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DISCUSSION PAPER SERIES

IZA DP No. 16070

Technological Change, Firm Heterogeneity and Wage Inequality

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ABSTRACT

Technological Change, Firm Heterogeneity and Wage Inequality*

We argue that skill-biased technological change not only affects wage gaps between skill groups, but also increases wage inequality within skill groups, across workers in different workplaces. Building on a heterogeneous firm framework with labor market frictions, we show that an industry-wide skill-biased technological change shock will increase between-firm wage inequality within the industry through four main channels: changes in the skill wage premium (as in traditional models of technological change); increased employment concentration in more productive firms; increased wage dispersion between firms for workers of the same skill type; and increased dispersion in the skill mix that firms employ, due to more sorting of skilled workers to more productive firms. Using rich administrative matched employer-employee data from Germany, we provide empirical evidence of establishment-level patterns that are in line with the predictions of the model. We further document that industries with more technological adoption exhibit particularly pronounced patterns along the dimensions highlighted by the model.

JEL Classification: J31

Keywords: heterogeneous firms, skill-biased technological change, between-firm inequality

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1 Introduction

Income inequality has risen dramatically over the past decades in many high-income countries. The development of new technologies has been proposed as a key driver of this pattern. The literature has argued that technology has asymmetric impacts across different groups of workers, depending on their skill levels or the tasks that they perform (e.g. Katz & Murphy, 1992; Autor et al., 2003, 2006; Goos et al., 2014; Jaimovich & Siu, 2020). According to this view, technology has impacted wage inequality by changing the demand for different skills and tasks, thus changing the employment structure of the economy and the relative wage returns for different groups.

Intriguingly, however, a recent parallel literature has shown that most of the rise in wage inequality can be traced back to increasing wage differentials among observationally similar individuals, working in different firms (Card et al., 2013; Barth et al., 2016; Helpman et al., 2017; Song et al., 2019). This literature has argued that individual-level wages have become increasingly dependent on where people work, rather than the skills that they possess or the tasks that they perform.

While the literature on between-firm inequality has documented many novel empirical facts, it is not yet entirely clear what the driving forces behind these patterns are. In comparison, while the literature on technological change has provided deep insights into the evolution of relative wage gaps *across* skill and task groups, it has, by drawing on models of perfectly competitive labor markets with a representative firm, so far provided limited insights into the growing wage differentials observed *within* groups, across firms.

In this paper, we argue that the development of skill-biased automation technologies can account not only for increases in inequality between skill groups, but also for increases in inequality within groups, across workers in different workplaces, as observed in the data. We show this theoretically, using a rich yet tractable heterogeneous firm framework, and empirically, verifying the predictions of the model using administrative matched employer-employee data from Germany between 1990 and 2010.

Our theoretical framework embeds an aggregate skill-biased technological change shock within the heterogeneous firm model of Helpman et al. (2010). Their model extends the Melitz (2003) framework by introducing search and matching frictions, heterogeneous match-specific ability, and a screening technology. These extensions support an equilibrium in which firms with different productivity levels pay heterogeneous wages to observationally equivalent workers. In line with empirical evidence, we consider a version of the model in which firms within industries differ in terms of their productivity as well as their technology of production (i.e. their optimal mix of skilled and unskilled workers). In equilibrium, more productive firms find it optimal to employ more workers of both types, have a higher skilled employment share, and pay higher wages (overall and conditional on skill type).

The skill-biased technological change (SBTC) shock that we embed in the model is in the spirit of Katz & Murphy (1992) and Autor et al. (1998), namely, it involves an aggregate increase in the factor-augmenting technology parameter for skilled workers in the production function. As in traditional models of SBTC, this shock leads to an increase in the skilled wage premium and therefore increases between-group wage inequality. However, in spite of being an aggregate shock that is common across all firms, SBTC also induces a number of endogenous heterogeneous firm-level changes that lead to an increase in between-firm inequality.

First, the model predicts that SBTC leads to differential employment growth, whereby the more productive, higher-paying firms in the industry grow more. This leads to a rise in employment concentration, which contributes to an increase in worker-weighted measures of between-firm wage inequality. Second, the model predicts that SBTC leads to an endogenous increase in worker segregation by skill, driven by increased sorting of skilled workers to high-productivity (and hence high-wage) firms. Thirdly, the model generates endogenous within-firm wage changes, with more productive firms disproportionately increasing the wage that they pay to workers of each skill group, thus further contributing to the increase in between-firm wage inequality.

We provide empirical support for these theoretical predictions using administrative social security data from Germany. Our data set is the Beschäftigtenhistorik (BEH) from the Institute for Employment Research (IAB), which includes the universe of private sector workers and establishments in Germany. We focus on the patterns observed in West Germany between 1990 and 2010. We supplement the BEH data with information from the IAB Establishment Panel (IABEP), which provides measures of establishment-level sales and allows us to construct a measure of labor productivity for the establishments covered by the survey.

We first show that more productive establishments within industries are larger and pay higher wages compared to less productive establishments. This is true for both skilled and unskilled workers, and is in line with the equilibrium relationships implied by the model. We verify that the higher wages paid by more productive establishments are not merely due to sorting of workers based on fixed unobservable characteristics: they also pay higher premiums as measured by their Abowd et al. (1999) or AKM establishment fixed effect.

We then provide empirical support for the key predictions of the model regarding the impacts of SBTC. Consistent with the presence of ongoing SBTC, we find that the within-industry establishment-level associations between productivity, employment, skill shares and wages have become stronger over our sample period. For example, while a 1% increase in the establishment's labor productivity was associated with a 0.1% increase in establishment size in 1995, this association had increased to more than 0.4% by 2010. Similarly, while a 1% increase in establishment productivity was associated with an increase of 0.06% in the establishment average wage in 1995, this association increased to almost 0.16% in 2010. This is partly due to a strengthening of the relationship between productivity and skill shares and, more importantly, due to a strong strengthening of the relationship between productivity and skill-specific wages. These patterns are consistent with the channels highlighted by the model, namely the differential increases in employment, skill shares and wages in more productive workplaces relative to less productive ones, as a result of SBTC.

We provide similar evidence based on longitudinal changes within establishments. In particular, we find that larger establishments tend to pull further away from smaller establishments in the same industry, by experiencing faster productivity growth, employing an even larger share of skilled workers, and further increasing the wages that they pay to workers of a given skill group. Moreover, in line with recent evidence on increased employment concentration (e.g. Autor et al., 2020), we show that establishments that are more productive, employ more skilled workers or pay higher wages at baseline experience higher employment growth than other establishments in the same industry. Our paper can rationalize these patters as being driven by an aggregate SBTC shock.

In order to provide more direct evidence of the link between technological change and the establishment-level patterns that we have identified, we leverage variation across industries in technology adoption, which we measure in three different ways: based on the industry's skill premium; based on industry-level robot adoption data from the International Federation of Robotics; and based on ICT capital usage data from EUKLEMS. We first find that the within-industry establishment-level patterns that we have documented are significantly stronger within industries that are more technology-intensive, a finding that persists when we control for differential trade and offshorability exposure across industries. We further show that the between-establishment dispersion in wages and skill shares as well as the sorting of skilled workers into high-wage establishments have increased more in industries more exposed to technological change, corroborating the importance of SBTC as a driver of between-establishment inequality.

Our findings connect to several strands of the literature. First, we provide an important innovation to the literature that studies the impacts of technological change on wage inequality. This literature has primarily relied on representative firm frameworks with perfect competition, and has thus solely focused on the impacts of technological change on inequality that operate via changes in the skill or task structure of the economy (see e.g. Katz &

Murphy, 1992; Machin & Van Reenen, 1998; Acemoglu & Autor, 2011; Michaels et al., 2014; Autor et al., 2015; Akerman et al., 2015; Graetz & Michaels, 2018; Dauth et al., 2021).

As our framework and empirical analysis demonstrate, an industry-wide technology shock has very different impacts on different firms within an industry, and hence on different workers within a skill group. Our results paint a much richer picture about the individual- and firm-level impacts of skill-biased technological change, highlighting the fact that the way in which individuals are impacted by technological change will depend not only on their skill level, but also on the type of firm that they are matched to.

Our analysis also provides an important contribution to the literature on the rise in between-firm wage inequality (Card et al., 2013; Song et al., 2019; Barth et al., 2016; Helpman et al., 2017; Criscuolo et al., 2020). This literature has been very successful in documenting the increasing importance of firms for individual wages, and has provided evidence of rising worker sorting and segregation (e.g. Kramarz et al., 1996; Cortes & Salvatori, 2019; Wilmers & Aeppli, 2021). It has, however, been more limited in terms of characterizing the underlying driving forces behind these patterns. We provide a tractable theoretical framework that allows us to study the interplay between workplace heterogeneity and aggregate skill-biased technological change.[1] Consistent with the idea that the rise in between-workplace inequality is at least partly driven by SBTC, we show that sorting and between-establishment wage dispersion patterns are more pronounced within industries that have been more exposed to technological change.

Our paper further relates to the literature on the rise in concentration and the increased dominance of so-called superstar firms (Autor et al., 2017, 2020; Azar et al., 2020a,b; Bajgar et al., 2019). We show that skill-biased technological change leads to rising employment concentration in highly productive firms. Even absent any wage changes within firms, this rise in concentration will imply an increase in worker-weighted measures of between-establishment wage inequality.[2]

Finally, we relate to recent studies which investigate the impact of *firm-level* adoption of industrial robots (e.g. Acemoglu et al., 2020; Bonfiglioli et al., 2020; Koch et al., 2021), automation expenditures (Bessen et al., 2020; Aghion et al., 2020) or innovation (Lindner et al., 2021) on firm-level outcomes. These papers generally find that technology adoption is associated with increases in employment, sales and skill intensities at the firm level. While we are also interested in the firm-specific impacts of technological advances, out study highlights

[1] Other papers in the literature have provided a rich analysis of how technology affects the sorting of workers to jobs (e.g. Lindenlaub, 2017). However, these types of models often have no natural definition of a firm and assume that worker types are perfect substitutes in production.

[2] See Webber (2015); Mueller et al. (2017); Rinz (2020) and Cortes & Tschopp (2020) for more detailed analyses of the link between rising concentration and rising wage inequality.

that an *industry-wide* shock can have differential effects between firms.

The paper most related to ours is Haanwinckel (2020). While we share a similar goal in terms of understanding the role of technological change for wage inequality, our framework and our approach are substantially different. While the Haanwinckel (2020) model generates wage differences between firms by assuming that workers have idiosyncratic tastes for different workplaces (as in e.g. Bhaskar et al., 2002; Card et al., 2018), our model generates wage heterogeneity due to search and matching frictions and match-specific worker ability, and hence firms that pay higher wages in our model do so for reasons that are directly related to productivity. Haanwinckel (2020) disentangles the role of different shocks (including skill-biased technological change, changes in the supply of skilled workers and minimum wages) by performing a quantitative analysis of the model supported by data from Brazil. We instead use the closed form solutions from our model to derive comparative statics results that illuminate the intuition behind the mechanisms through which changes in technology lead to changes in between-firm inequality. We provide novel empirical evidence regarding the workplace-level changes underlying the rise in between-establishment inequality in Germany, which we can directly link to our model mechanisms. We also exploit variation in technology adoption across industries in order to provide further evidence of the role of technological change for between-workplace inequality.

2 Theoretical Motivation

In this section we set up a theoretical framework that helps guide our analysis of the link between skill-biased technological change and between-firm wage inequality. We consider a version of the model developed by Helpman et al. (2010), which provides a rich yet tractable framework in which to study wage heterogeneity across firms within industries conditional on observable worker skills. Our key innovation is to embed into the model an aggregate skill-biased technological change shock in the spirit of Katz & Murphy (1992) and Autor et al. (1998), modelled as an exogenous aggregate change in the factor-augmenting parameter associated with skilled workers.

2.1 Overview of the Helpman et al. (2010) Framework

Helpman et al. (2010) extend the Melitz (2003) model by introducing Diamond–Mortensen–Pissarides search and matching frictions (Diamond, 1982a,b; Mortensen & Pissarides, 1994), as well as match-specific ability heterogeneity and a screening technology. We focus on the closed economy version of the extension of the model that allows for two types of labor inputs

(Section 5.2 of their paper) which, in our setting, we think of as two different skill groups (skilled and unskilled).

Consumption Within each sector, consumers demand a continuum of differentiated varieties. The aggregate consumption index is

$$Q = \left[\int_{j \in J} q(j)^{\beta} dj \right]^{1/\beta},$$

where j indexes varieties, J is the set of varieties within the sector, $q(j)$ denotes consumption of variety j, and $0 < \beta < 1$.

Production As in Melitz (2003), there is a competitive fringe of potential firms that can choose to enter the market by paying an entry cost $f_e > 0$. Once a firm incurs the sunk entry cost, it observes its idiosyncratic value of θ, a parameter that is related to its productivity and its optimal production structure (as discussed below). θ is drawn from a Pareto distribution with scale parameter θ_{min} and shape parameter z, i.e. $G_{\theta}(\theta) = 1 - (\theta_{min}/\theta)^z$ for $\theta \geq \theta_{min} > 0$ and $z > 2$.[3] Once firms observe θ, they decide whether to exit or produce. Production involves a fixed cost of $f_d > 0$ units of the numeraire. Since in equilibrium all firms with the same value of θ behave symmetrically, firms can be indexed by θ.

Firms produce using a Constant Elasticity of Substitution (CES) technology with two types of labor inputs: skilled and unskilled workers (indexed by s and r, respectively). A firm's output depends on its value of θ, as well as its choice of how many workers of each type to hire (h_s and h_r), and the average match-specific ability of these workers ($\overline{a}_s$ and $\overline{a}_r$). Specifically, the production function is

$$y = \left[(\theta \mu_s \overline{a}_s h_s^{\gamma})^{\nu} + (\mu_r \overline{a}_r h_r^{\gamma})^{\nu} \right]^{1/\nu}, \tag{1}$$

where $0 < \nu < \beta$, and μ_s and μ_r are aggregate skill-augmenting technology parameters.[4] For simplicity, we normalize $\mu_r = 1$. μ_s can therefore be interpreted in relative terms, as the relative aggregate skill-bias of technology. The parameter θ enters into the production function as a firm-specific skill-augmenting parameter. Firms that draw higher values of θ will be more productive overall (absolute advantage), but productivity will be particularly high for their skilled workers (comparative advantage). Hence, θ is related both to the productivity and to the skill-bias of production of each firm. The model therefore incorporates a link

[3] The assumption that $z > 2$ ensures that the variance of θ is finite.

[4] The assumption that $\nu < \beta$ ensures that employment and wages of both types of workers are increasing in θ, in line with the empirical evidence presented below.

between firm productivity and technological skill bias, which will be in line with the empirical evidence presented below.

Search, Screening and Wage Bargaining Labor markets are skill-specific and there is a fixed aggregate supply of workers of each type. The firm must pay a search cost of b_ℓ in order to be matched with n_ℓ workers, $\ell = \{s, r\}$.[5] Skilled workers are relatively scarce and hence command a higher search cost, i.e. $b_s > b_r$. Workers of a given skill type are ex-ante identical but, upon matching with a firm, draw match-specific abilities from a Pareto distribution with shape parameter k and scale parameter a_{min}: $G_a(a) = 1 - (a_{min}/a)^k$; $a \geq a_{min} > 0$ and $k > 1$.[6] Ability is not observable by the firm or the worker, but a screening technology is available. By paying a screening cost $c\widetilde{a}_\ell^\delta/\delta$, firms are able to identify whether a worker's match-specific ability is above or below an (endogenously chosen) cutoff $\widetilde{a}_\ell$, where $\ell = \{s, r\}$, $c > 0$, and $\delta > k$.[7]

Wages are determined through Stole & Zwiebel (1996a,b) bargaining, under conditions of symmetric information. Since the screening technology only reveals whether a worker's match-specific ability is above or below $\widetilde{a}_\ell$, but not the specific ability of any individual worker, the expected ability of all hired workers of type ℓ is the same, and equal to $\overline{a}_\ell$, the expected value of a conditional on being above the threshold $\widetilde{a}_\ell$. Therefore, all workers of a given type within a given firm receive the same wage.

2.2 Key Equilibrium Properties

Closed-form solutions can be obtained for the equilibrium values of firm-level employment, wages, revenue, and profits for operating firms. Here we highlight the key properties of interest for our purposes. Derivation details are provided in Appendix A.1.

Firm-Level Employment Firm-level employment by worker type is given by

$$h_r(\theta) = h_{dr}\left[1 + \varphi(\theta)\right]^{\left(\frac{\beta\Lambda}{\nu\Gamma} - 1\right)\left(1 - \frac{k}{\delta}\right)} \quad \text{and} \quad h_s(\theta) = \frac{b_r}{b_s}\varphi(\theta)^{1-k/\delta}h_r(\theta),$$

where Λ, Γ and h_{dr} are defined in Appendix A.1.1 and where $\varphi(\theta)$ only depends on firm productivity θ and parameters in equilibrium.

[5] b_ℓ is determined endogenously by labor market tightness and is proportional to workers' expected income outside the sector.

[6] This distribution is assumed to be common across both types of workers.

[7] The assumption that $\delta > k$ is also needed in order to ensure that employment and wages of both types of workers are increasing in θ.

Given that $\partial\varphi(\theta)/\partial\theta > 0$, as shown in Appendix A.2, these equilibrium equations imply

$$\frac{\partial h_r(\theta)}{\partial\theta} > 0, \qquad \frac{\partial h_s(\theta)}{\partial\theta} > 0, \qquad \frac{\partial h_s(\theta)/h(\theta)}{\partial\theta} > 0, \tag{2}$$

where $h(\theta) = h_s(\theta) + h_r(\theta)$.

The model therefore predicts that more productive firms (i.e. firms with a higher value of θ) will employ a larger number of both skilled and unskilled workers and, as a consequence, will be larger than less productive firms. More productive firms will also have a higher skilled employment share $h_s(\theta)/h(\theta)$, implying that skilled workers disproportionately sort towards high-productivity firms.

Firm-Level Wages Firm-level wages by worker type are

$$w_r(\theta) = w_{dr}\left[1+\varphi(\theta)\right]^{\left(\frac{\beta\Lambda}{\nu\Gamma}-1\right)\frac{k}{\delta}} \quad \text{and} \quad w_s(\theta) = \frac{b_s}{b_r}\varphi(\theta)^{k/\delta}w_r(\theta),$$

where w_{dr} is defined in Appendix A.1.1. It follows that (see Appendix A.2):

$$\frac{\partial w_r(\theta)}{\partial\theta} > 0, \qquad \frac{\partial w_s(\theta)}{\partial\theta} > 0, \qquad \frac{\partial w_s(\theta)/w_r(\theta)}{\partial\theta} > 0. \tag{3}$$

The model therefore generates wage differences between firms conditional on worker skill, with more productive firms paying higher wages to workers of both types, and particularly so to skilled workers. Intuitively, the wage differentials between firms arise in the model due to the complementarity between workers' match-specific abilities and firm productivity, which gives an incentive for more productive firms to screen more intensively and choose a higher match-specific ability threshold. In equilibrium, wages are bargained down to the replacement cost of a worker, and given that more productive firms set higher hiring standards, their workers are costlier to replace and hence are paid a higher wage.[8]

[8] Note that both the match-specific heterogeneity and the screening technology are crucial elements (in addition to the search and matching frictions) in order to generate wage differences between firms for workers of a given skill type. If workers (within skill groups) were homogeneous, firms would have no incentive to screen, and wages would be bargained down to the replacement cost of a worker, which would simply be the search cost b_ℓ, which is common across firms for workers of a given type. Firms would be heterogeneous along the size margin (employment), but there would be no wage inequality between firms conditional on skill (as in Felbermayr et al. (2011)). On the other hand, if screening were not feasible, then the average expected ability of workers across all firms would be common and equal to the average match-specific ability in the population. In this case, the bargaining process would lead to a common wage across firms for all workers and once again there would be no wage inequality.

Productivity Threshold As is standard in heterogeneous firm models, the presence of a fixed production cost implies that there is a zero-profit cutoff for productivity, θ_d, such that a firm that draws a productivity below this threshold exits without producing. Appendix A.1.2 shows how this productivity threshold can be pinned down using the Zero-Cutoff Profit condition, which requires the firm at the cutoff θ_d to make zero profits, along with the Free Entry condition, which states that the expected profits for a potential entrant should equal the fixed entry cost.

Summary To summarize, the cross-sectional predictions of the model are that firms that draw a higher value of θ are larger, have a higher skilled worker share, and pay higher wages, both because they hire a larger proportion of skilled workers (who earn higher average wages than unskilled workers), and because they pay higher wages to their workers conditional on skill type. As discussed later on in Section 4, these relationships are strongly supported by the data.

2.3 Impacts of Skill-Biased Technological Change

Following the literature, we model skill-biased technological change (SBTC) as an exogenous aggregate increase in the factor-augmenting parameter for the skilled labor input, i.e. an increase in μ_s in the production function in Equation (1). We focus on the *relative* effects of SBTC – that is, the effects of SBTC on wages and employment of skilled and unskilled workers in low vs high productivity firms – rather than the *absolute* effects of SBTC on overall wage and employment levels.[9]

Prediction 1: *Increased Skilled Wage Premium* – Skill-biased technological change increases the skilled wage premium within all firms, and in the aggregate.

Proof: *As shown in Appendix A.3:*

$$\frac{\partial\left[w_s(\theta)/w_r(\theta)\right]}{\partial\mu_s} > 0$$

Implications: As in traditional models with perfect competition and homogeneous firms, holding the supply of skilled workers constant, the rise in demand for skilled workers induced

[9]In what follows, we assume that the search costs b_s and b_r are not affected by technological change. The search costs are proportional to workers' expected income outside the sector (outside option). Helpman et al. (2010) discuss conditions under which the outside options can be assumed to be constant, even when there are shocks with aggregate implications (such as trade opening, in the setting analyzed in their paper).

by SBTC leads to a higher wage differential between skilled and unskilled workers. In our setting, given that more productive (higher wage) firms have a higher skilled share, the increased skilled wage premium also leads to higher between-firm inequality in average wages, all else equal.

Prediction 2: *Differential Employment Growth* – SBTC strengthens the cross-sectional relationship between employment and productivity.

Proof: *As shown in Appendix A.3:*

$$\frac{\partial\left(\frac{\partial h_r(\theta)}{\partial\theta}\right)}{\partial\mu_s} > 0 \qquad \text{and} \qquad \frac{\partial\left(\frac{\partial h_s(\theta)}{\partial\theta}\right)}{\partial\mu_s} > 0.$$

Implications: SBTC induces more productive firms to become disproportionately larger in terms of employment relative to less productive firms, and leads to increased employment concentration in more productive firms within industries. This shift in employment of both types of workers towards more productive firms (which pay higher wages) leads to an increase in (worker-weighted) between-firm wage inequality (overall and conditional on skill).

Prediction 3: *Increased Sorting and Segregation by Skill* – SBTC strengthens the cross-sectional relationship between productivity and skilled employment shares, provided that firms employ relatively more unskilled than skilled workers at baseline (the empirically relevant case).[10]

Proof: *As shown in Appendix A.3:*

$$\text{If} \quad \frac{h_s(\theta)}{h_r(\theta)} < 1, \quad \text{then} \quad \frac{\partial\left(\frac{\partial h_s(\theta)/h(\theta)}{\partial\theta}\right)}{\partial\mu_s} > 0.$$

Implications: SBTC induces more productive firms to increase their skilled employment share by more than less productive firms. This implies that skilled (high-wage) workers will increasingly sort to more productive (high-wage) firms. This increased sorting also implies more segregation of workers by skill, as firms within industries become more heterogeneous in terms of their skill mix. These changes in sorting patterns will contribute to the overall increase in between-firm wage inequality.

[10]More than 80% of workers in our sample are in workplaces that employ more unskilled than skilled workers.

Prediction 4: *Differential Wage Growth* – SBTC strengthens the cross-sectional relationship between productivity and wages conditional on worker skill, as well as between productivity and the skill premium.

Proof: *As shown in Appendix A.3:*

$$\frac{\partial\left(\frac{\partial w_r(\theta)}{\partial\theta}\right)}{\partial\mu_s} > 0, \qquad \frac{\partial\left(\frac{\partial w_s(\theta)}{\partial\theta}\right)}{\partial\mu_s} > 0 \qquad \text{and} \qquad \frac{\partial\left(\frac{\partial\left[\frac{w_s(\theta)}{w_r(\theta)}\right]}{\partial\theta}\right)}{\partial\mu_s} > 0.$$

Implications: As a result of SBTC, wages for both types of workers and the skill premium disproportionately increase within more productive firms relative to less productive firms. Thus, firm wages conditional on skill become more dispersed, leading to a further increase in wage inequality across firms (overall and conditional on skill).

Prediction 5: *Selection* – SBTC increases the productivity threshold for production θ_d.

Proof: *See Appendix A.3.*

Implications: By increasing the productivity threshold θ_d, SBTC leads to the exit of firms at the bottom of the productivity distribution. Although this reduces the support of the distribution among operating firms, the variance of productivity among these firms increases. This is due to the fact that the distribution of productivity among operating firms is a truncated Pareto distribution with scale parameter θ_d and shape parameter z, and the variance of this distribution is increasing in the scale parameter θ_d.[11] Intuitively, with a Pareto distribution, the increase in θ_d entails the exit of a mass of relatively homogeneous unproductive firms. This mass is shifted towards the tail of the distribution, leading to an increase in the variance of productivity among the firms that remain in operation. While this change does not affect the variance of *log* productivity, log wages are not directly proportional to log productivity. Instead, they are a more complicated function of θ. Hence, the increase in the variance of productivity may lead to an increase in the variance of log wages among firms operating in the market, which would contribute to the rise in between-firm inequality.

[11] The variance is given by $\frac{z\theta_d^2}{(z-1)^2(z-2)}$. It should be noted that an increase in the productivity threshold θ_d will not increase the variance of productivity among operating firms for all distributions of firm productivity. For example, if firm productivity were uniformly distributed, an increase in the productivity threshold θ_d would lower the variance of firm productivity among operating firms. The Pareto assumption, however, is standard in the literature, and is supported by empirical evidence (see e.g. Axtell, 2001; Corcos et al., 2012).

Summary To summarize, the model predicts that an aggregate skill-biased technological change shock leads to an increase in between-firm wage inequality. This operates through various distinct channels. The first is an extension to the heterogeneous firm setting of the channel highlighted by traditional models of SBTC with competitive markets and no firm heterogeneity; that is, a rise in the wage of skilled workers relative to unskilled workers. The other channels are novel to our setting; namely differential employment growth, segregation and sorting, and differential within-firm wage growth. All of these channels compound each other in driving the increase in wage inequality between firms. Selective entry and exit of firms may additionally contribute to the rise in between-firm inequality. We verify the empirical validity of these predictions in the remainder of the paper.

3 Data

3.1 Social Security Records (Beschäftigtenhistorik (BEH))

Our main data are drawn from social security records for Germany provided by the Institute for Employment Research (IAB) – the so-called Beschäftigtenhistorik (BEH, 2016 version). This data set includes all men and women covered by the social security system – roughly 80% of the German workforce. Not included are civil servants, the self-employed, and military personnel.

We focus on developments after 1990 when wage inequality started to increase sharply in Germany across the entire distribution of wages (see for example Dustmann et al., 2014; Card et al., 2013). We end the analysis in 2010 due to structural breaks in key variables such as workers' full-time status, which affect comparability with subsequent years.

We begin by selecting all full- and part-time employment spells that refer to June 30 of each year. We then restrict the sample to workers who are currently not in an apprenticeship, are aged between 16 and 65, and are employed in West Germany. We exclude industries in the primary sector and some small industries such as private households and international organizations. We further drop workers with missing occupation, missing education level, missing employment status, or implausibly low wages below the limit for which social security contributions have to be paid, as well as establishments with missing industry affiliation and establishments employing only part-time workers. These sample restrictions affect less then 1% of all worker-level observations.

As is common in administrative data sources, wages are censored at the highest social security limit, affecting on average about 8% of observations. We follow Dustmann et al. (2009) and Card et al. (2013) and impute censored wages, assuming that (log) wages are normally distributed with heterogeneous variances that vary by year, age, education and sex; see Appendix B.1 for details. We deflate wages using 1995 as the base year.[12]

We classify individuals as either skilled or unskilled, using information on their education level as well as their apprenticeship occupation. Specifically, technical college and university graduates are classified as skilled, while individuals with no further education are classified as unskilled. Individuals with apprenticeship or vocational training – which comprise the largest share of the workforce in Germany (around 70%) – are categorized as skilled or unskilled depending on whether their apprenticeship occupation is a primarily "skilled" (e.g., technicians) or "unskilled" (e.g., manual labor) occupation, following the mapping of Blossfeld (1987); see Appendix Table A.1.[13] This classification of skill groups mimics the distinction between college and non-college graduates typically used in the US context, as apprenticeship graduates whom we classify as skilled would typically enroll in college in the US whereas those whom we classify as unskilled would typically enter the labor market without post-secondary education.

We make use of the unique establishment identifiers available in the data in order to aggregate the worker-level information to the establishment level (in each year). Our establishment-level employment counts include part-time workers with a weight of 0.5. Since we do not observe hours worked, our measures of establishment wages are based on full-time workers only.[14]

We focus on establishment patterns within industries, where industries refer to 3-digit NAICS codes, which distinguish between 196 sectors. In order to address the change in the industry classification in the social security data that occurred in 1999, we harmonize industry codes as described in Appendix B.2.

3.2 The IAB Establishment Panel (IABEP)

Since the social security records drawn from the BEH do not contain information on establishment outcomes such as total sales or labor productivity, we augment the social security records with data from the IAB Establishment Survey (IABEP). The IABEP survey was first administered in 1993 to 4,265 West German establishments. By 2010, the number of surveyed establishments had increased to over 16,000. From this database, we select all West

[12]Note that wages in the data set always refer to a single establishment and are never averaged across establishments.

[13]If an individual with apprenticeship education is not observed at the time of their training, we use the occupation when they are first observed in the data to classify them as skilled or unskilled.

[14]Fitzenberger & Seidlitz (2020) provide evidence that a fraction of part-time workers are misclassified as full-time workers. Even though this affects inequality measures in a given year, the authors show that this misclassification is not driving the rise in inequality over time.

German establishments with at least one full-time employee that participated in the IABEP at least once. Using the unique establishment identifiers, we merge information from the IABEP to the BEH social security records. We compute an establishment's labor productivity as total sales (obtained from the IABEP), divided by the number of full-time equivalent workers (obtained from the BEH). In the empirical analysis based on the IABEP, we use the weights provided by the survey in order to guarantee representativeness for workers.

3.3 Industry-Level Technology Adoption Measures

We supplement these two main data sources with industry-level data on technology adoption. First, following Graetz & Michaels (2018) and Acemoglu & Restrepo (2020), we use data on robot usage from the International Federation of Robotics (IFR).[15] We rely on the crosswalk provided by Dauth et al. (2021) to match industry codes in the robot data to industry codes in the BEH social security data.

Second, we use data on the adoption of capital related to information and communication technologies (ICT) from the EUKLEMS data set. We obtain the data from the November 2009 release, which is based on ISIC revision 3 industry codes that can be matched to the industry codes in the BEH social security data at the 2-digit level. Our measure of ICT assets is based on the real fixed capital stock of computing and communication equipment, and computer software.

4 Empirical Evidence

4.1 Aggregate Patterns

We begin by verifying the aggregate empirical patterns that form an important backdrop to our analysis. First, we confirm the traditional empirical evidence for the implication of SBTC that arises in models with perfect competition and homogeneous firms: a rise in the relative wage of skilled workers over time. Importantly, the literature has pointed to the simultaneous rise in the relative wage *and* the relative employment of skilled workers over time as evidence that increases in relative demand for skilled workers (due to SBTC) have outstripped the increase in relative supply (due to increasing educational attainment).

Panel A of Figure 1 shows that the aggregate employment share of skilled workers in Germany steadily rose from 38.8% in 1990 to 47.1% in 2010 – a rise of more than 20% over

[15] A robot is defined as an "automatically controlled, re-programmable, and multipurpose machine" and as "fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks such as welding, painting, assembling, handling materials, or packaging."

two decades. This increase was in part driven by differential industry growth: industries which employ a larger share of skilled workers grew at a faster rate than industries which predominantly employ unskilled workers. Yet, even when keeping the industry structure constant at 1990 levels (the grey dashed line), the employment share of skilled workers rose substantially by more than 10%.

Panel B shows that, alongside the rise in the employment share of skilled workers, we also observe a rise in the skill premium (i.e., the wage gap between skilled and unskilled workers), regardless of whether we allow the industry composition by skill to vary over time or we hold it constant at 1990 levels (see Appendix C.1 for details). This is in line with Prediction 1 from our model and suggests that overall demand for skilled workers has been rising in Germany, as predicted by models of SBTC.

Next, we provide evidence on the evolution of wage inequality in Germany, and the extent to which this is driven by wage differences between establishments. The solid black line in Panel C of Figure 1 shows that overall wage inequality in West Germany, measured as the variance of individual-level log wages, rose sharply from the mid-1990s onwards, from 0.202 in 1995 to 0.280 in 2010, a 38.6% increase (see also Dustmann et al., 2009, 2014).

The dashed lines decompose this overall inequality into a within and a between establishment component (see Appendix C.2 for details). In line with the evidence in the literature (e.g. Card et al., 2013), the figure shows that the increase in overall wage inequality is entirely driven by increasing wage differences between establishments; within-establishment inequality remains quite stable over this time period.

Panel D explores the extent to which between-establishment wage differentials are due to differences between establishments in the same 3-digit industry or due to differences between establishments in different industries (see Appendix C.2 for details). While both of the components are important, within-industry differences account for more than half of the between-establishment variance in the cross-section, and more than half of its change over time. A similar pattern holds if we keep the industry structure constant at 1990 levels.

These results indicate that there is substantial heterogeneity in pay across establishments, implying that we are far from having a 'representative establishment', in terms of pay, even within detailed industries. Moreover, this heterogeneity between establishments within industries has been growing over time and is an important driver of the overall rise in wage inequality. It is these within-industry differences across establishments that we focus on for the remainder of the paper.[16]

[16] Recent work by Haltiwanger et al. (2021), in contrast, focuses on the importance of the between-industry component in accounting for the rise in between-firm wage inequality in the U.S. Their study finds that in the U.S., 25% of the increase in between-firm wage inequality over the past three decades occurred within very detailed 4-digit industries.

4.2 Establishment-level Cross-sectional Relationships

We now verify the cross-sectional relationships across establishments within industries that are predicted by the model equilibrium discussed in Section 2.2. Panel A of Table 1 runs a set of regressions of various establishment characteristics on our measure of establishment productivity (sales per full-time equivalent worker), as well as a set of fully interacted 3-digit industry and year fixed effects, so that identification is limited to variation across establishments within industry-year cells. Observations are weighted by establishment size and survey weights in order to make results representative for workers, and standard errors are clustered at the establishment level.

Columns (1) and (2) show that more productive establishments employ more workers – both skilled and unskilled – and hence are larger in terms of total employment.[17] Column (3) confirms that more productive establishments have a higher skilled employment share. Column (4) shows that more productive establishments pay, on average, higher wages. In Columns (5) and (6), we analyze the relationship between productivity and wages separately for skilled and unskilled workers. To this end, we restrict the sample to establishments that employ workers of both types. The estimated coefficients indicate that more productive establishments pay higher wages to both skilled and unskilled workers, but particularly so for skilled workers. In consequence, more productive establishments pay higher skill premiums, as verified in Column (7). Taken together, these results imply that, as predicted by the model, the higher wages observed for more productive establishments result from the combination of (i) their higher share of skilled workers, and (ii) their higher pay conditional on worker skill.

One simplification embedded in the model in Section 2 for tractability purposes is that there are only two skill categories. In practice, of course, one could define worker skills much more granularly. The wage differences that we have documented in Columns (5) and (6) conditional on (broad) worker skill could potentially be driven by sorting along more granular skill dimensions. To determine whether this is the driving force behind the pattern in Columns (5) and (6), or whether more productive establishments pay higher wages also conditional on more granular skill measures, we run a set of AKM-style regressions using the individual-level wage data in order to obtain an estimate of the AKM establishment fixed effect (Abowd et al., 1999), which measures the establishment wage premium conditional on the composition of their workforce by including a full set of individual fixed effects. In order to allow for potentially heterogeneous wage policies across skill groups, we estimate the

[17] For the analysis in these two columns, establishments with no workers of a given type are imputed to have one part-time worker (i.e., 0.5 full-time equivalent workers) of that type in order to be able to compute log employment.

establishment fixed effects separately for skilled and unskilled workers.[18] Moreover, to allow for variation over time in establishment pay, we compute the AKM fixed effects separately for three 7-year windows: 1990-1996, 1996-2002 and 2002-2008. We then attach the estimated AKM fixed effects to the data corresponding to the years at the midpoint of each of these time windows, i.e. 1993, 1999 and 2005.

In Columns (8) and (9) of Table 1 we regress the estimated AKM fixed effects on (log) establishment productivity (as well as a full set of industry-year fixed effects) using the data for these three years.[19] The results indicate that more productive establishments pay higher premiums for each skill type, even after conditioning on workers' unobserved time-invariant characteristics. Hence, the fact that more productive establishments pay higher wages is not solely explained by workers' sorting on (non-match-specific) unobserved abilities.

Panel B of Table 1 performs an analogous set of regressions, but using log establishment size as the key regressor of interest. Column (1) confirms the positive and statistically significant relationship between establishment size and establishment productivity – in line with the evidence in Columns (1) and (2) of Panel A. In the remaining columns we are able to draw on the full BEH records and can therefore analyze the relationships using this much larger sample. The results show that larger firms pay higher average wages, partly because they employ a larger share of skilled workers, and partly because they pay higher wages conditional on skill (measured either in terms of our broad skill groups, or using individual fixed effects).

Overall, the patterns documented in Table 1 are in line with the equilibrium relationships implied by the model. Recall that these relationships occur within 3-digit industries and are thus not accounted for by differences across industries in establishment sizes, wages or productivities.

4.3 Associations over Time

We now explore the evidence for the predicted impacts of SBTC outlined in Section 2.3. The model predicts that ongoing SBTC should lead to a strengthening over time of the cross-sectional relationship between establishment productivity and size (Prediction 2), skilled worker shares (Prediction 3), and wages conditional on worker type (Prediction 4). To test whether these predictions hold in the data, we estimate the associations from Table 1 separately for each year, controlling for 3-digit industry fixed effects, thereby focusing once

[18]This is similar in spirit to the exercise of Card et al. (2016), who estimate firm fixed effects using Portuguese data, and allow these to differ between men and women. In our setting, we find establishment fixed effects for skilled and unskilled workers to be strongly positively correlated at 0.687.

[19]The sample is further restricted to establishments that are part of the connected set.

again on within-industry associations.

Figure 2 plots the coefficients from yearly regressions analogous to those in Panel A of Table 1, i.e. with log establishment productivity as the key regressor of interest. Each panel considers a different outcome variable. The results across all panels of Figure 2 show that these establishment-level relationships have indeed all become stronger over our sample period. In particular, as shown in Panel A, while in the early 1990s a 1% increase in the establishment's productivity was associated with an increase in establishment size of about 0.1%, the association had increased to more than 0.4% by 2010. Similarly, Panel B shows a strengthening of the relationship between productivity and skilled employment shares, which is indicative of increased sorting over time of skilled workers towards high-productivity establishments, albeit only weakly. Panel C shows that the coefficient from the regression of average establishment log wages on log labor productivity tripled from about 0.05 in the early 1990s to 0.15 by 2010. The association between (log) establishment productivity and establishment wages by worker type nearly tripled over the time period (Panels D and E). Panel F shows that the relationship between productivity and the skill premium at the establishment level also became stronger over time. Finally, the top two panels of Appendix Figure A.1 show that the association between productivity and the AKM establishment fixed effects for both worker types also strengthened over time.

Appendix Figure A.2 and the bottom two panels of Appendix Figure A.1 show the corresponding results when estimating the relationships from Panel B of Table 1, i.e. using log establishment size as the key regressor of interest, separately by year. The relationships between establishment size and establishment skill shares and wages have also become stronger over time within industries.

4.4 Longitudinal Changes within Establishments

In order to complement the evidence above, Table 2 analyzes longitudinal changes within establishments over (non-overlapping) 5-year windows. Panel A regresses changes in various establishment outcomes (conditional on survival) on baseline establishment size, plus a set of fully interacted 3-digit industry and year fixed effects. The results show that surviving establishments that are larger within their industry at baseline exhibit a larger increase in labor productivity, a larger increase in the employment share of skilled workers, higher wage growth overall and by worker type, and a larger increase in their AKM establishment fixed effects, by worker type.[20] In line with the predictions of the model, these results show that establishments that perform better at baseline (in terms of their size) pull away even further

[20]Note that our estimated AKM fixed effects are attached to the data for 1993, 1999 and 2005; therefore, Columns (6) and (7) are based on 6-year (rather than 5-year) windows.

from other establishments in their industry (in terms of their productivity, skilled worker share and the wages they pay). If viewed through the lens of the model, ongoing SBTC has amplified, rather than reduced, differences in productivity, skill usage and pay across establishments within industries.

Panel B provides further evidence of differential employment growth across establishments, considering also establishments that exit the market. This panel shows the results of a set of regressions that use within-establishment percentage changes in employment over 5-year windows as the dependent variable, and link these changes to various baseline establishment characteristics (controlling for a set of fully interacted 3-digit industry and year fixed effects).[21] Column (1) uses establishment productivity as the regressor of interest and confirms that establishments that are more productive at baseline (within their 3-digit industry) grow significantly more than less productive establishments in the industry. The remaining columns show that establishments with initially higher skill shares and establishments that pay higher wages at baseline – overall and conditional on worker skill – also exhibit significantly larger employment growth over subsequent years. This evidence is consistent with the idea that SBTC leads to differential establishment growth, shifting employment towards establishments that are more productive, more skill-intensive, and higher paying.

4.5 Segregation and Sorting

The patterns documented above are consistent with an increase in worker clustering by skill, driven by the increased sorting of skilled workers towards higher paying establishments. Figure 3 provides further evidence of these patterns.

Panel A plots the within-industry variance of establishments' skilled employment shares over time, averaged across industries using either the contemporaneous or the 1990 industry structure (see Appendix C.3 for details). The figure shows a clear increase in the variance of skilled employment shares across establishments within industries. Thus, rather than having converged towards a more uniform mode of production, establishments have become increasingly heterogeneous (within industries) in terms of the skill input mix that they use. Put differently, segregation by skill has increased across establishments within industries.

Panel B of Figure 3 explores the sorting of skilled workers towards high-paying establishments. We do this by analyzing the evolution of the within-industry covariance between establishments' skilled employment shares and the log wage of unskilled workers. While the skill share and the overall average wage in an establishment will be mechanically positively correlated due to the fact that skilled workers earn higher wages than unskilled workers, there

[21] As in Panel A, Columns (6) and (7) of Panel B are based on 6-year (rather than 5-year) windows, given the way in which we estimate the AKM fixed effects.

is no mechanical relationship between the skill share and the wage of unskilled workers. Our previous results indicate that establishments that pay high wages to unskilled workers also pay high wages to skilled workers. Hence, this covariance can be interpreted as a measure of the extent to which skilled workers sort into high-paying establishments.[22]

The figure plots the covariance using either the contemporaneous or the 1990 industry structure (see Appendix C.4 for details). The sharp rise over time in this covariance implies that skilled workers increasingly sort into establishments that pay high wages, while unskilled workers are increasingly clustered in low-paying establishments. Appendix Figure A.3 shows that we obtain similar results in terms of the covariance between the skill share and the AKM fixed effects for both types of workers.

The patterns in Figure 3 are consistent with the findings of Card et al. (2013) and Song et al. (2019), who show that high-wage workers increasingly sort into high-wage firms and that high-wage workers are increasingly likely to work with each other. Our model can rationalize these patterns as being driven by an aggregate SBTC shock.

4.6 Industry-Level Variation in Technology Adoption

In order to provide more direct evidence of the role of technological change in driving the patterns that we have documented, we leverage variation in the extent to which different industries have adopted new technologies. Specifically, we analyze whether the within-industry relationships between establishment productivity and other establishment outcomes that we have documented in Table 1 are stronger in industries that have been more exposed to technological change. To this end, we run a set of regressions of the following type:

$$y_{fkt} = \alpha_0 + \alpha_1 \ln Prod_{ft} + \alpha_2 \left(\ln Prod_{ft} \times Tech_k\right) + d_{kt} + \epsilon_{fkt}, \tag{4}$$

where f denotes an establishment, k an industry and t time. y_{fkt} is the establishment-level outcome of interest (employment by worker type, skill share, average wage, wage by worker type or skill premium). $Prod_{ft}$ denotes establishment productivity and $Tech_k$ is an industry-specific indicator variable which is equal to one for industries with a high exposure to skill-biased technological change. We describe this indicator variable in further detail below. d_{kt} is a set of industry-year fixed effects and ϵ_{fkt} is the error term. Standard errors are clustered at the establishment level. We are interested in the coefficient on the interaction term, α_2, which captures the differential within-industry relationship between productivity and outcome y_{fkt}

[22]In Appendix Figure A.3, we show that the covariance between the skill share and the wage of skilled workers is also positive and rising over time. We prefer to focus on the covariance with the wage of unskilled workers given that almost all establishments in our dataset have at least one full-time unskilled worker, while not all have at least one full-time skilled worker.

in industries that are more exposed to technological change. Following the predictions of the model, one would expect $\alpha_2 > 0$, i.e. the relationship between productivity and various establishment-level outcomes should be stronger in more technology-exposed industries.[23]

We consider three measures for $Tech_k$. First, we infer an industry's exposure to technological change indirectly, and classify industries with an above-median skill premium to be more exposed to technological change.[24] We additionally consider two more direct measures of technology exposure: one based on the industry's robot usage (operational stock), and one based on ICT capital stock per worker, using data from the International Federation of Robotics and from EUKLEMS, respectively.[25] Once again we divide industries into two groups, according to whether robot usage or ICT capital stock per worker is below or above the median.

Panel A of Table 3 shows the results based on the first indirect measure, the industry's skill premium. Estimates on the interaction term are positive and precisely estimated across the board, implying that the relationships documented in Table 1 are indeed more pronounced in industries where the skill premium is higher and which are thus more exposed to skill-biased technological change. Consistent with Prediction 2 of the model, in industries with higher skill premiums, more productive establishments are disproportionately larger relative to less productive establishments (Columns (1) and (2)). Moreover, the sorting of skilled workers to high productivity establishments is more pronounced in industries with higher skill premiums, which is in line with Prediction 3 of the model (Column (3)). Columns (4)-(6) show that in high-exposure industries, wages of skilled and unskilled workers are disproportionately higher in more productive establishment relative to less productive establishments, consistent with the differential wage growth channel implied by Prediction 4. In Column (7) we find a similar pattern for the skill premium, as also implied by Prediction 4. Finally, the last two columns show results based on the estimated AKM establishment fixed effects, and confirm that, in high exposure industries, highly productive establishment pay disproportionately higher premiums to both skill groups relative to less productive establishments, even after accounting fully flexibly for unobserved worker characteristics.

Panels B and C of Table 3 repeat the analysis using the more direct measures of technology exposure (robot usage and in ICT capital stock per worker). The estimates obtained on the

[23]Note that the industry-wide effect of technology adoption is absorbed by the industry-year fixed effects and hence the technology measure on its own is not included as a separate regressor in the estimation. All of the identifying variation is across establishments within industry-year cells.

[24]The median is computed using the employment distribution across industries in 1990 and is taken over the entire time period. This means that the median is fixed, while industries can switch between exposure groups depending on their yearly skill premium.

[25]Note that EUKLEMS data is only available at a more aggregated industry level and hence this analysis is based on 48 2-digit industries.

interaction term are broadly similar to those obtained in Panel A.

Overall, the results in Table 3 indicate that the associations between establishment productivity and establishment outcomes, such as size, skill shares, skill-specific wages and skill wage premiums, are more pronounced within industries that are more SBTC-intensive. In principle, however, these industries may also have been more exposed to other shocks, such as trade or offshoring, which may also have impacted these associations. To rule out this possibility as much as possible, in Appendix Table A.2 we re-estimate the regressions from Table 3, but add controls for industry-level measures of trade exposure and offshorability, interacted with establishment-level productivity.[26]

Our measure of trade captures the industry-level change between 1990 and 2010 in exports and imports per worker to and from China and Eastern Europe.[27] To measure offshorability we draw on data provided by Goos et al. (2014) on occupation-level offshorability and aggregate them up to the industry level using each industry's 1990 occupational structure. As shown in Appendix Table A.2, adding the interaction of these variables with productivity to Equation (4) has little impact on our coefficients of interest.

While these findings do not rule out the possibility that shocks other than SBTC have also contributed to the stronger associations between establishment productivity and establishment outcomes, they corroborate the importance of SBTC as a driver, even conditional on other shocks at the industry level.

To complement the evidence in Table 3, Panel A of Figure 4 shows that industries that experienced a larger change over time in their skill premiums, robot usage or ICT capital stock per worker also experienced a larger increase over time in between-establishment inequality, measured as the variance of establishment (log) wages.[28]

Panel B of Figure 4 further highlights that industries that adopt more technology over time also experience a stronger increase in the between-establishment variance of the employment share of skilled workers. Hence, establishments have become increasingly heterogeneous in their skill mix particularly in those industries that experienced a larger overall increase in technology adoption, and workers have become more segregated along skill dimensions within these industries.

Finally, Panel C provides evidence of larger increases in the sorting of skilled workers to

[26]Here again, the direct effect of trade exposure and offshorability at the industry level is absorbed by the industry-year fixed effects; instead, we are interested in controlling for the interaction terms, which capture the differential effects of these shocks across establishments with different productivity levels within industries.

[27]Trade data is obtained from the UN Comtrade Database.

[28]In the figure, we split industries in terms of whether they experienced above- or below-median changes in our three measures of technology exposure over time. The median is computed based on the employment distribution across industries in 1990.

high wage establishments (measured by the covariance between the share of skilled workers in the establishment and the establishment's wage paid to unskilled workers) in industries characterized by larger increases in technology adoption.

Overall, the results in Figure 4 provide strongly suggestive evidence of the role of SBTC in driving the rise of between-establishment wage inequality, segregation and sorting in the German economy during this 20-year period.

5 Conclusions

In this paper, we show that skill-biased technological change is an important driver of the rise in between-establishment wage inequality in Germany between 1990 and 2010. While a large literature has considered the role of skill-biased technological change for wage inequality, it has focused on representative firm frameworks with perfectly competitive labor markets and has hence had implications solely in terms of wage differentials *between* workers with different skill levels. Empirically, however, a major component of the increase in wage inequality is observed *within* skill groups, across establishments within industries.

By embedding a skill-biased technological change shock within a rich, yet tractable heterogeneous firm framework, we show that this type of shock will lead to heterogeneous responses at the firm level, thereby generating a rise in between-firm wage inequality. Using detailed administrative social security data from Germany, we document a number of novel empirical patterns at the establishment level, and show that these patterns are in line with the predictions of the model. The model highlights that an industry-wide skill-biased technological change shock will increase between-firm dispersion in skill shares, employment, and wages for each worker type, while also increasing the sorting of skilled workers to high-productivity and hence high-wage firms. We find that all of these channels are empirically relevant.

We also provide evidence that the key workplace-level patterns that we identify as being driven by the technological change shock are indeed more pronounced within industries more exposed to technological change, even when controlling for trade shocks and offshorability at the industry level.

Overall, our results point to the importance of moving beyond the traditional representative firm setting with competitive labor markets when considering the impact of aggregate shocks such as technological change. While the literature has generally thought about the individual-level impacts of skill-biased technological change as being related to the skills that individuals possess or the tasks that they perform (e.g. Cortes, 2016; Blien et al., 2021), our findings indicate that the type of firm that individuals are matched to is at least as important: Unskilled workers employed in low-productivity firms lose out not only relative to skilled workers in these firms, but also relative to unskilled workers in high-productivity firms. Understanding what type of policies can mitigate the negative impacts of technological change on some groups of workers, within the context of a more realistic environment with heterogeneous firms and various market frictions such as the ones considered in this paper, remains a crucial direction for future work.

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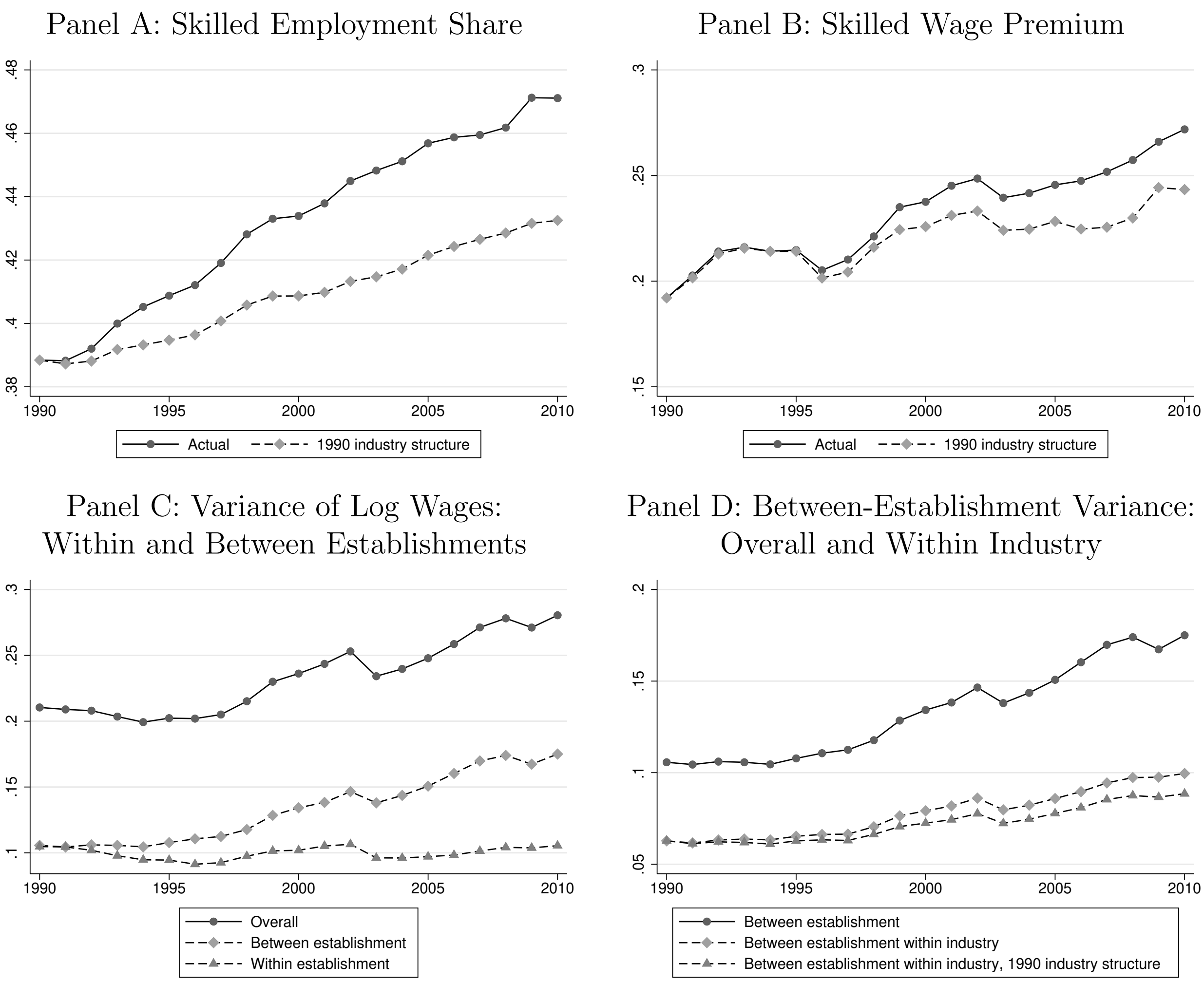
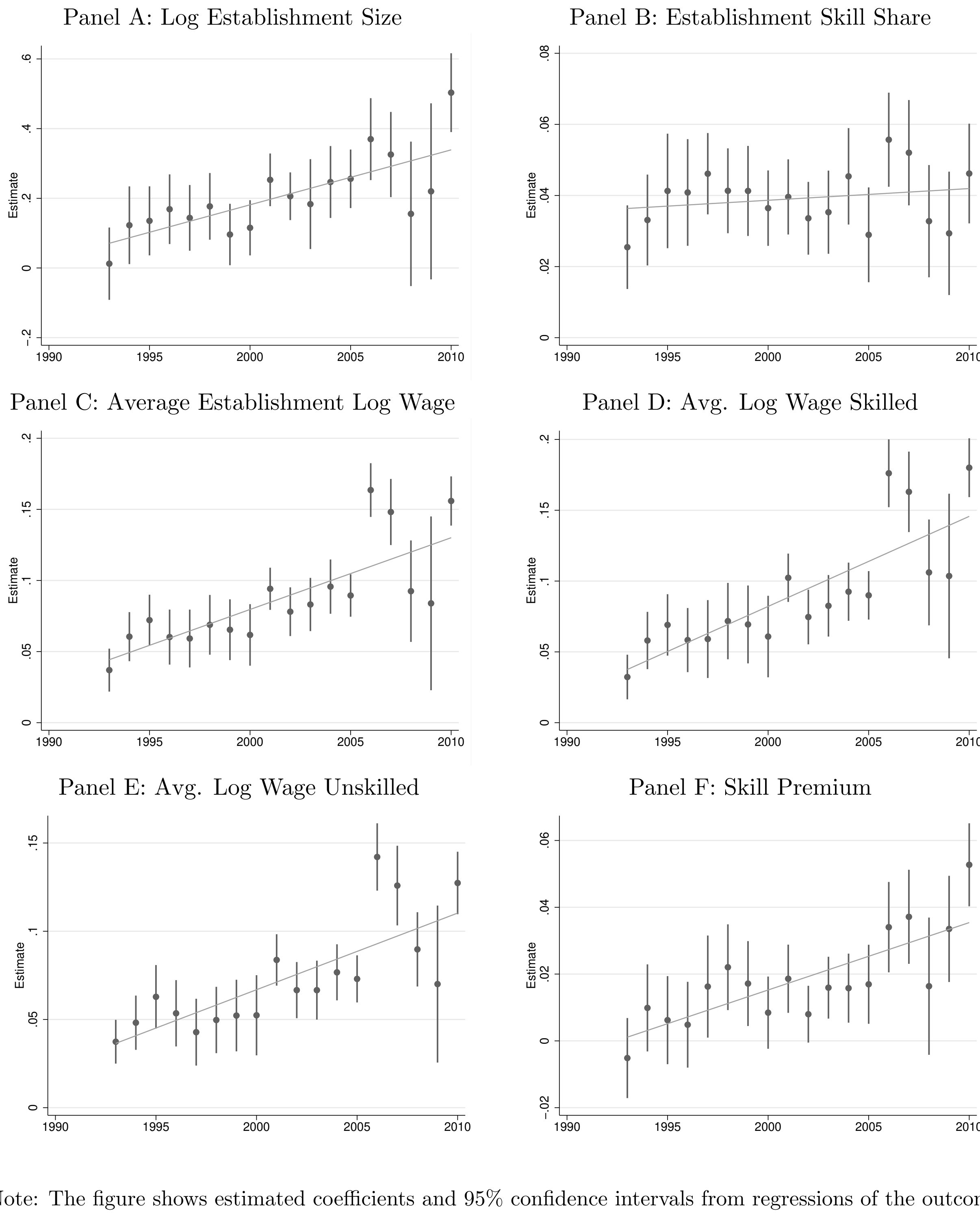
Figure 1: Aggregate Patterns over Time



Note: Panel A shows the evolution of the share of skilled workers in overall employment in Germany between 1990 and 2010 based on data from the Beschäftigtenhistorik (BEH). The solid line uses the contemporaneous industry structure in each year, while the dashed line fixes the industry composition using 1990 employment shares and therefore captures only changes in the skill composition of employment within industries. Panel B shows the evolution of the skilled wage premium, calculated as the difference between the average log wage of full-time skilled and unskilled workers in each year, using the actual or counterfactual 1990 industry structure (see Appendix C.1). Panel C displays the evolution of the overall variance of individual log wages and its within- and between-establishment components (see Appendix C.2). Panel D displays the overall and the within-industry between-establishment wage variance, computed using the actual and 1990 industry structure (see Appendix C.2).

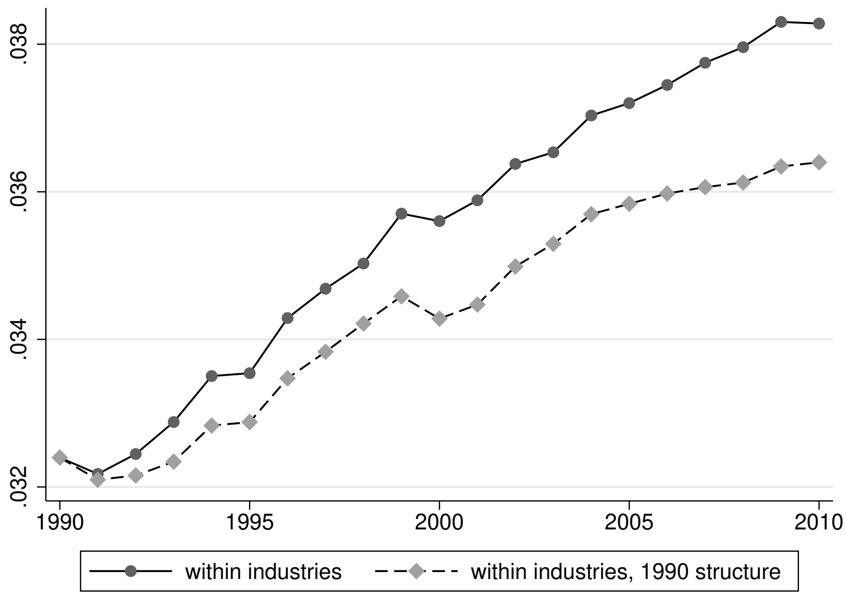
Figure 2: Year-by-Year Associations between Establishment Productivity and Other Establishment Characteristics



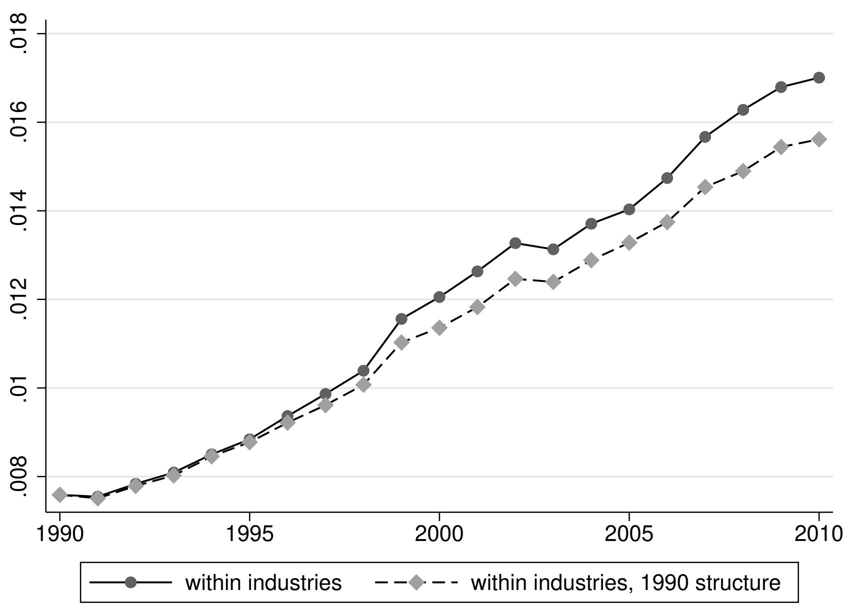
Note: The figure shows estimated coefficients and 95% confidence intervals from regressions of the outcome that appears in the title of each panel on log establishment productivity and a full set of 3-digit industry fixed effects, with the regressions estimated separately for each year. Results are based on establishments in the IABEP and observations are weighted by establishment size and survey weights.

Figure 3: Skilled Share Heterogeneity and Sorting

Panel A: Variance of Skilled Employment Shares



Panel B: Establishment-Level Covariance between Skill Share and Unskilled Worker Wage

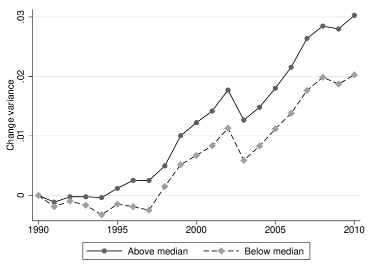


Note: Panel A shows the evolution of the variance of the skilled employment share across establishments within industries, averaging across industries using either observed industry employment shares in each year (solid line) or constant 1990 industry employment shares in all periods (dashed line); see Appendix C.3. Panel B shows the covariance between establishments' skilled employment shares and their average log unskilled worker wage; see Appendix C.4.

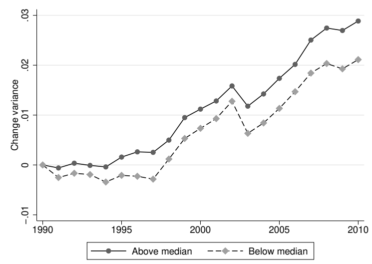
Figure 4: Industries with Below vs Above Median Changes in Technology Adoption

Panel A: Change in Variance of Establishment (log) Wages

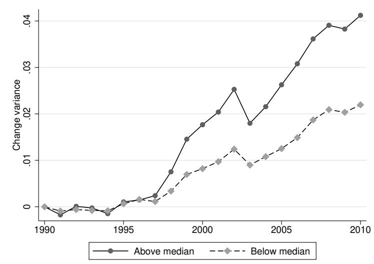
Increases in Skill Premium



Robot Adoption

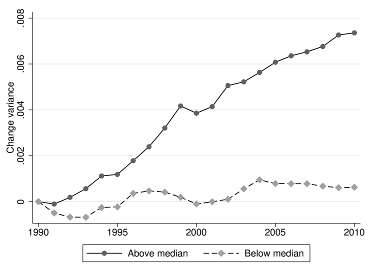


ICT Capital Adoption



Panel B: Change in Variance of Establishment Skill Shares

Increases in Skill Premium



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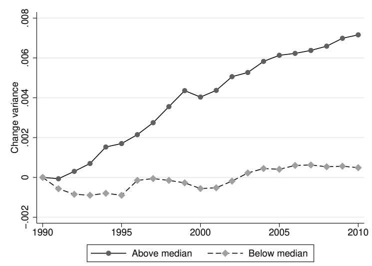

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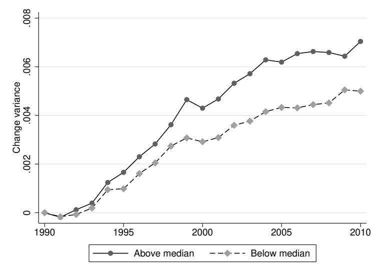
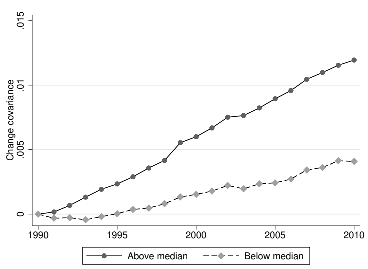
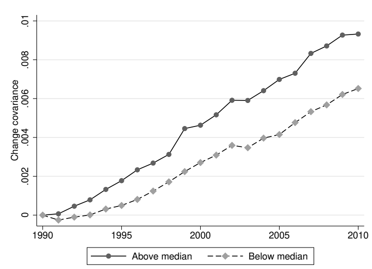


Panel C: Change in Covariance of Establishment Unskilled Wage and Skill Shares

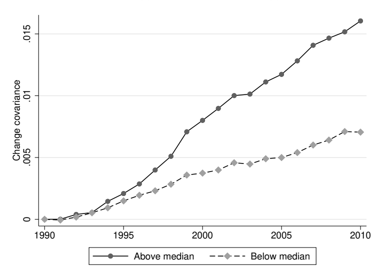
Increases in Skill Premium



Robot Adoption



ICT Capital Adoption



Note: The figures contrast the evolution of the variance of average establishment (log) wages (Panel A), the variance of establishments' skilled employment shares (Panel B), and the covariance between establishments' skilled employment shares and average unskilled (log) wages (Panel C) for industries with below and above median changes in the skill premium between 1990 and 2010 based on 196 3-digit industries (Column 1), changes in robot usage per worker between 1993 and 2010 based on 193 3-digit industries and data from the International Federation of Robotics (Column 2), and changes in ICT capital per worker between 1991 and 2007 based on 48 2-digit industries and EUKLEMS data (Column 3). We average across industries using the 1990 industry employment structure as weights.

Table 1: Cross-Sectional Relationships between Productivity, Skill Shares and Wages

Panel A: Relationship with (Log) Productivity

	Log Skilled Workers	Log Unskilled Workers	Skilled Share	Avg. Log wage	Avg. Log Wage Skilled	Avg. Log Wage Unskilled	Skill Premium	AKM FE Skilled	AKM FE Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Prod.	0.32***	0.13***	0.038***	0.082***	0.085***	0.068***	0.017***	0.024***	0.027***
	(0.029)	(0.025)	(0.0031)	(0.0051)	(0.0062)	(0.0047)	(0.0028)	(0.0033)	(0.0035)
N	87,050	87,050	87,050	87,050	65,838	65,838	65,838	8,353	8,353

Panel B: Relationship with Establishment Size

	Productivity	Skilled Share	Avg. Log wage	Avg. Log Wage Skilled	Avg. Log Wage Unskilled	Skill Premium	AKM FE Skilled	AKM FE Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Size	0.047***	0.00051	0.078***	0.091***	0.056***	0.035***	0.032***	0.031***
	(0.0056)	(0.00059)	(0.00068)	(0.00094)	(0.00068)	(0.00053)	(0.00045)	(0.00048)
N	87,050	26,895,758	26,895,758	10,200,126	10,200,126	10,200,126	955,759	955,759

Note: All regressions include a set of fully interacted 3-digit industry and year fixed effects. Productivity is measured as total sales per full-time equivalent worker using sales data from the IABEP and employment data from the BEH. For Columns (1) and (2) of Panel A, establishments with no workers of a given type are imputed to have one part-time workers (i.e. 0.5 full-time equivalent workers) of that type in order to be able to compute log employment. All columns in Panel A and Column (1) in Panel B are based on establishments observed in the IABEP; observations are weighted by establishment size and survey weights. All other columns of Panel B are based on establishments observed in the full BEH data, and observations are weighted by establishment size. AKM establishment fixed effects by worker type are computed for the periods 1990–1996, 1996–2002 and 2002–2008, separately for skilled and unskilled workers, and attached to the data corresponding to the years at the midpoint of each of these time windows, i.e. 1993, 1999 and 2005. Standard errors are clustered at the establishment level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Baseline Establishment Characteristics and Within-Establishment Changes

Panel A: Baseline Establishment Size and Longitudinal Changes in Other Outcomes

	Dependent Variable:						
	Δ Estab Productivity	Δ Skilled Share	Δ Avg. Log Wage	Δ Avg. Log Wage Skilled	Δ Avg. Log Wage Unsk	Δ AKM FE Skilled	Δ AKM FE Unsk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estab size at baseline	0.032***	0.0048***	0.0081***	0.0073***	0.0071***	0.0030***	0.0044***
	(0.0096)	(0.00035)	(0.00036)	(0.00037)	(0.00051)	(0.00037)	(0.00034)
N	5,468	3,467,093	3,467,093	1,219,112	1,219,112	318,465	318,465

Panel B: Baseline Establishment Characteristics and Longitudinal Changes in Size

	Dependent Variable: Δ Employment (Incl. Exits)						
	Independent Variable: Baseline Level of ...						
	Estab Productivity	Skilled Share	Avg. Log Wage	Avg. Log Wage Skilled	Avg. Log Wage Unsk	AKM FE Skilled	AKM FE Unsk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\hat{\beta}$	0.050***	0.12***	0.11***	0.014***	0.066***	0.045***	0.040***
	(0.0083)	(0.0063)	(0.0042)	(0.0037)	(0.0049)	(0.0098)	(0.013)
N	15,816	5,123,787	5,123,787	1,941,157	1,941,157	619,444	619,444

Note: All regressions include a set of fully interacted 3-digit industry and year fixed effects. Panel A shows estimated coefficients from regressions of within-establishment changes in the outcome variable shown in each column of the table on baseline establishment size (log employment), conditioning on surviving establishments. Panel B shows estimated coefficients from regressions of the within-establishment percentage change over time in employment (including exiting establishment) on the baseline establishment characteristic shown in each column. Within-establishment changes are taken over non-overlapping 5-year windows from 1990 to 2010 in Columns (1) to (5), and over non-overlapping 6-year windows from 1993 to 2005 in Columns (6) and (7). With the exception of Column (1), results are based on establishments in the full BEH data, and observations are weighted by establishment size. Column (1) uses establishments in the IABEP; productivity is measured as total sales per full-time equivalent worker (in logs), and observations are weighted by establishment size and survey weights. Standard errors are clustered at the establishment level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Heterogeneous Impacts of Technology Adoption

	Log Skilled Workers	Log Unskilled Workers	Skill Share	Avg. Log Wage	Avg. Log Wage Skilled	Avg. Log Wage Unskilled	Skill Premium	AKM FE Skilled	AKM FE Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Industry Skill Premium									
Log Productivity	0.19***	0.069**	0.025***	0.054***	0.052***	0.043***	0.0095***	0.012***	0.014***
	(0.034)	(0.03)	(0.0036)	(0.0062)	(0.0074)	(0.0056)	(0.0035)	(0.0036)	(0.0038)
Log Productivity ×	0.33***	0.16***	0.033***	0.072***	0.085***	0.065***	0.020***	0.036***	0.040***
High Tech Ind	(0.055)	(0.05)	(0.0061)	(0.0087)	(0.01)	(0.008)	(0.0053)	(0.0064)	(0.0067)
N	87050	87050	87050	87050	65838	65838	65838	8353	8353
Panel B: Industry Robot Usage									
Log Productivity	0.14***	-0.012	0.033***	0.052***	0.049***	0.042***	0.0065**	0.012***	0.016***
	(0.032)	(0.029)	(0.0039)	(0.0059)	(0.0069)	(0.0053)	(0.0032)	(0.0034)	(0.0038)
Log Productivity ×	0.56***	0.45***	0.017***	0.091***	0.11***	0.078***	0.033***	0.047***	0.044***
High Tech Ind	(0.053)	(0.049)	(0.0059)	(0.0083)	(0.01)	(0.0078)	(0.0054)	(0.0072)	(0.0065)
N	86177	86177	86177	86177	65131	65131	65131	8273	8273
Panel C: Industry ICT Capital									
Log Productivity	0.26***	0.079**	0.036***	0.046***	0.051***	0.035***	0.016***	0.015***	0.020***
	(0.046)	(0.035)	(0.0051)	(0.0071)	(0.0096)	(0.0065)	(0.0047)	(0.0044)	(0.0049)
Log Productivity ×	0.092*	0.080*	0.0062	0.064***	0.055***	0.057***	-0.0025	0.021***	0.016**
High Tech Ind	(0.054)	(0.047)	(0.006)	(0.0087)	(0.011)	(0.0081)	(0.0056)	(0.0063)	(0.0067)
N	71914	71914	71914	71914	55271	55271	55271	8353	8353

Note: All regressions include a set of fully interacted 3-digit industry and year fixed effects. ‘High Tech Ind’ is an indicator variable for technology adoption at the industry level and is equal to one in a given year if the industry skill premium (Panel A), robot usage (Panel B) or ICT usage (Panel C) is above the median for the time period considered (1990-2010 for the skill premium, 1993-2010 for robot usage and 1991-2007 for ICT usage). AKM establishment fixed effects by worker type are computed for the periods 1990–1996, 1996–2002 and 2002–2008, separately for skilled and unskilled workers. Results are based on establishments in the IABEP, and observations are weighted by establishment size and survey weights. Standard errors are clustered at the establishment level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix for:

Technological Change, Firm Heterogeneity and Wage Inequality

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Adrian Lerche (LMU Munich and IAB)
Uta Schönberg (University College London and IAB)
Jeanne Tschopp (University of Bern)

Appendix A Model

This section contains details of the model and of derivations that were omitted in the main text. The presentation is not necessarily self-contained but rather complementary with Section 2 of the paper. We also refer the reader to Section 5.4 of the technical appendix of Helpman et al. (2010) for more details on the model with a CES production function and two types of workers.

For the derivations below, it is useful to note that $\varphi(\theta)$ and $\phi_\ell(\theta)$, where $\ell \in \{s, r\}$, are defined as follows:

$$\varphi(\theta) \equiv \frac{\mu_s^\nu \left(\theta \overline{a}_s h_s^\gamma\right)^\nu}{\left(\overline{a}_r h_r^\gamma\right)^\nu}, \qquad \phi_s(\theta) \equiv \frac{\varphi(\theta)}{1+\varphi(\theta)}, \qquad \phi_r(\theta) \equiv \frac{1}{1+\varphi(\theta)}. \tag{A.1}$$

A.1 Derivations of the Key Equilibrium Relationships

This section derives the equilibrium relationships for the variables which play a crucial role when examining the impact of skill-biased technological change on wage inequality.

A.1.1 Firm-level Equilibrium Variables

Below we use the following first-order conditions from the profit maximization problem to derive firm-level equilibrium revenue, employment and wages by skill:

$$\frac{\beta\gamma}{1+\beta\gamma}\phi_\ell(\theta) r(\theta) = b_\ell n_\ell(\theta) \tag{A.2}$$

$$\frac{\beta(1-\gamma k)}{1+\beta\gamma}\phi_\ell(\theta) r(\theta) = c\widetilde{a}_\ell(\theta)^\delta \tag{A.3}$$

Revenue As Helpman et al. (2010) mention in Appendix 5.4 footnote 1, revenue can be expressed as:

$$r(\theta) = \kappa_y^{\beta} A \left[1 + \varphi(\theta)\right]^{\beta/\nu} \left[\widetilde{a}_r(\theta)^{1-k\gamma} n_r(\theta)^{\gamma}\right]^{\beta}, \tag{A.4}$$

where A is a sectoral demand shifter and $\kappa_y \equiv \frac{k a_{min}^{\gamma k}}{k-1}$. Using the first-order conditions along with equation (A.4) and the definition of ϕ_r, one obtains the revenue equation:

$$r(\theta) = \kappa_r \left[1 + \varphi(\theta)\right]^{\frac{\beta\Lambda}{\nu\Gamma}}, \tag{A.5}$$

where $\Lambda \equiv 1 - \nu\gamma - \nu(1-\gamma k)/\delta > 0$, $\Gamma \equiv 1 - \beta\gamma - \beta(1-\gamma k)/\delta > 0$, and $\Lambda > \Gamma$ due to the assumption that $\nu < \beta$. κ_r is equivalent to:

$$\kappa_r \equiv A^{1/\Gamma} \left[\kappa_y \left(\frac{\beta}{1+\beta\gamma}\right)^{\frac{1-k\gamma}{\delta}+\gamma} \left(\frac{1-\gamma k}{c}\right)^{\frac{1-k\gamma}{\delta}} \left(\frac{\gamma}{b_r}\right)^{\gamma}\right]^{\beta/\Gamma}. \tag{A.6}$$

Employment by skill and the employment share of skilled workers To obtain firm-level employment, note that from equation (A.2):

$$\begin{aligned} n_r(\theta) &= \frac{\beta\gamma}{1+\beta\gamma}\left[1+\varphi(\theta)\right]^{-1} b_r^{-1} r(\theta) \\ &= \left(\frac{\beta\gamma}{1+\beta\gamma}\right) b_r^{-1}\kappa_r \left[1+\varphi(\theta)\right]^{\frac{\beta-\nu}{\nu\Gamma}}, \end{aligned} \tag{A.7}$$

where $\frac{\beta-\nu}{\nu\Gamma} = \frac{\beta\Lambda}{\nu\Gamma} - 1 > 0$, and from equation (A.3):

$$\begin{aligned} \widetilde{a}_r(\theta) &= \left\{\frac{\beta(1-\gamma k)}{1+\beta\gamma}\left[1+\varphi(\theta)\right]^{-1} c^{-1} r(\theta)\right\}^{1/\delta} \\ &= \left[\frac{\beta(1-\gamma k)}{1+\beta\gamma}\right]^{1/\delta} c^{-1/\delta}\kappa_r^{1/\delta}\left[1+\varphi(\theta)\right]^{\frac{\beta-\nu}{\delta\nu\Gamma}}. \end{aligned} \tag{A.8}$$

Using expression $h_\ell(\theta) = n_\ell(\theta)\left(\frac{a_{min}}{\widetilde{a}_\ell(\theta)}\right)^k$, along with (A.7) and (A.8), we have that:

$$\begin{aligned} h_r(\theta) &= n_r(\theta)\left(\frac{a_{min}}{\widetilde{a}_r(\theta)}\right)^k \\ &= \left(\frac{\beta\kappa_r}{1+\beta\gamma}\right)^{1-k/\delta}\left(\frac{c}{1-\gamma k}\right)^{k/\delta} b_r^{-1} a_{min}^k \left[1+\varphi(\theta)\right]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)} && \text{(A.9)} \\ &= h_{dr}\left[1+\varphi(\theta)\right]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)}, && \text{(A.10)} \end{aligned}$$

where:

$$h_{dr} \equiv \left(\frac{\beta\kappa_r}{1+\beta\gamma}\right)^{1-k/\delta}\left(\frac{c}{1-\gamma k}\right)^{k/\delta} b_r^{-1} a_{min}^{k}. \tag{A.11}$$

Proceeding in a similar way for firm-level employment of skilled workers, we obtain:

$$h_s(\theta) = \frac{b_r}{b_s}\varphi(\theta)^{1-k/\delta} h_r(\theta), \tag{A.12}$$

and it follows that the firm's employment share of skilled workers is given by:

$$\frac{h_s(\theta)}{h(\theta)} = \frac{b_r\varphi(\theta)^{1-k/\delta}}{b_s + b_r\varphi(\theta)^{1-k/\delta}}, \tag{A.13}$$

where $h(\theta) = h_s(\theta) + h_r(\theta)$.

Wages by skill To derive equilibrium firm-level wages by skill, it is useful to note that the solution of the Stole and Zwiebel bargaining game takes the following form:

$$w_\ell(\theta) = \frac{\beta\gamma}{1+\beta\gamma}\frac{\phi_\ell(\theta)r(\theta)}{h_\ell(\theta)} \tag{A.14}$$

Using (A.14) along with (A.4) and (A.10), we have that firm wages of unskilled workers are given by:

$$\begin{aligned} w_r(\theta) &= \frac{\beta\gamma}{1+\beta\gamma}\phi_r(\theta)\frac{r(\theta)}{h_r(\theta)} \\ &= \left(\frac{\beta\gamma}{1+\beta\gamma}\right)\left(\frac{\kappa_r}{h_{dr}}\right)\left[1+\varphi(\theta)\right]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{k}{\delta}} &\text{(A.15)} \\ &= w_{dr}\left[1+\varphi(\theta)\right]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{k}{\delta}}, &\text{(A.16)} \end{aligned}$$

where:

$$w_{dr} \equiv \left(\frac{\beta\gamma}{1+\beta\gamma}\right)\left(\frac{\kappa_r}{h_{dr}}\right). \tag{A.17}$$

Proceeding in a similar way for firm-level wages of skilled workers, we obtain:

$$w_s(\theta) = \frac{b_s}{b_r}\varphi(\theta)^{k/\delta} w_r(\theta). \tag{A.18}$$

Finally, combining the definition of $\varphi(\theta)$ together with the first-order conditions of the profit maximization problem, we obtain:

$$\varphi(\theta) = \mu_s^{\nu/\Lambda} \left(\frac{b_s}{b_r}\right)^{-\gamma\nu/\Lambda} \theta^{\nu/\Lambda}. \tag{A.19}$$

Hence, $\varphi(\theta)$ only depends on firm productivity and parameters.

A.1.2 Determination of the Productivity Threshold

As is standard in Melitz-type heterogeneous firm models, the productivity threshold for production, θ_d, is pinned down by both the Zero-Cutoff Profit (ZCP) and the Free Entry (FE) conditions.

The ZCP condition, which requires that the firm at the cutoff θ_d makes zero profits, implies:[1]

$$\frac{\Gamma}{1+\beta\gamma} r(\theta_d) = f_d. \tag{A.20}$$

Moreover, given equation (A.5), relative revenues across two firms with productivities θ_1 and θ_2 can be written as:

$$\frac{r(\theta_1)}{r(\theta_2)} = \left[\frac{1+\varphi(\theta_1)}{1+\varphi(\theta_2)}\right]^{\frac{\beta\Lambda}{\nu\Gamma}}. \tag{A.21}$$

Combining equation (A.21) along with the ZCP condition (A.20) we obtain:

$$r(\theta) = f_d \left(\frac{\Gamma}{1+\beta\gamma}\right)^{-1} \left[\frac{1+\varphi(\theta)}{1+\varphi(\theta_d)}\right]^{\frac{\beta\Lambda}{\nu\Gamma}}. \tag{A.22}$$

The FE condition states that the expected profits for a potential entrant should equal the fixed entry cost:

$$\int_{\theta_d}^{\infty} \pi(\theta) dG(\theta) = f_e. \tag{A.23}$$

Therefore, combining equations (A.22) and (A.23) implies:

$$f_d \int_{\theta_d}^{\infty} \left(\left[\frac{1+\varphi(\theta)}{1+\varphi(\theta_d)}\right]^{\frac{\beta\Lambda}{\nu\Gamma}} - 1 \right) dG(\theta) = f_e. \tag{A.24}$$

Equation (A.24) pins down the equilibrium threshold θ_d as a function of the parameters of the model and the search costs b_s and b_r.

[1]This is obtained by noting that profits can be written as:

$$\pi(\theta) = \frac{\Gamma}{1+\beta\gamma} r(\theta) - f_d.$$

A.2 Relationship between Firm-Specific Equilibrium Outcomes and θ

This section presents the proofs for the results in Equations (2) and (3).

First, note that:

$$\frac{\partial \varphi(\theta)}{\partial \theta} = \frac{\nu}{\Lambda} \mu_s^{\frac{\nu}{\Lambda}} \left(\frac{b_s}{b_r}\right)^{-\frac{\gamma\nu}{\Lambda}} \theta^{\frac{\nu}{\Lambda}-1} \quad > \quad 0, \tag{A.25}$$

and recall that $\beta > \nu$, $\Lambda > \Gamma$ and $\delta > k$ such that $\frac{\beta-\nu}{\nu\Gamma} > 0$ and $1 - \frac{k}{\delta} > 0$.

Proof of Equation (2): Taking the derivative of equations (A.10) and (A.12), we obtain:

$$\begin{aligned} \frac{\partial h_r(\theta)}{\partial \theta} &= h_{dr} \left(\frac{\beta-\nu}{\nu\Gamma}\right) \left(1 - \frac{k}{\delta}\right) [1+\varphi(\theta)]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)-1} \cdot \frac{\partial \varphi(\theta)}{\partial \theta} && > \quad 0 \\ \frac{\partial h_s(\theta)}{\partial \theta} &= \frac{b_r}{b_s} \left[\left(1 - \frac{k}{\delta}\right) \varphi(\theta)^{-\frac{k}{\delta}} \cdot \frac{\partial \varphi(\theta)}{\partial \theta} \cdot h_r(\theta) + \varphi(\theta)^{1-\frac{k}{\delta}} \cdot \frac{\partial h_r(\theta)}{\partial \theta}\right] && > \quad 0 \end{aligned} \tag{A.26}$$

Taking the derivative of equation (A.13), we have that:

$$\frac{\partial}{\partial \theta}\left[\frac{h_s(\theta)}{h(\theta)}\right] = \frac{b_s b_r \left(1-\frac{k}{\delta}\right) \varphi(\theta)^{-\frac{k}{\delta}} \cdot \frac{\partial \varphi(\theta)}{\partial \theta}}{\left[b_s + b_r \varphi(\theta)^{1-\frac{k}{\delta}}\right]^2} \quad > \quad 0 \tag{A.27}$$

Proof of Equation (3): Taking the derivative of equations (A.16) and (A.18), and of the ratio of the two, we obtain:

$$\begin{aligned} \frac{\partial w_r(\theta)}{\partial \theta} &= w_{dr} \left(\frac{\beta-\nu}{\nu\Gamma}\right) \frac{k}{\delta} [1+\varphi(\theta)]^{\left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{k}{\delta}-1} \cdot \frac{\partial \varphi(\theta)}{\partial \theta} && > \quad 0 \\ \frac{\partial w_s(\theta)}{\partial \theta} &= \frac{b_s}{b_r} \left[\frac{k}{\delta} \varphi(\theta)^{\frac{k}{\delta}-1} \cdot \frac{\partial \varphi(\theta)}{\partial \theta} \cdot w_r(\theta) + \varphi(\theta)^{\frac{k}{\delta}} \cdot \frac{\partial w_r(\theta)}{\partial \theta}\right] && > \quad 0 \\ \frac{\partial}{\partial \theta}\left[\frac{w_s(\theta)}{w_r(\theta)}\right] &= \frac{b_s}{b_r} \frac{k}{\delta} \varphi(\theta)^{\frac{k}{\delta}-1} \cdot \frac{\partial \varphi(\theta)}{\partial \theta} && > \quad 0 \end{aligned} \tag{A.28}$$

A.3 Impact of Skill-Biased Technological Change

In order to evaluate how skill-biased technological change (SBTC) – modelled as an increase in the parameter μ_s – affects firms differentially across the productivity distribution, we examine the second-order derivative of firm outcome variables, with respect to both the common skill-augmenting technology parameter μ_s and firm productivity. To this end note that:

$$\frac{\partial\varphi(\theta)}{\partial\mu_s} = \frac{\nu}{\Lambda}\mu_s^{-1}\varphi(\theta) \;>\; 0 \;, \qquad \frac{\partial^2\varphi(\theta)}{\partial\mu_s\partial\theta} = \left(\frac{\nu}{\Lambda}\right)^2\mu_s^{-1}\theta^{-1}\varphi(\theta) \;>\; 0 \;, \tag{A.29}$$

and

$$\frac{\partial\varphi(\theta)}{\partial\mu_s}\cdot\frac{\partial\varphi(\theta)}{\partial\theta} = \varphi(\theta)\cdot\frac{\partial^2\varphi(\theta)}{\partial\mu_s\partial\theta} > 0 \;. \tag{A.30}$$

Prediction 1: *Increased Skilled Wage Premium* – SBTC increases the skilled wage premium within all firms, and in the aggregate.

Proof: Taking the first-order derivative of (A.16), we have:

$$\frac{\partial}{\partial\mu_s}\left[\frac{w_s(\theta)}{w_r(\theta)}\right] \;=\; \frac{k\nu}{\delta\Lambda}\mu_s^{-1}\frac{w_s(\theta)}{w_r(\theta)} \;>\; 0 \tag{A.31}$$

Prediction 2: *Differential Employment Growth* – SBTC strengthens the cross-sectional relationship between employment and productivity.

Proof: Taking the first- and second-order derivatives of (A.10) and (A.12), we obtain:

$$\frac{\partial h_r(\theta)}{\partial\mu_s} = \left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)h_r(\theta)\left[1+\varphi(\theta)\right]^{-1}\frac{\nu}{\Lambda}\mu_s^{-1}\varphi(\theta)$$

$$\frac{\partial^2 h_r(\theta)}{\partial\mu_s\partial\theta} = \left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)h_r(\theta)\left[1+\varphi(\theta)\right]^{-2}\cdot\frac{\partial^2\varphi(\theta)}{\partial\mu_s\partial\theta}\left[1+\varphi(\theta)\left(\frac{\beta-\nu}{\nu\Gamma}\right)\left(1-\frac{k}{\delta}\right)\right] \;>\; 0$$

$$\frac{\partial h_s(\theta)}{\partial\mu_s} = \frac{\nu}{\Lambda}\mu_s^{-1}\left(1-\frac{k}{\delta}\right)\left[1+\left(\frac{\beta-\nu}{\nu\Gamma}\right)\cdot\frac{\varphi(\theta)}{1+\varphi(\theta)}\right]h_s(\theta)$$

$$\frac{\partial^2 h_s(\theta)}{\partial\mu_s\partial\theta} = \frac{\nu}{\Lambda}\mu_s^{-1}\left(1-\frac{k}{\delta}\right)\left\{\frac{\beta-\nu}{\nu\Gamma}\left[1+\varphi(\theta)\right]^{-2}\frac{\partial\varphi(\theta)}{\partial\theta}h_s(\theta)+\left[1+\left(\frac{\beta-\nu}{\nu\Gamma}\right)\cdot\frac{\varphi(\theta)}{1+\varphi(\theta)}\right]\frac{\partial h_s(\theta)}{\partial\theta}\right\} > 0$$

Hence, SBTC disproportionately increases employment of skilled and unskilled workers in more productive firms, relative to less productive firms.

Prediction 3: *Increased Sorting and Segregation by Skill* – SBTC strengthens the cross-sectional relationship between productivity and skilled employment shares, provided that firms employ relatively more unskilled than skilled workers at baseline (the empirically relevant case).

Proof: Taking the first-order derivative of (A.13) we get:

$$\frac{\partial}{\partial \mu_s}\left[\frac{h_s(\theta)}{h(\theta)}\right] = b_s\left(1-\frac{k}{\delta}\right)\frac{\nu}{\Lambda}\mu_s^{-1}\cdot\frac{1}{b_s+b_r\varphi(\theta)^{1-\frac{k}{\delta}}}\cdot\frac{h_s(\theta)}{h(\theta)}$$

The second-order derivative yields:

$$\frac{\partial^2}{\partial \mu_s \partial\theta}\left[\frac{h_s(\theta)}{h(\theta)}\right] = \frac{1}{\left[b_s+b_r\varphi(\theta)^{1-\frac{k}{\delta}}\right]^3}\left(1-\frac{k}{\delta}\right)\varphi(\theta)^{-\frac{k}{\delta}}\frac{\partial\varphi(\theta)}{\partial\theta}\left[b_s-b_r\varphi(\theta)^{1-\frac{k}{\delta}}\right]$$

Given that the ratio of skilled to unskilled workers is $h_s(\theta)/h_r(\theta) = \frac{b_r}{b_s}\varphi(\theta)^{1-\frac{k}{\delta}}$, the term $\left[b_s-b_r\varphi(\theta)^{1-\frac{k}{\delta}}\right]$ is positive if $h_s(\theta)/h_r(\theta) < 1$ and negative if $h_s(\theta)/h_r(\theta) > 1$. Therefore,

$$\frac{\partial^2}{\partial \mu_s \partial\theta}\left[\frac{h_s(\theta)}{h(\theta)}\right] \quad > \quad 0 \quad \text{if} \quad \frac{h_s(\theta)}{h_r(\theta)} < 1 \tag{A.32}$$

Prediction 4: *Differential Wage Growth* – SBTC strengthens the cross-sectional relationship between productivity and wages conditional on worker skill, as well as between productivity and the skill premium.

Proof: Taking the first- and second-order derivatives of (A.16) we obtain:

$$\begin{aligned}
\frac{\partial w_r(\theta)}{\partial \mu_s} &= \left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{k\nu}{\delta\Lambda}\mu_s^{-1}w_r(\theta)\frac{\varphi(\theta)}{1+\varphi(\theta)} \\
\frac{\partial^2 w_r(\theta)}{\partial \mu_s\partial\theta} &= \left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{k\nu}{\delta\Lambda}\mu_s^{-1}\frac{1}{1+\varphi(\theta)}\left[\varphi(\theta)\frac{\partial w_r(\theta)}{\partial\theta}+\frac{w_r(\theta)}{1+\varphi(\theta)}\cdot\frac{\partial\varphi(\theta)}{\partial\theta}\right] \quad > \quad 0
\end{aligned}$$

Hence, SBTC disproportionately increases the wages of unskilled workers in more productive firms, relative to less productive firms.

Similarly, taking the derivatives of (A.18):

$$
\begin{aligned}
\frac{\partial w_s(\theta)}{\partial \mu_s} &= \frac{k\nu}{\delta\Lambda}\mu_s^{-1} w_s(\theta)\left[1+\left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{\varphi(\theta)}{1+\varphi(\theta)}\right] \\
\frac{\partial^2 w_s(\theta)}{\partial \mu_s \partial\theta} &= \frac{k\nu}{\delta\Lambda}\mu_s^{-1}\left\{\frac{\partial w_s(\theta)}{\partial\theta}\left[1+\left(\frac{\beta-\nu}{\nu\Gamma}\right)\frac{\varphi(\theta)}{1+\varphi(\theta)}\right]+w_s(\theta)\left(\frac{\beta-\nu}{\nu\Gamma}\right)[1+\varphi(\theta)]^{-2}\frac{\partial\varphi(\theta)}{\partial\theta}\right\} > 0
\end{aligned}
$$

Thus, the wages of skilled workers increase disproportionately in more productive firms (relative to less productive firms) as a result of SBTC.

Finally, taking the derivatives of (A.31) with respect to productivity we obtain:

$$
\frac{\partial^2}{\partial \mu_s \partial\theta}\left[\frac{w_s(\theta)}{w_r(\theta)}\right] = \frac{k\nu}{\delta\Lambda}\mu_s^{-1}\frac{\partial}{\partial\theta}\left[\frac{w_s(\theta)}{w_r(\theta)}\right] > 0
$$

Thus, the skill premium increases disproportionately in more productive firms (relative to less productive firms) as a result of SBTC.

Prediction 5: *Selection* – SBTC increases the productivity threshold for production θ_d.

Proof: We prove Prediction 5 by contradiction. Consider equation (A.24), which pins down the equilibrium threshold as a function of parameters of the model:

$$
f_d\int_{\theta_d}^{\infty}\left(\left[\frac{1+\varphi(\theta)}{1+\varphi(\theta_d)}\right]^{\frac{\beta\Lambda}{\nu\Gamma}}-1\right)dG(\theta)=f_e \tag{A.33}
$$

Suppose first that SBTC has no effect on θ_d. Holding θ_d fixed, the increase in $[1+\varphi(\theta)]/[1+\varphi(\theta_d)]$ induced by the increase in μ_s would imply an increase in the term in the square brackets for all relevant values of θ evaluated in the integral. Hence, with a fixed θ_d the LHS of equation (A.33) would increase while the RHS would remain fixed. This implies that θ_d cannot remain constant if μ_s increases.

Suppose now that θ_d falls as a reaction to the increase in μ_s. This would lead to a further increase in the value of the term in the square brackets for all relevant values of θ (as there would now be a larger gap between θ and θ_d). At the same time, a fall of θ_d would increase the range of values of θ that are integrated over. Hence, a decrease in θ_d would unambiguously increase the LHS of equation (A.33) while the RHS would remain fixed. This implies that θ_d cannot decrease either.

This proves that the only change in θ_d consistent with condition (A.33) is an increase in

θ_d when μ_s increases. Therefore:

$$\frac{\partial \theta_d}{\partial \mu_s} \quad > \quad 0 \tag{A.34}$$

Appendix B Data

B.1 Imputation of Censored Wages

To impute top-coded wages, we first define age-education cells based on five age groups (with 10-year intervals) and three education groups (no post-secondary education, vocational degree, college or university degree). Within each of these cells, following Dustmann et al. (2009) and Card et al. (2013), we estimate Tobit wage equations separately by year while controlling for age; firm size (quadratic, and a dummy for firm size greater than 10); occupation dummies; the focal worker's mean wage and mean censoring indicator (each computed over time but excluding observations from the current time period); and the firm's mean wage, mean censoring indicator, mean years of schooling, and mean university degree indicator (each computed at the current time period by excluding the focal worker observations). For workers observed in only one time period, the mean wage and mean censoring indicator are set to sample means, and a dummy variable is included. A wage observation censored at value c is then imputed by the value $\mathrm{X}\hat{\beta} + \hat{\sigma}\Phi^{-1}[\mathrm{k} + \mathrm{u}(1-\mathrm{k})]$, where Φ is the standard normal CDF, u is drawn from a uniform distribution, $\mathrm{k} = \Phi[(\mathrm{c} - \mathrm{X}\hat{\beta})/\hat{\sigma})]$ and $\hat{\beta}$ and $\hat{\sigma}$ are estimates for the coefficients and standard deviation of the error term from the Tobit regression.

B.2 Harmonization of Industry Codes

In 1999, the industry classification in the BEH social security data changed in order to make the industry classification compatible with international NAICS codes. In 1999, both the old and new industry code are included for all establishments. We use this information to compute the most common NAICS industry code for each old industry code. For establishments that still exist in 1999, we assign their 1999 NAICS industry code for all earlier years. For establishments that have exited by 1999, we assign the NAICS industry code that, in 1999, is the most common given the establishment's old industry code.

Appendix C Empirical Analysis

C.1 Skilled Wage Premium (Figure 1, Panel B)

The skilled wage premium, $SkillPrem_t$, at time t (the black line in Figure 1, Panel B) is computed as follows:

$$SkillPrem_t = \overline{\ln w_t}^s - \overline{\ln w_t}^r, \tag{C.1}$$

where $\overline{\ln w_t}^s$ and $\overline{\ln w_t}^r$ is the average log wage of skilled and unskilled workers at time t, respectively.

Note that this can also be expressed as:

$$SkillPrem_t = \sum_k \frac{n_{kt}^s}{n_t^s}\overline{\ln w}_{kt}^s - \sum_k \frac{n_{kt}^r}{n_t^r}\overline{\ln w}_{kt}^r, \tag{C.2}$$

where $\overline{\ln w}_{kt}^s$ ($\overline{\ln w}_{kt}^r$) denotes the average log wage of skilled (unskilled) workers in industry k at time t. n_{kt}^s (n_{kt}^r) is the total number of skilled (unskilled) workers in industry k and year t and n_t^s (n_t^r) denotes the total number of skilled (unskilled) workers at time t. In other words, the skilled wage premium can be written as the difference between a weighted average of the average log wage of skilled and unskilled workers by industry and year, with the industrial employment shares by worker type as weights.

The counterfactual skilled wage premium in year t holding the industry structure constant at its 1990 employment level (the grey line in Figure 1, Panel B) is computed as:

$$SkillPrem_t^{1990} = \sum_k \frac{n_{k1990}^s}{n_{1990}^s}\overline{\ln w}_{kt}^s - \sum_k \frac{n_{k1990}^r}{n_{1990}^r}\overline{\ln w}_{kt}^r. \tag{C.3}$$

C.2 Between-Establishment Inequality (Figure 1, Panels C and D)

Panel C of Figure 1 decomposes the variance of individual log wages, denoted Var_t, into a within-establishment and a between-establishment component as follows:

$$
\begin{aligned}
Var_t &= \frac{1}{n_t}\sum_i(\ln w_{it} - \overline{\ln w}_t)^2 \\
&= \underbrace{\frac{1}{n_t}\sum_f\sum_{i\in i_{ft}}(\ln w_{it} - \overline{\ln w}_{ft})^2}_{\text{within establishments}} + \underbrace{\frac{1}{n_t}\sum_f n_{ft}(\overline{\ln w}_{ft} - \overline{\ln w}_t)^2}_{\text{between establishments } (Var_t^{BE})}, \qquad \text{(C.4)}
\end{aligned}
$$

where i denotes an individual and f indexes establishments. $\ln w_{it}$ is the log wage of individual i at time t, $\overline{\ln w}_t$ is the average log wage in period t, and $\overline{\ln w}_{ft}$ is the average log wage in establishment f in period t. n_t is the total number of workers and n_{ft} is the total number of workers at establishment f in year t (i_{ft} denotes this set of individuals).

Panel D decomposes between-establishment wage differentials, Var_t^{BE} in Equation (C.4), as follows:

$$
Var_t^{BE} = \underbrace{\frac{1}{n_t}\sum_k\sum_{f\in f_{kt}} n_{ft}(\overline{\ln w}_{ft} - \overline{\ln w}_{kt})^2}_{\text{between establishments, within industries}} \quad + \underbrace{\frac{1}{n_t}\sum_k n_{kt}(\overline{\ln w}_{kt} - \overline{\ln w}_t)^2}_{\text{between industries}}, \qquad \text{(C.5)}
$$

where k indexes 3-digit industries, f_{kt} is the set of establishments in industry k in year t, n_{kt} is the total number of workers in industry k and year t, and $\overline{\ln w}_{kt}$ is the average log wage in industry k at time t.

We compute the counterfactual within-industry between-establishment wage inequality using the 1990 industry structure, denoted by $Var_t^{WIBE,1990}$, as follows:

$$
Var_t^{WIBE,1990} = \sum_k \frac{n_{k1990}}{n_{1990}} \underbrace{\sum_{f\in f_{kt}} \frac{n_{ft}}{n_{kt}}(\overline{\ln w}_{ft} - \overline{\ln w}_{kt})^2}_{Var_{kt}(\overline{\ln w}_{ft})}. \qquad \text{(C.6)}
$$

where f indexes establishments, f_{kt} is the set of establishments in industry k in year t, n_{ft} is the total number of workers at establishment f in year t, $\overline{\ln w}_{ft}$ is the average log wage in establishment f at time t and $\overline{\ln w}_{kt}$ is the average log wage in industry k at time t. The term $Var_{kt}(\overline{\ln w}_{ft})$ refers to the variance of establishment log wages in industry k at time t.

C.3 Within-Industry Heterogeneity in the Employment Share of Skilled Workers (Figure 3, Panel A)

Within-industry heterogeneity in establishments' employment share of skilled workers, denoted V_t, is given by the within-industry variance in establishments' employment share of skilled workers, averaged over industries using industrial employment shares as weights:

$$V_t = \sum_k \frac{n_{kt}}{n_t} \sum_{f \in f_{kt}} \frac{n_{ft}}{n_{kt}} (S_{ft} - S_{kt})^2,$$

where n_{kt}, n_t and n_{ft} denote the number of workers employed in industry k, the total number of employed workers and the total number of workers at establishment f in year t, respectively. f_{kt} is the set of establishments in industry k in year t. S_{kt} and S_{ft} denote the employment share of skilled workers in industry k and in firm f at time t, respectively.

The counterfactual within-industry variance in establishments' employment shares of skilled workers, holding the industry structure constant at its 1990 level, V_t^{1990}, equals:

$$V_t^{1990} = \sum_k \frac{n_{k1990}}{n_{1990}} \sum_{f \in f_{kt}} \frac{n_{ft}}{n_{kt}} (S_{ft} - S_{kt})^2,$$

where (n_{k1990}/n_{1990}) captures industry k's share of employment in 1990.

C.4 Within-Industry Sorting (Figure 3, Panel B)

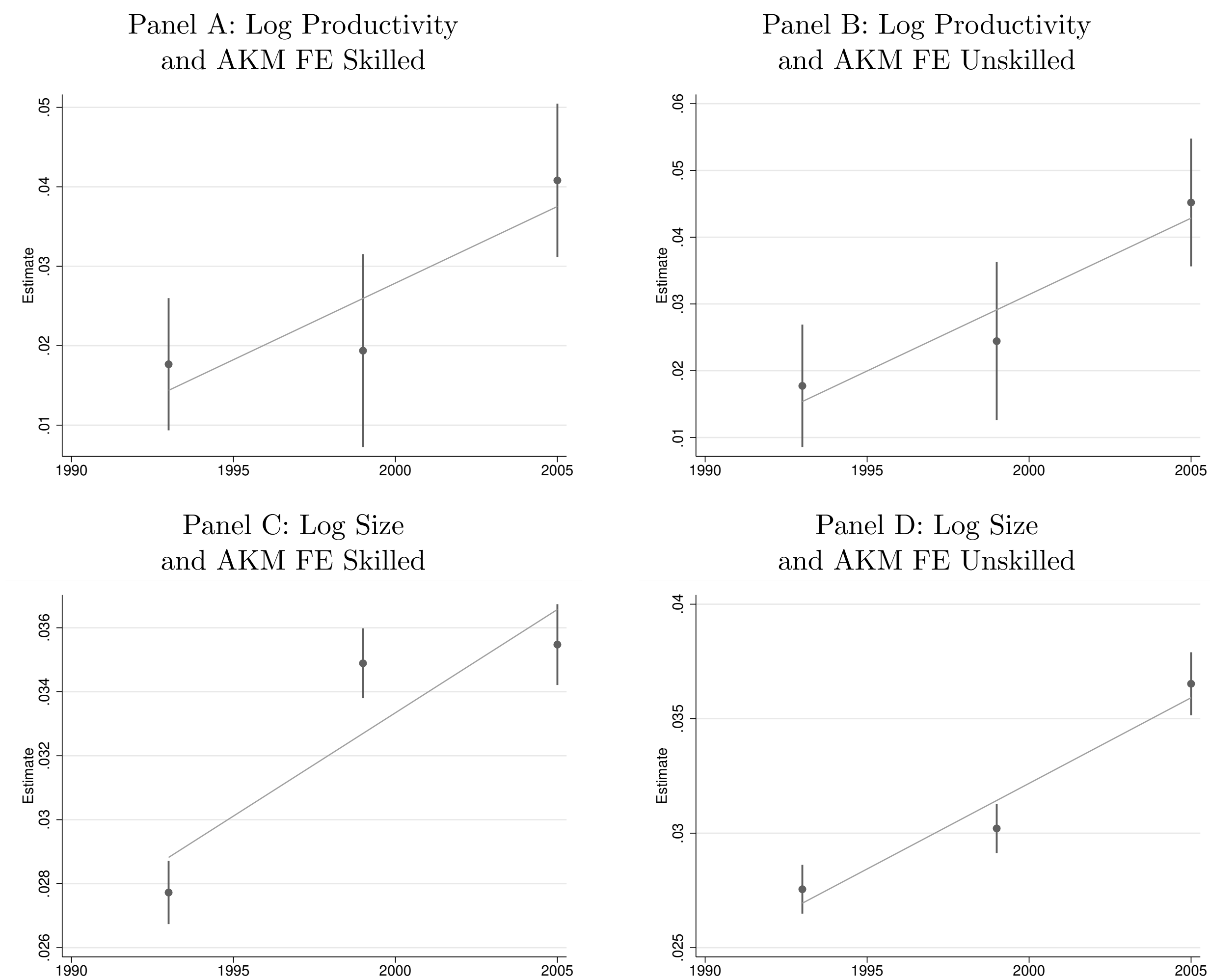
We capture the extent of sorting of skilled workers into high-wage establishments using the within-industry covariance between establishments' employment shares of skilled workers and the average log wage of unskilled workers in the establishment, averaged across industries using industrial employment shares. This covariance, denoted Cov_t, is computed as follows (using information on all firms that have at least one full-time unskilled worker for the industry-level covariance):

$$Cov_t = \sum_k \frac{n_{kt}}{n_t} \sum_{f \in f_{kt}} \frac{n_{ft}}{n_{kt}} (S_{ft} - S_{kt})(\ln w_{ft}^r - \overline{\ln w}_{kt}^r),$$

where $\ln w_{ft}^r$ is the average log wage of unskilled workers in establishment f at time t and $\overline{\ln w}_{kt}^r$ is the average wage of unskilled workers in industry k at time t. The corresponding counterfactual covariance, holding the industry structure constant at its 1990 level, denoted Cov_t^{1990}, equals:

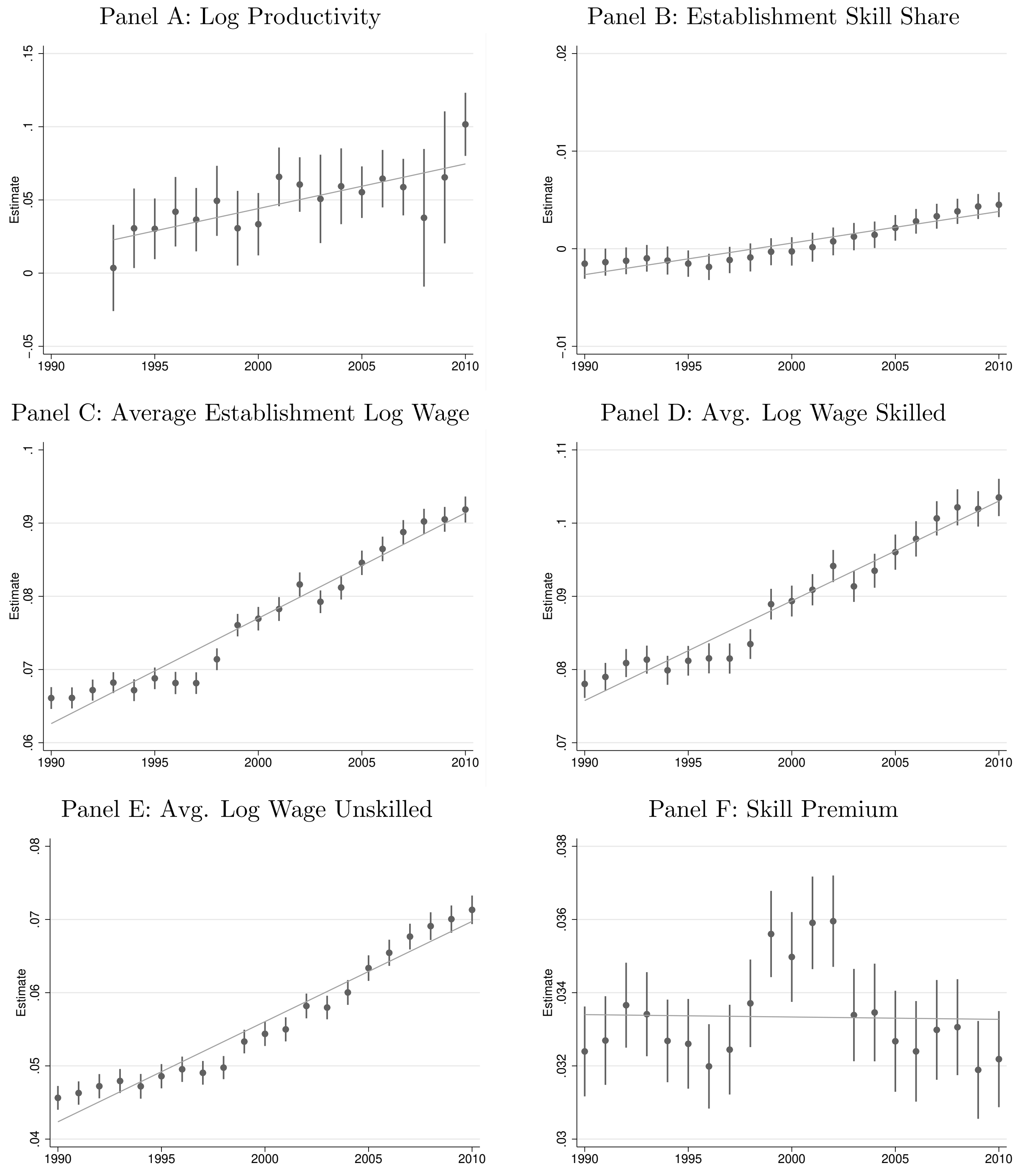
$$Cov_t^{1990} = \sum_k \frac{n_{k1990}}{n_{1990}} \sum_{f \in f_{kt}} \frac{n_{ft}}{n_{kt}} (S_{ft} - S_{kt})(\ln w_{ft}^r - \overline{\ln w}_{kt}^r).$$

Figure A.1: Year-by-Year Associations with AKM Establishment Wage Premiums



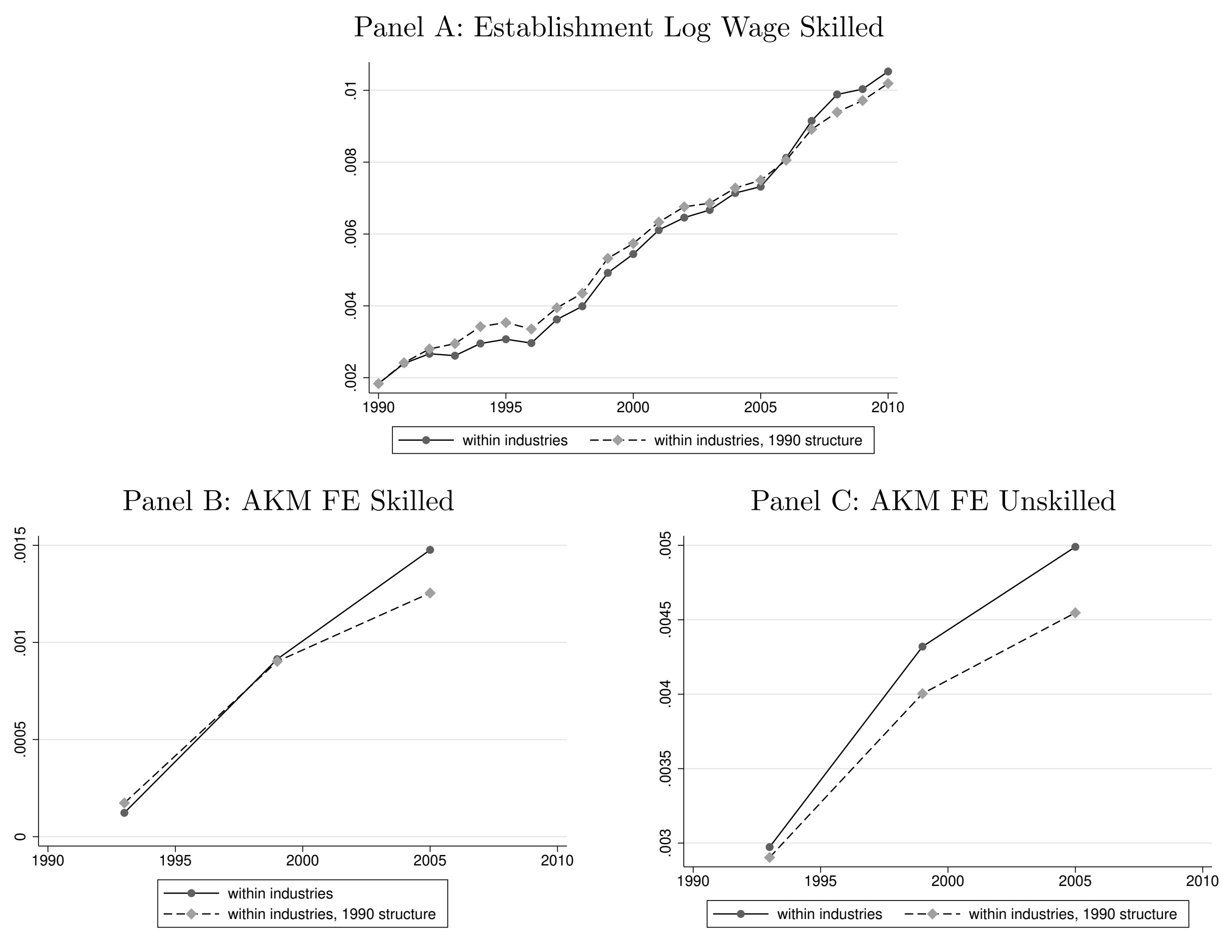
Note: The figure shows estimated coefficients and 95% confidence intervals from regressions of the AKM establishment fixed effects on either log productivity or log establishments size, as well as a full set of 3-digit industry fixed effects, with the regressions estimated separately for each year.

Figure A.2: Year-by-Year Associations between Establishment Size and Other Establishment Characteristics



Note: The figure shows estimated coefficients and 95% confidence intervals from regressions of the outcome that appears in the title of each panel on log establishment size and a full set of 3-digit industry fixed effects, with the regressions estimated separately for each year. Results are based on establishments in the BEH and observations are weighted by establishment size (except Panel A which uses establishments in the IABEP and weights observations based on establishment size and survey weights).

Figure A.3: Covariance between Skill Share and Different Establishment Wage Measures



Note: The figure shows the covariance between establishments' skilled employment shares and: their average log skilled worker wage (Panel A), their estimated AKM fixed effect for skilled workers (Panel B), and their estimated AKM fixed effect for unskilled workers (Panel C).

Table A.1: Classification of Vocational Occupations (Blossfeld, 1987)

Vocational category	Occupation	Occupation Codes (KldB88)
Skilled Vocational	Technician, Engineer, Skilled Service, Skilled Administrative, Semiprofessions, Professions, Managers	11–22, 41–51, 53–549 excl. 303 & 304; 682, 685–688, 706, 713–716, 723–725, 731, 732, 734–744, 773, 782–794, 805, 838, 911–913, 923–937
Unskilled Vocational	Agricultural, Unskilled Manual, Unskilled Service, Unskilled Administrative, Skilled Manual	31, 32, 52, 303, 304, 601–684 excl. 682; 683, 684, 691–712 excl. 706; 721, 722, 726, 733, 751–781 excl. 773; 801–902 excl. 805 & 838; 921, 922

Table A.2: Heterogeneous Impacts of Technology Adoption, Controlling for Trade Exposure and Offshorability

	Log Skilled Workers	Log Unskilled Workers	Skill Share	Avg. Log Wage	Avg. Log Wage Skilled	Avg. Log Wage Unskilled	Skill Premium	AKM FE Skilled	AKM FE Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Industry Skill Premium									
Log Productivity	0.16***	0.035	0.025***	0.051***	0.054***	0.043***	0.012***	0.015***	0.015***
	(0.038)	(0.033)	(0.0036)	(0.0063)	(0.0072)	(0.0054)	(0.0037)	(0.0040)	(0.0039)
Log Productivity × High Tech Ind	0.22***	0.071	0.031***	0.064***	0.080***	0.059***	0.022***	0.034***	0.037***
	(0.058)	(0.054)	(0.0067)	(0.0094)	(0.011)	(0.0087)	(0.0058)	(0.0073)	(0.0076)
N	85231	85231	85231	85231	64362	64362	64362	8196	8196
Panel B: Industry Robot Adoption									
Log Productivity	0.11***	-0.040	0.032***	0.050***	0.053***	0.043***	0.010***	0.016***	0.018***
	(0.037)	(0.033)	(0.0038)	(0.0061)	(0.0070)	(0.0053)	(0.0035)	(0.0038)	(0.0039)
Log Productivity × High Tech Ind	0.46***	0.38***	0.0096	0.081***	0.10***	0.070***	0.032***	0.045***	0.041***
	(0.054)	(0.052)	(0.0064)	(0.0088)	(0.011)	(0.0086)	(0.0060)	(0.0092)	(0.0077)
N	84358	84358	84358	84358	63655	63655	63655	8116	8116
Panel C: Industry ICT Capital									
Log Productivity	0.20***	0.020	0.034***	0.037***	0.050***	0.029***	0.022***	0.015***	0.018***
	(0.051)	(0.040)	(0.0053)	(0.0072)	(0.0097)	(0.0067)	(0.0055)	(0.0052)	(0.0052)
Log Productivity × High Tech Ind	0.063	0.069	0.0037	0.062***	0.049***	0.056***	-0.0067	0.018***	0.013**
	(0.054)	(0.048)	(0.0060)	(0.0084)	(0.011)	(0.0080)	(0.0058)	(0.0063)	(0.0065)
N	70480	70480	70480	70480	54096	54096	54096	8196	8196

Note: All regressions include a set of fully interacted 3-digit industry and year fixed effects, as well as controls for the interaction between establishment productivity and industry-level import exposure and export exposure, and the interaction between establishment productivity and industry-level offshorability. Industry-level trade exposure is measured as the per-worker exports and imports with China and Eastern Europe in the industry in a given year between 1990 and 2010. Industry-level offshorability is constructed from the occupational-level offshorability index from Goos et al. (2014), aggregated to the industry level for each year. 'High Tech Ind' is an indicator variable for technology adoption at the industry level and is equal to one in a given year if the industry skill premium (Panel A), robot usage (Panel B) or ICT usage (Panel C) is above the median for the time period considered (1990-2010 for the skill premium, 1993-2010 for robot usage and 1991-2007 for ICT usage). AKM establishment fixed effects by worker type are computed for the periods 1990–1996, 1996–2002 and 2002–2008, separately for skilled and unskilled workers. Results are based on establishments in the IABEP, and observations are weighted by establishment size and survey weights. Standard errors are clustered at the establishment level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.