent less than the policy threshold (NOK 4 million) on R&D, on average, during the pre-reform years 1998-2001. We assign firms to the control group if they reported R&D expenses above NOK 4 million, but less than 40 million, prior to the reform. We also restrict the sample to firms operating in the manufacturing sector that had at least 50 workers in 2001. Panel A shows the evolution of (employment-weighted) average log R&D spending relative to the pre-reform firm averages. Panels B and C use the evolution of (employment-weighted) average college share and skill ratio relative to the pre-reform firm averages. To study the change in growth of college ratio and college premium we also remove group specific (treated/non-treated) trends estimated only based on the pre-2002 periods. Panel D shows the change in skill premium for workers at treated and control firms. We report wage premiums calculated for each skill group after filtering out the pre-reform firm-level average wages and group specific (treated/non-treated) trends.

Tables

Table 1: Descriptive Statistics: Characteristics of Innovative and Non-innovative firms in Norway

	All	Non-innovative	Innovative
Average years of education	13.11	12.83	13.49
	(1.57)	(1.44)	(1.67)
Share of college graduates	0.26	0.21	0.32
	(0.27)	(0.24)	(0.28)
Skill ratio (log)	-1.20	-1.41	-0.96
	(1.31)	(1.24)	(1.35)
Skill premium (log)	0.16	0.14	0.19
	(0.31)	(0.34)	(0.28)
Log hourly wage rate (NOK)	5.35	5.32	5.40
	(0.33)	(0.33)	(0.32)
Number of employees	86.98	60.61	122.00
	(360.11)	(193.45)	(500.01)
Average age of employees	41.79	41.95	41.59
	(5.08)	(5.36)	(4.67)
Firm-years	27,686	15,791	11,895
Firms	13,463	9,982	6,400

Notes: This table shows the characteristics of innovative and non-innovative firms in the Community Innovation Survey (CIS). We measure firm-level technological change in the CIS. Innovative firms report that they introduced new or significantly modified products/technologies/organization, which are new from their point of view. Non-innovative firms are the rest of the firms in the survey. We report average values of outcomes for the biennial CIS-survey years 2002-2014 (for which we estimate the firm-level regressions). The table shows the mean of firm-level average years of schooling, firm-level share of college graduates, firm-level skill ratio (log college to non-college ratio), log skill premium, firm-level average log daily wage, firm-level average age of workers, firms' number of employees. Standard deviations of these variables are reported in parentheses below.

Table 2: Change in Firm Skill Demand Following Firm-level Technological Change

	(1) College share	(2) Skill ratio	(3) Skill premium	(4) Skill premium incumbents	(5) Log employment
Innovation	0.004	0.018	0.005	0.008	0.016
	[0.001]	[0.008]	[0.004]	[0.004]	[0.011]
Observations	27,122	21,135	21,135	14,662	27,122
Firms	13,141	9,545	9,545	6,912	13,141
R-squared	0.11	0.12	0.09	0.12	0.29
2-digit Nace x Year FEs	yes	yes	yes	yes	yes
District x Year FEs	yes	yes	yes	yes	yes

Notes: This table shows the relationship between firm-level technological change and change in firm-level college employment share (Column (1)), firm-level skill ratio (Column (2)), firm-level skill premium (Column (3)), firm level skill premium for incumbent workers (defined as workers who worked in the firm in the baseline year, in Column (4)), and log employment (Column (5)). We measure firm-level technological change in the CIS which asks whether any new or significantly modified product/service/process/organizational change (i.e. innovation) was introduced in the previous three years. The table reports the δ coefficients from regression equation (14). The dependent variable is 4-year growth between years $t-4$ and t, where t is the year of the CIS wave. All regressions include industry-year and district-year fixed effects. We weight all regressions by employment in year t. Standard errors are clustered at the firm level and are reported in square brackets.

Table 3: Change in the Skill Premium Following Firm-level Technological Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation	-0.006	-0.005	-0.007	-0.009	-0.006	-0.007		
	[0.004]	[0.004]	[0.004]	[0.004]	[0.006]	[0.007]		
Innovation x College	0.011	0.011	0.013	0.014	0.014	0.021	0.012	0.018
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.006]	[0.004]	[0.005]
Observations	1,863,477	1,863,477	1,863,440	1,849,039	1,863,302	1,861,095	1,863,229	1,846,326
R2	0.035	0.035	0.042	0.100	0.073	0.079	0.118	0.154
Firms	13,378	13,378	13,372	13,216	13,203	13,106	13,198	12,904
Workers	690,671	690,671	690,651	686,204	690,525	688,814	690,504	684,168
Ind-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
College-dist.-year FEs	no	yes	no	no	no	no	no	yes
College-dist.-wage-sh.--year FEs	no	no	yes	no	no	no	no	yes
Occupation-dist.-ind.--year FEs	no	no	no	yes	no	no	no	yes
Firm FEs	no	no	no	no	yes	yes	yes	yes
Firm-college FEs	no	no	no	no	no	yes	no	yes
Firm-year FEs	no	no	no	no	no	no	yes	yes

Notes: This table reports results from worker-level regressions where the dependent variable is the change in the worker's log hourly wage between years $t-4$ and t and the main explanatory variable is the firm's innovation status, as reported in the CIS in year t, referring to the period between $t-2$ and t. We measure firm-level technological change in the CIS which asks whether any new or significantly modified product/service/process/organizational change (i.e. innovation) was introduced. We report the estimated coefficients on the innovation dummy, δ^u, and the innovation dummy interacted with an indicator variable for whether the individual has a college degree, δ^s, from equation (15) described in Section 4.2. Our primary interest lies in the coefficient of the "Innovation x College" interaction, which shows the extent to which the college premium changes following technological change relative to firms not reporting a technological change. All specifications include skill-year fixed effects, representing interactions of primary, secondary, vocational and college dummies with year dummies, as well as 2-digit industry-year and district-year fixed effects. Column (1) includes only these baseline sets of fixed effects, while Columns (2)-(8) show how the estimates change when further fixed effects are included. The table includes firm-years when firms were surveyed by the biennial CIS (years 2001, 2004, 2006, 2008, 2010, 2012, 2014), and firms which reported positive sales and value added in both $t-4$ and t. Standard errors are clustered at the firm level and are reported in square brackets.

Table 4: Change in Skill Premium Following Firm-level Technological Change for Incumbent Workers and for New Entrants

	(1) Incumbent Sample	(2) New entrant Sample	(3) New entrant Sample	(4) New entrant Sample
Innovation	-0.004	-0.010	-0.003	-0.011
	[0.004]	[0.007]	[0.007]	[0.008]
Innovation x College	0.011	0.014	0.015	0.018
	[0.005]	[0.008]	[0.009]	[0.010]
AKM firm FE			0.504	
			[0.008]	
AKM firm-skill FE				0.332
				[0.007]
Observations	1,310,609	552,862	416,841	416,841
R2	0.039	0.037	0.130	0.099
Firms	12,936	11,828	10,449	10,449
Workers	523,045	367,208	287,259	287,259
Industry-year FEs	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes

Notes: This table reports worker-level regressions—in the same setup as in Table 3, column (1)—but distinguishes between incumbent workers and new entrants. Column (1) reports results for incumbents, workers who worked at the same firm in both year $t-4$ and t. Column (2) reports results for new entrants (i.e. non-incumbent workers). Column (3) repeats the regression for new entrants, but adds a control for the difference in estimated firm fixed effects of worker i's firm in year t and $t-4$. We estimate an Abowd et al. (1999) two-way fixed effects model based on data from the period between years $t-8$ and $t-4$, and calculate the fixed effects for both firms. The 'AKM firm FE' variable is the difference in fixed effects between the worker's two firms. In column (4), we run the AKM model with worker and firm-college fixed effects to allow for heterogeneous skill premiums. This gives us the 'AKM firm-skill FE' for the two firms, and we calculate the difference for each worker and include it in the regression. Columns (3) and (4) are restricted to observations with available AKM estimates in the largest connected sets. Standard errors are clustered at the firm level and are reported in square brackets.

Table 5: Change in Skill Demand Following Different Forms of Technological Change

Panel A: By R&D

	(1) College share (beta)	(2) College share (s.e.)	(3) Skill ratio (beta)	(4) Skill ratio (s.e.)	(5) Skill premium (beta)	(6) Skill premium (s.e.)	(7) Skill bias
Any innovation	0.004	[0.001]	0.018	[0.008]	0.011	[0.005]	0.022
No R&D	0.000	[0.002]	-0.001	[0.012]	0.010	[0.006]	0.009
R&D	0.006	[0.002]	0.026	[0.010]	0.011	[0.006]	0.027
R&D and new to market	0.008	[0.002]	0.032	[0.011]	0.007	[0.006]	0.027

Panel B: By Type

Only technical	0.001	[0.002]	0.000	[0.011]	0.018	[0.006]	0.017
Only process	-0.002	[0.003]	-0.006	[0.020]	0.017	[0.013]	0.013
Only product	0.000	[0.002]	0.006	[0.012]	0.011	[0.007]	0.015
Only organizational	0.001	[0.003]	0.005	[0.015]	0.009	[0.009]	0.012
Both technical and organizational	0.007	[0.002]	0.036	[0.010]	0.003	[0.006]	0.025
R&D + Tech. + Mfg	0.006	[0.002]	0.024	[0.012]	0.012	[0.008]	0.027

Panel C: By Industry

Low tech manuf.	0.004	[0.003]	-0.001	[0.018]	0.017	[0.008]	0.017
High tech manuf.	0.005	[0.002]	0.028	[0.015]	0.007	[0.010]	0.024
Not know. int. serv.	-0.001	[0.002]	-0.003	[0.013]	0.015	[0.007]	0.013
Know. int. serv.	0.014	[0.005]	0.053	[0.031]	-0.014	[0.012]	0.019

Notes: This table shows the estimated college share, skill ratio and skill premium effects following different types of technological change. The estimates are calculated from Tables A.20, A.19 and A.21 in the Appendix. Column (7) calculates the implied skill bias, by using the formula from equation (18) and using the value $\sigma = 2.94$. Row 1 repeats our benchmark estimates (corresponding to Columns (1) and (2) of Table 2 for the college share and premium, and Columns 1 of Table 3). Rows 2-3 distinguish between non-R&D based and R&D-based innovation. In row 4, we look at R&D-based innovation that was also considered new to market by the firm. Rows 5-9 distinguish between different types of innovation, as well as whether the firm conducts only one type of innovation, or both technical and organizational innovation. Row 10 reports the impact of R&D-based technical innovation in the manufacturing sector. Finally, rows 11-14 distinguish between different sectors, based on Eurostat definitions. 'manuf.' stands for manufacturing and 'know. int. serv.' for knowledge-intensive services.

Table 6: The Impact of the R&D Tax Credit Policy in Norway

Panel A: All Firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.697	0.094	0.227	0.005	0.043	0.010
	[0.174]	[0.075]	[0.073]	[0.002]	[0.016]	[0.006]
Observations	438,319	291,710	291,710	923,420	916,684	817,372
R2	0.67	0.26	0.31	0.20	0.18	0.03
Firms	600	737	737	962	953	970
Workers						221,321
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel B: Only Firms with Positive R&D Spending Between 1998-2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.750	0.026	0.104	0.006	0.053	0.016
	[0.194]	[0.078]	[0.073]	[0.002]	[0.018]	[0.008]
Observations	397,920	191,541	191,541	598,331	596,417	542,441
R2	0.69	0.38	0.41	0.22	0.23	0.04
Firms	498	406	406	494	493	499
Workers						151,256
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel C: Only Firms with No R&D Spending Between 1998-2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.000	0.231	0.444	0.006	0.046	0.005
	[.]	[0.084]	[0.079]	[0.003]	[0.020]	[0.006]
Observations	264,561	189,963	189,963	608,545	603,549	531,812
R2	0.66	0.41	0.51	0.27	0.26	0.03
Firms	243	444	444	608	600	612
Workers						152,007
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Notes: This table shows the effect of an R&D tax credit, introduced in 2002 in Norway, on R&D spending, innovation, the skill ratio and the skill premium. The tax credit allowed firms to deduct up to 20% of their R&D expenses up to a threshold of NOK 4 million (approx 450,000 USD). This implied a reduction in the marginal cost of R&D investments for firms investing less than the threshold. We assign firms to the treated group if they spent less than the policy threshold (NOK 4 million) on R&D, on average, during the pre-reform years 1998-2001. Panel B restricts the treated group to firms with positive R&D spending (below NOK 4 million) in at least one of the pre-reform years. Panel C restricts the treated group to firms with no R&D spending pre-reform years. Control firms spent between NOK 4-40 million over the same pre-reform period. Our main sample in this table consists of manufacturing firms with at least 50 employees in 2001. Columns (1)-(5) report estimates from regression equation (19). We report the δ coefficients, which show the estimated treatment effect (the interaction of the treated group indicator with a post-2001 dummy) on different outcomes. Columns (1)-(3) show the effect on innovative inputs and outputs (measured by R&D spending in Column 1, by a dummy variable on whether technological change was introduced in Column 2, and by a dummy variable on whether a technological change with a technical aspect was implemented in Column 3). Columns (4) and (5) report the estimated treatment effect on one-year growth rates of the firm-level college share and college ratio, respectively. In Column (6) we report the estimated treatment effect on the one-year growth rate of the skill premium based on equation (20). We report the δ^s coefficient (interaction of college, treated group and post indicators). All regression cover the years 1998-2001 and 2004-2008. Standard errors are clustered at the firm level and reported in parentheses. The firm-level regressions are weighted by the number of employees.

Table 7: Change in Firm Skill Demand Following Firm-level Technological Change in Hungary

	(1) College share	(2) Skill ratio	(3) Skill premium	(4) Log employment
Innovation	0.002	0.037	0.014	0.012
	[0.002]	[0.016]	[0.007]	[0.014]
Observations	23,050	14,846	14,846	23,050
Firms	10,528	6,573	6,573	10,528
R-squared	0.144	0.148	0.323	0.169
2-digit Nace x Year FEs	yes	yes	yes	yes
District FEs	yes	yes	yes	yes

Notes: This table shows the relationship between firm-level technological change and 4-year changes in the firm-level college employment share (Column (1)), firm-level skill ratio (Column (2)), firm-level skill premium (Column (3)) and log employment (Column (4)). We measure firm-level technological change in the CIS which asks whether any new or significantly modified product/service/process/organizational change (i.e. innovation) was introduced. The table reports the δ coefficients from regression equation (14). The dependent variable is the 4-year growth between years $t-4$ and t in the variables in question, where t is the year of the CIS wave. The "Innovation" dummy indicates whether the firm innovated according to the CIS wave conducted in year t (referring to the period between $t-2$ and t). The table includes firm-years when firms were surveyed by the biennial CIS (years 2008, 2010, 2012, 2014, 2016), and firms which reported positive sales and value added in both $t-4$ and t. All regressions include industry-year and district-year fixed effects. We weight all regressions by employment in year t. Standard errors are clustered at the firm level and are reported in parentheses.

Table 8: The Contribution of Technological Change to the Economy-wide College Premium Over a Ten-Year Period

Panel A: Norway

	(1) Any	(2) R&D	(3) Non R&D	(4) R&D and new	(5) Only tech.	(6) Only org.	(7) Both
Reallocation effects	0.05	0.09	0.00	0.13	0.00	-0.00	0.06
Wage premium effect	3.32	2.87	0.55	2.59	0.88	0.40	1.98
Total ($\Delta\Theta$)	3.37	2.96	0.56	2.72	0.88	0.40	2.04

Panel B: Hungary

	(1) Any	(2) R&D	(3) Non R&D	(4) R&D and new	(5) Only tech.	(6) Only org.	(7) Both
Reallocation effects	1.02	0.94	0.18	0.79	0.10	0.03	1.23
Wage premium effect	3.94	2.50	1.17	2.10	0.96	0.40	2.28
Total ($\Delta\Theta$)	4.96	3.44	1.35	2.89	1.05	0.42	3.51

Notes: This table shows the change in the aggregate college premium (in percentage points) over a ten-year period due to firm-level technological change. The table reports estimates based on equation (G.8). The reallocation effect represents the change in wage premium resulting from workers moving between firms introducing new technologies (innovative firms) and firms that do not introduce new technologies (non-innovative firms). The wage premium effect captures the change in wage premium in firms introducing new technologies (innovative firms) and Total is the sum of the reallocation and wage premium effects, which reflects the overall contribution of technological change to inequality. The different columns quantify the contribution of firms conducting different forms of innovation to the aggregate college premium. We measure different forms of technological change from the detailed questionnaire of the CIS on firms' innovation activities. Column (1) captures the contribution of all innovative firms. Columns (2) and (3) calculate the contribution of innovators that conduct R&D and of those that do not, respectively, while Column (4) presents results for firms that both conduct R&D and introduce a product that is new to the market. Finally, Columns (5), (6) and (7) calculate the contributions of firms that conducted innovations only with technical aspects (product and process), only with organizational changes, or both, respectively.

Appendix A Additional Tables and Figures

A.1 Cross-country Relationship between Innovation and Skill Premium

Figure 1 in the main paper shows the cross-country relationship between the share of innovative firms and the skill premium among "old" EU member states. To create the figure, we use country-level data from Eurostat's webpage on the premium of college educated workers, the share of innovative firms, and the share of firms conducting R&D activities. The source of R&D and innovation variables is the 2014 Community Innovation Survey (CIS) conducted in 23 (mainly EU) countries. Innovative firms are defined as firms that change their technology between 2012 and 2014 by introducing any new (from the viewpoint of the firm), or significantly modified products/services/technologies/organizational solutions. It follows that innovation, according to this broad definition, does not have to be R&D-driven. The college premium is estimated using the 2014 wave of the Structure of Earnings Survey. In particular, we run cross-sectional regressions of the form:

$$\text{college premium}_j = \alpha + \delta_{inn}\text{ShareInnov}_j + \delta_{R\&D}\text{ShareR\&D}_j + \gamma X_j + \epsilon_j, \tag{A.1}$$

where ShareInnov_j is the share of innovative firms in country j, $\text{ShareR\&D}_j$ is the share of R&D conducting firms, and X_j includes three variables: the share of college-educated workers; CEE_j, which shows whether the country is a new member state (i.e. admitted after 2000); and log GDP per capita.

Table A.1 shows the estimates from this cross-sectional regression. Column (1) shows that there is a positive and statistically significant (at the 5% level) relationship between the share of innovative firms and the college premium among old EU member states. Column (2) includes the new EU member states as well as controls for economic development (log GDP per capita) and the college share. The estimated relationship is almost the same, though the estimates become a bit noisy. Columns (3) and (4) show the estimates when we replace the share of innovative firms with the share of R&D-conducting ones. Surprisingly, no clear relationship emerges here, which underscores the the key role played by non-R&D innovative firms to increasing inequality, especially in countries farther from the technology frontier. Finally, in column (5) we include both the share of innovative and the share of R&D-conducting firms. We find that the share of innovative firms is more strongly correlated to the college premium than the share of R&D-conducting firms. This again corroborates our key finding that non-R&D based innovation is responsible for a substantial amount of skill bias in technological change.

Table A.1: Innovation and the College Premium: Cross-country Evidence

LHS: College premium	(1)	(2)	(3)	(4)	(5)
Innovative firms (share)	0.894**	0.909*			0.832
	(0.408)	(0.486)			(0.606)
R&D firms (share)			-0.130	0.530	0.049
			(0.521)	(0.576)	(0.662)
Share of college educated		-0.013**		-0.017**	-0.015**
		(0.005)		(0.007)	(0.007)
GDP/capita		-0.001		0.206	0.043
		(0.186)		(0.180)	(0.211)
CEE		0.361**		0.303**	0.370**
		(0.129)		(0.130)	(0.136)
Constant	0.945***	1.443	1.490***	-0.203	1.058
	(0.237)	(1.764)	(0.135)	(1.788)	(1.970)
Sample	No CEE	All	No CEE	All	All
Observations	17	23	16	22	22
R-squared	0.242	0.479	0.004	0.433	0.493

Notes: This table shows the cross-country relationship between the college premium and the share of innovative firms (δ_{inn}) and the share of R&D-conducting firms ($\delta_{R\&D}$) from the regression equation A.1. Innovative firms are those firms changing their technology between 2012 and 2014 by introducing any new or significantly modified products/services/technologies/organization, which are new from the viewpoint of the firm, but that are not necessarily new to the market. Therefore, innovation, according to this broad definition, does not have to be R&D-driven. Columns (1) and (3) show the raw correlation among the old EU member states. Columns (2), (4) and (5) include all EU members states in the regression as well. CEE is a dummy for new EU member states. Standard errors in parentheses. Significance levels are: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.2 Country-industry Level Relationship between Technological Change and Skill Demand

In this section we complement our findings on firm-level technological change and skill demand and present evidence at the country-industry level. For this exercise, we use data from the Eurostat, which reports statistics on innovation activities, as well as the share and premium of college educated workers at the 1-digit country-industry level. The source of innovation variables is the Community Innovation Survey (CIS). The college share and college premium is calculated from the Structure of Earnings Survey (SES). We have access to the micro data for both the CIS and SES in Norway and Hungary. For the other countries we only have access to aggregate statistics that can be downloaded from Eurostat's webpage.[43]

Figure A.1 shows the descriptive relationship between the share of innovative firms in 2010 and the change in the skill premium and the skill share between 2010 and 2014. We apply the same definition of innovation as in the main paper: innovative firms in 2010 are those that introduced any new or significantly modified product/service/process/organizational change, which is new from the viewpoint of the firm, but not necessary to the market, between 2008 and 2010. Therefore, innovative firms are those experiencing technological change. The figure shows that there is a clear positive relationship between the share of innovative firms (our measure of technological change) and the change in the skill premium and the change in the skill ratio.

We investigate the robustness of these relationships in Table A.2. We follow Machin & Van Reenen (1998), and regress the four-year change in skill demand on the share of innovative firms. In particular, we run regressions of the type:

$$\Delta y_{cst} = \delta_{inn} innovation_{cst} + \delta_{R\&D} R\&D_{cst} + \gamma_y y_{cst} + \eta_c + \zeta_s + \epsilon_{cst}, \tag{A.2}$$

where c indexes countries, s industries (1-digit) and t time periods. Δy_{cst} is the long difference, the change of y_{cst} between years t and $t+4$, η_c denotes country fixed effects, while ζ_s denotes industry fixed effects. $innovation_{cst}$ is the share of innovative firms, while $R\&D_{cst}$ is the R&D intensity of the industry (the ratio of the total R&D expenditures and total the revenue of firms at the industry-country level). This long-difference regression removes differences in the level of the skill premium an the skill ratio at the country-industry level and identifies only from changes in skill demand. Country fixed effects also remove country-level shocks to skill supply or general economic conditions. In some specifications we also include industry fixed effects to filter out industry-level shocks. We weight the regressions by the number of firms in the CIS in the given country-industry cell to give more weight to observations which represent an average calculated from more observations. We cluster standard errors at the country level, as skill premiums are likely to be strongly correlated within each country.

Table A.2 presents the regression results both for the change in the share of college educated workers (top panel) and the college premium (bottom panel). Column (1) reports basic regressions

[43] This merged sample includes EU27 countries (with the exception of Greece, Malta) and Norway, altogether 25 countries.

when both the share of innovative firms and the R&D intensity are included.[44] The estimates suggest that the increase in skill demand is linked to broadly defined innovation activities rather than only R&D. A ten percentage point higher share of innovative firms is associated with a one percentage point stronger growth of the college employment share and a three percentage points higher increase in the college premium at the industry level. The estimated coefficient of the R&D variable is small and often negative.

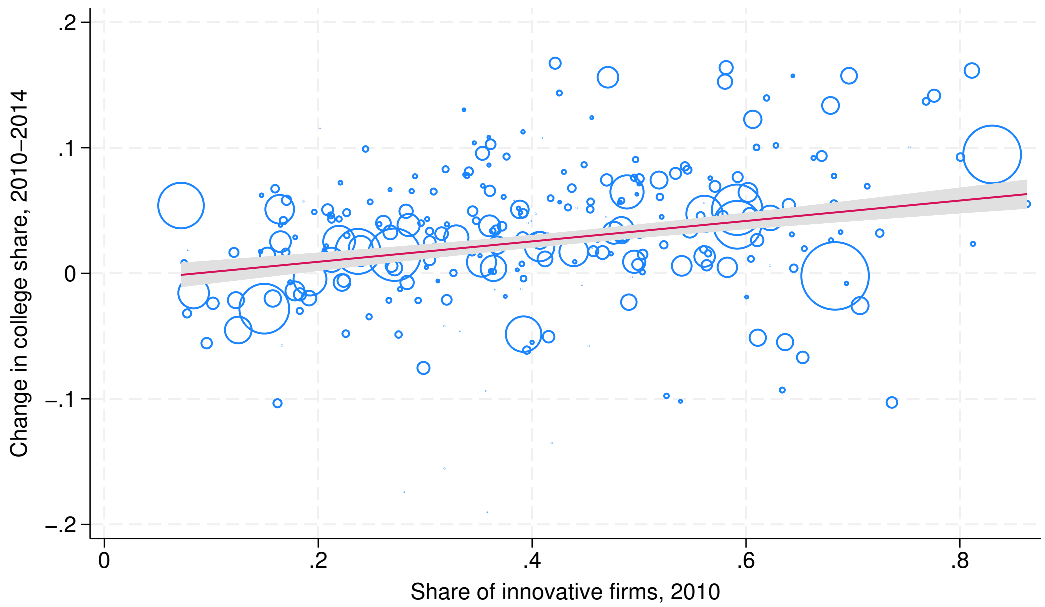
Column (2) includes country fixed effects to control for country-level shocks to skill supply or economic growth, while column (3) includes industry fixed effects, but not country fixed effects. The inclusion of these fixed effects has only a small impact on the point estimates, however, some of the coefficients become less precisely estimated. In Column (4) we include both country and industry fixed effects. The change in the college share becomes insignificant, while the point estimates of the college premium are unaffected by including these two sets of fixed effects. Overall, the results reveal a strong relationship between the share of innovative firms and subsequent increase in the college premium.

Our conclusion from this exercise is that the broadly defined innovation measure, capturing many different forms of technological change (including technology adoption), is strongly related to skill demand at the country-industry level as well. For most specifications, we also see a response both in the relative quantity (college share) and in the relative wage margin (college premium), which motivates our investigation of both margins at the firm level.

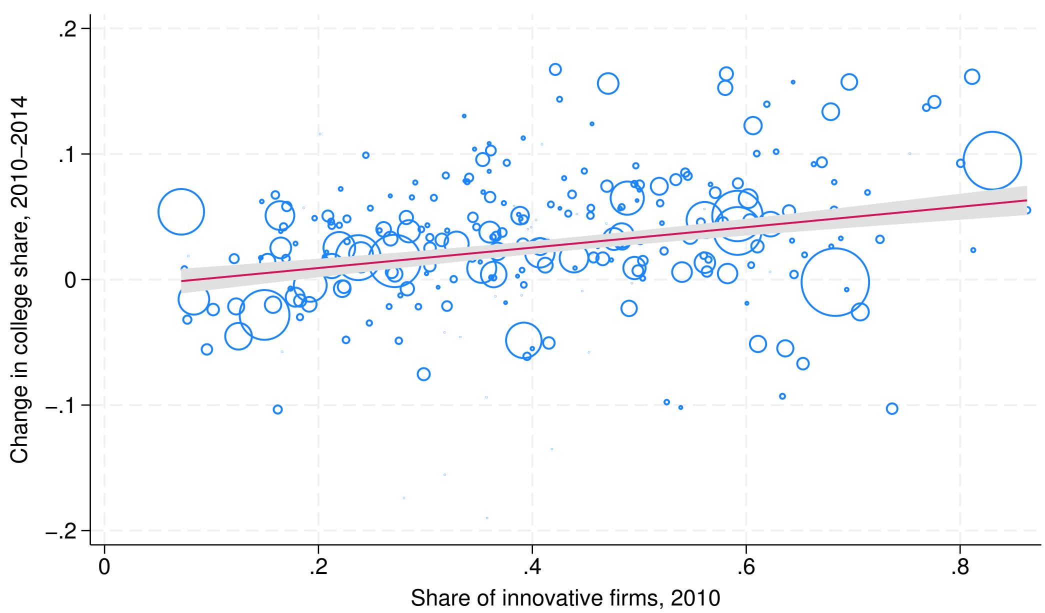
[44] Including only the share of innovative firms in the regression yields similar results.

Figure A.1: Technological Change and the Change in Skill Demand: Country-industry Level Analysis

Panel A: Share of Innovators and the Change in the Share of College-educated Employees



Panel B: Share of Innovators and the Change in the College Premium



Notes: The figures illustrate the relationship between the share of innovative firms and subsequent change in skill demand at the 1-digit country-industry level for 25 European countries. We apply the same definition of innovation as in the main paper: innovative firms in 2010 are those that introduced any new or significantly modified product/service/process/organizational change, which is new from the viewpoint of the firm, but not necessary to the market, between 2007 and 2010. Therefore, innovative firms are those experiencing technological change. In particular, they show how the share of innovative firms in 2010 is related to the change in the share of college educated workers (Panel A) and the change in college premium (Panel B) between 2010 and 2014. The size of the circles is proportional to the number of firms in that cell, and the line shows a weighted regression line with a 95 percent confidence interval.

Table A.2: Technological Change and the Change in Skill Demand: Country-industry Level Regression Analysis

	College share change, 2010-2014			
	(1)	(2)	(3)	(4)
Share of innovative firms (2010)	0.104***	0.075	0.122***	0.011
	(0.025)	(0.049)	(0.031)	(0.050)
R&D-intensity (2010)	-0.008***	-0.000	-0.012***	-0.003
	(0.003)	(0.002)	(0.004)	(0.002)
Country FE		Yes		Yes
Industry FE			Yes	Yes
Observations	158	156	157	155
R-squared	0.154	0.697	0.255	0.770

	College premium change, 2010-2014			
	(1)	(2)	(3)	(4)
Share of innovative firms (2010)	0.284**	0.250**	0.185	0.242*
	(0.128)	(0.119)	(0.124)	(0.136)
R&D-intensity (2010)	-0.020**	-0.003	-0.028**	-0.007
	(0.009)	(0.006)	(0.011)	(0.006)
Country FE		Yes		Yes
Industry FE			Yes	Yes
Observations	154	152	153	151
R-squared	0.192	0.670	0.303	0.714

Notes:These tables show the relationship between technological change and skill demand at the 1-digit country-industry level for 25 European countries. We present the estimated coefficients of the share of innovative firms (δ_{inn}) and R&D intensity ($\delta_{R\&D}$) from Regression Equation (A.2). The dependent variable is the change in the share of college educated workers (top panel) and college premium (bottom panel). The main explanatory variables are the share of innovative firms and the industry's R&D intensity. We apply the same definition of innovation as in the main text: innovative firms in 2010 are those that introduced any new or significantly modified product/service/process/organizational change, which is new from the viewpoint of the firm, but not necessary to the market, between 2008 and 2010. All columns include the dependent variable in 2010. Column (2) also includes country fixed effects, column (3) industry fixed effects, while column (4) both country and industry fixed effects. Observations are weighted by the number of firms in the country-industry cell. Standard errors, clustered at the country level, are reported in parentheses. Significance levels are: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

A.3 Number of Observations in the Firm- and Worker-level Analyses

The table shows that each year there are around 120,000 firms Norway. Of these, around 15-19,000 firms are included in the sampling frame of the CIS. The CIS samples only firms with at least 10 employees that operate in NACE 2-digit industries 10-73. Around 30% of the firms in the sampling frame are surveyed. Since the CIS over-samples larger firms, this covers around 60% of the workers in the sampling frame. We further lose around 15-20% of firms as they do not report a positive value added, another 20% from calculating the (long) change in outcomes, and another 20% from taking the log skill ratio (missing for firms with no college or non-college workers). Therefore, focusing on within-firm variation in our skill ratio and premium regressions implies that we lose around 40% of the observations in the CIS sample.

Table A.4 illustrates the distribution of firms across the number of CIS-participations. A significant proportion of firms that were sampled multiple times are neither consistently innovators nor non-innovators. For instance, of the 654 firms surveyed seven times, 465 experienced changes in their innovation status at least once. This highlights that our measure of technological innovation reflects significant changes in firm-specific technologies, rather than a permanent firm characteristic.

Table A.3: Number of Observations in Norway

Panel A: Firm level

	2001	2004	2006	2008	2010	2012	2014	Total
(1) All firms	112,558	111,853	114,871	118,639	119,724	122,948	130,121	830,714
(2) Sampling frame	15,460	15,817	18,203	18,138	18,282	18,611	19,246	123,757
(3) CIS sample	3,682	4,598	6,331	5,936	6,486	6,203	5,939	39,175
(4) Positive Fixed Assets and VA, from CIS sample	3,066	3,997	5,473	4,702	5,609	5,335	5,085	33,267
(5) In college share reg. sample	2,392	3,165	4,411	3,882	4,722	4,255	4,326	27,153
(6) In skill ratio/premium sample	1,929	2,502	3,033	2,989	3,738	3,393	3,581	21,165

Panel B: Worker level

	2001	2004	2006	2008	2010	2012	2014	Total
(1) All workers	1,553,984	1,614,914	1,685,003	1,796,195	1,812,323	1,891,595	1,968,796	12322810
(2) Sampling frame	725,818	699,929	739,952	802,433	805,793	851,935	886,840	5,512,700
(3) CIS sample	412,150	420,794	442,361	510,124	513,358	520,701	550,096	3,369,584
(4) Firm sample	247,756	272,854	301,443	344,937	390,780	362,471	393,655	2,313,896
(5) Change observed	211,491	220,726	245,258	265,628	309,267	297,150	313,957	1,863,477

Notes: This table shows the number of observations in the firm- (Panel A) and worker-level (Panel B) sample in Norway. In panel A, the first row shows the total number of firm-year observations in the sample. The second row restricts the sample to firms which are in the CIS sampling frame according to the Eurostat documentation (https://ec.europa.eu/eurostat/cache/metadata/en/inn_cis12_esms.htm): have at least 10 employees and operate in NACE 2-digit industries 10-73. In row (3), we further restrict our attention to firms which also report positive fixed assets and value added in the survey year. Given that our main specifications look at change between years $t-4$ and t, row (4) reports the number of firms which also existed 4 years ago. The final sample size for the college share regression is reported in row (5), while that of the college ratio regression (which requires that the firm has both college and non-college workers in years $t-4$ and t) is reported in row (6).
Panel B reports similar numbers for the worker level sample. Row (1) shows the total number of workers in the database, row (2) the number of workers when the firm belongs to the CIS sampling frame, and row (3) the number of workers working at firms which were surveyed by the CIS in the given year, while row (4) restrict the sample to workers working in firms which are in the firm sample, i.e. row (5) in Panel A. Finally, row (5) further restricts the sample to workers for whom we can observe the wage change between years $t-4$ and t.

Table A.4: Number of CIS Waves Firms Are Surveyed and Innovation Status

	1	2	3	4	5	6	7	Total
Firms	6,074	3,165	1,495	946	593	536	654	13,463
Never innovator	4299	1586	503	214	97	49	28	6776
Always innovator	1775	595	230	177	96	99	161	3133
Switcher	0	984	762	555	400	388	465	3554

Notes: This Table shows how many times each firm was surveyed by the CIS. For example, the second column shows the number of firms that were surveyed in exactly two CIS waves. The table also shows the number of firms that innovated zero times ('Never innovator') or that innovated in every wave ('Always innovator'). The number of switchers includes firms that are neither never innovators nor always innovators.

A.4 Technological Change and Change in Skill Demand: Robustness and Additional Analysis at the Firm-Level

This section provides robustness checks as well as some additional analyses extending the firm-level results.

Table A.5 shows the change in the (log) number of college and non-college workers rather than the college ratio. Following innovation, the number of college workers increases significantly by 2.8% (s.e. 1.4%), while there is an insignificant increase in the number of non-college workers (0.08%, s.e. 1.3%).

Table A.6 shows various robustness checks for our benchmark specification shown in Table 2. Panel A restricts the analysis sample to full-time workers before calculating the skill ratio and skill premium. Panel B includes firm controls in the regressions such as the change in value added per worker or the change in capital stock. Panel C includes firm fixed effect in the regression equation (14). Panel D explores the possibility that the impact of local labor market shocks varies by the skill ratio. Specifically, we classify firms into quartiles based on their initial skill ratio and include quartile-district-year fixed effects in the regression. Across the panels, the association between technological and skill ratio/premium change little.

To examine the possible presence of growth differences in skill demand before the technological change, Table A.7 also includes one lead of our main innovation variable. The findings indicate no evidence of pre-existing trends in the college share (0.0%, s.e. 0.2%) or in the college ratio (0.1%, s.e. 1.1%). For the college premium, there is a small but statistically insignificant decline (-0.6%, s.e. 0.7%) prior to innovation, followed by a significant increase in wages post-innovation. These patterns appear more muted for incumbent workers. As shown later in Table A.9, once accounting for worker composition by estimating worker-level regressions, the decline in the college premium prior to innovation becomes even smaller. These findings highlight that innovative and non-innovative firms had parallel trends in skill demand that breaks when new technologies are implemented.

Table A.5: Change in the (log) Number of Workers, College Workers and Non-College Workers Following Firm-level Technological Change

	(1) Total emp.	(2) College emp.	(3) Non-coll emp.	(4) Total emp.	(5) College emp.	(6) Non-coll emp.
Innovation	0.016	0.027	0.007	0.018	0.028	0.008
	[0.011]	[0.014]	[0.013]	[0.011]	[0.014]	[0.013]
Observations	27,122	21,707	26,540	21,135	21,135	21,135
Firms	13,141	9,866	12,814	9,545	9,545	9,545
R-squared	0.29	0.23	0.25	0.29	0.23	0.25
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Sample	all	all	all	coll. rat.	coll. rat.	coll. rat.

Notes: This table shows the firm-level relationship between innovation and the (log) number of workers, college workers and non-college workers. Column (1) repeats Column (5) of Table 2. In Columns (2) and (3) we use regression equation (14) with the log number of college/non-college workers as the dependent variable (instead of the ratio of the two) in columns (2) and (3). We restrict the sample to firms with both college and non-college workers in columns (4)-(6). Apart from changing the outcome variables we apply the same specifications as in Table 2. Standard errors are clustered at the firm level, and the regressions are weighted by the number of employees.

Table A.6: Change in Firm Skill Demand Following Firm-level Technological Change; Robustness Analysis

Panel A: Only Full-Time Workers

	(1) College share	(2) Skill ratio	(3) Skill premium	(4) Skill premium incumbents	(5) Log employment
Innovation	0.003	0.014	0.003	0.007	0.015
	[0.001]	[0.009]	[0.004]	[0.004]	[0.011]
Observations	27,056	20,498	20,498	14,653	27,056
Firms	13,096	9,145	9,145	6,905	13,096
R-squared	0.11	0.11	0.09	0.12	0.26

Panel B: Firm Controls

Innovation	0.004	0.018	0.005	0.007	0.015
	[0.001]	[0.008]	[0.004]	[0.004]	[0.010]
Observations	27,122	21,135	21,135	14,662	27,122
Firms	13,141	9,545	9,545	6,912	13,141
R-squared	0.12	0.12	0.09	0.12	0.34

Panel C: With Firm Fixed Effects

Innovation	0.003	0.018	0.008	0.013	0.022
	[0.002]	[0.010]	[0.007]	[0.007]	[0.013]
Observations	20,110	16,339	16,339	11,166	20,110
Firms	6,138	4,757	4,757	3,422	6,138
R-squared	0.48	0.44	0.34	0.43	0.61

Panel D: With District $\times$ Initial Wage-Share FEs

Innovation	0.004	0.025	0.006	0.007	0.010
	[0.001]	[0.008]	[0.004]	[0.004]	[0.010]
Observations	27,120	21,134	21,134	14,658	27,120
Firms	13,139	9,544	9,544	6,908	13,139
R-squared	0.14	0.14	0.10	0.13	0.31

Notes: This table shows robustness checks for the relationship between firm-level technological change and subsequent change in firm-level skill demand. The table follows the structure of Table 2, reporting the relationship between 4-year changes in the outcomes and whether the firm reported innovation in the Community Innovation Survey. Panel A restricts the sample to full-time workers, working at least 30 hours per week, and without weighting by hours worked. Panel B includes firm change in value added per worker and change in the capital stock in the regression. Panel C includes firm fixed effects. Panel D includes district-year fixed effects interacted with initial college wage-share quartiles. Standard errors are clustered at the firm level and are reported in square brackets.

Table A.7: Change in Firm Skill Demand Following Firm-level Technological Change; Checking For Possible Pre-Trends

	(1) College share	(2) Skill ratio	(3) Skill premium	(4) Skill premium incumbents	(5) Log employment
Innovation (t)	0.005	0.022	0.011	0.013	0.013
	[0.002]	[0.010]	[0.007]	[0.006]	[0.013]
Innovation (t+2)	0.000	0.001	-0.006	-0.005	0.017
	[0.002]	[0.011]	[0.007]	[0.006]	[0.013]
Observations	10,345	9,015	9,015	8,211	10,345
Firms	4,648	3,847	3,847	3,492	4,648
R-squared	0.15	0.14	0.12	0.15	0.32
2-digit Nace x Year FEs	yes	yes	yes	yes	yes
District x Year FEs	yes	yes	yes	yes	yes

Notes: This table investigates the presence of pre-trends in outcomes for the firm-level results. The table follows the structure of Table 2, and reports the relationship between 4-year changes in the outcomes and whether the firm reported innovation in the Community Innovation Survey conducted in year *t*. Additionally, we add the firm's innovation status in the subsequent CIS wave (in year t+2) to check for possible pre-trends in outcomes.

A.5 Technological Change and Change in Skill Demand: Inclusion of Firm-College Fixed Effects and Checking for Possible Pre-Trends in the Worker-Level Regressions

In our benchmark worker-level specification (equation 15), we do not include firm-college fixed effects (the change specification controls for inherent differences between firms and the inclusion of firm-college fixed effects filters out differences in growth between innovative and non-innovative firms), but we report robustness for the inclusion of these effects in columns (6) and (8) in Table 3. To further investigate the robustness of our results to adding these fixed effects, in Table A.8 we add firm-college fixed effects to the full set of specifications from the main worker-level results in Table 3. Comparing Column 1 of the two tables, we see that the point estimate increases from 1.3% (s.e. 0.5%) to 2.1% (s.e. 0.6%) with the inclusion of these fixed effects. Also the benchmark specifications that include various local-level controls are robust to the inclusion of firm-college fixed effects.

Table A.9 examines pre-trends in the worker-level specification by including one lead of our innovation variable. The college-premium coefficients (Innovation (t+2) interacted with college) are close to zero and insignificant in almost all specifications – suggesting that innovative and non-innovative firms follow parallel trends in outcomes before technological change. For example, in the baseline specification we see a 0.4% (s.e. 0.7%) decline in the college premium, followed by a significant 1.8% (s.e. 0.6%) increase. In specifications (4) and (6) we find even more limited pre-trends, while the estimated effects of technological change is very similar (if anything larger). In some specifications (e.g. in Column (7)), we find larger pre-trends but those are insignificant. Overall, these findings underscore that the increase in college premium is related to the implementation of new technologies.

Table A.8: Worker-Level Results with Firm-College Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation	-0.007	-0.007	-0.008	-0.011	-0.007	-0.007		
	[0.007]	[0.007]	[0.007]	[0.006]	[0.007]	[0.007]		
Innovation x College	0.021	0.019	0.023	0.023	0.021	0.021	0.020	0.018
	[0.006]	[0.007]	[0.008]	[0.006]	[0.006]	[0.006]	[0.008]	[0.005]
Observations	1,861,095	1,861,095	1,861,063	1,846,460	1,861,095	1,861,095	1,861,013	1,846,326
R2	0.079	0.080	0.084	0.128	0.079	0.079	0.124	0.154
Firms	13,106	13,106	13,105	12,913	13,106	13,106	13,097	12,904
Workers	688,814	688,814	688,803	684,213	688,814	688,814	688,785	684,168
Ind-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
College-dist.-year FEs	no	yes	no	no	no	no	no	yes
College-dist.-wage-sh.--year FEs	no	no	yes	no	no	no	no	yes
Occupation-dist.-ind.--year FEs	no	no	no	yes	no	no	no	yes
Firm-college FEs	yes	yes	yes	yes	yes	yes	yes	yes
Firm-year FEs	no	no	no	no	no	no	yes	yes

Notes: This Table shows how the main results reported in Table 3 change when we include firm-college fixed effects into all specifications. Standard errors are clustered at the firm level.

Table A.9: Worker-Level Results, Checking for Possible Pre-Trends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation (t)	-0.010	-0.009	-0.011	-0.012	-0.015	-0.018		
	[0.007]	[0.007]	[0.007]	[0.007]	[0.009]	[0.010]		
Innovation (t) x College	0.017	0.016	0.020	0.019	0.017	0.028	0.017	0.023
	[0.006]	[0.007]	[0.007]	[0.006]	[0.006]	[0.009]	[0.008]	[0.007]
Innovation (t+2)	-0.005	-0.006	-0.006	-0.008	0.004	0.002		
	[0.008]	[0.008]	[0.008]	[0.007]	[0.008]	[0.008]		
Innovation (t+2) x College	-0.005	-0.005	-0.007	-0.001	-0.006	0.001	-0.012	0.004
	[0.008]	[0.008]	[0.010]	[0.006]	[0.009]	[0.009]	[0.010]	[0.005]
Observations	1,126,317	1,126,317	1,126,295	1,117,866	1,126,297	1,125,783	1,126,288	1,117,245
R2	0.041	0.042	0.049	0.111	0.078	0.083	0.117	0.156
Firms	4,713	4,713	4,711	4,680	4,693	4,683	4,693	4,647
Workers	478,289	478,289	478,278	475,082	478,269	477,827	478,267	474,575
Ind-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
College-dist.-year FEs	no	yes	no	no	no	no	no	yes
College-dist.-wage-sh.--year FEs	no	no	yes	no	no	no	no	yes
Occupation-dist.-ind.--year FEs	no	no	no	yes	no	no	no	yes
Firm FEs	no	no	no	no	yes	yes	yes	yes
Firm-college FEs	no	no	no	no	no	yes	no	yes
Firm-year FEs	no	no	no	no	no	no	yes	yes

Notes: This table shows how the main results reported in Table 3 change when, in addition to the firm's innovation status in year t, we also include the innovation status in year $t+2$ to check for possible pre-trends. Standard errors are clustered at the firm level.

A.6 Additional Analysis for Incumbent Workers and New Entrants

This section studies compositional change of incumbent workers, leavers, and newly hired workers at firms following an innovation. We do this by estimating wage premium effects for six different groups of workers: incumbents, leavers and newly hired workers, further split into groups by whether or not they are college-educated. Incumbents are defined as workers who stay at the firm between $t-4$ and t, new entrants are defined as workers who were not at the at the firm in $t-4$, but moved to to the firm by t, and leavers are defined as workers who were at the firm in $t-4$, but left the firm by t. We estimate the following worker-level regression:

$$\ln wage_{it-4} = \delta innov_{j(i,t)} + \xi_{s(j(i,t))t} + \varsigma_{l(j(i,t))t} + \chi_{g(i)t} + \varepsilon_{it}, \tag{A.3}$$

where $\xi_{s(j(i,t))t}$ are industry-time, $\varsigma_{l(j(i,t))t}$ location-time fixed effects. $\chi_{g(i)t}$ are interaction of four dummies representing the worker's education level (primary, secondary, vocational, college) with the year dummies.

Table A.10 presents the main findings of our analysis. We observe no clear evidence that college-educated workers earned higher wages at innovative firms compared to non-innovative firms prior to innovation ($t-4$). Additionally, there is no strong indication of selective patterns in staying at the firm, entering, or exiting among college workers. Most estimates are close to zero and lack statistical significance. For non-college workers, there is some evidence of selective patterns among new hires, but not among incumbents or those exiting the firm. These findings suggest a limited role for worker selection in explaining our results. Furthermore, the data does not indicate that innovative firms initially employ a particularly "elite" or highly skilled college-educated workforce, which could have potentially driven the innovation process.

We also evaluate the wage changes post innovation separately for incumbents, leavers, and new entrants by employing our benchmark worker level regression equation (15). Table A.11 summarize the results below. The table highlights the presence of a college premium for new entrants and incumbents (with similar magnitude). Leavers, on the other hand, do not experience any wage change. This evidence further supports the notion that the observed wage changes at innovative firms reflect specific firm-level adjustments in the wage premium, rather than general labor market trends that would be also experienced by the leavers.

Table A.10: Pre- and Post-Innovation Wages for Incumbents, New Entrants and Leavers by Skill Group

Panel A: Pre-innovation wages (year $t-4$)

	(1) Incumbents College	(2) New entrants College	(3) Leavers College	(4) Incumbents non-College	(5) New entrants non-College	(6) Leavers non-College
Innovation	0.005	0.003	-0.010	0.005	0.025	-0.008
	[0.009]	[0.008]	[0.014]	[0.007]	[0.006]	[0.009]
Observations	328,210	178,226	137,144	982,389	374,009	299,892
R2	0.21	0.09	0.16	0.29	0.15	0.20
Firms	8,893	7,592	6,771	12,417	11,084	10,297
Workers	133,666	114,752	93,499	390,213	252,613	215,800
Ind-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Sample	college	college	college	non-college	non-college	non-college

Panel B: Post-innovation wages (year t)

	(1) Incumbents College	(2) New entrants College	(3) Leavers College	(4) Incumbents non-College	(5) New entrants non-College	(6) Leavers non-College
Innovation	0.013	0.030	-0.002	-0.000	0.021	-0.017
	[0.009]	[0.012]	[0.010]	[0.009]	[0.010]	[0.007]
Observations	328,210	324,933	137,144	982,392	678,339	299,893
R2	0.20	0.17	0.17	0.25	0.19	0.19
Firms	8,893	9,386	6,771	12,417	12,363	10,297
Workers	133,666	191,700	93,499	390,215	423,491	215,801
Ind-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Sample	college	college	college	non-college	non-college	non-college

Notes: The table shows the wages of various workers before and after innovation. In particular, Panel A reports δ from equation A.3, showing wages in 4 years before the current CIS wave $(t-4)$ while Panel B shows the wages of the workers in t, the year of the CIS. Columns (1)-Column (3) restrict the sample to college workers, while Columns (4)-(6) restrict the sample to non-college workers. Columns (1) and (4) show the estimates for incumbents (who stay at the firm between t and $t-4$), Columns (2) and (5) for new entrants (who were not at the at the firm in $t-4$, but moved to to the firm by t), and Columns (3) and (6) for leavers (who were at the firm in $t-4$, but exited by t)

Table A.11: Incumbents, New Entrants and Leavers; Wage Effect

	(1) Incumbents	(2) New entrants	(3) Leavers
Innovation	-0.005	-0.018	
	[0.007]	[0.009]	
Innovation x College	0.020	0.024	0.005
	[0.007]	[0.010]	[0.007]
Observations	1,307,813	548,993	210,655
R2	0.09	0.11	0.26
Firms	12,289	10,020	3,808
Workers	520,469	364,326	156,425
Ind-year FEs	yes	yes	yes
Schooling-year FEs	yes	yes	yes
Firm-college FEs	yes	yes	yes

Notes: This table shows the wage growth of workers separately for incumbents (who stay at the firm between $t-4$ and t), for new entrants (who were not at the at the firm in $t-4$, but moved to to the firm by t) and for leavers (who were at the firm in $t-4$, but exited by t).

A.7 Labour Supply Elasticity and the Change in Skill Demand at High- and Low-density Districts

We can calculate the labour supply elasticities, β from our baseline estimates. Equations (7a) and (7b) of our conceptual framework show that the extent to which firms adjust their skill ratio relative to their skill premium depends on the elasticity of labor supply (β). In particular, the impact of $\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}$ on the skill premium is $\frac{\sigma}{\sigma+\beta}$, while its impact on the skill ratio is $\frac{\beta\sigma}{\sigma+\beta}$ if amenities do not change along with innovation.[45]

Therefore, the ratio of the impact on the skill ratio relative to the impact on the skill premium is roughly equal to β, the elasticity of the firm-level labor supply. The estimated increase in the skill ratio is 1.8% (Column 2 in Table 2), while the estimates for the skill premium vary between 0.5% (Column 3 in Table 2) and 1.1% (Column 1 in Table 3). Consequently, the implied firm-level labor supply elasticity is between 1.6 and 3.6 depending on the specification. These results fall within the range of existing estimates in the literature. For instance, Saez et al. (2019), studying payroll tax cuts in Sweden, find that the elasticity of firm-specific labor supply is between 1.8 and 2.4.[46]

In addition, whenever firms have less wage setting power (face a more elastic firm-level labor supply), we expect a relatively larger impact on the skill ratio and a smaller impact on the skill premium. Remember that, in our model, the firm-level labor supply elasticity, β, is a function of ϕ, the dispersion of workers' idiosyncratic preferences for working at a particular firm. A key component of this dispersion is commuting distance, which is presumably smaller in local areas with higher firm density (or areas where the average distance between firms is smaller). Consequently, we expect that in local areas with a high firm density (and a low average commuting time), firms face a more elastic labor supply and, therefore, the increase in the skill ratio will be larger, while the increase in the skill premium will be smaller.

We explore this hypothesis in Table A.12, where we show estimates for the skill ratio and the skill premium by firm density. Following Ciccone & Hall (1996), we measure firm density as the average number of firms per square kilometer in the the local area for each industry. As local areas, we use the 46 commuting zones in Norway, as defined in Bhuller (2009). We estimate the changes in the skill ratio and the skill premium separately for local areas which are below and above the (population-weighted) median by including interaction terms into Equation (14) (skill ratio) and in Equation (15) (skill premium). In particular, we interact the density proxy with the innovation dummy in the firm-level regressions, and we interact the density proxy with the college dummy, innovation dummy as well as college $\times$ innovation in the worker-level regressions. Panel A shows the estimates for the skill ratio (Column 1) and skill premium (Column 3). The results show that in local areas with a high firm density, the skill ratio changes more, while the skill premium changes less. This is consistent with the idea that firms operating in these markets face a more elastic labor supply. The implied labor supply elasticity is around 2 in these areas. In contrast, the estimates imply a quite inelastic labor supply in

[45] Studies estimating labor supply elasticities typically examine the effect of exogenous wage shifters (e.g., productivity shocks) on labor supply, assuming that job amenities remain constant – an assumption that parallels ours.

[46] According to the meta-analysis by Sokolova & Sorensen (2018), the median firm-level labor supply elasticity is around 1.7. Recent quasi-experimental studies (e.g. Caldwell & Oehlsen 2018, Cho 2018, Kroft et al. 2020, Dube et al. 2017) find estimates between 2 and 5 (see more details in Bassier et al. 2020).

commuting zones with a low firm density, which suggests that wage-setting power is considerable in areas with low firm density.

Panels B-D of Table A.12 control for differences across local areas in the share of innovative firms, average labor productivity and average wages respectively.[47] These controls have some effect on the implied elasticity (e.g. the implied labor supply elasticity moves to 5.7 when we control for average labor productivity; see panel C), but the overall pattern remains the same. Overall, these findings corroborate a key prediction of our theoretical model: the relative changes in the skill ratio and the skill premium are related to our proxy of firm-specific labor supply elasticities. Furthermore, these geographic differences imply that rural and urban labor markets can be quite differently affected by technological change.

[47] In particular, we begin by calculating these variables for each commuting zone. Then we create dummies representing quartiles (weighted by the number of firms) of the distribution of these variables across commuting zones. Next, we regress the change in various firm-level outcomes on innovation, its interaction with the density dummy, the density dummy itself, the productivity quartiles, and their interaction with innovation. Similarly, when examining worker-level wage changes, we include all these variables interacted with college education. This approach allows us to compare innovative and non-innovative firms within areas that exhibit similar productivity (or other characteristics).

Table A.12: Change in Skill Demand Following Firm-level Technological Change in High- and Low-density Districts

Panel A: Without Controls

	(1) Skill ratio coeff.	(2) Skill ratio (s.e.)	(3) Skill premium coeff.	(4) Skill premium (s.e.)	(5) Implied LS elast.	(6) Implied skill bias
High density regions	0.026	[0.011]	0.012	[0.006]	2.196	0.028
Low density regions	0.003	[0.011]	0.014	[0.005]	0.233	0.016

Panel B: Control: Share of Innovative Firms

High density regions	0.032	[0.029]	0.007	[0.012]	4.311	0.027
Low density regions	0.004	[0.011]	0.009	[0.005]	0.425	0.011

Panel C: Control: Average Labour Productivity

High density regions	0.024	[0.021]	0.004	[0.009]	5.729	0.019
Low density regions	0.003	[0.011]	0.009	[0.005]	0.286	0.010

Panel D: Control: Average Wage

High density regions	0.014	[0.023]	0.009	[0.007]	1.598	0.017
Low density regions	0.001	[0.011]	0.011	[0.005]	0.116	0.012

Notes: This table compares changes in the skill ratio, and the skill premium following innovation in low- and high firm density districts (commuting zones). The density of a district is defined as the number of firms per square kilometer. A district is defined as high density if it is above the (population-weighted) median. Panel A Columns (1) and (2) show results from regressions similar to Column (2) of Table 2, but the innovation dummy in the regression is interacted with the high-density dummy. Columns (3) and (4) present results from worker-level regressions similar to Column (1) of Table 3, but further include interactions of the firm-density dummies with college, innovation and college × innovation. The coefficients reported in this table are those of the triple interaction terms. The implied labor supply (LS) elasticity is the ratio of the skill ratio and skill premium coefficients, while the implied skill bias is based on the formula from equation (8) and using the value $\sigma = 2.94$. Panels B-D also add interactions representing the quartiles of the distributions of the "share of innovative firms", "average labor productivity" and "average wage" variables across firm-years, respectively. In particular, we calculate the average of these variables for each district, and then group the districts into 4 quartiles (weighted by the number of firms in the districts). These dummies, along with their interactions with the innovation indicator and with the high/low density indicator, are included in the firm-level skill ratio regression in Column (1). Similarly, when estimating worker-level wage changes, our benchmark equation incorporates all interactions between innovation, college education, and the quartiles of these variables in Column (3). Standard errors are clustered at the firm level and are reported in parentheses.

A.8 Various Timing Assumptions

In the benchmark specification we study changes in outcomes between $t-4$ and t and and study how these changes relate to innovations taking place between time $t-2$ and t. In table A.13, we assess the robustness of our results to adjusting the time frame during which we measure changes in outcomes: extending forward the time window from t to $t+1$ or starting the baseline year in $t-3$ instead of $t-4$.

Adjusting the time frame used to measure changes in outcomes has a limited effect on the results. Furthermore, as we extend the time frame forward, and capture longer-term effects of innovation, we obtain larger changes in skill demand. If we consider the change between $t+2$ and $t-4$, the change in college share increases from 0.4 percentage point to 0.6, the skill ratio from 1.8% to 2.1%, and the skill premium from 1.1% to 1.7%.

Table A.13: Various Timing Assumptions

	(1) College share (beta)	(2) College share (s.e.)	(3) Skill ratio (beta)	(4) Skill ratio (s.e.)	(5) Skill premium (beta)	(6) Skill premium (s.e.)
from t-4 to t	0.004	[0.001]	0.018	[0.008]	0.011	[0.005]
from t-4 to t+1	0.006	[0.002]	0.021	[0.011]	0.016	[0.007]
from t-4 to t+2	0.006	[0.002]	0.021	[0.013]	0.017	[0.007]
from t-4 to t+3	0.006	[0.003]	0.016	[0.016]	0.017	[0.007]
from t-3 to t	0.003	[0.001]	0.013	[0.008]	0.006	[0.004]
from t-3 to t+1	0.005	[0.002]	0.014	[0.011]	0.010	[0.006]
from t-3 to t+2	0.006	[0.002]	0.015	[0.013]	0.012	[0.006]
from t-3 to t+3	0.006	[0.003]	0.015	[0.016]	0.015	[0.007]

Notes: This table reports the main results when adjusting the time frame used to measure the dependent variable. In our main specification, the dependent variable is the long change between $t-4$ and t, where t is the time of the CIS wave. The first row in this table repeats the main estimates (from $t-4$ to t) while the rows below show the results applying different timings. The College share, Skill Ratio estimates follow the firm-level specifications in Columns (1) and (2) in Table 2, while the skill premium estimates come from the worker-level specifications in column (1) of Table 3. Standard errors are clustered at the firm-level.

A.9 Firm-level Technological Change: Different Wage Measures and Hours Worked

Table A.14 investigates the relationship between various measures of wages and hours worked, and technological change by estimating equation (15). Column (1) repeats the results with our main measure, hourly wage (same as Table 3, column (1)). The measure in Column (2) also includes non-cash benefits. Note that non-cash benefits can be interpreted as a proxy for the relative change in one component of amenities. The results are unchanged, providing evidence that cash and non-cash elements of workers' compensation change in a similar way following innovation.

Columns (3) and (4) of Table A.14 investigate whether innovation led to a change in hours worked. In Column (3), we use daily, rather than hourly change as the dependent variable. The estimated coefficient is very similar to that of the hourly wage. Finally, Column (4) reports estimates using working hours (instead of wages) as outcome variable in regression equation (15). We find no significant change in working hours of college workers. Increased college wages after innovation are unlikely to result from longer hours worked by college workers.

Table A.14: Firm-level Technological Change; Different Wage Measures and Hours Worked

	(1) Hourly Wage	(2) Hourly wage + ben.	(3) Daily Wage	(4) Hours
Innovation	-0.006	-0.005	-0.006	0.000
	[0.004]	[0.004]	[0.004]	[0.001]
Innovation x College	0.011	0.011	0.012	0.001
	[0.005]	[0.005]	[0.005]	[0.001]
Observations	1,863,477	1,863,477	1,863,477	1,863,478
R2	0.035	0.036	0.034	0.015
Firms	13,378	13,378	13,378	13,378
Workers	690,671	690,671	690,671	690,671
Industry-year FEs	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes

Notes: This table reports worker-level regressions, corresponding to Column (1) of Table 3, for different outcomes. Column (1) reports results with the change in log hourly wage as the dependent variable. Column (2) reports results when the dependent variable also include non-cash benefits, while column (3) reports the change in daily wage. Finally, column (4) reports results for the change in log hours. Standard errors are reported in brackets and are clustered at the firm level.

A.10 Firm-level Technological Change, Polarization, and Changes in Tasks

So far, we have classified workers into two skill groups, and looked at whether innovation affects the skill premium for college workers relative to non-college workers. However, Acemoglu & Autor (2011b) argue that the middle-skilled occupation categories, such as middle-skilled clerical, administrative, production and operative occupations, tend to be more affected by "routinization" than either high or low-skilled occupation categories, and that this has contributed to the observed wage polarization in the US.

We study wage polarization by assessing the impact of innovation at a more detailed level of schooling. Panel A of A.15 reports the change in the log number of workers (similar to Columns (1) and (2) in Table A.5) with different schooling levels. There is a small or no change in the workers with primary, vocational, or secondary education. The only significant change is observed for college workers.

We also report the change in the skill premium by interacting the innovation dummy in equation (15) with the more detailed schooling variable. Panel B shows that following innovation there is no significant change in the wage premium received by workers with vocational or secondary education relative to the workers with primary education (base level). The college premium, on the other hand, increases significantly following innovation.

In the framework of this paper, we follow the seminal work by Katz & Murphy (1992) and Goldin & Katz (2010) and model technological change as potentially increasing the productivity of skilled workers (relative to the unskilled) in production. An alternative (or complementary) framework of technological change is a task-based one, where technological change affects both the productivity of high- and low-skilled labor in performing different tasks, as well as the allocation of tasks between the different types of labor (Autor et al. 2003, Acemoglu & Autor 2011b, Acemoglu & Restrepo 2020). Having a college degree may strongly correlate with the ability to perform non-routine tasks. Our findings suggest that innovation affects the skill share and the skill premium, potentially capturing changes in the task composition within firms, rather than merely capturing changes in the productivity associated with the performance of different tasks.

To investigate this possibility, we create a measure of the degree to which an occupation contains routine tasks (RTI) following Autor et al. (2003).[48] Next, we include an interaction of $1 - RTI$ with the innovation dummy in regression equation (15). A higher $1 - RTI$ represents a higher non-routine content of the worker's occupation. The results from this exercise are presented in Table A.16. We find that the task content premium for non-routine jobs do not increase following innovation once we control for the education of the worker. Probably even more importantly, the innovation college premium is not affected by the inclusion of the task content variables, showing that the effect of innovation on the college premium does not merely reflect the different task content of the jobs performed by college and non-college workers.[49]

[48] We map the US occupation codes to Norwegian occupation codes.

[49] Given that $1 - RTI$ is continuous variable, it is not straightforward to implement this approach at the firm-level.

Table A.15: Technological Change and Skill Demand for Workers with Different Educational Attainment

Panel A: Number of Workers

	(1) Primary	(2) Vocational	(3) Secondary	(4) College
Innovation	0.001	0.009	0.005	0.028
	[0.015]	[0.014]	[0.016]	[0.014]
Observations	19,342	20,231	12,854	21,135
Firms	8,594	8,999	5,253	9,545
R-squared	0.24	0.23	0.19	0.23
2-digit Nace x Year FEs	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes

Panel B: Skill Premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
innovation	-0.004	-0.004	-0.005	-0.008	-0.006	-0.007		
	[0.004]	[0.004]	[0.004]	[0.004]	[0.006]	[0.007]		
Innovation x Vocational	-0.003	-0.002	-0.004	-0.003	0.000	-0.000	-0.000	-0.000
	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]
Innovation x Secondary	-0.003	-0.003	-0.005	0.001	0.005	0.004	0.005	0.003
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.004]
Innovation x College	0.010	0.010	0.010	0.013	0.015	0.021	0.012	0.018
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]
Observations	1,863,477	1,863,477	1,863,440	1,849,039	1,863,302	1,861,095	1,863,229	1,846,326
R2	0.035	0.035	0.042	0.100	0.073	0.079	0.118	0.154
Firms	13,378	13,378	13,372	13,216	13,203	13,106	13,198	12,904
Workers	690,671	690,671	690,651	686,204	690,525	688,814	690,504	684,168
Ind-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
College-dist.-year FEs	no	yes	no	no	no	no	no	yes
College-dist.-wage-sh.--year FEs	no	no	yes	no	no	no	no	yes
Occupation-dist.-ind.--year FEs	no	no	no	no	no	no	yes	yes
Firm FEs	no	no	no	yes	no	no	no	yes
Firm-college FEs	no	no	no	no	yes	yes	yes	yes
Firm-year FEs	no	no	no	no	no	yes	no	yes

Notes: This table investigates whether firm-level technological change is associated with the polarization of workers. Panel A reports the firm-level relationship between innovation and the (log) number workers at various schooling levels. We employ regression equation (14) with the log number of primary/vocational/secondary/college workers as outcome variables. Panel B shows the change in skill premium for vocational/secondary/college workers (relative to primary workers). This is estimated based on regression equation (15) where we interact the innovation dummy with the education level of workers. The structure of the table follows Table 3. Standard errors are clustered at the firm level and are reported in square brackets.

Table A.16: Technological Change and the Skill Premium: the Role of Routine Task Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Innovation	-0.005	-0.005	-0.007	-0.011	-0.006	-0.008		
	[0.005]	[0.005]	[0.005]	[0.005]	[0.007]	[0.008]		
Non-routine	-0.000	-0.000	0.000		0.000	0.000	0.001	
	[0.002]	[0.002]	[0.002]		[0.001]	[0.001]	[0.001]	
Innovation x College	0.012	0.011	0.014	0.014	0.014	0.021	0.012	0.020
	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.007]	[0.005]	[0.005]
Innovation x Non-routine	-0.000	-0.000	-0.000	-0.002	-0.001	-0.000	-0.002	-0.003
	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]	[0.002]
Observations	1,486,931	1,486,931	1,486,892	1,474,324	1,486,703	1,484,561	1,486,572	1,471,607
R2	0.035	0.035	0.043	0.107	0.080	0.087	0.129	0.168
Firms	12,561	12,561	12,552	12,367	12,333	12,219	12,317	11,997
Workers	591,953	591,953	591,931	587,318	591,766	589,998	591,725	585,183
Ind-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes	yes
College-dist.-year FEs	no	yes	no	no	no	no	no	yes
College-dist.-wage-sh.- -year FEs	no	no	yes	no	no	no	no	yes
Occupation-dist.-ind.- -year FEs	no	no	no	yes	no	no	no	yes
Firm FEs	no	no	no	no	yes	yes	yes	yes
Firm-college FEs	no	no	no	no	no	yes	no	yes
Firm-year FEs	no	no	no	no	no	no	yes	yes

Notes: This table investigates whether firm-level technological change is associated with changes in workers' wage premium in non-routine jobs when controlling for education. We start from the the regressions reported in Table 3, but augment regression equation (15) with a continuous variable of non-routine intensity, as well as an interaction of this variable with the innovation dummy. Non-routine intensity measures the degree to which a worker's occupation contains non-routine tasks, following Autor et al. (2003). Standard errors are clustered at the firm level and are reported in square brackets.

A.11 Technological Change, Outsourcing and Changes in Skill Demand

Domestic outsourcing of lower-skilled tasks to low-wage contractors, or international outsourcing to lower-wage countries may contribute to simultaneous increases in the skill premium and skill ratio. In this section, we investigate the change in the skill ratio and skill premium following technological change in firms that do not simultaneously engage in outsourcing. A key advantage of the Community Innovation Survey is that we directly measure outsourcing. Outsourcing is considered as a type of organizational innovation that is conducted by around 15% of innovative firms (see Table B.2).

To assess the role of outsourcing on the college ratio and college share we include interaction terms in regression equation (14) on whether innovation took place with or without outsourcing. Column (1) and (2) shows that innovation activities without outsourcing lead to an increase in the college share (0.4 percentage point, s.e. 0.2) and the college ratio (1.3%, s.e. 0.9). For the skill premium we include interaction terms in regression equation (15). Column (3) shows that skill premium increases significantly (1.0%, s.e. 0.5%) for technological change without outsourcing.

Table A.17: Technological Change and Skill Demand with and without Outsourcing

	(1) Coll. share	(2) Skill ratio	(3) Skill premium
Innovation, no outsourcing	0.004	0.013	-0.003
	[0.002]	[0.009]	[0.005]
Innovation, with outsourcing	0.005	0.027	-0.010
	[0.002]	[0.012]	[0.006]
College x Innovation, no outsourcing			0.010
			[0.005]
College x Innovation, outsourcing			0.015
			[0.007]
Observations	27,122	21,135	1,863,477
Firms	13,141	9,545	13,378
R-squared	0.11	0.12	0.03
2-digit Nace x Year FEs	yes	yes	yes
District-Year FEs	yes	yes	yes
Schooling-year FEs			yes

Notes: This table compares changes in the collage share, college ratio and college premium for innovative firms engaging in outsourcing and innovative firms not engaging in outsourcing. We measure outsourcing from the Community Innovation Survey, which considers it as a type of organizational innovation; see table B.1 for more details. Columns (1)-(2) of the table reports firm-level regressions, similar to Columns (1)-(2) in Table 2, but additionally includes an interaction of the innovation variable with a dummy for whether the firm engaged in outsourcing. As a result, the 'Innovation, no outsourcing' coefficient shows the relationship between innovation and the different outcomes for innovative firms that did not outsource, while the 'Innovation, with outsourcing' coefficient shows the same relationship for innovative firms while also outsourcing. Column (4) reports worker-level regressions, similar to Column (1) of Table 3, but interacts both 'Innovation' and 'Innovation x College' with the Outsourcing dummy. Standard errors are clustered at the firm level and are reported in parentheses.

A.12 R&D Intensity and Changes in Skill Demand

So far, we have studied skill bias following innovation defined as an either-or event. In this section, we investigate whether R&D intensity–R&D expenditure per worker–matters for skill bias. This expenditure variable comes from the R&D survey that we also exploit in our analysis on tax credits. To make the timing of this more in line with that of the innovation variable, we calculate the R&D intensity of an innovation reported in the CIS in year t by taking the average R&D expenditure of the firm in year $t-2$, $t-1$ and t and dividing that with the number of workers in year t. Given the data constraints (see more details in Section A.15) we make two sample restrictions: First, we exclude firms with fewer than 50 employees, as there is non-random selection into being surveyed for smaller firms and the R&D expenditure is missing for those observations. Second, we exclude the 2001 CIS wave, as there was no R&D survey in 2000. Next, we create an annual categorical variable taking on four different values by firm innovation expenditure intensity. Then we compare the impact of different levels R&D expenditures among firms introducing a new innovation according to the CIS.

Table A.18 shows the key findings. Columns (1) and (2) estimate the impact on the college share and college ratio using regression equation (14) augmented with spending quartiles. The results show that both the college share and the college ratio increases more in the highest spending quartiles (than in the lower spending quartiles). Columns (4) and (5) show the same pattern when we measure spending using a continuous variable.

Column (3) shows the change in the college premium estimated by including categorical variables of different spending quartiles in regression equation (15), as well as its interaction with the college dummy. We find larger changes in the skill premium in the second through fourth spending quartiles than in the first quartile. Similarly, we find a positive association between R&D spending and skill-premium when we us a continuous measure of intensity.

Table A.18: Technological Change and Skill Demand: Innovative Firms with Different Levels of R&D Intensity

	(1) Coll. share	(2) Skill ratio	(3) Skill premium	(4) Coll. share	(5) Skill ratio	(6) Skill premium
Innovation x R&D intensity Q1	0.0088	0.0483	0.0020			
	[0.0076]	[0.0371]	[0.0232]			
Innovation x R&D intensity Q2	0.0315	0.1594	-0.0319			
	[0.0108]	[0.0515]	[0.0277]			
Innovation x R&D intensity Q3	0.0261	0.1360	-0.0605			
	[0.0104]	[0.0505]	[0.0238]			
Innovation x R&D intensity Q4	0.0341	0.2036	-0.0219			
	[0.0124]	[0.0602]	[0.0287]			
College x Innovation x R&D intensity Q1			0.0168			
			[0.0249]			
College x Innovation x R&D intensity Q2			0.0298			
			[0.0265]			
College x Innovation x R&D intensity Q3			0.0278			
			[0.0260]			
College x Innovation x R&D intensity Q4			0.0233			
			[0.0269]			
Innovation x R&D intensity				0.0103	0.0539	-0.0299
				[0.0038]	[0.0188]	[0.0093]
College x Innovation x R&D intensity						0.0163
						[0.0085]
Observations	2,449	2,415	687,251	2,449	2,415	687,251
Firms	812	797	1,553	812	797	1,553
R-squared	0.66	0.63	0.10	0.66	0.63	0.10
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
District-Year FEs	yes	yes	yes	yes	yes	yes
Firm FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs			yes			yes
Firm-college FEs			yes			yes

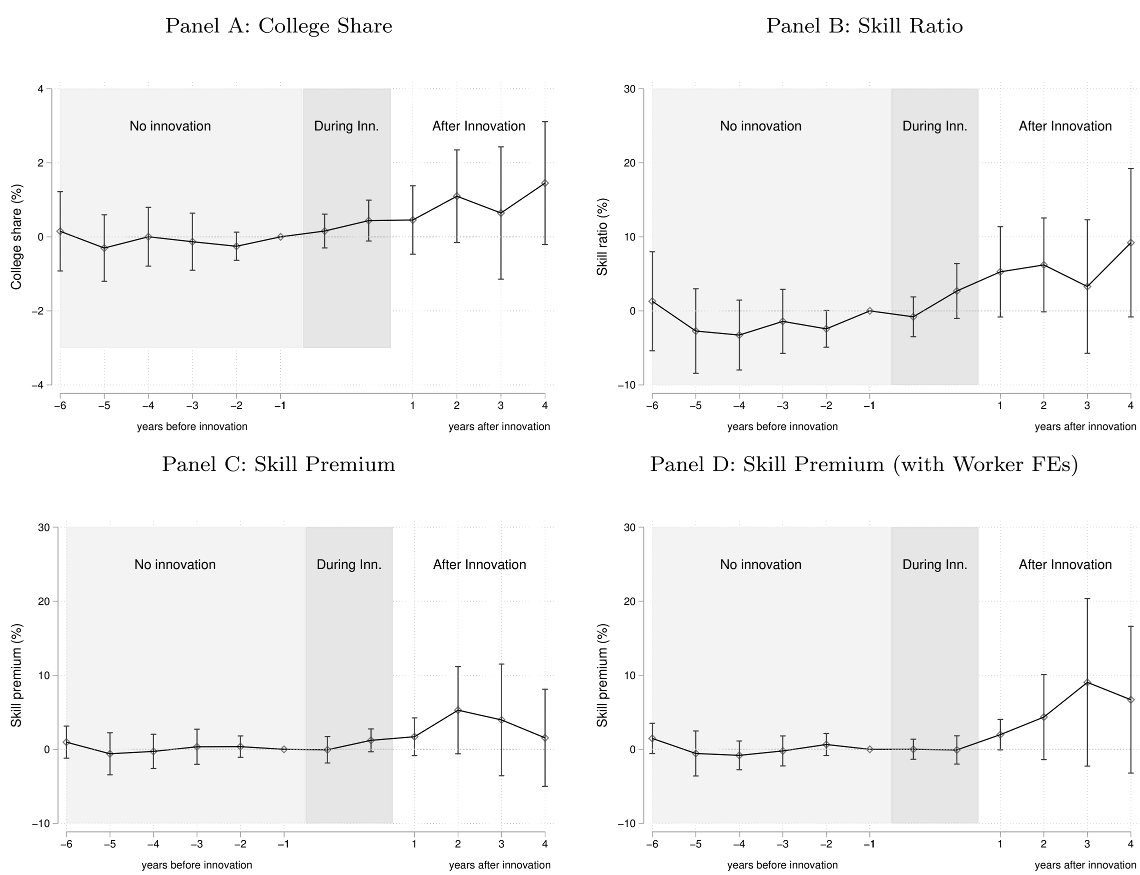
Notes: This table compares changes in the skill ratio, collage share and skill premium in innovative firms, by R&D intensity. We measure R&D intensity as log R&D spending per worker, where R&D spending is the average reported in the R&D survey in the years t, $t-1$ and $t-2$. We restrict the sample to firms that reported an innovation in the CIS in year t. We also exclude firms with fewer than 50 employees as R&D spending is often missing among these firms (as there is non-random sampling among smaller firms). We further exclude the 2001 CIS wave, as there was no R&D survey in 2000. Columns (1)-(2) and (4)-(5) report firm-level regressions, similar to columns (1)-(2) in Table 2, but additionally includes measures of R&D intensity and firm fixed effects. Columns (3) and (6) report results from worker-level regressions, similar to column (1) of Table 3, but we distinguish between innovations with different levels of R&D intensity and include firm-college fixed effects. In columns (1)-(3) we include four dummies representing the quartiles of R&D intensity, with the base category being innovative firms that do not spend on R&D. In columns (4)-(6) we include the logarithm of R&D intensity. To avoid missing values being dropped we input a very low innovation spending for the zero-spending firms (the the 10th percentile of the distribution). Standard errors are clustered at the firm level and are reported in square brackets.

A.13 Event Study Estimates: Further Analyses and Robustness

In the main text we present event-study estimates from three years prior to innovation (four years before a firm reports an innovation in the CIS for the first time), and four years after. Figure A.2 examines an extended time frame prior to innovation and highlights the absence of pre-trends even when going as far back as six years prior to innovation (seven years before the first reported innovation in CIS).

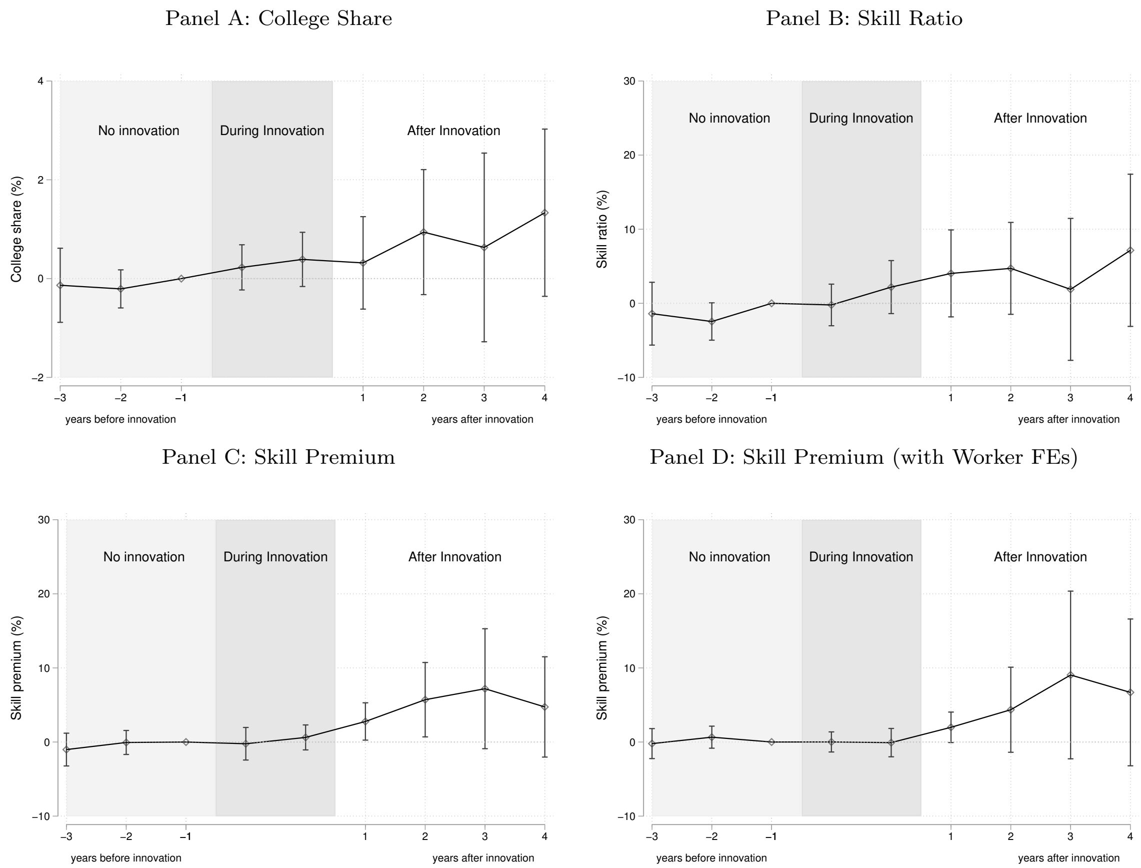
Figure A.3 reports the event-study estimates by applying the methodology in Sun & Abraham (2021) to adjust for heterogeneous treatment effects. The estimates are a bit more noisy, but remain very similar to our benchmark estimates.

Figure A.2: Event Study with Extended Pre-Innovation Period



Notes: This figure extends the event-study Figure 2 with an extended pre-innovation period. The figure shows event-study results for the evolution of the college share (Panel A), the skill ratio (Panel B) and the skill premium (Panels C and D) around the time a firm starts to innovate. Standard errors are clustered at the firm level in both regressions and 95% confidence intervals are reported.

Figure A.3: Event Study Estimates Employing the Methodology from Sun and Abraham (2001)



Notes: This figure extends the event-study Figure 2 to employing the Sun & Abraham (2021) estimator. Regressions are estimated using the *eventstudyinteract* Stata module (Sun 2021). The figure shows event-study results for the evolution of the college share (Panel A), the skill ratio (Panel B) and the skill premium (Panels C and D) around the time a firm starts to innovate. Standard errors are clustered at the firm level in both regressions and 95% confidence intervals are reported.

A.14 Change in Skill Demand Following Different Forms of Technological Change

In the main paper, we discuss the relationship between various forms of technological change and changes in skill demand. In this section, we present the corresponding changes in the college share, the skill ratio and the skill premium by extending regression equations (14) and (15). In particular, we include a set of dummy variables representing the different forms of technological change in the firm-level equation and their interaction with the college dummy in the worker-level regression. The results are presented in Tables A.19, A.20 and A.21.

The first columns of Table A.19 and A.20 report the baseline estimate from columns (1) and (2) of Table 2, respectively. Column (2) investigates whether technological change in firms conducting R&D is more skill-biased than in non-R&D firms. The results are produced by extending regression equation (14) to including both the basic innovation variable—capturing the effect of non-R&D innovation—and its interaction with a dummy variable for whether the firm conducts R&D—capturing the additional effect of R&D-driven technological change. The results from this regression suggest that non-R&D innovation has no positive effect on the college share or college ratio. Second, R&D-driven technological change has a more positive impact on the college share and college ratio than non-R&D innovation. Column (3) investigates whether it matters for the effect of technological change on the skill share whether the innovation has a high-novelty value. The results are produced by extending regression equation (14) by including both an R&D dummy, and a dummy variable for whether the innovation is new to the firm's market. The estimated coefficients on the latter is non-trivial (albeit noisily estimated) suggesting that 'new to the market' innovations have an even larger impact on the college share and ratio than less novel innovations.

Column (4) distinguishes between technical and organizational innovations. Note that a firm can conduct both at the same time; therefore, we introduce separate dummies for the different types of innovations in regression equation (14). We find that introducing only one type of innovation has a small impact on the college ratio, but the technical and organizational innovation reinforce each other. In Column (5) we further distinguish between product and process innovations within innovations with technical aspects.

Finally, in Column (6) we study whether the change in the college share depends on the sector the firm operates in, as well as the technology intensity of the sector. We classify industries into four groups: high- and low-technology manufacturing, and high- and low-knowledge-intensive services (see the details about the classification in footnote [30] in the main paper). The change in the college share and college ratio is largest in high-tech manufacturing, and smallest in high-knowledge (HK) services.

Table A.21, which estimates the change in the skill premium, follows a similar structure as above. We extend the worker-level regression equation (15), and report the δ_s coefficients (the interaction between innovation and college). Column (1) reports the baseline results from Table 3. Column (2) extends regression equation (15) by including both the basic innovation variable—capturing the effect of non-R&D innovation—and its interaction with a dummy variable for whether the firm conducts R&D—capturing the additional effect of R&D-driven technological change, along with the interaction of these variables with the college dummy. The results suggests that non-R&D and R&D-driven innovation have positive effects on the skill premium. Further, the differences between the two are small. Column (3) extends regression equation (15) by including the basic innovation variable, R&D-based innovation, a dummy variable for whether the innovation is new to the market and their interaction with college. The estimated coefficients suggest no significant changes in the skill premium coming from implementing 'new to the market' innovations.

Column (4) introduces separate dummies for the different types of innovations and their interactions with college in regression equation (15). We find that introducing only one type of innovation has a significant impact on the college premium, but the reinforcement effect is small. In column (5) we further distinguish between product and process innovation within innovations with technical aspects.

Finally, in Column (6) we include separate innovation dummies for firms operating in different sectors, along with their interactions with the college dummy. The skill premium increases most in low-tech manufacturing and non-knowledge intensive services. The effect on highly knowledge-intensive services is limited.

Finally, in Table A.22 we study the change in skill demand following R&D-based innovation in the manufacturing sector in particular. We compare these estimates to the estimates reported in Panel C of Table 6. The results are discussed in Section 5.4.

Table A.19: Change in the College Share Following Different Types of Innovation

	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.004	-0.000	-0.001			
	[0.001]	[0.002]	[0.002]			
R&D		0.006	0.004			
		[0.002]	[0.003]			
New to country			0.004			
			[0.002]			
Only technical				0.001		
				[0.002]		
Only organizational				0.001	0.001	
				[0.003]	[0.003]	
Both tech. and org.				0.008	0.007	
				[0.002]	[0.002]	
Only process					-0.002	
					[0.003]	
Only product					-0.000	
					[0.002]	
Low-tech manuf						0.004
						[0.003]
High-tech manuf						0.005
						[0.002]
Not know. int. serv						-0.001
						[0.002]
Know. int. serv						0.014
						[0.005]
Observations	27,122	27,122	27,122	27,122	27,122	24,966
Firms	13,141	13,141	13,141	13,141	13,141	12,212
R-squared	0.11	0.11	0.11	0.11	0.11	0.12
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
District-Year FEs	yes	yes	yes	yes	yes	yes

Notes: This table investigates how the college share changes after different types of innovations, as reported in the CIS (for detailed definitions, see Table B.1). The table reports firm-level regressions, following the approach Table 2, with 4-year change in the college share as the dependent variable and the innovation status reported in the CIS as the explanatory variable. Column (1) includes the innovation dummy for comparison. Column (2) also includes an R&D dummy, which captures the additional effect of conducting R&D – but the innovation dummy remains one for R&D conducting firms. In column (3), we also include a dummy, to show the additional effect of innovations that are considered new for the firm's market. In column (4), we distinguish between firms conducting only technical, only organizational and both types of innovations. In column (5), we also distinguish between process and product innovation. Finally, in column (6) we distinguish between innovators in different types of industries: Low- and high-tech manufacturing and highly knowledge-intensive and less knowledge-intensitve services, following Eurostat definitions, and include the interaction of these variables with the innovation dummy. Standard errors, clustered at the firm level, are reported in square brackets.

Table A.20: Change in the College Ratio Following Different Types of Innovation

	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.018	-0.001	-0.003			
	[0.008]	[0.012]	[0.012]			
R&D		0.027	0.021			
		[0.014]	[0.015]			
New to country			0.015			
			[0.012]			
Only technical				-0.000		
				[0.011]		
Only organizational				0.004	0.005	
				[0.015]	[0.015]	
Both tech. and org.				0.036	0.036	
				[0.010]	[0.010]	
Only process					-0.006	
					[0.020]	
Only product					0.006	
					[0.012]	
Low-tech manuf						-0.001
						[0.018]
High-tech manuf						0.028
						[0.015]
Not know. int. serv						-0.003
						[0.013]
Know. int. serv						0.053
						[0.031]
Observations	21,135	21,135	21,135	21,135	21,135	19,563
Firms	9,545	9,545	9,545	9,545	9,545	8,919
R-squared	0.12	0.12	0.12	0.12	0.12	0.12
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
District-Year FEs	yes	yes	yes	yes	yes	yes

Notes: This table investigates how the college ratio changes after different types of innovations, as reported in the CIS (for detailed definitions, see Table B.1). The table reports firm-level regressions, following the approach of Table 2, with four-year changes in the skill ratio as the dependent variable and the innovation status reported in the CIS as the explanatory variable. Column (1) includes the innovation dummy for comparison. Column (2) also includes an R&D dummy, which captures the additional effect of conducting R&D – but the innovation dummy remains one for R&D conducting firms. In column (3), we also include a dummy to show the additional effect of innovations that are considered new to the firm's market. In Column (4), we distinguish between firms conducting only technical, only organizational and both types of innovations. In Column (5), we also distinguish between process and product innovation. Finally, in Column (6) we distinguish between innovators in different types of industries: Low- and high-tech manufacturing and highly knowledge-intensive and less knowledge-intensitve services, following Eurostat definitions, and include the interaction of these variables with the innovation dummy. Standard errors, clustered at the firm level, are reported in square brackets.

Table A.21: Change in the College Premium Following Different Forms of Technological Change

	(1)	(2)	(3)	(4)	(5)	(6)
Innovation x College	0.011	0.010	0.011			
	[0.005]	[0.006]	[0.007]			
R&D x College		0.001	0.005			
		[0.007]	[0.007]			
New to country x College			-0.009			
			[0.007]			
Only technical x College				0.018		
				[0.006]		
Only organizational x College				0.013	0.009	
				[0.010]	[0.009]	
Both tech. and org. x College				0.007	0.003	
				[0.006]	[0.006]	
Only process x College					0.017	
					[0.013]	
Only product x College					0.011	
					[0.007]	
Low-tech manuf x College						0.017
						[0.008]
High-tech manuf x College						0.007
						[0.010]
Not know. int. serv x College						0.015
						[0.007]
Know. int. serv x College						-0.014
						[0.012]
Observations	1,863,477	1,863,477	1,863,477	1,863,477	1,863,477	1,678,926
Firms	13,378	13,378	13,378	13,378	13,378	12,425
R-squared	0.03	0.03	0.03	0.03	0.03	0.03
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs	yes	yes	yes	yes	yes	yes
District-Year FEs	yes	yes	yes	yes	yes	yes

This table investigates how the college premium changes after different types of innovations, as reported in the CIS (for detailed definitions, see Table B.1). The table reports the college interaction terms from the worker-level regressions, following the approach of column (1) of Table 3, with 4-year change in the worker's wage as the dependent variable and the innovation status reported in the CIS and its interaction with the college premium as explanatory variables. Column (1) includes the base result for comparison. Column (2) also includes an R&D dummy, which captures the additional effect of conducting R&D – but the innovation dummy remains one for R&D conducting firms. In column (3), we also include a dummy, to show the additional effect of innovations that are considered new to the firm's market. In column (4), we distinguish between firms conducting only technical, only organizational and both types of innovations. In column (5), we also distinguish between process and product innovation. Finally, in column (6) we distinguish between innovators in different types of industries: Finally, in column (6) we distinguish between innovators in different types of industries: Low- and high-tech manufacturing and highly knowledge-intensive and less knowledge-intensitve services, following Eurostat definitions, and include the interaction of these variables with the innovation dummy. Standard errors, clustered at the firm level, are reported in square brackets.

Table A.22: Change in the College Premium Following Technical Innovation with R&D in Manufacturing

	(1) Coll. share	(2) Skill ratio	(3) Skill premium
R&D + Innov. + Mfg	0.006	0.024	0.003
	[0.002]	[0.012]	[0.008]
Other innov.	0.003	0.015	-0.009
	[0.002]	[0.010]	[0.005]
College x (R&D + Innov. + Mfg)			0.012
			[0.008]
College x Other innov			0.012
			[0.006]
Observations	27,122	21,135	1,863,477
Firms	13,141	9,545	13,378
R-squared	0.11	0.12	0.03
2-digit Nace x Year FEs	yes	yes	yes
District-Year FEs	yes	yes	yes
Schooling-year FEs			yes

This table shows the change in the college share (Column 1), college ratio (Column 2), and college premium (Column 3) separately for R&D-based innovation in the manufacturing sector compared to all other innovations. Columns (1) and (2) reports results from firm-level regressions, similar to the one behind the results presented in Table 2, with a four-year change in the skill ratio as the dependent variable and the innovation status reported in the CIS as the explanatory variable. We extend the regression to including two innovation dummies: "Innov. + R&D + Mfg." is a dummy representing R&D-based innovation in the manufacturing sector, while "Other innov." is a dummy for all other innovations, inclusing those that take place in other sectors of the economy. Column (3) reports the college interaction terms from worker-level regressions, similar to the one behind the results presented in Column (1) of Table 3, with a four-year change in the worker's wage as the dependent variable. The regression is extended to including the two innovation dummies ("Innov. + R&D + Mfg." and "Other innov", as well as their interaction with the college premium as explanatory variables. Standard errors, clustered at the firm level, are reported in square brackets.

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A.15 Relationship Between the R&D Tax Credit Policy and Skill Demand

In Section 5.4 we study the effect of the introduction of an R&D tax credit on skill demand. In this section we provide further details on the tax credit and the estimation of the main results presented in Table 6 We also present a number of robustness checks.

We exploit a reform called Skattefunn that was introduced in Norway in 2002. The reform allowed firms to deduct 20 percent of their R&D expenditures up to a threshold of 4 million NOK (approx 450,000 USD). As a consequence, firms conducting R&D investments below the cost deduction threshold of 4 million NOK experienced a reduction in the marginal cost of investing in R&D. We follow Bøler et al. (2015) and Bøler (2015) and classify a firm as treated if its average pre-reform R&D investments (for the years 1998-2001) are below 4 million NOK. For this exercise we use the R&D survey, which was conducted annually from 1998, except for the year 2000.

We conduct our regression analysis for the period between 1998 and 2012, using the following outcome variables:

- R&D spending: Log R&D spending in NOK, according to the R&D Survey.
- Innovation: The Innovation from the CIS, which we use in the main regressions. Note that we observe only one wave (2001) conducted before the reform.
- Technical Innovation: The measure of technical innovation from the CIS.
- College share: Change in the firm-level college share between $t-1$ and t. As the worker data is available between 1998 and 2012, we can calculate this change for the years 1999 to 2011.
- Skill ratio: Change in the firm-level skill ratio between $t-1$ and t. As the worker data is available between 1998 and 2012, we can calculate this change for the years 1999 to 2011.
- Hourly wage: Change in the worker's hourly wage between $t-1$ and t. As the worker data is available between 1998 and 2012, we can calculate this for the years 1999 to 2011. Note that we do not have precise hours for the period until 2000, so for the earliest years, we impute hours from information on the worker's contract type (full-time/ part-time).

In our main specification we impose several sample restrictions, which are later relaxed in Tables A.24 - A.27. First, our main specification looks at manufacturing, where R&D and innovation is likely to be more strongly connected (this is also in line with Bøler et al. 2015). Second, following Bøler et al. (2015), we restrict the sample to firms with at least 50 employees (in 2001). This restriction is due to the sampling procedure for smaller firms which involves oversampling firms that spend more than NOK 1million in the previous survey period, potentially introducing a bias. All firms with at least 50 employees on the other hand, are sampled all years.[50] Third, firms that spend substantially above the threshold are likely to be large and more globalised than the treated group. Therefore we restrict the control group to firms which did not spend more than ten times the threshold, NOK

[50]Throughout the analysis we consistently exclude all observations of one particular outlier firm, that increases its number of employees from approximately 150 to 5,000 in 2006. The results are robust to including this firm.

40 million.[51] Fourth, in our main specification we exclude the three years (2002-2004) immediately following the introduction of the policy. One reason is that the policy was introduced a year later for larger firms. Another reason is that in our framework the change in skill demand is associated with the introduction of an innovation, and not an increase in innovation inputs. We expect that it takes some time before increased innovation spending results in an innovation and thereby a change in skill bias. Fifth, we narrow the analysis time frame of to end in 2008, as we recognize that R&D spending prior to 2002 R&D may not be a relevant predictor of R&D spending many years later.

We estimate the change in the skill ratio following the introduction of the R&D tax credit policy using regression equation (19), and we estimate the effect of the introduction of the R&D tax credit on the college premium using the regression equation (20). Our main results, for manufacturing firms with at least 50 employees, are reported in Figure 3 and Table 6, and discussed in the main paper in Section 5.4.

This section presents a number of robustness checks. First, Table A.24 shows results when we include firm fixed effects (firm-college fixed effects in column (7)) in the regression to control for different growth trends across firms. Second, Table A.25 shows the results when including the two years, 2002-2004, immediately following the policy change. Third, Table A.26 presents results when small firms (less then 50 employees in 2001) are added to the sample. Fourth, Table A.27 excludes workers in R&D-related occupations[52] to filter out the mechanical effect of the introduction of the R&D tax credit on occupational structure. Overall, the results are robust to these changes.

Finally, in Table A.28 we present result for firms in the service sector. We find no evidence of increased R&D spending among firms in the service sector, suggesting that the policy had a limited impact on their innovation activities. In line with this finding, there is no increase in skill demand among firms in this sector following the introduction of the policy.

[51]The results are similar if we use different threshold, such as NOK 10 or 20 mn.

[52]Occupation codes 21 (Science and Engineering Professionals) and 31 (Science and Engineering Associate) Professionals).

Table A.23: The Impact of Technological Innovation in Norway: Two-sample 2SLS results

Panel A: All Firms

	(1) College Share	(2) Skill Ratio	(3) Skill premium
Treatment effect	0.024	0.187	0.034
	[0.016]	[0.173]	[0.034]
Observations	5,466	5,266	817,372
R2	0.20	0.18	0.03
Firms	962	953	970
Workers			221,321
Industry-year FEs	yes	yes	yes
District-year FEs	yes	yes	yes
Schooling-year FEs			yes

Panel B: Firms with No R&D Spending between 1998 and 2001

	(1) College Share	(2) Skill Ratio	(3) Skill premium
Treatment effect	0.014	0.102	0.010
	[0.007]	[0.065]	[0.018]
Observations	3,341	3,206	531,812
R2	0.27	0.26	0.03
Firms	608	600	612
Workers			152,007
Industry-year FEs	yes	yes	yes
District-year FEs	yes	yes	yes
Schooling-year FEs			yes

Notes: This table presents Two-sample 2SLS estimates of the results presented in Table 6. In these 2SLS regressions we instrument technical innovation with the interaction between a post 2001 dummy and a dummy showing whether the firm spent below the threshold pre-policy. The first stage for the firm-level regressions (columns (1) and (2)) is reported in Table 6 column (3). In the firm-level regression, we instrument technical innovation in the same way and we instrument the interaction of technical innovation and college with the interaction of the IV and college. Here we include all firms with at least 50 employees in 2001. Given that the first step is only run on a smaller sample, we use a two-sample 2SLS estimator, and bootstrap the standard errors, clustered at the firm-level. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Table A.24: The Impact of the R&D Tax Credit Policy in Norway: Estimates with Firm Fixed Effects

Panel A: All Firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium	(7) Skill premium
Treatment effect	0.653	0.105	0.269	0.005	0.040	0.010	0.011
	[0.145]	[0.080]	[0.075]	[0.003]	[0.021]	[0.006]	[0.007]
Observations	438,319	291,710	291,710	923,420	916,684	817,371	817,354
R2	0.91	0.66	0.69	0.35	0.33	0.04	0.04
Firms	600	737	737	962	953	969	969
Workers						221,320	221,308
Industry-year FEs	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes
Firm FEs	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes	yes
Firm-college FEs							yes

Panel B: Firms with Positive R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium	(7) Skill premium
Treatment effect	0.656	0.041	0.142	0.007	0.058	0.015	0.017
	[0.145]	[0.086]	[0.080]	[0.003]	[0.022]	[0.008]	[0.008]
Observations	397,920	191,541	191,541	598,331	596,417	542,441	542,437
R2	0.90	0.68	0.71	0.35	0.36	0.05	0.05
Firms	498	406	406	494	493	499	499
Workers						151,256	151,254
Industry-year FEs	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes
Firm FEs	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes	yes
Firm-college FEs							yes

Panel C: Firms with No R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium	(7) Skill premium
Treatment effect	0.000	0.205	0.464	0.006	0.040	0.003	0.002
	[.]	[0.099]	[0.089]	[0.004]	[0.027]	[0.007]	[0.007]
Observations	264,561	189,963	189,963	608,545	603,549	531,811	531,796
R2	0.91	0.72	0.76	0.42	0.42	0.04	0.04
Firms	243	444	444	608	600	611	611
Workers						152,006	151,995
Industry-year FEs	yes	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes	yes
Firm FEs	yes	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes	yes
Firm-college FEs							yes

Notes: This table presents robustness checks for our benchmark results concerning the impact of the R&D tax credit, as presented in Table 6. Columns (1)-(5) of this table report estimates from regression equation (19) augmented with firm fixed effects. Columns (6)-(7) report estimates from regression equation (20) augmented with firm-college fixed effects. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Table A.25: The Impact of the R&D Tax Credit Policy in Norway: Including the Years 2002-2004

Panel A: All firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.728	0.066	0.183	0.002	0.025	0.007
	[0.148]	[0.052]	[0.054]	[0.002]	[0.012]	[0.005]
Observations	567,017	392,535	392,535	1,128,962	1,120,903	1,002,484
R2	0.66	0.26	0.30	0.19	0.18	0.03
Firms	633	742	742	965	956	970
Workers						226,171
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel B: Firms with Positive R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.706	0.014	0.067	0.003	0.037	0.012
	[0.157]	[0.054]	[0.058]	[0.002]	[0.014]	[0.006]
Observations	503,942	255,526	255,526	727,659	725,424	661,890
R2	0.68	0.35	0.39	0.22	0.23	0.04
Firms	498	407	407	496	495	499
Workers						154,394
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel C: Firms with No R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.000	0.173	0.389	0.002	0.021	0.003
	[.]	[0.062]	[0.054]	[0.002]	[0.016]	[0.005]
Observations	343,271	257,682	257,682	744,855	738,849	653,633
R2	0.66	0.40	0.49	0.26	0.25	0.03
Firms	276	448	448	609	601	612
Workers						155,781
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Notes: This table presents robustness checks for our benchmark results concerning the impact of the R&D tax credit, as presented in Table 6. Columns (1)-(5) of this table report estimates from regression equation (19) and Columns (6)-(7) report estimates from regression equation (20) . In this table we include the three years between 2002 and 2004 that are excluded in the benchmark specification. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Table A.26: The Impact of the R&D Tax Credit Policy in Norway: Including Firms with Fewer Than 50 Workers

Panel A: All Firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.672	0.099	0.237	0.004	0.033	0.008
	[0.160]	[0.067]	[0.066]	[0.002]	[0.015]	[0.005]
Observations	476,170	339,493	339,493	1,177,890	1,118,873	1,035,257
R2	0.64	0.21	0.26	0.11	0.10	0.02
Firms	1,113	1,853	1,853	2,827	2,513	2,836
Workers						277,873
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel B: Firms with Positive R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.686	0.025	0.102	0.005	0.042	0.013
	[0.180]	[0.070]	[0.066]	[0.002]	[0.017]	[0.007]
Observations	426,828	208,528	208,528	663,341	654,800	599,158
R2	0.67	0.33	0.36	0.16	0.17	0.04
Firms	870	692	692	864	841	871
Workers						166,421
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel C: Firms with No R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.000	0.211	0.420	0.004	0.033	0.004
	[.]	[0.071]	[0.068]	[0.002]	[0.016]	[0.006]
Observations	280,020	223,862	223,862	807,084	756,254	701,073
R2	0.63	0.36	0.46	0.14	0.14	0.02
Firms	422	1,305	1,305	2,141	1,850	2,144
Workers						199,518
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Notes: This table presents robustness checks for our benchmark results concerning the impact of the R&D tax credit, as presented in Table 6. Columns (1)-(5) of this table report estimates from regression equation (19) and Columns (6)-(7) report estimates from regression equation (20) . In Table 6 we include all firms with at least 50 employees in 2001. In this table, we lower the requirement to having at least 10 workers in 2001. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Table A.27: The Impact of the R&D Tax Credit Policy in Norway: Excluding Workers in R&D occupations

Panel A: All firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.605	0.048	0.188	0.004	0.034	0.009
	[0.152]	[0.064]	[0.066]	[0.002]	[0.017]	[0.007]
Observations	1,963	1,643	1,643	5,466	5,228	989,209
R2	0.67	0.27	0.31	0.16	0.16	0.03
Firms	600	737	737	962	948	970
Workers						208,727
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel B: Firms with Positive R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.652	-0.014	0.074	0.005	0.040	0.014
	[0.159]	[0.069]	[0.067]	[0.003]	[0.020]	[0.008]
Observations	1,733	915	915	2,943	2,856	645,279
R2	0.69	0.38	0.41	0.21	0.24	0.04
Firms	498	406	406	494	491	499
Workers						142,318
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel C: Only firms with No R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.000	0.188	0.407	0.005	0.042	0.004
	[.]	[0.074]	[0.071]	[0.003]	[0.020]	[0.007]
Observations	852	992	992	3,341	3,178	647,482
R2	0.66	0.40	0.52	0.21	0.24	0.03
Firms	243	444	444	608	597	612
Workers						142,153
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Notes: This table presents robustness checks for our benchmark results concerning the impact of the R&D tax credit, as presented in Table 6. Columns (1)-(5) of this table report estimates from regression equation (19) and Columns (6)-(7) report estimates from regression equation (20) . In all columns, we exclude workers in R&D-occupations (occupation codes 21 (Science and Engineering Professionals) and 31 (Science and Engineering Associate Professionals)). In Columns (4)-(5) we report estimates when excluding R&D workers from the calculation of the college ratio. Column (6) shows the change in the worker-level college premium when excluding workers in R&D-occupations from the estimation. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Table A.28: The Impact of the R&D Tax Credit Policy in Norway: Firms in the Service Sector

Panel A: All Firms

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.494	0.028	0.011	-0.001	-0.014	-0.000
	[0.279]	[0.107]	[0.142]	[0.003]	[0.019]	[0.007]
Observations	354,564	410,879	410,879	1,439,836	1,432,136	1,243,811
R2	0.73	0.27	0.26	0.13	0.13	0.03
Firms	423	844	844	1,208	1,203	1,220
Workers						359,742
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel B: Firms with Positive R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.737	0.115	0.086	-0.005	-0.033	0.005
	[0.290]	[0.131]	[0.131]	[0.004]	[0.022]	[0.009]
Observations	293,518	189,401	189,401	601,303	600,736	536,158
R2	0.76	0.41	0.41	0.21	0.23	0.04
Firms	328	258	258	326	324	333
Workers						165,131
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Panel C: Firms with No R&D Spending between 1998 and 2001

	(1) R&D spending (ln)	(2) Innov.	(3) Technical Innov.	(4) College Share	(5) Skill Ratio	(6) Skill premium
Treatment effect	0.000	-0.016	-0.012	-0.000	-0.013	-0.003
	[.]	[0.105]	[0.160]	[0.003]	[0.022]	[0.007]
Observations	223,026	317,469	317,469	1,150,139	1,142,636	986,735
R2	0.64	0.34	0.30	0.14	0.14	0.03
Firms	194	670	670	979	976	988
Workers						297,839
Industry-year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Schooling-year FEs						yes

Notes: This table presents robustness checks for our benchmark results concerning the impact of the R&D tax credit, as presented in Table (6). Columns (1)-(5) of this table report estimates from regression equation (19) and Columns (6) reports estimates from regression equation (20) . In this table, we include firms in the service sector instead of manufacturing firms. In everything else, we follow the benchmark specification; see the table notes for Table 6 for further details on the regressions.

Appendix B Institutional Details and Data Appendix

B.1 The Community Innovation Survey

Table B.1: Questions in the 2002-2004 CIS

Innovation	The sum of product, process and organizational innovation.
Product innovation	A product innovation is the market introduction of a new good or service or a significantly improved good or service with respect to its capabilities, such as improved software, user friendliness, components or sub-systems. The innovation (new or improved) must be new to your enterprise, but it does not need to be new to your sector or market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises. During the three years 2002 to 2004, did your enterprise introduce: 1. New or significantly improved goods (exclude the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature). 2. New or significantly improved services?
Process innovation	A process innovation is the implementation of a new or significantly improved production process, distribution method, or support activity for your goods or services. The innovation (new or improved) must be new to your enterprise, but it does not need to be new to your sector or market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises. Exclude purely organisational innovations. During the three years 2002 to 2004, did your enterprise introduce: 1. New or significantly improved methods of manufacturing or producing goods or services. 2. New or significantly improved logistics, delivery or distribution methods for your inputs, goods or services. 3. New or significantly improved supporting activities for your processes, such as maintenance systems or operations for purchasing, accounting, or computing?
Organizational innovation	An organisational innovation is the implementation of new or significant changes in firm structure or management methods that are intended to improve your firm's use of knowledge, the quality of your goods and services, or the efficiency of work flows. A marketing innovation is the implementation of new or significantly improved designs or sales methods to increase the appeal of your goods and services or to enter new markets. During the three years 2002 to 2004, did your enterprise introduce: 1. New or significantly improved knowledge management systems to better use or exchange information, knowledge and skills within your enterprise. 2. A major change to the organisation of work within your enterprise, such as changes in the management structure or integrating different departments or activities. 3. New or significant changes in your relations with other firms or public institutions, such as through alliances, partnerships, outsourcing or sub-contracting?
Intramural (in-house) R&D	During the three years 2002 to 2004, did your enterprise engage in the following innovation activities: 1. Creative work undertaken within your enterprise to increase the stock of knowledge and its use to devise new and improved products and processes (including software development)?
R&D spending	Please estimate the amount of expenditure for each of the following (...) innovation activities in 2004 only (include personnel and related costs): 1. Intramural (in-house) R&D (Include capital expenditures on buildings and equipment specifically for R&D). 2. Acquisition of R&D (extramural R&D).
Non-R&D innovation spending	Please estimate the amount of expenditure for each of the following (...) innovation activities in 2004 only (include personnel and related costs): 1. Acquisition of advanced machinery, equipment and computer hardware or software to produce new or significantly improved products and processes (Exclude expenditures on equipment for R&D). 2. Acquisition of other external knowledge. (Purchase or licensing of patents and non-patented inventions, know-how, and other types of knowledge from other enterprises or organisations).
New-to-the-market innovation	Were any of your goods and service innovations during the three years 2002 to 2004 new to your market? Your enterprise introduced a new or significantly improved good or service onto your market before your competitors (it may have already been available in other markets).
Outsourcing	During the three years 2002 to 2004, did your enterprise introduce new or significant changes in your relations with other firms or public institutions, such as through alliances, partnerships, outsourcing or sub-contracting.

Source: The definitions come from the CIS 2004 Questionnaire, available at: https://ec.europa.eu/eurostat/web/microdata/community-innovation-survey.

Table B.2: Firm Innovation Activities

	2001	2004	2006	2008	2010	2012	2014
Technical innovation	0.39	0.39	0.33	0.34	0.29	0.26	0.46
	(0.49)	(0.49)	(0.47)	(0.47)	(0.46)	(0.44)	(0.50)
Product innovation	0.36	0.32	0.26	0.27	0.24	0.21	0.37
	(0.48)	(0.47)	(0.44)	(0.44)	(0.43)	(0.41)	(0.48)
Process innovation	0.28	0.24	0.20	0.21	0.17	0.14	0.30
	(0.45)	(0.43)	(0.40)	(0.41)	(0.37)	(0.35)	(0.46)
Organizational innovation	0.38	0.27	0.15	0.19	0.19	0.20	0.30
	(0.49)	(0.44)	(0.36)	(0.39)	(0.39)	(0.40)	(0.46)
R&D	0.29	0.33	0.24	0.26	0.25	0.24	0.35
	(0.45)	(0.47)	(0.43)	(0.44)	(0.43)	(0.43)	(0.48)
New-to-the-market innovation	0.17	0.17	0.15	0.13	0.19	0.17	0.25
	(0.38)	(0.37)	(0.36)	(0.34)	(0.40)	(0.38)	(0.44)
R&D inv. intensity	0.03	0.04	0.04	0.05	0.06	0.06	0.06
	(0.14)	(0.16)	(0.15)	(0.18)	(0.25)	(0.20)	(0.22)
Non-R&D innovation spendings	0.01	0.01	0.00	0.01	0.01	0.00	0.05
	(0.09)	(0.09)	(0.00)	(0.06)	(0.15)	(0.18)	(0.65)
Outsourcing	0.35	0.09	0.06	0.07	0.07	0.07	0.12
	(0.48)	(0.28)	(0.24)	(0.26)	(0.25)	(0.25)	(0.32)
Observations	2440	3204	4490	3980	4823	4337	4412

Notes: This Table shows the share of firms from our mean sample conducting different type of innovation in the different CIS waves. The definitions of these activities are explained in Table B.1 in detail. Innovation intensity is measured in 1000 NOK/employee.

B.2 Labor Markets in Norway and Hungary

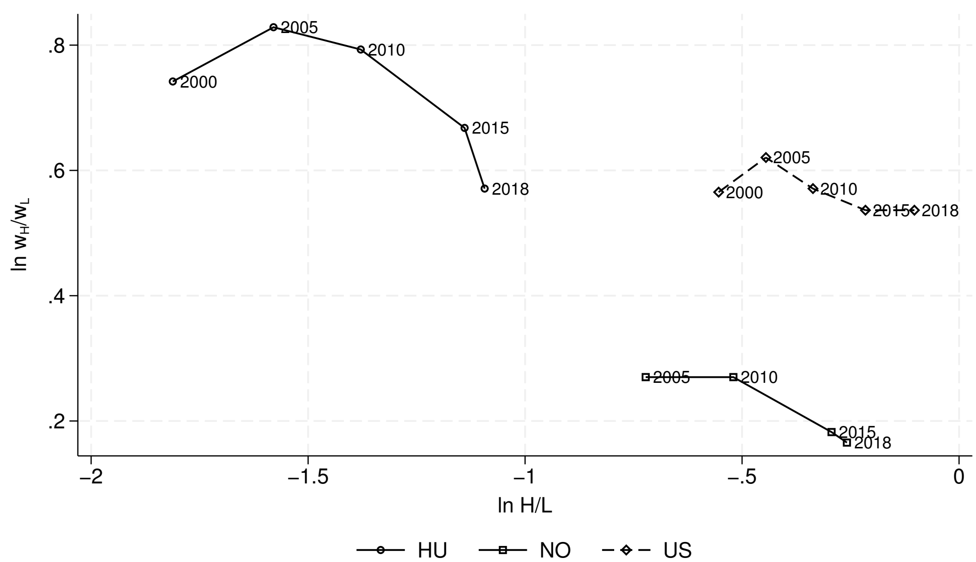
We study the impact of technological change on skill demand in Norway and Hungary. Here, we describe how the labor markets operates in these two countries.

The Norwegian labor market is an example of the Nordic model with its three key features: (i) flexible hiring and firing, (ii) a generous social safety net and (iii) active labor market policies. Labor markets are less regulated than in many other European labor markets, as collective agreements assume some of the regulatory functions. Union density is very high: more than 38% of workers in the private sector were union members in 2014 (Nergaard 2014). Wages are typically determined through a two-step process involving industry-wide negotiations followed by local bargaining at the firm level. The industry-level negotiations results in proposed minimum wages, covering approximately half of private-sector workers (Blandhol et al. 2020). However, for these worker, subsequent firm-level wage-bargaining often results in substantially higher wage increases than those implied by the industry minimum wages, highlighting the firm's role in wage determination. Notably, for the majority of white-collar workers in the private sector, centrally negotiated collective agreements do not specify wages. As a result, wage formation mainly occurs at the firm-level, incorporating strong individual-level elements (Nergaard 2014).

Hungarian employment protection institutions, in contrast, are closer to the Anglo-Saxon institutions than to those found in continental countries. It is relatively easy to dismiss workers (Tonin et al. 2009) and wage bargaining takes place mostly at the individual level. Collective wage bargaining is based on firm-level agreements with unions. Union membership was 10.2% percent in 2014, one of the lowest in the OECD.[53] Apart from firm-level bargaining, industry-level agreements are rare and set only weak requirements. Unions participate in the country-level bargaining forum called National Interest Reconciliation Council, which makes only non-binding recommendations (Rigó 2012). Employment contracts usually assume full time employment and pre-specify 8-hour working days. The actual working hours in these contracts are not monitored and firms can decide whether they want to measure and compensate for overtime hours. Part time work contracts add up to only 5 percent of the workforce and contracts on hourly basis are also rare.

Figure B.1 sketches the evolution of the two key variables in our study at the macro level for Norway, Hungary and the US between 2000 and 2018. The share of college graduates increased in all three countries throughout the period. This expansion started from a much lower level and was faster in relative terms in Hungary compared to the other two countries. In parallel with the education expansion, the skill premium fell in all three countries from 2005. The fall was strongest in Hungary, in line with the quick increase in the share of college workers. The evolution of the premium was nearly parallel in Norway and the US, but it is at a much lower level in Norway.

Figure B.1: The Evolution of the Skill Share and Wage Ratio in Norway, Hungary and the US



Notes: H/L is based on the share of people with tertiary degrees among workers and the wage premium shows the average wage of 25-64 year-olds with income from employment compared to upper secondary education. Source: OECD Education at a Glance 2014, Table A62a and OECD Education at a Glance 2014 database ("eduadult" variable).

[53]OECD Employment and Labor Market Statistics.

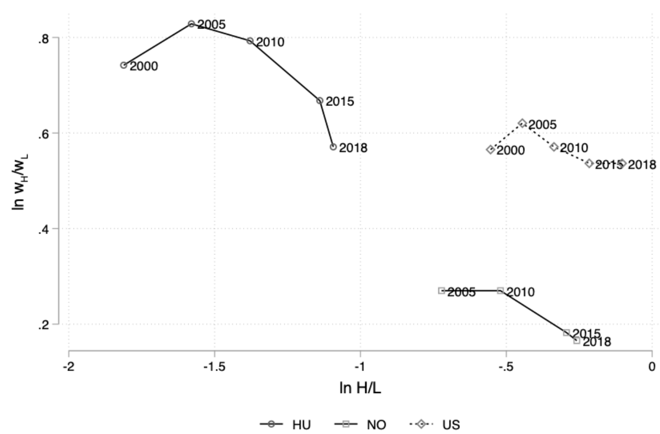
B.3 Innovation in Norway and Hungary

The European Innovation Scoreboard provides a comprehensive picture of innovation activities of European countries.[54] It uses four categories to rank the countries' innovation system, and classifies Norway as a 'Strong innovator' (the second group), and Hungary as a 'Moderate Innovator' (third group), suggesting that Norway is substantially closer to the world technology frontier than Hungary, where technology adoption plays a much larger role.[55]

These differences are reflected by a number of indicators. In terms of GDP/capita, Norway's GDP was 20% above that of the USA (66 vs 55 thousand USD) and more than 150% above that of Hungary (25 thousand USD). On the innovation input side, the overall R&D/GDP ratio (in 2014) was 1.35% in Hungary and 1.71% in Norway compared to an EU average of 2% and 2.7% in the USA.[56]

Figure B.2 shows the share of firms conducting different types of innovation in the two countries and the average among the EU 27 and the United Kingdom. In Norway, 59% of firms are innovative compared to 25.5% in Hungary and 49% in the EU. Other differences than the share of innovative firms are present: Norwegian innovators are much more likely to combine technical and organizational changes then either the EU or Hungary. Norwegian firms are also much more likely to rely on high novelty innovation while Hungarian firms conduct technology adoption to a larger extent. Among innovators, 26% introduced a "World first" innovation in Norway, compared to 5% in Hungary.

Figure B.2: Prevalence of Innovation Types in Norway and Hungary



Notes: This Figure shows the share of innovative firms by the main type of innovation from the Community Innovation Survey 2014. "European Union" is the average of the EU 27 countries and the United Kingdom.

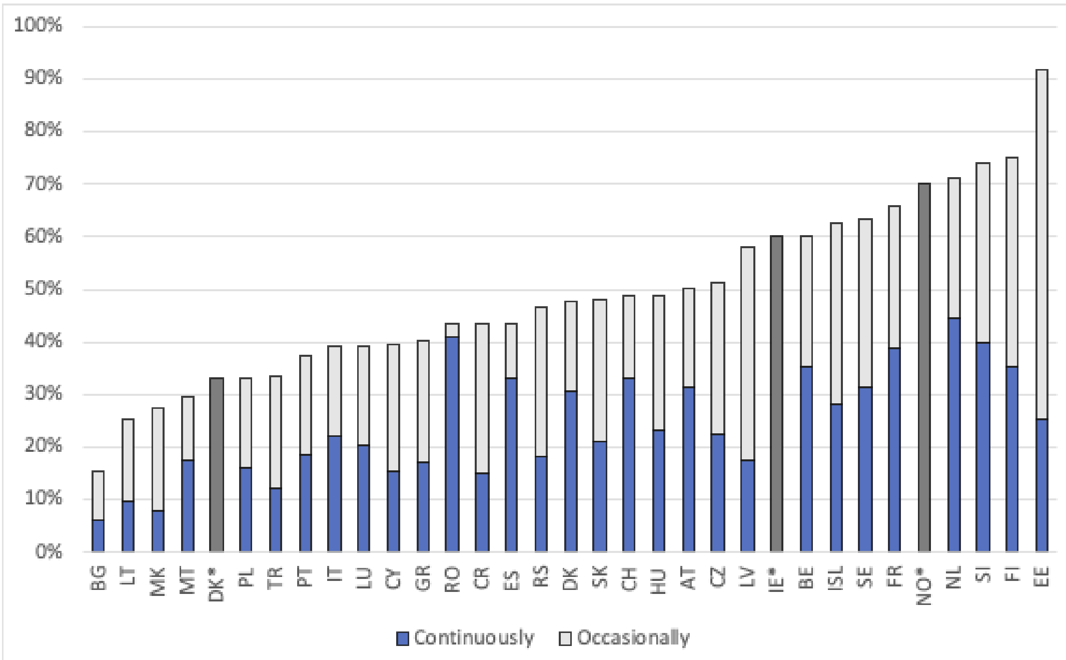
The CIS data also show characteristic differences in the inputs used by innovative firms in the two countries (Figure B.3). In line with a larger role of high-novelty innovations, Norwegian firms are much more likely to rely on R&D than Hungarian firms, with Norway having one of the highest share of R&D conducting firms among innovative firms (Panel A). Panel B shows a breakdown of the

[54]Available at https://ec.europa.eu/growth/industry/policy/innovation/scoreboards_en.
[55]We use numbers from 2014 around the end of our sample period, unless otherwise indicated.
[56]Source: https://data.oecd.org/rd/gross-domestic-spending-on-r-d.htm.

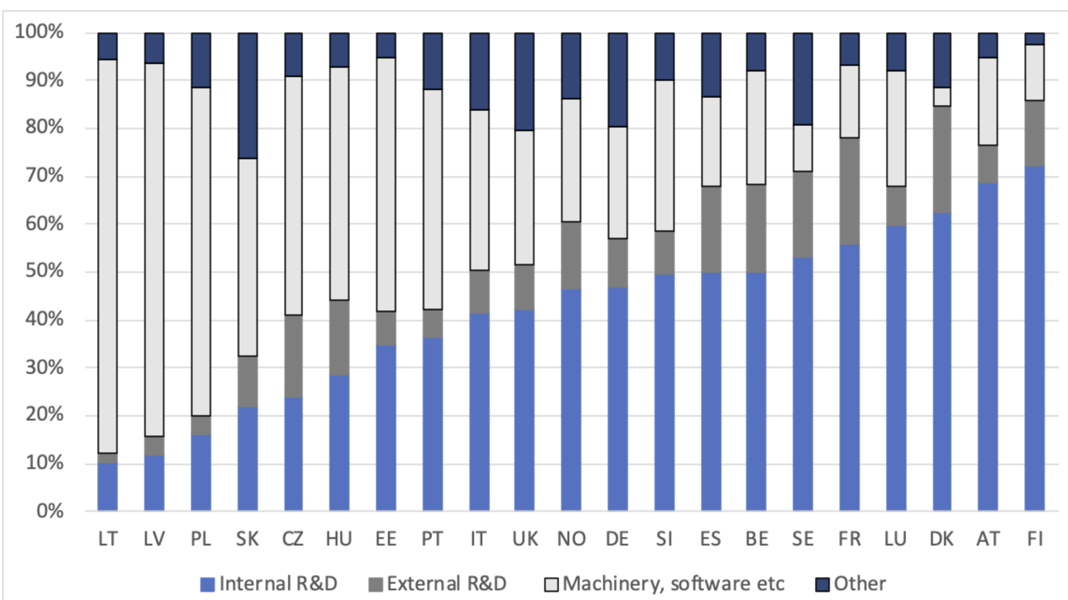
different types of innovation costs. It clearly demonstrates that the type of innovation costs captured by the CIS goes much beyond R&D, and also that in many European countries R&D is not the dominant component of innovation costs. The sum of external and internal R&D represents about 60% of Norwegian firms' innovation costs, but this number is closer to 45% in Hungary. In fact, the dominant innovation cost for Hungarian firms is machinery and software, in line with an innovation model which mainly relies on technology adoption, partly based on embodied knowledge (see e.g. Koren & Csillag 2017).

Figure B.3: Innovation Inputs and Outputs

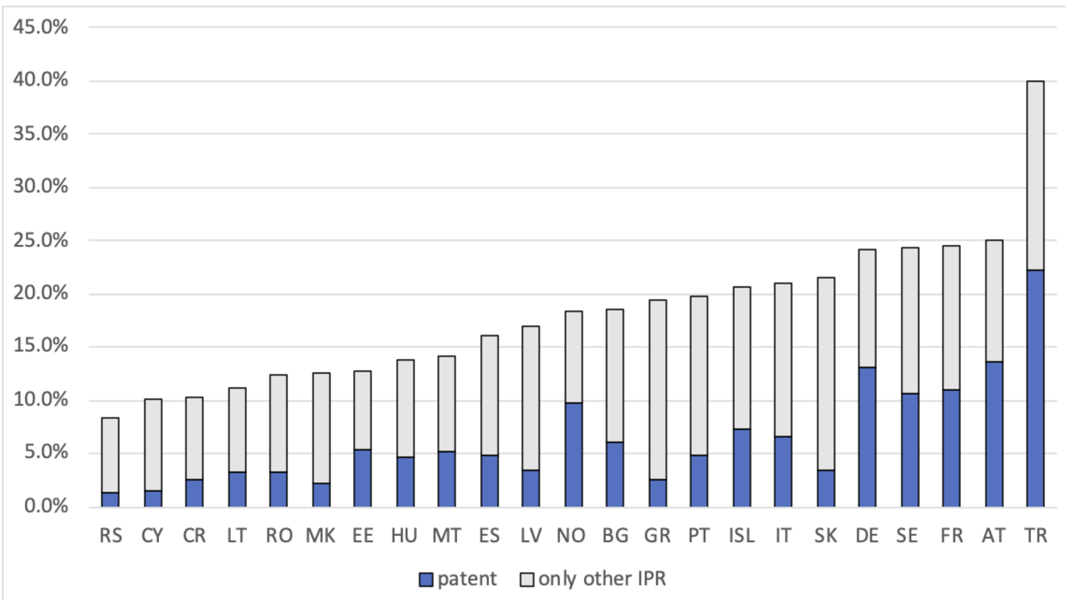
Panel A: Share of Firms Conducting R&D Continuously or Occasionally Among Technical Innovators (%)



Panel B: Share of Different Expenditures in Total Innovation Costs (%)



Panel C: Share of Innovative Firms Applying for Patents and Other IP



Notes: Panel A of this figure shows the share of firms which conducted in-house R&D in firms which reported product and/or process innovations. The breakdown between continuous and occasional R&D spending is not available in countries denoted by *. Panel B shows the share of different types of innovation expenditures relative to total expenditures on product and process innovation. Panel C reports the share of firms which applied for a patent or other IP (a European utility model or that registered an industrial design right or a trademark). All the figures refer to the period between 2012 and 2014. Source: CIS, 2014.

Appendix C Firm-level Skill Demand and Technological Change in Hungary

In this section we provide more details about the empirical analysis from Hungary.

C.1 Data

Hungarian administrative data does not contain information on education. As a first step, we create a proxy by using the Hungarian Structure of Earnings Survey (HSES), which has information on approximately 150,000 workers annually.[57] In the HSES, all firms with more than 50 employees, as well as a random sample of firms with fewer than 50 employees, have to report annually their detailed wage and occupational structure, and the highest educational level of their workforce. We compute the share of college graduates for each year and within four-digit occupational categories in the HSES.[58]

Figure C.1 shows the distribution of the workers by the share of college graduates in their occupations. Approximately 10 percent of workers are in occupation where the share of college graduates constitute more than 95 percent of the workforce, whereas more than 50 percent of workers are in occupations where the share of college graduates is less than 5 percent. Relatively few workers are in occupations with a college share between these thresholds. We merge the occupation shares of college graduates from HSES to the administrative wage data at the occupational level. We consider a worker to have a college degree if the share of college graduates in her occupation is more than 50 percent.

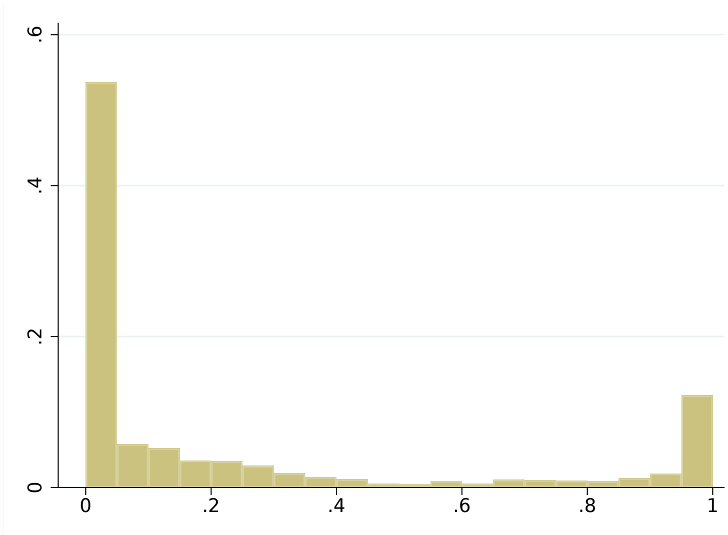
The Hungarian administrative data we use in the analysis (called Admin3) is maintained by the Centre for Economic and Regional Studies. It is a linked employer- employee database and it provides employment and wage information on a 50 percent random sample of the Hungarian population between 2003 and 2017. We use the administrative data to compute the average wage growth of workers with and without college degrees between year $t-4$ and year t. Then we use probabilistic matching based on balance sheet information to link the wage growth from the administrative data to the information on technological change in the CIS. We make use of the fact, that both data sets have balance sheet data. Following the strategy of Card et al. (2016), we assume that two firms are identical if they have the same industry, employment, revenue, and material costs in both datasets.

Table C.1 shows the number of observations by year. There are 357,000 firms, out of which 3,508 participates in the CIS in 2004. The number of surveyed firms increased year by year and exceeds 6,700 observations in 2014 and 2016. The total number of observations in the CIS over the relevant waves is 33,364. We can compute the growth in the college share only for firms oberved in both year $t-4$ and year t. This is not possible for the 2004 and 2006 waves of the CIS because the administrative data is only available form 2003. In total the 4-year change in the collage share is available for 23,694

[57] More information about this survey is available at https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Structure_of_earnings_survey_(SES).

[58] Hungarian occupational categorization is called FEOR. They are similar to ISCO categories and define more than 300 occupations at the four-digit level.

Figure C.1: The Share of College Workers by Occupational Categories



Notes: This figure plots the histogram of the share of college graduates by occupations. The horizontal axis shows the share of college graduates in the four-digit occupational category. The figure is weighted by the number of workers in the occupation

observations. Out of these, the change in the (log) college share and the skill premium (which require that the firm has both college and non-college workers both in $t-4$ and t could be calculated for 15,159 observations.

Table C.1: Number of Observations in Hungary - Firm level

	2004	2006	2008	2010	2012	2014	2016	Total
(1) All firms	357,844	380,678	445,211	447,549	469,287	460,831	449,057	3,010,457
(2) Sampling frame	52,465	71,007	52,695	59,082	78,659	84,843	89,003	487,754
(3) CIS sample	3,361	4,305	4,611	4,344	4,568	6,098	6,077	33,364
(4) Positive Value added			4,203	3,955	4,235	5,682	5,619	23,694
(5) Skill share nonmissing			4,101	3,866	4,131	5,537	5,449	23,084
(6) Skill ratio/premium nonmissing			2,697	2,503	2,883	3,497	3,579	15,159

Notes: This Table shows the number of observations in the firm- level sample in Hungary. The first row shows the total number of firm-year observations in the sample. The second row restricts the sample to firms that are in the CIS sampling frame according to the Eurostat documentation (https://ec.europa.eu/eurostat/cache/metadata/en/inn_cis12_esms.htm); i.e. firms that have at least 10 employees and operate in NACE 2-digit industries 10-73. In row (3), we further restrict our attention to firms that report positive fixed assets and value added in the survey year. Given that our main specifications look at changes between years $t-4$ and t, row (4) reports the number of firms that also existed in year $t-4$, for which the long change can be calculated. The final sample size for the college share regression is reported in row (5). The final sample size for the college ratio regression, which requires that the firm has both college and non-college workers in years $t-4$ and t, is reported in row (6).

Table C.2: Descriptive Statistics: Characteristics of Innovative and Non-Innovative Firms in Hungary

	All	Non-innovative	Innovative
Share of college graduates	0.144	0.127	0.179
	(0.17)	(0.16)	(0.19)
Skill ratio (log)	-1.852	-1.912	-1.752
	(1.09)	(1.06)	(1.14)
Skill premium (log)	0.510	0.505	0.518
	(0.38)	(0.38)	(0.36)
Log hourly wage rate (HUF)	2.909	2.846	3.040
	(0.44)	(0.43)	(0.44)
Number of employees	131.9	80.1	239.0
	(616.2)	(321.2)	(966.2)
Average of firm age	16.517	16.384	16.793
	(5.88)	(5.91)	(5.83)
Firm-years	23,084	15,564	7,520
Firms	10,545	8,615	4,271

Notes: This table shows the characteristics of innovative and non-innovative firms in the Community Innovation Survey (CIS), where we measure firm-level technological change. Innovative firms report that they introduced new or significantly modified products/technologies/organization, which are new from the firm's point of view. Non-innovative firms are the rest of the firms in the survey. We report average values of outcomes for the biennial CIS-years 2004-2016 (for which we estimate the firm level regressions). The table shows the mean, firm-level share of college graduates, firm-level skill ratio (log college to non-college ratio), log skill premium, firm-level average log daily wage, average firm age, firms' number of employees. Standard deviations of these variables are reported in parentheses below.

C.2 Main Results for Hungary

C.2.1 Technological Change and Change in Skill Demand: Robustness of the Hungarian results

Table C.3 examines the robustness of the Hungarian results by reproducing Table A.6.[59] Similar to the Norwegian analysis, we control for the growth in capital and value added in the top panel, for firm fixed effects in the middle panel, and for the initial wage share in the bottom panel. The results are qualitatively the same in each specification.

Table C.4 examines changes in the number of college-educated and non-college-educated workers. The results show a notable 5.7% increase (s.e. 1.7%) in the number of college-educated workers, while the number of non-college-educated workers experiences a small rise of 1% (s.e. 1.5%). These findings

[59] The Hungarian sample consists only of full-time workers, so we do not report panel A here.

suggest that the increase in the college-educated worker ratio is primarily driven by the growth in the number of college-educated workers.

Table C.3: Change in Firm Skill Demand Following Firm-level Technological Change: Robustness Analysis for Hungary

Panel A: Firm Controls

	(1) College share	(2) Skill ratio	(3) Skill premium	(4) Log employment
Innovation	0.001	0.027	0.015	0.037
	[0.002]	[0.015]	[0.007]	[0.012]
Observations	23,050	14,846	14,846	23,050
Firms	10,528	6,573	6,573	10,528
R-squared	0.166	0.177	0.323	0.385

Panel B: Including Firm Fixed Effects

Innovation	0.004	0.034	0.008	0.011
	[0.002]	[0.020]	[0.012]	[0.015]
Observations	18,208	11,871	11,871	18,208
Firms	5,690	3,601	3,601	5,690
R-squared	0.487	0.460	0.492	0.590

Panel C: Including District-Initial Wage-Share FEs

Innovation	0.003	0.034	0.015	0.018
	[0.002]	[0.016]	[0.007]	[0.013]
Observations	23,048	14,844	14,844	23,048
Number of firms	10,527	6,572	6,572	10,527
R-squared	0.143	0.142	0.306	0.164

Notes: This table shows robustness checks regarding sample restrictions for the relationship between firm-level technological change and subsequent change in firm-level skill demand. The different panels follow the structure of Table 7, reporting the relationship between four-year changes in the outcomes and whether the firm reported innovation in the Community Innovation Survey. Standard errors are clustered at the firm level and are reported in square brackets.

Table C.4: Change in the (log) Number of All Workers, College Workers, and Non-College Workers Following Firm-level Technological Change in Hungary

	(1) Total emp.	(2) College emp.	(3) Non-coll emp.	(4) Total emp.	(5) College emp.	(6) Non-coll emp.
Innovation	0.012	0.061	0.002	0.018	0.057	0.010
	[0.014]	[0.017]	[0.014]	[0.015]	[0.017]	[0.015]
Observations	23,050	15,231	22,609	14,846	14,846	14,846
Firms	10,528	10,287	6,792	6,573	6,573	6,573
R-squared	0.173	0.161	0.361	0.169	0.175	0.183
2-digit Nace x Year FEs	yes	yes	yes	yes	yes	yes
District-year FEs	yes	yes	yes	yes	yes	yes
Sample	all	all	all	coll. rat.	coll. rat.	coll. rat.

Notes: This table shows the firm-level relationship between innovation and the (log) number of workers, college workers and non-college workers. Column (1) repeats Column (4) of Table 7. In Columns (2)-(3) we replace the college ratio with the log number of college/non-college workers as the dependent variable in regression equation (14). In Columns (4)-(6), we restrict the sample to firms with both college and non-college workers (for which the college ratio is not missing). Apart from changing the outcome variables we apply the same specifications as in Table 7. Standard errors are clustered at the firm level, and the regressions are weighted by the number of employees.

Table C.5: Firm Level Results: Various Timing Assumptions

	(1) College share (beta)	(2) College share (s.e.)	(3) Skill ratio (beta)	(4) Skill ratio (s.e.)	(5) Skill premium (beta)	(6) Skill premium (s.e.)
from t-4 to t+0	0.002	[.001]	0.036	[.014]	0.013	[.006]
from t-4 to t+1	0.000	[.002]	0.026	[.017]	0.018	[.007]
from t-4 to t+2	0.001	[.003]	0.038	[.023]	0.005	[.008]
from t-4 to t+3	0.000	[.003]	0.030	[.025]	0.011	[.009]
from t-3 to t+0	0.002	[.001]	0.010	[.012]	0.005	[.004]
from t-3 to t+1	0.000	[.001]	0.003	[.014]	0.007	[.005]
from t-3 to t+2	0.001	[.002]	0.023	[.018]	0.007	[.007]
from t-3 to t+3	0.001	[.002]	0.016	[.020]	0.009	[.007]

Notes: This table reports the main results when adjusting the time frame used to measure the dependent variable. In our main specification, the dependent variable is the long change between $t-4$ and t, where t is the time of the CIS wave. The first row in this table repeats the main estimates (from $t-4$ to t) while the rows below show the results applying different timings. The estimations follow the firm-level specifications in Columns (1) - (3) in Table 7. Standard errors are clustered at the firm-level.

C.2.2 Various Timing Assumptions - Hungary

This table reproduces the table A.13. Similar to Norway, the main specification for Hungary examines the changes in outcomes between t and $t-4$ and how these are related to the innovation that took place between t and $t-2$. The table below examines alternative timing assumptions.

The Norwegian results show an increase in the point estimates when we consider longer time periods. The Hungarian results are somewhat noisier, as the sample size decreases more when we examine longer-term changes in output variables. Nevertheless, we find that innovation has a positive effect on the skill ratio and the skill premium. Moreover, the point estimates in Hungary increase slightly when we consider six-year changes in the outcome variables, compared to four-year changes.

C.2.3 Change in the College Share and College Premium Following Different Forms of Technological Change in Hungary

The findings from Norway indicate that the impact of innovation on skill bias varies depending on the type of innovation. Notably, innovations driven by R&D activities are more inclined to favor skilled labor.

We examine the heterogeneity of Hungarian innovation activities by reproducing Table 5. Importantly, we cannot estimate the change in the skill premium at the worker level in Hungary, so we use the firm level approach for that as well. The results in Panel A show that innovation accompanied by R&D activities is more than twice as skill biased as innovation without R&D activities (0.39 vs. 0.16).

Panel B examines the heterogeneity by type of innovation. Similar to Norway, we find that all the different types of innovation have positive effects on skill demand. Furthermore, technical innovation is more skill biased than organizational change.

Finally, Panel C examines heterogeneity across sectors. Following the estimation strategy in

Table C.6: Change in Skill Demand Following Different Forms of Technological Change

Panel A: By R&D

	(1) College share (beta)	(2) College share (s.e.)	(3) Skill ratio (beta)	(4) Skill ratio (s.e.)	(5) Skill premium (beta)	(6) Skill premium (s.e.)	(7) Skill bias
1. Any innovation	0.002	[0.002]	0.037	[0.016]	0.014	[0.007]	0.037
2. No R&D	0.000	[0.002]	0.017	[0.018]	0.010	[0.008]	0.021
3. R&D	0.005	[0.004]	0.060	[0.023]	0.019	[0.008]	0.057
4. R&D and new to mark.	0.005	[0.004]	0.051	[0.024]	0.024	[0.010]	0.056

Panel B: By Type

5. Only technical	0.003	[0.003]	0.027	[0.020]	0.017	[0.010]	0.034
6. Only process	0.005	[0.004]	0.054	[0.029]	-0.005	[0.014]	0.028
7. Only product	0.008	[0.003]	0.068	[0.024]	0.008	[0.012]	0.051
8. Only organizational	-0.004	[0.005]	0.004	[0.033]	0.015	[0.014]	0.017
9. Both tech. and org.	0.005	[0.003]	0.067	[0.022]	0.009	[0.008]	0.051

Panel C: By Industry

10. Low tech manuf	0.000	[0.005]	0.005	[0.026]	0.034	[0.012]	0.037
11. High tech manuf	0.001	[0.002]	0.024	[0.019]	0.013	[0.012]	0.027
12. Not know. int. serv	-0.001	[0.015]	-0.032	[0.089]	0.045	[0.031]	0.024
13. know. int. serv	0.008	[0.004]	0.096	[0.035]	-0.009	[0.011]	0.051

Notes: This table shows the estimated college share, skill ratio and skill premium effects following different types of technological change based on firm-level regressions and following the specifications of Tables A.20, A.19 for Norway. The skill premium is also estimated at the firm level. Column (7) calculates the implied skill bias, by using the formula from equation (18) and using the value $\sigma = 2.94$. Row (1) repeats our benchmark estimates (corresponding to Columns (1) and (2) of Table 2 for the college share and premium, and Columns 1 of Table 3). Rows 2-3 distinguish between non-R&D based and R&D-based innovation. In row 4, we look at R&D-based innovation that is also considered new to market by the firm. Rows 5-9 distinguish between different types of innovation and whether the firm conducts only one type or both technical and organizational innovation. Finally, rows 10-14 distinguish between different sectors, based on Eurostat definitions. 'manuf.' stands for manufacturing and 'know. int. serv.' for Knowledge Intensive Services.

Norway, we define the same four industry categories. The results are remarkably similar and show that innovation is more skill biased in low-tech manufacturing and in low-knowledge-intensive service sectors. The only difference to Norway is that we find a positive effect of innovation on skill bias in knowledge-intensive sectors. The possible explanation for this difference is that the Hungarian knowledge-intensive sectors are less developed than in Norway, so there is still room for skill biased advancement.

Appendix D Model

D.1 Basic Set-up

This section describes the firm's and worker's problem in detail. We also define the equilibrium and derive equations (3c) and (3d) in the main paper. Throughout the section we drop the time subscript from the notation.

Worker's side. We model the worker's decision as in Card et al. (2018). For workers in skill group $S \in \{L, H\}$, the indirect utility of working at firm j is

$$u_{ij} = \ln \tau w_{Sj}^{\lambda} + \ln a_{Sj} + \epsilon_{ij}, \tag{D.1}$$

where w_{Sj} is the firm-specific wage paid to individual i who belongs to skill group S, τ and λ approximate the progressivity of the tax system, and $\ln a_{Sj}$ is a firm-specific amenity common to all workers in group S, and ϵ_{ij} captures idiosyncratic preferences for working at firm j, arising e.g. from commuting distance, work flexibility and so on. We assume that the ϵ_{ij} are independent draws from a type I Extreme Value distribution with dispersion parameter ϕ.

Given posted wages, workers are free to work at any firm they wish. Hence by standard arguments (McFadden et al. 1977), workers have logit choice densities of the following form:

$$\begin{aligned} P_{ij}^{s}\left(\arg \max_{k\in\{1,..J\}} \{u_{ij}^{s}\} = j\right) =& \frac{\exp\left(\frac{\lambda}{\phi}\ln w_{Sj} + \ln a_{Sj}\right)}{\sum_{k=1}^{J}\exp\left(\frac{\lambda}{\phi}\ln w_{Sk} + \ln a_{Sk}\right)} \\ =& \Lambda_S \exp\left(\frac{\lambda}{\phi}\ln w_{Sj} + \ln a_{Sj}\right), \end{aligned}$$

where $\Lambda_S = \frac{1}{\sum_{k=1}^{J}\exp\left(\frac{\lambda}{\phi}\ln w_{Sk} + \ln a_{Sk}\right)}$ is the same for all firms. This equation leads to the following upward sloping labor supply curve:

$$\ln S_j(w_{Sj}) = \ln\left(S \cdot P_{ij}^{s}\left(\arg \max_{k\in\{1,..J\}} \{u_{ij}^{s}\} = j\right)\right) = \ln(S\Lambda_S) + \beta \ln w_{Sj} + \ln a_{Sj},$$

where S is the total supply of workers from skill group S and $\beta = \frac{\lambda}{\phi}$.

Firm's side. Firms solve the following problem:

$$\pi_j(A_j, \theta_j) = \max_{w_{Hj}, w_{Lj}} p_j Q_j - H_j(w_{Hj})w_{Hj} - L_j(w_{Lj})w_{Lj}, \tag{D.2}$$

subject to

$$Q_j = A_j \left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j) L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{D.3}$$

$$\ln p_j = \frac{1}{\rho}\ln \kappa_j - \frac{1}{\rho}\ln Q_j + \frac{\rho-1}{\rho}\ln p + \frac{1}{\rho}\ln I, \tag{D.4}$$

$$\ln L_j(w_{Lj}) = \ln(L\mathit{\Lambda}_L) + \beta \ln w_{Lj} + \ln a_{Lj}, \tag{D.5}$$

$$\ln H_j(w_{Hj}) = \ln(H\mathit{\Lambda}_H) + \beta \ln w_{Hj} + \ln a_{Hj}. \tag{D.6}$$

The first budget constraint (equation (D.3)) comes from the CES production function. While here we abstract away from capital or the presence of intermediate goods in the production function, we relax this assumption in Appendix Section D.3. The presence of capital does not change any of our conclusions presented here. The second budget constraint (equation (D.4)) represents the firm-specific output demand function that firms face. We micro found this equation in Appendix Section D.4 using a monopolistic competition model and show that κ_j is a firm specific demand shifter, p is the price index and I is the total income of the consumer. The third (equation (D.5)) and fourth (equation (D.6)) constraints represent the upward sloping labor supply function we just derived above. As we describe above, $\mathit{\Lambda}_L$ and $\mathit{\Lambda}_H$ are determined by other firms' wage-setting behavior. Following Card et al. (2018) and Lamadon et al. (2022) we assume that firm's behavior has no direct effect on this outcome.

We close the model by requiring that supply and demand are equal in the two labor markets, as well as in the product market:

$$L = \sum_j L_j, \tag{D.7}$$

$$H = \sum_j H_j, \tag{D.8}$$

$$I = \sum_j p_j Q_j = \sum_j \kappa^{\frac{1}{\rho}} p^{\frac{\rho-1}{\rho}} I^{\frac{1}{\rho}} Q_j^{\frac{\rho-1}{\rho}}. \tag{D.9}$$

Equilibrium. We define the market equilibrium in the following way.

Definition 1. Given firm characteristics (A_j, θ_j, κ_j, a_{Hj}, a_{Lj}), worker distribution (L, H), and preference parameter (ϕ), we define equilibrium as the worker's decision on which firm to choose $j(i,t)$, market-level price index p, wage indices $\mathit{\Lambda}_H$, $\mathit{\Lambda}_L$, and firm's decision on prices p_j and wages w_{Hj}, w_{Lj} such that:

1. Workers choose firms that maximize their utility, as defined in equation (D.1).

2. Firms choose labor demand by setting wages w_{Sj} for each worker type to maximize profits (equation (D.2)) subject to the production function (equation (D.3)), product market constraint (equation (D.4)) and labor supply constraints (equations (D.5) and (D.6)).

3. The market level wage indices (Λ_L and Λ_H) and price index (p) are generated from the workers' optimal decisions and supply and demand are equal in the two labor markets and the product market (Equations D.7, D.8, D.9).

Solution. We solve the firm problem described above.

The FOC of the problem is the following:

$$\frac{\partial \pi_j(A_j,\theta_j)}{\partial w_{Lj}} = Q_j \frac{\partial p_j}{\partial Q_j}\frac{\partial Q_j}{\partial L_j}\frac{\partial L_j}{\partial w_{Lj}} + p_j \frac{\partial Q_j}{\partial L_j}\frac{\partial L_j}{\partial w_{Lj}} - \frac{\partial L_j}{\partial w_{Lj}} w_{Lj} - L_j = 0, \tag{D.10}$$

$$\frac{\partial \pi_j(A_j,\theta_j)}{\partial w_{Hj}} = Q_j \frac{\partial p_j}{\partial Q_j}\frac{\partial Q_j}{\partial H_j}\frac{\partial H_j}{\partial w_{Hj}} + p_j \frac{\partial Q_j}{\partial H_j}\frac{\partial H_j}{\partial w_{Hj}} - \frac{\partial H_j}{\partial w_{Hj}} w_{Hj} - H_j = 0. \tag{D.11}$$

The first FOC, representing the decision about low-skilled workers, can be rewritten as:

$$\left(\frac{Q_j}{p_j}\frac{\partial p_j}{\partial Q_j} + 1\right) p_j \frac{\partial Q_j}{\partial L_j}\frac{L_j}{w_{Lj}}\frac{\partial L_j}{\partial w_{Lj}}\frac{w_{Lj}}{L_j} - \left(1 + \frac{\partial L_j}{\partial w_{Lj}}\frac{w_{Lj}}{L_j}\right) L_j = 0.$$

The second (equation (D.4)) and third (equation (D.5)) constraints imply that:

$$\frac{1+\rho}{\rho} p_j \frac{\partial Q_j}{\partial L_j} = \frac{1+\beta}{\beta} w_{Lj}.$$

The CES production function implies that:

$$\frac{\partial Q_j}{\partial L_j} = A_j \left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j) L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (1-\theta_j) L_j^{-\frac{1}{\sigma}} = A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} (1-\theta_j) L_j^{-\frac{1}{\sigma}},$$

and so we get the following expression for the FOC:

$$\frac{1+\rho}{\rho} p_j A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} (1-\theta_j) L_j^{-\frac{1}{\sigma}} \frac{\beta}{1+\beta} = w_{Lj}.$$

A similar expression leads to the following expression for high skilled workers:

$$\frac{1+\rho}{\rho} p_j A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-\frac{1}{\sigma}} \frac{\beta}{1+\beta} = w_{Hj}.$$

Dividing the two first order conditions leads to the following expression:

$$\frac{\theta_j H_j^{-\frac{1}{\sigma}}}{(1-\theta_j) L_j^{-\frac{1}{\sigma}}} = \frac{w_{Hj}}{w_{Lj}},$$

which can be rearranged to derive the following relationship between the skill premium and the skill ratio:

$$\ln\frac{w_{Hj}}{w_{Lj}} = \ln\frac{\theta_j}{1-\theta_j} - \frac{1}{\sigma}\ln\frac{H_j}{L_j}. \tag{D.12}$$

The second and the third constraints also imply that:

$$\ln\frac{H_j}{L_j} = \ln\frac{H\mathit{\Lambda}_H}{L\mathit{\Lambda}_H} + \beta\ln\frac{w_{Hj}}{w_{Lj}} + \ln\frac{a_{Hj}}{a_{Lj}},$$

which lead to equation (6a) in the main paper:

$$\ln\frac{w_{Hj}}{w_{Lj}} = \frac{\sigma}{\sigma+\beta}\ln\frac{\theta_j}{1-\theta_j} - \frac{1}{\sigma+\beta}\ln\frac{H\mathit{\Lambda}_H}{L\mathit{\Lambda}_L} - \frac{1}{\sigma+\beta}\ln\frac{a_{Hj}}{a_{Lj}},$$

and to equation (6b) in the main paper:

$$\ln\frac{H_j}{L_j} = \frac{\beta\sigma}{\sigma+\beta}\ln\frac{\theta_j}{1-\theta_j} + \frac{\sigma}{\sigma+\beta}\ln\frac{H\mathit{\Lambda}_H}{L\mathit{\Lambda}_L} + \frac{\sigma}{\sigma+\beta}\ln\frac{a_{Hj}}{a_{Lj}}.$$

The relationship between the skill premium and the skill ratio can be also used to demonstrate the key idea of the paper. The change in skill premium in response to innovation will be the following:

$$\underbrace{\Delta\ln\frac{w_{Hj}}{w_{Lj}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \underbrace{\Delta\ln\frac{\theta_j}{1-\theta_j}}_{\substack{\text{Change in}\\ \text{skill bias}}} - \frac{1}{\sigma}\underbrace{\Delta\ln\frac{H_j}{L_j}}_{\substack{\text{Change in}\\ \text{skill ratio}}}. \tag{D.13}$$

Since $\sigma \geq 0$, this equation shows that the skill premium (w_{Hj}/w_{Lj}) and skill ratio (H_j/L_j) will be negatively related when there is no change in the skill bias component. As a result, a joint increase in the premium and the skill ratio provides *prima facie* evidence for innovation activities being skill-biased.

D.2 Skill-Specific Dispersion in Idiosyncratic Preferences

Now we can extend the baseline framework by allowing differential dispersion of the idiosyncratic error term (ϵ_{ij}) for high- (ϕ_H) and low-skilled workers (ϕ_L). The upward-sloping labor supply curves firms face will have differential elasticities:

$$\ln S_j(w_{Sj}) = \ln(S\mathit{\Lambda}_S) + \beta_S\ln w_{Sj} + \ln a_{Sj},$$

where $\beta_S = \frac{\lambda}{\phi_S}$.

Solution. We follow the same steps as above. The FOC of the problem leads to the following two equations:

$$\frac{1+\rho}{\rho} p_j A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} (1-\theta_j) L_j^{-\frac{1}{\sigma}} \frac{\beta_L}{1+\beta_L} = w_{Lj},$$

$$\frac{1+\rho}{\rho} p_j A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-\frac{1}{\sigma}} \frac{\beta_H}{1+\beta_H} = w_{Hj}.$$

The ratio of the two first order conditions leads to the following expression:

$$\frac{\theta_j H_j^{-\frac{1}{\sigma}} \frac{\beta_H}{1+\beta_H}}{(1-\theta_j) L_j^{-\frac{1}{\sigma}} \frac{\beta_L}{1+\beta_L}} = \frac{w_{Hj}}{w_{Lj}}.$$

This can be rearranged to get the following relationship between skill premium and skill demand:

$$\underbrace{\ln \frac{w_{Hj}}{w_{Lj}}}_{\substack{\text{skill}\\ \text{premium}}} = \underbrace{\ln \frac{1+\frac{1}{\beta_L}}{1+\frac{1}{\beta_H}}}_{\substack{\text{relative}\\ \text{mark-down}}} + \underbrace{\ln \frac{\theta_j}{1-\theta_j}}_{\substack{\text{skill}\\ \text{bias}}} - \frac{1}{\sigma} \underbrace{\ln \frac{H_j}{L_j}}_{\substack{\text{skill}\\ \text{ratio}}}. \tag{D.14}$$

The main difference between this equation and the one derived under constant dispersion (equation (D.12)) is the new term reflecting the relative mark-down on the two labor markets. This new term reflects that the wage premium in this case also depends on the extent to which firm-level labor supply elasticities differ across skill groups. Nevertheless, it is worth pointing out that once we look at the change in skill premium and skill ratio, this mark-down term will cancel out as β_H and β_L are determined entirely by workers' preferences (i.e. the low and high skilled workers' dispersion of idiosyncratic preferences toward the workplace), which are unlikely to be affected by firm-level innovation activities. Thus, the change in skill premium will be driven by the following equation:

$$\underbrace{\Delta \ln \frac{w_{Hj}}{w_{Lj}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \underbrace{\Delta \ln \frac{\theta_j}{1-\theta_j}}_{\substack{\text{Change in}\\ \text{skill bias}}} - \frac{1}{\sigma} \underbrace{\Delta \ln \frac{H_j}{L_j}}_{\substack{\text{Change in}\\ \text{skill ratio}}}. \tag{D.15}$$

This equation is the same as equation (D.13), which was derived when $\beta_H = \beta_L$.

Going back to the problem of finding the equilibrium H_j and L_j, the above equation (D.14) expresses the relationship between skill premium and skill demand. Then $\beta_L \neq \beta_H$, the third (equation (D.5)) and fourth (equation (D.6)) constraints become:

$$\ln L_j(w_{Lj}) = \ln(L\Lambda_L) + \beta_L \ln w_{Lj} + \ln a_{Lj}, \tag{D.16}$$

$$\ln H_j(w_{Hj}) = \ln(H\Lambda_H) + \beta_H \ln w_{Hj} + \ln a_{Hj}, \tag{D.17}$$

which implies that:

$$\ln\frac{H_j}{L_j}=\ln\frac{H\varLambda_H}{L\varLambda_L}+\beta_H\ln w_{Hj}-\beta_L\ln w_{Lj}+\ln\frac{a_{Hj}}{a_{Lj}}. \tag{D.18}$$

Unfortunately, we cannot express the solution simply in terms of the ratios of $\ln\frac{w_{Hj}}{w_{Lj}}$ and $\ln\frac{H_j}{L_j}$ as the solution also depends on $\ln w_{Lj}$. While this latter can be expressed from one of the first order conditions, it is not possible to express the ratios in closed-form any more. Nevertheless, we can characterize the impact of changes of various factors on $\ln\frac{w_{Hj}}{w_{Lj}}$ and $\ln\frac{H_j}{L_j}$. We do this in Proposition 1.

Proposition 1. *Suppose firms maximize profits given the constraints in equations (D.3), (D.4), (D.16), (D.17). Changes in A_j and κ_j have the following effect on the firm-level skill ratio $\left(\ln\frac{H_j}{L_j}\right)$ and on the wage ratio $\left(\ln\frac{w_{Hj}}{w_{Lj}}\right)$.*

1. *If $\beta_H=\beta_L$, then $\ln\frac{w_{Hj}}{w_{Lj}}$ and $\ln\frac{H_j}{L_j}$ are unaffected by A_j and κ_j.*
2. *If $\beta_H>\beta_L$, then $\ln\frac{w_{Hj}}{w_{Lj}}$ is decreasing and $\ln\frac{H_j}{L_j}$ is increasing in A_j and in κ_j.*
3. *If $\beta_H<\beta_L$, then $\ln\frac{w_{Hj}}{w_{Lj}}$ is increasing and $\ln\frac{H_j}{L_j}$ is decreasing in A_j and in κ_j.*

Proof. We prove the proposition for A_j, but applying the same steps one can prove the statement for κ_j. Plugging equation (D.18) into equation (D.14) on the skill ratio leads to the following expression:

$$\sigma\left(\ln\frac{1+\frac{1}{\beta_L}}{1+\frac{1}{\beta_H}}+\ln\frac{\theta_j}{1-\theta_j}-\ln\frac{w_{Hj}}{w_{Lj}}\right)=\ln\frac{H\varLambda_H}{L\varLambda_L}+\beta_H\ln w_{Hj}-\beta_L\ln w_{Lj}+\ln\frac{a_{Hj}}{a_{Lj}}. \tag{D.19}$$

Taking the derivative of that with respect to $\ln A_j$ leads to the following expression:

$$\sigma\frac{\partial\ln w_{Hj}}{\partial\ln A_j}-\sigma\frac{\partial\ln w_{Lj}}{\partial\ln A_j}=\beta_L\frac{\partial\ln w_{Lj}}{\partial\ln A_j}-\beta_H\frac{\partial\ln w_{Hj}}{\partial\ln A_j}$$

$$(\sigma+\beta_H)\frac{\partial\ln w_{Hj}}{\partial\ln A_j}=(\sigma+\beta_L)\frac{\partial\ln w_{Lj}}{\partial\ln A_j}. \tag{D.20}$$

Since the third (equation (D.16)) and the fourth (equation (D.17)) constraints imply that $\frac{\partial\ln w_{Hj}}{\partial\ln H_j}=\frac{1}{\beta_H}$ and $\frac{\partial\ln w_{Lj}}{\partial\ln L_j}=\frac{1}{\beta_L}$, we can express $\frac{\partial\ln w_{Hj}}{\partial\ln A_j}$ and $\frac{\partial\ln w_{Lj}}{\partial\ln A_j}$ as:

$$\frac{\partial\ln w_{Hj}}{\partial\ln A_j}=\frac{\partial\ln w_{Hj}}{\partial\ln H_j}\frac{\partial\ln H_j}{\partial\ln A_j}=\frac{1}{\beta_H}\frac{\partial\ln H_j}{\partial\ln A_j}$$

and

$$\frac{\partial\ln w_{Lj}}{\partial\ln A_j}=\frac{\partial\ln w_{Lj}}{\partial\ln L_j}\frac{\partial\ln L_j}{\partial\ln A_j}=\frac{1}{\beta_L}\frac{\partial\ln L_j}{\partial\ln A_j}.$$

Plugging these two expressions into equation (D.20) leads to:

$$\left(\frac{\sigma}{\beta_H}+1\right)\frac{\partial\ln H_j}{\partial\ln A_j}=\left(\frac{\sigma}{\beta_L}+1\right)\frac{\partial\ln L_j}{\partial\ln A_j}. \tag{D.21}$$

It is easy to see that if $\beta_H > \beta_L$, then we have $\frac{\partial \ln H_j}{\partial \ln A_j} > \frac{\partial \ln L_j}{\partial \ln A_j}$ and $\frac{\partial \ln w_{Hj}}{\partial \ln A_j} < \frac{\partial \ln w_{Lj}}{\partial \ln A_j}$, and so

$$\frac{\partial \ln \frac{H_j}{L_j}}{\partial \ln A_j} > 0 \quad \textit{and} \quad \frac{\partial \ln \frac{w_{Hj}}{w_{Lj}}}{\partial \ln A_j} < 0.$$

□

Proposition 1 states that the Hicks-neutral technological shock (A_j) or firm specific demand shifter (κ_j) directly affect the skill ratio and the skill premium if $\beta_H \neq \beta_L$. Nevertheless, the effects of these shocks on $\ln \frac{w_{Hj}}{w_{Lj}}$ and $\ln \frac{H_j}{L_j}$ always have a different sign. So if one of them increases, then the other will fall. This implies that demand shifters (κ_j) or Hicks-neutral shocks (A_j) cannot explain a joint increase in skill demand and skill ratio even if $\beta_H \neq \beta_L$.

Why does even a Hicks-neutral change (A_{jt}) affect the skill ratio when $\beta_H \neq \beta_L$? When a firm experiences an increase in A_{jt}, it will expand and, therefore, increase its demand for both type of workers. If, for example, $\beta_H > \beta_L$, high skilled workers are more responsive to changes in wages than the low skilled ones, and, therefore, firms can expand their skilled labor force more when they increase the wages of both types similarly. In optimum, firms adjust both on the wage and quantity margins: they raise high skilled workers' wages less ($\Delta \ln \frac{w_{hj}}{w_{lj}} < 0$), but hire more of them ($\Delta \ln \frac{h_j}{l_j} > 0$).

An important implication of Proposition 1 is that finding that the skill ratio is increasing after an innovation does not prove that the innovation is skill-biased. In the presence of non-competitive labor markets even an (exogenous) Hicks-neutral shock can affect the skill ratio if firms have different wage-setting power at the high and low skilled labor markets (for instance, if $\beta_H > \beta_L$). Nevertheless, as equation (D.15) above demonstrated, whenever both the skill premium and skill ratio increases, we can conclude that technological change is skill-biased.

Now we also characterize how changes in the key parameters of the firm-level labor supply affect firm's behavior.

Proposition 2. *Suppose firms maximize profits given the constraints in equations (D.3), (D.4), (D.16), (D.17). Then the change in $X = \{H\Lambda_H, a_{Hj}\}$ has the following impact on the skill premium and skill ratio*

$$\frac{\partial \ln \frac{w_{Hj}}{w_{Lj}}}{\partial \ln X} = -\left(\frac{1}{\sigma + \beta_H}\right)\left(1 + (\beta_H - \beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln X}\right),$$

$$\frac{\partial \ln \frac{H_j}{L_j}}{\partial \ln X} = \left(\frac{\sigma}{\sigma + \beta_H}\right)\left(1 + (\beta_H - \beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln X}\right),$$

where

$$1 + (\beta_H - \beta_L)\frac{\partial \ln w_{lj}}{\partial \ln X} = \frac{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}} A_j^{-\frac{1}{\sigma}} Q_j^{\frac{1}{\sigma}} - \beta_L}{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}} A_j^{-\frac{1}{\sigma}} Q_j^{\frac{1}{\sigma}} - \beta_L - \left(\frac{\theta_j H_j^{\frac{\sigma-1}{\sigma}}}{\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j) L_j^{\frac{\sigma-1}{\sigma}}} \left(\frac{\sigma(\beta_H - \beta_L)}{\sigma + \beta_H} \right) \right)}.$$

Proof. We prove the statement for $H\Lambda_H$, but the same steps could be used to prove the statement for a_{Hj}. As we derived in the proof of Proposition 1, the third (equation D.16) and fourth (equation (D.17)) constraints together with the FOC (equation (D.14)) imply that:

$$\sigma \left(\ln \frac{\beta_H}{1+\beta_H} - \ln \frac{\beta_L}{1+\beta_L} + \ln \frac{\theta_j}{1-\theta_j} - \ln \frac{w_{Hj}}{w_{Lj}} \right) = \ln \frac{H\Lambda_H}{L\Lambda_L} + \beta_H \ln w_{Hj} - \beta_L \ln w_{Lj} + \ln \frac{a_{Hj}}{a_{Lj}}.$$

Taking the derivative of that with respect to ln $H\Lambda_H$ leads to the following expression:

$$-\sigma \left(\frac{\partial \ln w_{Hj}}{\partial \ln H\Lambda_H} - \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} \right) = 1 + \beta_H \frac{\partial \ln w_{Hj}}{\partial \ln H\Lambda_H} - \beta_L \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H},$$

which can be rearranged to:

$$\frac{\partial \ln w_{Hj} - \partial \ln w_{Lj}}{\partial \ln H\Lambda_H} = -\frac{1}{\sigma + \beta_H} \left(1 + (\beta_H - \beta_L) \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} \right).$$

Using that $\frac{\partial \ln w_{Hj}}{\partial \ln H\Lambda_H} = \frac{1}{\beta_H} \frac{\partial \ln H_j}{\partial \ln H\Lambda_H} - \frac{1}{\beta_H}$ and $\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} = \frac{1}{\beta_L} \frac{\partial \ln L_j}{\partial \ln H\Lambda_H}$ from the constraints, one can also express the relationship between changes in wages as:

$$\frac{1}{\beta_H} \frac{\partial \ln H_j}{\partial \ln H\Lambda_H} - \frac{1}{\beta_H} - \frac{1}{\beta_L} \frac{\partial \ln L_j}{\partial \ln H\Lambda_H} = -\frac{1}{\sigma + \beta_H} \left(1 + (\beta_H - \beta_L) \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} \right),$$

$$\frac{\partial \ln H_j}{\partial \ln H\Lambda_H} - \frac{\partial \ln L_j}{\partial \ln H\Lambda_H} = \left(\frac{\sigma}{\sigma + \beta_H} \right) \left(1 + (\beta_H - \beta_L) \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} \right),$$

which proves the statement. Now we need to obtain the expression for $1 + (\beta_H - \beta_L) \frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$. The FOC for low-skilled workers of the profit maximization problem implies that:

$$\frac{1+\rho}{\rho} \left(\frac{I\kappa_j}{p^{1-\rho}} \right)^{\frac{1}{\rho}} A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma} - \frac{1}{\rho}} (1-\theta_j) L_j^{-\frac{1}{\sigma}} \frac{\beta_L}{1+\beta_L} = w_{Lj} = \left(\frac{L_j}{L\Lambda_L a_{Lj}} \right)^{\frac{1}{\beta_L}}.$$

Taking the log:

$$\ln \frac{1+\rho}{\rho} + \ln \left(\frac{I\kappa_j}{p^{1-\rho}} \right)^{\frac{1}{\rho}} + \frac{\sigma-1}{\sigma} \ln A_j + \left(\frac{1}{\sigma} - \frac{1}{\rho} \right) \ln Q_j + \ln(1-\theta_j) - \frac{1}{\sigma} \ln L_j + \ln \frac{\beta_L}{1+\beta_L} = \ln w_{Lj},$$

and the derivative with respect to $\ln H\Lambda_H$, leads to:

$$\left(\frac{1}{\sigma}-\frac{1}{\rho}\right)\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}-\frac{1}{\sigma}\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}=\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}.$$

Using that $\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}=\beta_L\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$ (see equation (D.18)) we get:

$$\left(\frac{1}{\sigma}-\frac{1}{\rho}\right)\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}=\left(1+\frac{\beta_L}{\sigma}\right)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H},$$

or:

$$\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}=\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}.$$

Denoting $N_j=\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]$ for notational convenience, we notice that:

$$\begin{aligned}
\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}=&\frac{\partial Q_j}{\partial H\Lambda_H}\frac{H\Lambda_H}{Q_j}\\
=&\frac{\partial A_j N_j^{\frac{\sigma}{\sigma-1}}}{\partial H\Lambda_H}\frac{H\Lambda_H}{Q_j}\\
=&A_j N_j^{\frac{\sigma}{\sigma-1}-1}\left(\theta_j H_j^{\frac{\sigma-1}{\sigma}-1}\frac{\partial H_j}{\partial H\Lambda_H}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}-1}\frac{\partial L_j}{\partial H\Lambda_H}\right)\frac{H\Lambda_H}{Q_j}\\
=&N_j^{\frac{\sigma}{\sigma-1}-2}\left(\theta_j H_j^{\frac{\sigma-1}{\sigma}}\frac{\partial \ln H_j}{\partial \ln H\Lambda_H}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}\right)\\
=&N_j^{\frac{\sigma}{\sigma-1}-2}\left(\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}+\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)\right)+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\frac{\partial \ln L_j}{\partial \mathrm{ln} H\Lambda_H}\right)\\
=&N_j^{\frac{\sigma}{\sigma-1}-2}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)+N_j^{\frac{\sigma}{\sigma-1}-2}\left(\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right)\frac{\partial \ln L_j}{\partial \mathrm{ln} H\Lambda_H}\\
=&N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)+\beta_L\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right).
\end{aligned}$$

This implies that:

$$N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)+\beta_L\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)=\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$$

$$N_j^{\frac{\sigma}{\sigma-1}-1}N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)=\left(\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)(\beta_H-\beta_L)+\beta_L\right)\right)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$$

$$N_j^{\frac{\sigma}{\sigma-1}-1}N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)=\left(\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma\left(\beta_H-\beta_L\right)}{\sigma+\beta_H}\right)+\beta_L\right)\right)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$$

$$\frac{N_j^{\frac{\sigma}{\sigma-1}-1}N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)}{\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)+\beta_L\right)}=\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}.$$

Which again implies that:

$$
\begin{aligned}
1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} &= 1+\frac{N_j^{\frac{\sigma}{\sigma-1}-1}N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)(\beta_H-\beta_L)}{\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)+\beta_L\right)} \\
&= \frac{\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-\beta_L N_j^{\frac{\sigma}{\sigma-1}-1}}{\frac{1+\frac{\beta_L}{\sigma}}{\frac{1}{\sigma}-\frac{1}{\rho}}-N_j^{\frac{\sigma}{\sigma-1}-1}\beta_L-N_j^{\frac{\sigma}{\sigma-1}-1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)\right)} \\
&= \frac{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}-\beta_L N_j^{\frac{1}{\sigma-1}}}{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}-N_j^{\frac{1}{\sigma-1}}\beta_L-N_j^{\frac{1}{\sigma-1}}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)\right)} \\
&= \frac{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}N_j^{\frac{1}{1-\sigma}}-\beta_L}{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}N_j^{\frac{1}{1-\sigma}}-\beta_L-\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)\right)} \\
&= \frac{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}A_j^{-\frac{1}{\sigma}}Q_j^{\frac{1}{\sigma}}-\beta_L}{\frac{\sigma+\beta_L}{1-\frac{\sigma}{\rho}}A_j^{-\frac{1}{\sigma}}Q_j^{\frac{1}{\sigma}}-\beta_L-\left(\frac{\theta_j H_j^{\frac{\sigma-1}{\sigma}}}{\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}}\left(\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}\right)\right)}.
\end{aligned}
$$

□

Proposition 2 highlights that whenever $\beta_H \neq \beta_L$, changes in the wage index (Λ_H), labor supply of the high skilled H, and a_H have opposite effects on the skill premium and skill ratio.[60] The statement also highlights that whenever the elasticity of substitution in production is roughly similar to the substitution elasticity across different type of goods $\sigma \approx \rho$, then $1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H} \approx 1$. It follows that the effects of $\ln \Lambda_H H$ on the skill ratio and skill premium are similar to those given by equations (3c) and (3d) in the main paper. Nevertheless, if σ and ρ are very different, the impacts of $\ln \Lambda_H H$ on the skill ratio and skill premium potentially depend on firm-level characteristics such as $A_j^{-\frac{1}{\sigma}}Q_j^{\frac{1}{\sigma}}$ and $\frac{\theta_j H_j^{\frac{\sigma-1}{\sigma}}}{\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}}$. We conclude that this issue has little empirical importance after conducting a robustness check where we include, in regression equation (15), an interaction of rdistrict-year fixed effects with dummies for firms' pre-innovation shares of high-skilled workers (see Table **??** in the main paper).

D.3 Extension: Derivations with Capital in the Production Function

So far we have abstracted away from other inputs in the production function. Nevertheless, it is straightforward to extend the problem with other inputs. Here we demonstrate this by adding capital to the production function.

The new profit maximization problem is the following:

[60] It is easy to show that an analogous statement holds for Λ_L, L, and a_L.

$$\pi_j(A_j,\theta_j) = \max_{w_{Hj},w_{Lj}} p_jQ_j - H_j(w_{Hj})w_{Hj} - L_j(w_{Lj})w_{Lj} - rK_j, \tag{D.22}$$

subject to

$$Q_j = A_j\left(\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}\frac{\varrho-1}{\varrho}} + K_j^{\frac{\varrho-1}{\varrho}}\right)^{\frac{\varrho}{\varrho-1}}, \tag{D.23}$$

and the constraints (D.4), (D.16), and (D.17).

The FOCs of the problem now become:

$$\frac{1+\rho}{\rho}p_jA_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1}{\varrho}}\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}}(1-\theta)L_j^{-\frac{1}{\sigma}} = \frac{1+\beta_L}{\beta_L}w_{Lj},$$

$$\frac{1+\rho}{\rho}p_jA_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1}{\varrho}}\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}}\theta H_j^{-\frac{1}{\sigma}} = \frac{1+\beta_H}{\beta_H}w_{Hj}.$$

As a result, the ratio remains unchanged:

$$\frac{\theta_j H_j^{-\frac{1}{\sigma}}\frac{\beta_H}{1+\beta_H}}{(1-\theta_j)L_j^{-\frac{1}{\sigma}}\frac{\beta_L}{1+\beta_L}} = \frac{w_{Hj}}{w_{Lj}},$$

and so we get the same relationship between skill premium and skill demand as before (see equation (D.14)):

$$\underbrace{\ln\frac{w_{Hj}}{w_{Lj}}}_{\substack{\text{skill}\\ \text{premium}}} = \underbrace{\ln\frac{1+\frac{1}{\beta_L}}{1+\frac{1}{\beta_H}}}_{\substack{\text{relative}\\ \text{mark-down}}} + \underbrace{\ln\frac{\theta_j}{1-\theta_j}}_{\substack{\text{skill}\\ \text{bias}}} - \underbrace{\frac{1}{\sigma}\ln\frac{H_j}{L_j}}_{\substack{\text{skill}\\ \text{ratio}}}. \tag{D.24}$$

Note that Proposition 1 only uses this equation and equations (D.16), and (D.17). And so the proposition can be proved by applying exactly the same steps.

Turning to Proposition 2, the first part of the statement says that changes in $X = \{H\Lambda_H, a_{Hj}\}$ have the following effect on the skill ratio and skill premium:

$$\frac{\partial \ln\frac{w_{Hj}}{w_{Lj}}}{\partial \ln X} = -\left(\frac{1}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln X}\right),$$

$$\frac{\partial \ln\frac{H_j}{L_j}}{\partial \ln X} = \left(\frac{\sigma}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln X}\right).$$

As for Proposition 1, this part of the statement only uses equations (D.24), (D.16), and (D.17), which are unaffected by the presence of capital.

The proposition also derives $1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln X}$. The presence of capital changes the derivation of that part, which we develop here. The FOC for low-skilled workers in the presence of capital becomes:

$$\ln\frac{1+\rho}{\rho}+\ln\left(\frac{I\kappa_j}{p^{1-\rho}}\right)^{\frac{1}{\rho}}+\frac{\varrho-1}{\varrho}\ln A_j+\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)\ln Q_j+\frac{\varrho-\sigma}{\varrho(\sigma-1)}\ln\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]+$$

$$+\ln(1-\theta_j)-\frac{1}{\sigma}\ln L_j+\ln\frac{\beta_L}{1+\beta_L}=\ln w_{Lj}.$$

And the FOC for capital is:

$$\ln\frac{1+\rho}{\rho}+\ln\left(\frac{I\kappa_j}{p^{1-\rho}}\right)^{\frac{1}{\rho}}+\frac{\varrho-1}{\varrho}\ln A_j+\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)\ln Q_j-\frac{1}{\varrho}\ln K_j+\ln\left(1-\frac{1}{\rho}\right)=r. \tag{D.25}$$

Taking the derivative with respect to $\ln H\Lambda_H$ leads to:

$$\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}+\frac{\varrho-\sigma}{\varrho(\sigma-1)}\frac{\partial \ln\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]}{\partial \ln H\Lambda_H}-\frac{1}{\sigma}\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}=\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}. \tag{D.26}$$

Now we want to express the three terms on the left hand side in the above equation in terms of $\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}$. We denote $N_j=\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]$ for notational convenience as before. For the first term we have:

$$\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}=\frac{\frac{\varrho}{\varrho-1}A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}}{1-A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}K_j^{\frac{\varrho-1}{\varrho}}\left(1-\frac{\varrho}{\rho}\right)}\cdot$$

$$\cdot\left(\frac{\varrho-1}{\varrho}N_j^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}+1}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)+\beta_L\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)\right),$$

where we used that equation (D.25). This implies that $\left(1-\frac{\varrho}{\rho}\right)\frac{\partial \ln Q_j}{\partial \ln H\Lambda_H}=\frac{\partial \ln K_j}{\partial \ln H\Lambda_H}$. For the second term in equation (D.26), we obtain:

$$\frac{\partial \ln\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}}+(1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]}{\partial \ln H\Lambda_H}=\frac{\sigma-1}{\sigma}\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\left(1-\frac{\beta_H}{\sigma+\beta_H}\right)\left(1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right)+\beta_L\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}\right).$$

Using as before that $\frac{\partial \ln w_{Lj}}{\partial \ln H\Lambda_H}=\frac{1}{\beta_L}\frac{\partial \ln L_j}{\partial \ln H\Lambda_H}$ for the third term, and plugging the three terms back into equation (D.26), we get the following expression:

$$\frac{\partial \ln w_{Lj}}{\partial \ln H\mathit{\Lambda}_H} = \frac{\left(\frac{\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}N_j^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}+1}}{1-A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}K_j^{\frac{\varrho-1}{\varrho}}\left(1-\frac{\varrho}{\rho}\right)}+\frac{\varrho-\sigma}{\varrho\sigma}\right)N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\frac{\sigma}{\sigma+\beta_H}}{1+\beta_L-\left(\frac{\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}N_j^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}+1}}{1-A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}K_j^{\frac{\varrho-1}{\varrho}}\left(1-\frac{\varrho}{\rho}\right)}+\frac{\varrho-\sigma}{\varrho\sigma}\right)\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}+\beta_L\right)}.$$

This implies that:

$$1+(\beta_H-\beta_L)\frac{\partial \ln w_{Lj}}{\partial \ln H\mathit{\Lambda}_H} = \frac{1+\beta_L-\left(\frac{\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}N_j^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}+1}}{1-A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}K_j^{\frac{\varrho-1}{\varrho}}\left(1-\frac{\varrho}{\rho}\right)}+\frac{\varrho-\sigma}{\varrho\sigma}\right)\beta_L}{1+\beta_L-\left(\frac{\left(\frac{1}{\varrho}-\frac{1}{\rho}\right)A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}N_j^{\frac{\varrho-\sigma}{\varrho(\sigma-1)}+1}}{1-A_j^{\frac{\varrho-1}{\varrho}}Q_j^{\frac{1-\varrho}{\varrho}}K_j^{\frac{\varrho-1}{\varrho}}\left(1-\frac{\varrho}{\rho}\right)}+\frac{\varrho-\sigma}{\varrho\sigma}\right)\left(N_j^{-1}\theta_j H_j^{\frac{\sigma-1}{\sigma}}\frac{\sigma(\beta_H-\beta_L)}{\sigma+\beta_H}+\beta_L\right)}.$$

This expression is similar to the one that we obtained without capital in Proposition 2.

D.4 The Derivation of the Downward-sloping Firm-level Demand Function

We assume that consumers in the market value variety, and solve the following maximization problem:

$$max_{\{Q_1,\dots,Q_J\}}\left(\sum_j \kappa_j^{\frac{1}{\rho}}Q_j^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}},$$

subject to the following constraint:

$$\sum_j p_j Q_j = I.$$

The Lagrangian of the problem is the following:

$$\mathcal{L} = \left(\sum_j \kappa_j^{\frac{1}{\rho}}Q_j^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} - \lambda\left(\sum_j p_j Q_j - I\right),$$

with corresponding FOCs:

$$\left(\sum_j \kappa_j^{\frac{1}{\rho}}Q_j^{\frac{\rho-1}{\rho}}\right)^{\frac{1}{\rho-1}}\kappa_j^{\frac{1}{\rho}}Q_j^{-\frac{1}{\rho}} - \lambda p_j = 0,$$

and so:

$$\left(\frac{\kappa_j}{\kappa_k}\right)^{\frac{1}{\rho}}\left(\frac{Q_j}{Q_k}\right)^{-\frac{1}{\rho}} = \frac{p_j}{p_k},$$

which can be rearranged to:

$$Q_j = \frac{\kappa_j}{\kappa_k}\left(\frac{p_j}{p_k}\right)^{-\rho}Q_k,$$

and:

$$p_j Q_j = \frac{Q_k}{\kappa_k} p_k^{\rho} \kappa_j p_j^{1-\rho}.$$

Taking the sum over the j firms leads to the following equation:

$$I = \sum_j p_j Q_j = \frac{Q_k}{\kappa_k} p_k^{\rho} \sum_j \kappa_j p_j^{1-\rho}.$$

Let us define the price index as: $p \equiv \left(\sum_j \kappa_j p_j^{1-\rho}\right)^{\frac{1}{1-\rho}}$, such that the above equation can be rewritten as:

$$Q_j = \frac{I}{p^{1-\rho}} \kappa_j p_j^{-\rho},$$

which leads to the following demand equation for firm j:

$$\ln Q_j = \ln I - (1-\rho) \ln p + \ln \kappa_j - \rho \ln p_j,$$

or:

$$\ln p_j = \frac{1}{\rho} \ln I - \frac{1-\rho}{\rho} \ln p + \frac{1}{\rho} \ln \kappa_j - \frac{1}{\rho} \ln Q_j,$$

or:

$$p_j = \left(\frac{I \kappa_j}{p^{1-\rho}}\right)^{\frac{1}{\rho}} Q_j^{-\frac{1}{\rho}}.$$

Appendix E Extension: Labor Market Power

Throughout the paper (and in Appendix D) we have assumed that firms are atomistic and so they do not take into account that their actions potentially affect other firms' behavior. Deb et al. (2020) derive the impact of firm-level technological changes on relative wages and employment by taking into account strategic interactions between firms. This relationship is characterized by

$$\ln \frac{w_{H_{jt}}}{w_{L_{jt}}} = \ln \frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}} + \ln \frac{\theta_{jt}}{1-\theta_{jt}} - \frac{1}{\sigma} \ln \frac{H_{jt}}{L_{jt}}, \tag{E.1}$$

where $\frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$ captures the contribution of relative market power differences on the skill premiums. Deb et al. (2020) derive that in their model the effect of market power on wages can be expressed as follows:

$$\varepsilon_{Sjmt} = \tfrac{1}{\hat{\beta}_S} e_{Sjmt} + \tfrac{1}{\hat{\eta}_S}(1 - e_{Sjmt}). \tag{E.2}$$

where e_{Sjmt} is the market share of firm j of workers in skill group S in market m at time t;[61] while $\hat{\beta}_S$ and $\hat{\eta}_S$ are preference parameters of the consumers that determine the firm- and labor market-level labor supply elasticity in skill group S.[62] Notice that equation (E.1) is very similar to equation (D.14), derived in Appendix D focusing on the atomistic agents except that the relative mark-down term $\frac{1+\frac{1}{\beta_L}}{1+\frac{1}{\beta_H}}$ is now replaced with $\frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$. Crucially, in the atomistic case the relative mark-down $\frac{1+\frac{1}{\beta_L}}{1+\frac{1}{\beta_H}}$ is not firm-specific, but when we introduce strategic interactions, the relative markdown becomes firm-specific and depends on the firm's market share.

Following technological change or innovation, the change in equation (E.1) is:

$$\underbrace{\Delta \ln \frac{w_{H_{jt}}}{w_{L_{jt}}}}_{\substack{\text{Change in}\\ \text{skill premium}}} = \underbrace{\Delta \ln \frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}}_{\substack{\text{Change in}\\ \text{markdown}}} + \underbrace{\Delta \ln \frac{\theta_{jt}}{1-\theta_{jt}}}_{\substack{\text{Change in}\\ \text{skill bias}}} - \frac{1}{\sigma} \underbrace{\Delta \ln \frac{H_{jt}}{L_{jt}}}_{\substack{\text{Change in}\\ \text{skill ratio}}}. \tag{E.3}$$

This equation is very similar to our benchmark equation (see equation (5)) except for the extra term that reflects the change in markdown coming from changes in labor market power (or rent sharing as called by Deb et al. 2020) following innovation. The intuition for that term is the following.

[61] Berger et al. (2019b) suggest to use the wage bill shares to calculate e_{Sjmt} when there are no productivity differences among workers. Nevertheless, if the productivity differences are large, the wage bill shares might simply be driven by those differences. As a result, we calculate market share based on market shares in terms of workers. Our results are robust to using the wage bill for calculating the market shares.

[62] Deb et al. (2020) present a model where $\hat{\beta}_S$ and $\hat{\mu}_S$ are the key parameters of the representative agent's labor supply function. Berger et al. (2019a) show in Appendix B.1 that such a representative agent's labor supply function can be micro-founded in a discrete choice framework as presented in our Section 2 and in Appendix D. When there are M distinct labor markets, the idiosyncratic preferences for working at a particular firm have the following type-I Extreme value distribution (where we applied our notation):

$$F(\epsilon_S ij, ..., \epsilon_S iJ) = \exp\left[-\sum_{m=1}^{M} \left(\sum_{j \in Market_m} e^{-(1+\hat{\beta_S})\epsilon_S ij} \right)^{\frac{1+\hat{\beta_S}}{1+\hat{\eta_S}}} \right].$$

When $\hat{\eta_S} = 0$, the distribution is the same as the one used in Appendix D. Whenever $\hat{\eta_S} > 0$, there is an increased correlation of draws within a labor market (McFadden et al. 1977), which creates a differential labor supply elasticity for moving across firms within a labor market, and moving across firms in different labor markets.

When firms innovate, they might grow, which could potentially change their employment share in a given labor market and so their market power on that market. If the increase in market share differs between the college and non-college labor markets (or if the within- and between-market elasticities are different for college and non-college workers), then relative changes in market power will have a direct effect on the the skill premium.

We quantify the change in market power following innovation in two steps. First, we estimate the firm-level change in market shares using regression equation (14). Since the definition of the "markets" is crucial for this exercise, we explore various definitions of labor markets. Second, we use the parameter values for $\hat{\beta}_S$ and $\hat{\eta}_S$ from Deb et al. (2020) and calculate the firm-specific relative markdown, $\frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$, using equation (E.2). Panel A of Table E.1 summarizes the parameter values that we use in equation (E.2) for calculating firm-level markdowns. In Panel B and C we report average markdowns for college and non-college workers under alternative labor market definitions. In Panel B we consider a local district-one digit industry combination as a labor market. In Panel C we follow Berger et al. (2019a) and apply a narrow definition with a combination of a district and a three-digit NACE industry.[63] Both definitions lead to very similar markdown estimates. The average markdown for college workers is between 0.58 and 0.61 and for non-college ones it is between 0.73 and 0.77 in both countries. The markdown is larger for college workers as their firm-level labor supply is less elastic.

Table E.2 shows the changes in market share and markdown following innovation. In rows (1)-(5), we define labor markets as two-digit NACE industry within a district (same as Table E.1 Panel B). Under this broader definition of labor markets we find no indication for any significant change in markdowns. In rows (5)-(10) we use a narrow definition of markets, where the college and non-college markets are defined as a three-digit NACE industry within a district (Table E.1 Panel C, following Berger et al. 2019a). When we use this narrow market definition, we find again a very small change in relative markdown. Row (10) demonstrates that, as a result, there is a 0.04 percent (s.e. 0.1) decrease in relative markdown if we apply this narrow definition of labor market.

This analysis highlights that relative changes in labor market power can only explain at most a tiny fraction of the change in skill premium observed in the data. In our preferred specification we estimate that the skill premium increased by 1.1 percent. This implies that at most (0.04/1.1) 4 percent of the skill premium increase can be attributed to changes in market power. As a result, even if we incorporate the changes in firm-level markdowns into the calculation of firm-level changes in skill bias (see Section 5.3 and equation (18)) we get very similar numbers.

[63] As described in Section **??**, in Norway we have 46 local labor markets. These are substantially smaller regional areas than commuting zones in the United States used by Berger et al. (2019a). As a result, our labor market definition is in fact narrower than the one used in Berger et al. (2019a).

Table E.1: Labor Market Power: Parameter Values and Descriptive Statistics

Variable	Value (NO)	Description
Panel A: Parameter values		
$\hat{\eta_H}$	0.66	College workers' market-level labor supply elasticity
$\hat{\eta_L}$	0.66	Non-college workers' market-level labor supply elasticity
$\hat{\beta_H}$	1.85	College workers' firm-level labor supply elasticity
$\hat{\beta_L}$	8.12	Non-college workers' firm-level labor supply elasticity
Panel B: Market size and average markdown (district × 2-digit industry)		
	40,402	Average number of workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1}{1+\varepsilon_{Hjmt}}$	0.61	Average markdown for college workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1}{1+\varepsilon_{Ljmt}}$	0.80	Average markdown for non-college workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$	0.77	Average relative markdown
Panel C: Market size and average markdown (district × 3-digit industry)		
	4,787	Average number of workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1}{1+\varepsilon_{Hjmt}}$	0.58	Average markdown for college workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1}{1+\varepsilon_{Ljmt}}$	0.73	Average markdown for non-college workers
$\frac{1}{N_j}\sum_{j=1}^{N_j}\frac{1+\varepsilon_{Ljmt}}{1+\varepsilon_{Hjmt}}$	0.80	Average relative markdown

Notes: The parameter values come from Deb et al. (2020) who use between-market labor supply elasticites from Berger et al. (2019a). The labor market shares are calculated based on all firms in the employer-employee register for Norway for out main sample.

Table E.2: Change in Labor Market Power Following Firm-level Technological Change

	Level	Innovation (s.e.)	Obs.	R-squared
(1) College market share	(CZ x 2-nace)	0.00395 (0.00134)	26813	0.0883
(2) Non-college market share	(CZ x 2-nace)	0.00221 (0.00110)	27113	0.124
(3) Log college markdown	(CZ x 2-nace)	-0.00214 (0.000671)	26813	0.0868
(4) Log non-college markdown	(CZ x 2-nace)	-0.00215 (0.000910)	27113	0.125
(5) Log relative markdown	(CZ x 2-nace)	0.000411 (0.000769)	26804	0.0733
(6) College market share	(CZ x 3-nace)	0.00724 (0.00189)	26246	0.0606
(7) Non-college market share	(CZ x 3-nace)	0.00376 (0.00156)	27087	0.0929
(8) Log college markdown	(CZ x 3-nace)	-0.00356 (0.000935)	26246	0.0596
(9) Log non-college markdown	(CZ x 3-nace)	-0.00302 (0.00124)	27087	0.0937
(10) Log relative markdown	(CZ x 3-nace)	-0.000450 (0.00107)	26212	0.0514

Notes: This table shows the relationship between firm-level technological change and change in firms' market power. Each row represents a firm-level regression similar to the ones reported in Table 2, but we replace the dependent variable with four-year changes in measures of market power. In rows (1)-(5) the labor markets are defined at the district and 2-digit NACE industry level, while in rows (6)-(10) at the district and 3-digit NACE industry level. Relative markdowns are calculated based on equation (E.2). All regressions include industry-year and district-year fixed effects. Standard errors are clustered at the firm level and are reported in parentheses.

Appendix F Extension: Skill-biased Technological Change with Bargaining

In the benchmark analysis we assume that wages are determined based on the imperfect competition model proposed by Card et al. (2018). In Appendix E we present an extension of the model where we allow for strategic interactions between firms. In this section, we show how the relationship between the skill ratio and the skill premium is very similar under two alternative wage setting procedures. First, we derive the optimal skill demand when applying the bargaining model of Van Reenen (1996). Next, we derive how skill demand is determined within the rent sharing framework proposed by Kline et al. (2019).

F.1 Wage Setting through Bargaining

Wage and Employment Determination.

Unions. We model wage and employment determination as a bargaining process between a firm and skill-specific unions. Assume that the union of workers with skill S at firm j has the following utility function (see equation (1) in Van Reenen 1996):

$$U_{Sj} = S_j u(w_{Sj}) = S_j \frac{1}{1-m_S} w_{Sj}^{1-m_S}, \tag{F.1}$$

where $0 \leq m_S \leq 1$ measures risk aversion of the workers that can vary by skill group S. This formulation reflects that unions care not only about the level of wages, but also about employment.

Firms. Firms' profit is given by the following function:

$$\Pi_j(A_j, \theta_j) = \max_{w_{Hj}, w_{Lj}} pQ_j - H_j w_{Hj} - L_j w_{Lj},$$

subject to

$$\begin{aligned} Q_j &= A_j \left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j) L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \\ \ln p_j &= \tfrac{1}{\rho}\ln\kappa_j - \tfrac{1}{\rho}\ln Q_j + \tfrac{\rho-1}{\rho}\ln p + \tfrac{1}{\rho}\ln I. \end{aligned}$$

We follow Van Reenen (1996) and assume that firms are price takers in the output market. Nevertheless, it is straightforward to incorporate firms' price setting power into the framework presented in this section.

Equilibrium Wage and Employment. Wages are determined through a Nash-bargaining process. The equilibrium solution maximizes Ω by optimally choosing the skill-specific wages (w_{Hj} and w_{Lj}) and the skill-specific employment (L_j and H_j) (see equation (3) in Van Reenen 1996):

$$\max_{w_{Lj}, w_{Hj}, L_j, H_j,} \Omega = U_{Lj}^{\beta_L} U_{Hj}^{\beta_H} \Pi_j^{1-\beta_L-\beta_H}, \tag{F.2}$$

where β_L and β_H denote the bargaining powers of the two unions.

Solution. Plugging U_{Lj} and U_{Hj} into the expression for Ω leads to the following formula:

$$\begin{aligned}\Omega \quad = \quad & \left[\tfrac{1}{1-m_L}\left(w_{Lj}\right)^{1-m_L} L_j\right]^{\beta_L} \times \left[\tfrac{1}{1-m_H}\left(w_{Hj}\right)^{1-m_H} H_j\right]^{\beta_H} \times \\ \times \quad & \left[pA_j\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - H_j w_{Hj} - L_j w_{Lj}\right]^{1-\beta_L-\beta_H}.\end{aligned}$$

The FOCs of this problem are the following:

$$\begin{aligned}\frac{\partial\Omega}{\partial w_{Lj}} &= \Omega \times \left[\frac{\beta_L (w_{Lj})^{-m_L} L_j}{U_{Lj}^{1-\beta_L}} + \frac{-(1-\beta_L-\beta_H)L_j}{\Pi_j^{\beta_L+\beta_H}}\right] &&= 0,\\ \frac{\partial\Omega}{\partial w_{Hj}} &= \Omega \times \left[\frac{\beta_H (w_{Hj})^{-m_H} H_j}{U_{Hj}^{1-\beta_H}} + \frac{-(1-\beta_L-\beta_H)H_j}{\Pi_j^{\beta_L+\beta_H}}\right] &&= 0,\\ \frac{\partial\Omega}{\partial L_j} &= \Omega \times \left[\frac{\beta_L \frac{1}{1-m_L}(w_{Lj})^{1-m_L}}{U_{Lj}^{1-\beta_L}} + (1-\beta_L-\beta_H)\frac{pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}}(1-\theta_j)L_j^{-\frac{1}{\sigma}} - w_{Lj}}{\Pi_j^{\beta_L+\beta_H}}\right] &&= 0,\\ \frac{\partial\Omega}{\partial H_j} &= \Omega \times \left[\frac{\beta_H \frac{1}{1-m_H}(w_{Hj})^{1-m_H}}{U_{Hj}^{1-\beta_H}} + (1-\beta_L-\beta_H)\frac{pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}}\theta_j H_j^{-\frac{1}{\sigma}} - w_{Hj}}{\Pi_j^{\beta_L+\beta_H}}\right] &&= 0.\end{aligned}$$

Rearranging and dividing the first and third, and the second and fourth FOCs, we get:

$$\begin{aligned}w_{Lj} &= \tfrac{m_L-1}{m_L} \times pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}}(1-\theta_j)L_j^{-\frac{1}{\sigma}},\\ w_{Hj} &= \tfrac{m_H-1}{m_H} \times pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}}\theta_j H_j^{-\frac{1}{\sigma}}.\end{aligned}$$

These equations show that both types of workers receive a share of their marginal product, which depends on their risk aversion parameter. Under risk neutrality, the marginal product is shared equally. Dividing these two equations yields:

$$\frac{w_{Hj}}{w_{Lj}} = \frac{\frac{m_H-1}{m_H}}{\frac{m_L-1}{m_L}} \times \frac{\theta_j H_j^{-\frac{1}{\sigma}}}{(1-\theta_j)L_j^{-\frac{1}{\sigma}}}, \tag{F.4}$$

and taking the logarithm yields:

$$\ln\frac{w_{Hj}}{w_{Lj}} = \ln\frac{\frac{m_H-1}{m_H}}{\frac{m_L-1}{m_L}} + \ln\frac{\theta_j}{1-\theta_j} - \frac{1}{\sigma}\frac{H_j}{L_j}. \tag{F.5}$$

The relative wage of the two types of workers depends on the relative marginal product and a wedge introduced by the bargaining process, when the risk aversion of the two types of workers is different. Since the wedge, $\frac{\frac{m_H-1}{m_H}}{\frac{m_L-1}{m_L}}$, depends only on the preference parameters of the workers (risk aversion of the high and low skilled workers), it is unaffected by a firm-level change in skill demand. Therefore, the change in the skill premium following innovation takes the following form:

$$\underbrace{\Delta \ln \frac{w_{Hj}}{w_{Lj}}}_{\substack{\text{Change in} \\ \text{skill premium}}} = \underbrace{\Delta \ln \frac{\theta_j}{1-\theta_j}}_{\substack{\text{Change in} \\ \text{skill bias}}} - \underbrace{\frac{1}{\sigma}\Delta \ln \frac{H_j}{L_j}}_{\substack{\text{Change in} \\ \text{skill ratio}}}. \tag{F.6}$$

This equation shows that the relationship between the change in the skill premium and skill demand is very similar in a bargaining model of wages and employment to the relationship derived in our main framework.

F.2 Wage Setting in a Rent Sharing Model

We derive the relative skill ratio and wages in a dynamic optimal contracting model that leads to rent sharing. We follow Kline et al. (2019) and assume that there is imperfect substitutability between incumbent workers and new hires as a result of the training and recruitment costs involved in new hires. The cost of hiring N_{Sj} workers at firm j from skill group S is $c(N_{Sj}/I_{Sj})I_{Sj}$, where I_{Sj} is the number of incumbent workers in skill group S. The firm can hire as many new workers as desired at the competitive market wage w_S^m. Further, firms are price takers in output markets.[64] The firm chooses a wage for the incumbent workers, w_{Sj}^I, at the beginning of the period. After the wage is posted, incumbent workers receive outside job offers. Each incumbent worker stays if their outside wage offer is smaller than their current wage. Let $G\left(w_{Sj}^I\right)$ denote the probability of an incumbent worker staying given w_{Sj}^I is posted. The firm's problem is as follows (equivalent with Section 2.2. in Kline et al. 2019).

$$\Pi_j(A_j,\theta_j) = \max_{w_{Hj}^I, w_{Lj}^I, N_{Lj}, N_{Hj}} pQ_j - \left[c\left(\frac{N_{Hj}}{I_{Hj}}\right) I_{Hj} + N_{Hj}w_H^m + w_{Hj}^I G\left(w_{Hj}^I\right) I_{Hj}\right] -$$

$$- \left[c\left(\tfrac{N_{Lj}}{I_{Lj}}\right) I_{Lj} + N_{Lj}w_L^m + w_{Lj}^I G\left(w_{Lj}^I\right) I_{Lj}\right],$$

subject to

$$Q_j = A_j\left[\theta_j H_j^{\frac{\sigma-1}{\sigma}} + (1-\theta_j)L_j^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where $H_j = N_{Hj} + G\left(w_{Hj}^I\right) I_{H_j}$ is the sum of new and retained high skilled workers, and $L_j = N_{Lj} + G\left(w_{Lj}^I\right) I_{L_j}$ is the sum of new and retained low skilled workers.

The FOC of this problem for skilled workers is the following:

$$pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-\frac{1}{\sigma}} G'\left(w_{Hj}^I\right) I_{H_j} - G\left(w_{Hj}^I\right) I_{Hj} - w_{Hj}^I G'\left(w_{Hj}^I\right) I_{Hj} = 0$$

[64] To simplify the notation we currently abstract away from amenities.

$$pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-\frac{1}{\sigma}} = c' \left(\frac{N_{Hj}}{I_{Hj}} \right) + w_H^m.$$

The first equation can be rearranged to:

$$pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-\frac{1}{\sigma}} = \frac{G\left(w_{Hj}^I\right)}{G'\left(w_{Hj}^I\right)} + w_{Hj}^I.$$

And this implies that:

$$\frac{G\left(w_{Hj}^I\right)}{G'\left(w_{Hj}^I\right)} + w_{Hj}^I = c' \left(\frac{N_{Hj}}{I_{Hj}} \right) + w_H^m,$$

which shows that the marginal cost of hiring and retaining a worker should be equal.

Kline et al. (2019) specify $G\left(w\right) = \left(\frac{w-w^m}{\bar{w}-w^m}\right)^{\beta}$. This implies that $\frac{G(w)}{G'(w)} = \frac{1}{\beta}\left(w - w^m\right)$, and so the above equation can be rewritten as:

$$\frac{1+\beta_H}{\beta_H}\left(w_{Hj}^I - w_H^m\right) = c'\left(\frac{N_{Hj}}{I_{Hj}}\right).$$

Plugging this back into the second FOC leads to the following expression:

$$pA_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{-}\frac{1}{\sigma} = \frac{1+\beta_H}{\beta_H}\left(w_{Hj}^I - w_H^m\right) + w_H^m.$$

Rearranging this equation leads to:

$$\beta_H p A_j^{\sigma} Q_j^{\frac{1}{\sigma}} \theta_j H_j^{\frac{1}{\sigma}} = \left(1+\beta_H\right) w_{Hj}^I - w_H^m.$$

The same holds for the low skilled workers:

$$\beta_L p A_j^{\frac{\sigma-1}{\sigma}} Q_j^{\frac{1}{\sigma}} (1-\theta_j) H_j^{-\frac{1}{\sigma}} = \left(1+\beta_L\right) w_{Lj}^I - w_L^m.$$

The ratio of these two leads to the following expression:

$$\frac{H_j^{-\frac{1}{\sigma}}}{L_j^{-\frac{1}{\sigma}}} \frac{\theta_j}{1-\theta_j} = \frac{\beta_L}{\beta_H} \frac{\left(1+\beta_H\right) w_{Hj}^I - w_H^m}{\left(1+\beta_L\right) w_{Lj}^I - w_L^m}.$$

Taking the logarithm and rearranging leads to the following expression:

$$-\frac{1}{\sigma} \ln \frac{H_j}{L_j} + \ln \frac{\theta_j}{1-\theta_j} = \ln \frac{\beta_L}{\beta_H} + \ln \frac{\left(1+\beta_H\right) w_{Hj}^I - w_H^m}{\left(1+\beta_L\right) w_{Lj}^I - w_L^m}.$$

Since the $\ln \frac{\beta_L}{\beta_H}$ are preference parameters of the workers (how responsive workers are to changes in wages), they are unaffected by a change in firm-level skill demand.

The relationship between the change in wages and employment following innovation is:

$$\underbrace{\Delta \ln \frac{(1+\beta_H)\, w_{Hj}^I - w_H^m}{(1+\beta_L)\, w_{Lj}^I - w_L^m}}_{\substack{\text{Relative Change in} \\ \text{incumbent wages}}} = \underbrace{\Delta \ln \frac{\theta_j}{1-\theta_j}}_{\substack{\text{Change in} \\ \text{skill bias}}} - \underbrace{\frac{1}{\sigma} \Delta \ln \frac{H_j}{L_j}}_{\substack{\text{Change in} \\ \text{skill ratio}}} . \tag{F.7}$$

This equation is similar to our benchmark equations (equations (5) and (8)) except for its left-hand side, which differs from the main model in two respects. First, while still capturing an increase in the skill premium, its functional form is slightly different. Second, in this rent sharing model, the change in skill bias does not affect new workers' wages, as firms can hire as many workers as they want at the prevailing competitive wage, w_S^m. Nevertheless, because of the training and retaining costs, the marginal cost of hiring increases with the number of new hires, providing firms stronger incentives to retain their workers, which drives up incumbent wages when skill demand increases. As a result, the relevant object for assessing skill bias in this model is the wage growth of incumbent workers.

To sum up, the basic logic of the main model applies to rent sharing models: skill-biased technological change leads to a joint increase in the skill premium and the skill ratio. However, these models only predict an increase in the skill premium for incumbent workers.

Appendix G Calibrating an illustrative model

We illustrate the impact of skill-biased change at the macro level by a back-of-the envelope calibration of our model.

We us a two-firm version of our model and calibrate it by using the inputs provided in Table G.1. These numbers are the (worker-weighted) average initial values (from 2008) for firms which will and will not innovate in the last wave we observe, from 2012. We denote the (future) innovative firm as firm 1, and the non-innovative firm as firm 2.

Our question is how innovation impacts the aggregate skill premium in a 4-year period. As our main estimates cover around 4-years worth of innovation (a CIS wave), we assume that the impact of innovations is about 2.5 times as large as our estimates from one CIS wave.

We calibrate the model in the following steps:

1. We take the share of H workers from Table 1 "Share of college graduates".
2. Based on the observed skill ratio and skill premium levels (Table G.1 rows (3) and (4)), we can use Equation (5) to pin down the level of skill bias θ_j for the two groups of firms.
3. Next, we also use the parameter $a_1 = a_{L1t} = a_{H1t}$ (as defined in Equations (3c) and (3d)) to match the share of the innovative firm in the high-skilled market (Table G.1 row (6)), while normalizing $a_2 = a_{L2t} = a_{H2t}$ to zero.[65]
4. Then, conditional on the skill biases and the amenities, we calibrate the the innovative firm's TFP, A_1 (while normalizing A_2 to 1) in way to match the observed L-wage gap (Table G.1 row (2)).
5. In our experiment, we increase the innovative firm's skill bias, $\ln \frac{\theta_1}{1-\theta_1}$, by the amount reported in Table 5 row (1) times 2.5.
6. We also allow for Hicks-neutral technological change, an increase in A_1. We calibrate the extent of this from the relative change in the number of college and non-college workers ($\Delta \ln H_1 - \Delta \ln H_2$, $\Delta \ln L_1 - \Delta \ln L_2$), reported in Table A.5 columns (2) and (3) (times 2.5 to capture a 10-year change).

Table G.2 shows the results from our calibration. Panel A shows that we assume that $\sigma = 1.6$ and $\beta = 3$ throughout our calibration.

Panel B of the Table shows the estimated parameters. We calibrate the relative size of the innovative firm (a) to about two thirds of that of non-innovative firms. The skill-bias parameter (θ) is about 13 percent higher pre-innovation for innovative firms compared to non innovative firms. It's value increases by 0.01 as a result of innovation. Finally, innovative firms have about 13 percent

[65] Note that here this parameter captures the relative share of innovative firms and does not represent amenities. Keeping the parameter the same – allowing for symmetric firms – does yield very similar results.

Table G.1: Model inputs

	Non-innovative	Innovative
(1) College wage	5.474	5.565
(2) Non-coll wage	5.319	5.374
(3) Skill premium	0.156	0.187
(4) Skill ratio	-1.317	-1.058
(5) Share: Non-college workers	0.554	0.446
(6) Share: College workers	0.509	0.491

Notes:

higher TFP pre-innovation compared to non-innovative firms and their TFP increases by 2.3 percent as a result of innovation. According to this calibration, innovation has similarly large skill-biased and Hicks-neutral components.

Panel C shows our model fit, with relative quantities showing the difference between innovative and non-innovative firms. It fits well the levels and changes for the skill ratio, and somewhat less well for the skill premium.

Finally, Panel D shows how the innovation changes the aggregate skill premium under different βs. We also report how the change in the aggregate skill premium can be decomposed into within-firm and reallocation components according to the following equation:

$$\begin{aligned}\Delta\Theta \equiv\ & \underbrace{\sum_j \left(\frac{H_{jt+1}}{H_{t+1}} - \frac{H_{jt}}{H_t}\right) \ln w_{Hjt+1} - \sum_j \left(\frac{L_{jt+1}}{L_{t+1}} - \frac{L_{jt}}{L_t}\right) \ln w_{Ljt+1}}_{\text{Reallocation Effect}} + \\ & + \underbrace{\sum_j \frac{H_{jt}}{H_t} \left(\ln w_{Hjt+1} - \ln w_{Hjt}\right) - \sum_j \frac{L_{jt}}{L_t} \left(\ln w_{Ljt+1} - \ln w_{Ljt}\right)}_{\text{Wage premium effect}}.\end{aligned} \tag{G.8}$$

the reallocation term captures the impact of innovative firms, that already pay a higher wage and premium before the innovation, expanding. The second term captures the impact of the increasing skill premium within the two firms firm.

We find that, at our baseline $\beta = 3$, innovation contributed about 2 percentage points to the increase in the skill premium. More than 90% of this resulted from the within-firm increase in the skill premium, with about 10% resulting from workers' reallocation to high-paying and higher premium firms. The aggregate impact is increasing with β: according to our simulation, the aggregate increase in the skill premium is 3.3% percent under perfect competition ($\beta = 50$), with no positive contribution from the reallocation effect.

Table G.2: Model summary

Panel A: Parametrization

Parameter	Value
σ	1.600
β (reported panels)	3.000

Panel B: Parameters by firm and period (A normalized: non-innovative pre = 1)

	Innovative (pre)	Innovative (post)	Non-innovative
Amenity (H), a^H	0.7312	0.7312	1.0000
Amenity (L), a^L	0.6194	0.6194	1.0000
Skill bias (θ)	0.383611	0.392903	0.339141
Productivity (A)	1.118154	1.144119	1.000000

Panel C: Baseline moments and fit (at $\beta = 3$)

Moment	Model	Data
SP (innov.)	0.0917	0.1870
SP (non-innov.)	0.0607	0.1560
SR (innov.)	-0.9055	-1.0580
SR (non-innov.)	-1.1645	-1.3170
Initial relative SP	0.0310	0.0310
Initial relative SR	0.2590	0.2590
Relative ΔSP	0.0136	0.0275
Relative ΔSR	0.0408	0.0450

Panel D: Results (BOTH; fixed calibration)

= 3 only

β	$\Delta\Theta$	Within	Reallocation
3	0.0228	0.0213	0.0015

Other β (fixed calibration)

β	$\Delta\Theta$	Within	Reallocation
1	0.0192	0.0182	0.0010
1.6	0.0204	0.0192	0.0012
6	0.0273	0.0256	0.0017
50	0.0425	0.0428	-0.0003

Panel E: Changes in wage dispersion (log wages; BOTH − BASE; fixed calibration)

= 3 only

β	ΔSD (total)	ΔSD (within)	ΔSD (between)
3	0.0122	0.0072	0.0100

Other β (fixed calibration)

β	ΔSD (total)	ΔSD (within)	ΔSD (between)
1	0.0117	0.0081	0.0084
1.6	0.0117	0.0077	0.0090
6	0.0135	0.0067	0.0120
50	0.0181	-0.0014	0.0186