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DISCUSSION PAPER SERIES

IZA DP No. 15364

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ABSTRACT

College Openings and Local Economic Development*

We study how the presence of a college affects the local economy using administrative data. Our analysis exploits the opening of new institutions of tertiary education across Germany in the 1980s and 1990s. The new college substantially increased the student population and share of high-skilled workers in the region. Yet, we find no effect on regional wages or employment indicating that the local economies did not experience additional growth through skill-biased technological change, for instance. Instead, there is sizable heterogeneity in the local gains: high-tech firms in manufacturing absorb most of the new college graduates, esp. in engineering professions. We find little impact on the low- or high-skilled service sector or employment in managerial professions. Finally, we show that local labor market conditions prior to the opening matter: in regions with a more dynamic labor market, the opening encourages firm creation and a permanent upskilling of the workforce. Areas with a less dynamic labor market experience little sustained growth in high-skilled workers who are absorbed by incumbent firms.

JEL Classification: J24, J31, J61, I23, I25

Keywords: colleges, local labor markets, human capital, substitutability

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1 Introduction

Income and unemployment rates differ substantially across cities and regions in many countries. In the United States, for example, wages in the highest and lowest paying metropolitan areas differ by a factor of three (Moretti 2011). Similar discrepancies in income per capita are observed between regions in the European Union (OECD 2009). The variation in unemployment rates can be even larger. In Germany, our empirical setting, local unemployment rates across metropolitan areas vary by a factor of six (BMWi 2013).

In response to these large regional disparities, many governments promote policies aimed at promoting regional convergence by reducing perceived inequalities. These place-based policies could be direct subsidies to firms located in or planning to move into a disadvantaged area; or, they could target workers and their families through residential subsidies. Alternatively, they can take the form of investments in infrastructure by local, state or federal governments in order to increase the economic attractiveness of a region to firms and individuals alike. One such policy is the opening of publicly funded institutions, which could be government agencies, publicly funded research institutes or institutions of higher education.

Universities and colleges in particular could be a powerful tool for regional development. First of all, universities and colleges might generate positive spillover effects to local firms through research collaborations or knowledge spillovers. Alternatively, staff and students as well as the universities and colleges themselves may stimulate the demand for local goods and services through local multiplier effects. Moreover, by improving the human capital base in the region, colleges increase the thickness of the local labor market, in particular for high-skilled workers. In labor markets with search frictions and heterogeneous firms and workers, the match quality between workers and firms would then improve when more high-skilled workers look for a job and firms offer suitable jobs in the same local labor market. Furthermore, the new high-skilled workers might generate positive spillover effects. Formal and informal interactions among individuals at work or in the neighborhood foster knowledge sharing and learning, which may result in positive production externalities across workers (see, e.g. Marshall 1890; Lucas 1988; Glaeser 1999; Serafinelli 2019). Finally, a better educated workforce and local productivity or knowledge spillovers might encourage firms to locate in the region or invest more in complementary technology and capital.

Yet, can colleges promote regional economic development independently of where they are located – even in more remote regions? If so, they could be an effective policy tool to balance agglomeration forces, which tend to concentrate economic activities and people in densely populated areas. A new college might have little impact in remote areas, however, if the new college graduates do not find adequate jobs or amenities and move to the urban centers after graduation with few gains to the local economy. Or, firms might not find it worthwhile to relocate or invest in new technology that complements high-skilled workers. Overall, the local economy might not be dynamic or advanced enough to make use of potential knowledge or productivity spillovers that colleges can create.

This paper provides answers to these important questions. An important challenge in this endeavor is that the location of colleges is not random. Many universities and colleges were established many centuries or decades ago, which makes it difficult to isolate the impact of a university from other local developments that accumulate over time. We solve this identification problem by focusing on the opening of new colleges. The college openings in our setting explicitly targeted areas outside the large urban centers to improve access to tertiary education. Yet, regions in which a new college is opened are likely to differ from other regions without a college opening in their economic base, innovative capacity or labor market dynamics. We therefore combine matching with a time-varying difference-in-differences approach. The matching approach works well in eliminating differences in observable characteristics and growth rates between event and matched control districts. Our empirical approach then compares flexibly employment and wages in regions with a college opening to employment and wages in suitable control regions without a college opening.

We have four main findings. First, the opening of a technical college results in large, persistent growth in the local student population relative to the control regions. The new colleges further successfully improve the human capital base in the region: young, high-skilled employment in the region increases by 13% within a decade after the opening. Second, we find little evidence that the new colleges raise regional employment or wages, which would indicate sustained growth or productivity gains. In particular, we find little evidence that wages of high-skilled workers change after the college opening. The absence of any wage effect on high-skilled workers stands in stark contrast to other studies on the local effects of high-skilled migration (Beerli et al. 2021) or college-induced growth in high-skilled labor (Carneiro et al. 2022; Fuest and Immel 2021). Yet, our results support studies that do not find a substantial impact on high-skilled labor and the skill premium (Beaudry and Green 2003; Blundell et al. 2022). Using a local production function approach, we show that in our setting the new colleges do generate little skill-biased technological change through changes in production (Acemoglu 1998) or research efforts (Beaudry and Green 2005; Caselli and Coleman 2006). This result is important when considering the placement of colleges as a regional policy instrument. Our results suggest that gains in metropolitan areas cannot be easily translated into gains in areas with a thinner labor market and weaker economic base.

Third, we explore who actually benefits from the new colleges in the local economy. In the average region, the additional high-skilled labor is largely absorbed by high-tech firms in manufacturing, while there are no effects in the service sector. We further find few local multiplier effects and little impact on the innovative capacity of the region. Finally, we document that the state of the local labor market matters: regions with more dynamic labor markets before the opening experience a permanent growth in high-skilled workers who get employed in new firms. Less dynamic regions, in contrast, experience a little sustained growth in high-skilled labor, which is mostly absorbed by incumbent firms.

Our study contributes to several strands of the literature. A number of studies have documented a strong correlation between the location of universities and patenting activity, innovation and business start-ups (Jaffe 1989; Bania et al. 1993; Audretsch and Feldman 1996; Cohen et al. 2002; Woodward et al. 2006). Most studies focus on the importance of academic research for the development of specific local industries, such as pharmaceuticals or electronic equipment. Closer to us are Beeson and Montgomery (1993) who study the link between the quality of a university and local employment growth; and Kantor and Whalley (2014) who use shocks to a university's financial endowment to identify wage effects outside the education sector.[1] Our study differs from this strand along several dimensions: we use the opening of new colleges as plausibly exogenous variation for identification; second, we study new colleges that are focused on teaching rather than research and startup activities. Finally, we analyze the impact on the whole local economy rather than the technology-driven spillover effects in particular industries.

Furthermore, our analysis contributes to the literature on the effects of local supply shocks. Several studies has studied the inflow of immigrants (Card 2001; Borjas 2003; Glitz 2012; Manacorda et al. 2012; Ottaviano and Peri 2012) or commuter flows (Beerli et al. 2021; Dustmann et al. 2016) on local wages and employment. Most studies using the local area approach suggest that the inflow of immigrants or commuters have a small effect on the local wages of natives. Others argue that migration induces negative employment effects locally (Glitz 2012; Dustmann et al. 2016). As immigrants in most countries are on average less skilled than the native population, these studies focus on adjustments to an increase in low-skilled labor. And if natives and immigrants are imperfect substitutes, a large inflow of immigrants need not have a sizable impact on native wages. Hence, local adjustments to a low-skill supply shock are likely to differ from the response to a shock to high-skilled labor if there are human capital externalities or other types of knowledge spillovers. If high-skilled workers raise the productivity or innovative

[1] Kantor and Whalley (2019) take a long-term view tracing the role of agricultural experiments for the level of agricultural production over more than a century.

capacity of other workers in the same firm or other firms in the region, for instance, the benefits for the local economy might be much larger than a growth in the low-skilled workforce (Moretti 2004; Ciccone and Peri 2006). Our study contributes to this literature by exploiting the opening of new colleges as a plausibly exogenous shock to the high-skilled workforce, which should be perfect substitutes to other high-skilled workers in the area.

Closest to us are studies on the wage and employment effects of the growth in college graduates (see, e.g. Beaudry and Green 2003; Blundell et al. 2022) or tertiary educational institutions (Carneiro et al. 2022; Fuest and Immel 2021; Lehnert et al. 2020). Unlike the former, we focus on the *local* impact of a *local* supply shock. Unlike the latter, we analyze colleges that are more focused on teaching than research and are not located in the large metropolitan areas. We further use a different identification strategy to address concerns of differential pre-trends and endogenous location choice.

Traditional open economy models emphasize changes in the output mix produced by the local economy in response to labor supply shocks (Lewis 2011; Dustmann and Glitz 2015). Regions with a relative growth in low-skilled labor, for instance, experience shifts to products and sectors that make intensive use of low-skilled labor. Another reason college openings may affect the regional economy is through local multiplier effects. Both college employees and the new college graduates might create additional demand for local goods and services. Recent research suggests that local multiplier effects may be sizable (see, e.g., Moretti 2010; Moretti and Thulin 2013; Faggio and Overman 2014). Our study relies on a different, plausibly exogenous source of identification to investigate changes in the output mix and local multiplier effects. We find few effects in the non-tradable sector, likely because the colleges we analyze are relatively small.

Our results provide important lessons for policy-makers. Knowing whether an increase in high-skilled labor improves the economic conditions of the regional economy and all workers; or only benefits certain sectors or firms has important implications. If there are indeed positive externalities from college openings on the local economy, this could be yet another argument for public subsidies of tertiary education. In addition, our results may also be important for the design of regional policies. National and state governments often use regional policies to support areas with high unemployment and low economic growth. Prominent examples include region-specific subsidies to firms or local governments, such as the Federal Empowerment Zones in the US (Busso et al. 2013), regional subsidy programs in France (Gobillon et al. 2012), Italy (Bronzini and de Blasio 2012), the UK (Criscuolo et al. 2019) or Germany (von Ehrlich and

Seidel 2018); or the European Structural Funds (Becker et al. 2010; 2013).[2] Our work sheds new light on the question of whether public investments like the opening a new college can improve employment prospects and local development and thus contribute to a decline in disparities across regions differing in economic prospects.

2 Institutional Background

2.1 College Openings in West Germany

The 1960s saw a rising need for educated workers coupled with a rising demand for formal education. Faced with capacity constraints at existing universities, the federal government decided in 1968 to establish technical colleges (*Fachhochschulen*) to complement regular universities.[3] The new technical colleges played an important role in making higher education accessible to the broader population. By 2010, about one in three students pursues a degree at a technical college.

Technical colleges offer study programs that are more specialized and practice-oriented than regular universities. The degree programs are heavily concentrated in fields like engineering, law and business.[4] Degree programs at technical colleges take three to four years and are thus comparable to Bachelor programs at universities but shorter than the traditional Diploma or Masters program. Most importantly, the degree programs at technical colleges combine academic study with periods of practical training where students obtain actual work experience in companies. Unlike universities, teaching staff at technical colleges are required to have several years of work experience outside academia. Today, most technical colleges ask for a Ph.D. though that was not the norm in the early years. To improve the practical relevance of teaching material, technical colleges often cooperate with local companies though the colleges are mostly publicly funded with little monetary contribution from private sources.

We focus on openings of public colleges, which could be either newly founded colleges or a new campus of an existing college, which is located in a different district. We thus drop openings of private colleges because they are very small, cover only a very narrow range of fields and are of minor importance for tertiary education in Germany. We further drop college openings that were converted from existing schools of secondary education (like vocational schools, for

[2] Earlier work has focused on the relationship between city (or local industry) size or density and productivity more generally (see, for example, Ciccone and Hall 1996, for a seminal contribution and Rosenthal and Strange 2004, for a survey).

[3] The legal basis is discussed in *Abkommen zwischen den Ländern der Bundesrepublik zur Vereinheitlichung auf dem Gebiet des Fachhochschulwesens.*

[4] In 2001, 42% of all students im technical colleges were enrolled in management or law, while roughly 30% studied engineering (Haug and Hetmeier 2003).

example). These openings generate only very small and smooth changes to high-skilled supply in the region (see Wissenschaftsrat 1991; Kulicke and Stahlecker 2004). We further exclude four cases where a new campus was opened in the same district as the parent institution. Finally, we combine college openings that occurred in the same district and year into a single event.[5]. To avoid problems of changes in sample composition, we work with a balanced sample dropping openings before 1980 in order to have a least four years of data prior to the event; and drop openings after 2000 in order to follow regions for at least a decade after the event.

Our final sample consists of twenty technical colleges in West Germany that were opened between 1988 and 1998. Appendix table A1 provides a list of the college openings and the opening year of the college. The last two columns in the appendix table show that the technical colleges are small relative to public universities. Five years after the opening, the college has on average 100 employees and 900 students. Given that the event districts have on average 50,000 regular employees (in the social security system), the new college is not a quantitatively important employer for the local economy. Yet, the 900 students provide a sizable supply shock to the districts, which could boost the stock of high-skilled labor by around 50 percent.

2.2 Local Predictors of College Openings

While the federal government decided on the overall expansion of tertiary education, state governments chose when and where the new colleges would be located. Municipalities and local governments, in contrast, had little influence on the location decision. The costs of financing the new colleges were shared between state and federal governments. State governments aimed at a more even spatial distribution of tertiary institutions in order to facilitate access for potential students and reduce the distance to the nearest college. A second consideration was to foster structural changes in the local economy. One example is the decline of the traditional coal mining and steel industries in the Ruhr area and the Saarland (Holuscha 2012). College openings were seen as an attractive tool to attract new companies, reduce out-migration and avoid population decline.[6] A third consideration was that regions could not be in remote locations, provide amenities to attract enough students and have an economic base to offer employment opportunities after graduation.

The political considerations just discussed suggest that new colleges were neither opened in the large metropolitan areas, nor in predominantly rural regions. To provide more systematic

[5] Two colleges were opened in the same year in *Göppingen* (1988) and *Rhein-Sieg* (1995).

[6] See Schindler et al. (1991); Landtag (1991); Wissenschaftsrat (1995) for examples of the political discussion in the individual states. Another example is the former capital of Bonn where the founding of a technical college was to compensate the city for the move of the federal government to Berlin starting in 1999 (see, e.g. Wissenschaftsrat 1996).

evidence on the adoption process, we relate the college openings to district-level characteristics three years prior to the opening, state and year fixed effects. The results in appendix table A2 show that colleges were more likely to be located in districts without a university, which is in line with the objective of a more even spatial distribution of tertiary institutions. The college openings are also negatively correlated with population density indicating that the openings occurred outside of the big cities and urban centers.[7] Districts where a new college was opened have a good economic base as shown by employment levels, which is in line with the last objective that the local labor markets should be attractive for students and college graduates.

Interestingly, none of the other local characteristics predict a college opening: Neither the detailed industry structure, nor the age or skill structure of the existing workforce play a role. Hence, the college opening is not explained by a local lack of skilled workers, an aging workforce or an industry-specific demand for skilled workers. Even more importantly, we find no evidence that wage levels or wage growth, past population or employment growth (measured between eight and three years before the event) had any effect on the decision to found a new college. The absence of meaningful correlations between economic prospects and the college openings is reassuring and reduces concerns that politicians picked the districts with the best economic performance or economically deprived regions lobbied successfully for a new college.

3 Data Sources and Empirical Strategy

Our empirical analysis proceeds in three steps. We first present the district-level data on labor markets and plants, on which we base our empirical analyses. We then discuss our matching approach to address the issue that districts that have a college opening differ from districts without a college opening (see the discussion in Section 2). The final step outlines the time-varying difference-in-differences approach we use to identify the impact of a college opening on the local economy comparing event regions to their matched control regions.

3.1 Data Sources

To analyze how the opening of a college affects the local economy, we draw on administrative data from Germany over several decades. Our data contain the universe of all social security records and provides detailed information on employment and wages aggregated at the district level (Stüber and Seth 2019). It covers all employees except civil servants, military personnel

[7]The proximity to an urban center has no bearing on the adoption decision (see column (2) of appendix table A2).

and the self-employed.[8] The data start in 1975 and end in 2010, which enables us to follow districts with a new college opening several years before and up to a decade after the opening.

We focus on workers in full-time employment as of June 30 each year. Hence, we exclude apprentices, student trainees, part-time work, marginal and seasonal employment. We have detailed information on the workforce by skill and age in each district. We distinguish two skill groups based on the highest qualification obtained. Highly skilled workers are workers who have graduated from a college or university. Less skilled workers have no university or college degree but might have a vocational degree. Missing values in the education variable are imputed by exploiting the panel structure of the data (Fitzenberger et al. 2006; Kruppe et al. 2014). We further distinguish three age groups: young workers (ages 20-29), prime-aged workers (ages 30-44) and older workers (ages 45-59).[9]

Our data also contain the mean daily wage (measured on June 30th of each year). As is common in social security records, wages are right-censored at the highest level of earnings that are subject to social security contributions. Individual wages are imputed based on the procedure used in Card et al. (2013) and then aggregated to averages by age and skill group. All wages are deflated using the consumer price index with 1995 as the base year.

We supplement the district-level data with plant-level information from the German Establishment History Panel (BHP), which draws on the same population of social security records. The BHP is a 50% random sample of all establishments with at least one employee covered by the social security system in Germany (Schmucker et al. 2016). The plant-level data of the BHP allow more detailed analyses along several dimensions: first, we observe the detailed industry of a plant to investigate in which industries the new graduates find employment. Second, we can distinguish whether the local supply of highly skilled workers is absorbed by incumbent plants or through the creation of new firms. The latter are defined as plants opening their business within the past five years; here, we rely on the procedure developed by Hethey and Schmieder (2010) to identify plant openings and distinguish them from simple changes in the establishment identifier due to spin-offs or mergers, for instance. Finally, we observe the broad occupational structure of the workforce in a plant, in particular the number of engineers and natural scientists, professionals, semi-professionals and unskilled or skilled manual workers. We aggregate the plant-level data from the BHP to the district level.

The average district in West Germany has a population of around 200,000 with 51,000 full-time employees in the social security system. We compute regional employment shares by

[8]The social security data cover around 80% of the German labor force.

[9]Data protection rules require that a cell is set to missing if the number of employees in a cell is below twenty. This restriction affects between 1.27% to 3.38% of observations. In our analysis, we set these employment shares to zero.

broad industry and occupation. Data on the number of college students in a district stems for German Federal Statistics Office. We add regional information on population from the European Regional Database of Cambridge Econometrics. Finally, we obtain data on population flows across districts by broad age groups from the State Statistical Offices. Every person who moves to an area has to register with the municipality of their residence.

3.2 Matching Procedure

Regions where a new college was opened might differ from regions that did not obtain a new college. While local politicians had little influence on where a new college opened, state governments took local conditions into account when deciding on the timing and the location of the new college (see discussion in Section 2). A means comparison of districts with a college opening to the average district in West Germany reveals that event regions are less densely populated and have fewer highly skilled workers than the average district (see the first columns of table 1). Moreover, event districts have a strong base in manufacturing and construction, but a smaller service sector than the average West German district. Finally, workers in event districts earn lower wages than the national average. Given that new colleges are more likely to be located in areas with a less favorable economic development than the average district, a comparison of the local development in event regions to the average local economy in West Germany would underestimate the benefits a college opening has had on the local economy.

To address the issue of regional differences, we employ a matching approach to find suitable control regions for districts with a college opening. We match on population density, the broad industry structure (ten sectors) and whether a district has another college or university. As shown in Section 2, these characteristics are systematically related to the location decision and might also influence regional economic performance after the opening. We use Mahalanobis distance matching, which minimizes the standardized Euclidean distance of all matching variables between treatment and control districts, to find the closest match.[10] We exclude from the pool of potential control districts those sharing a border with an event district to avoid that the development in control districts is contaminated by spillover effects from the event district.

Figure 1 shows the geographic location of treatment districts and control districts. Most college openings during our sample period occurred in *Baden-Württemberg* and *Bavaria*, two states in Southern Germany with a strong manufacturing base. The map also confirms once more that districts with a college opening and their controls are located outside the large

[10] The distances between each treatment and each potential control district are normalized by the variance-covariance matrix of the pooled sample of event and possible control districts. Normalizing by the variance-covariance matrix in the control group only does not alter the results.

urban centers. The right-hand side of table 1 shows that the selected control districts are very similar to the treated districts along observable characteristics. It is important to stress that the matching procedure not only eliminates differences in the characteristics we match on; but also differences in characteristics we did not match on, such as the age structure or the skill composition of the local labor force.

3.3 Empirical Model

Using our matched sample of regions, we compare labor market outcomes in the event regions to those in the control regions before and after a college opening. To illustrate the evolution of our results graphically, we estimate the following event study:

$$Y_{r\tau t} = \sum_{\tau=-7}^{-2} \beta_\tau Opening_r * Period_\tau + \sum_{\tau=0}^{11} \gamma_\tau Opening_r * Period_\tau + \eta_\tau + \lambda_t + \pi_r + \varepsilon_{r\tau t} \quad (1)$$

where r denotes the region, t the calendar year and τ the year relative to the college opening. Note that t and τ are distinct because colleges were opened in different calendar years. We consider a period of seven years before and eleven years after the college opening (i.e. $-7 \leq \tau \leq 11$). The opening occurs in period $\tau = 0$ and the base period is the year before the college opening, i.e. $\tau = -1$.

$Y_{r\tau t}$ denotes a local labor market outcome like employment or wages in region r in a given calendar year t for the event period τ. $Opening_r$ is a binary variable equal to one if there was a college opening in region r and zero for the control regions. $Period_\tau$ is an indicator equal to one if the college opening has happened τ years ago or will happen in τ years for both treatment and control region; and zero otherwise. The coefficients of interest in equation (1) are the γ_τ, which trace the evolution of the outcome of interest in the event region relative to the development in the control region between τ years after the college opening and the reference period ($\tau = -1$). The empirical model in (1) controls for event fixed effects (η_τ) to ensure that we compare event and control districts in the same period. We further include year fixed effects (λ_t) and region fixed effects (π_r) to account for aggregate shifts and region-specific, time-invariant unobservable differences. Standard errors are clustered at the district level to account for the level of aggregation in the treatment variable.

Given our small number of treatment regions, the estimates reported in our tables aggregate event years into three broad periods: the period before the opening, a transition period shortly after the opening and the longer-run development of the new college. More specifically, we estimate variants of the following model:

$$Y_{r\tau t} = \beta^B Opening_r * Before_\tau + \gamma^T Opening_r * Transition_\tau + \gamma^P Opening_r * Post_\tau + \\ + \eta^{Trans} + \eta^{Post} + \lambda_t + \pi_r + \varepsilon_{r\tau t} \quad (2)$$

where $Before_\tau$ denotes the period prior to the opening (from $\tau = -7$ to $\tau = -2$). The transition period $Transition_\tau$ spans the year from the opening to the graduation of the first cohort (from $\tau = 0$ to $\tau = 5$). The post period $Post_\tau$ covers the longer-run development in the event regions from six to eleven years after the opening (from $\tau = 6$ to $\tau = 11$). As before, $Opening_r$ is an indicator equal to one if a college opened in region r; and zero otherwise. The parameters of interest are γ^{Trans} and γ^{Post}, which characterize how the outcomes of interest evolve in the first few years after the college opening and in the long run, respectively. All other variables are defined as in equation (1) above.

The key identifying assumption is that labor market outcomes would have evolved similarly in the event and control district in the absence of a college opening conditional on our control variables. Specifically, we require that *trends* in outcomes would have involved similarly in event districts than in control districts. We show below that controlling flexibly for district-specific linear or quadratic trends to capture differential trajectories has little effect on our empirical results. The evolution of outcomes in the pre-event period provides further evidence on the plausibility of this assumption in the case of homogeneous treatment effects. We show below that the parameters β_τ in equation (1) resp. β^B in equation (2) are close to zero and statistically insignificant. We consider alternative estimators that are robust to heterogeneous treatment effects in Section 4.4; these do not affect our conclusions. We now turn to our main results.

4 Empirical Results

4.1 Student Population and High-Skilled Employment

We start out by analyzing the effect of a college opening on the student population in the region. A rise in the student population not only helps identifying the exact timing of the opening; but is also a prerequisite for a positive impulse on the local economy. Figure 2 traces the growth in registered college students in treated and control districts with the level normalized to one in the year before the opening ($\tau = -1$). Prior to the college openings, the evolution of college students is flat in both event and control regions.[11] We see a substantial increase in the number

[11]In line with our discussion on the spatial distribution of colleges in Section 2, the are stark level differences, however. Event regions had only 200 students on average prior to the opening as three districts had another college or university prior to the opening; control districts in turn had almost 2,000 students on average before

of students in the event region starting in the year of the college opening. Ten years after the college opening, the student population in the treatment regions has increased by a factor of 8 to about 1,600 students while we see no change in the control districts over the same period.

To quantify the impact on the student population, we estimate equation (2) where the dependent variables are the number of students measured either in absolute numbers or as a share of high-skilled employees in the region. The specification includes fixed effects for the district, calendar and event year. All results are cumulative estimates relative to the reference period, the year before the college opening ($\tau = -1$). Column (1) of table 2 shows that new colleges result in a large and significant increase in the student population. In the first five years after the college opening, the student population increases by 450% relative to control districts. The effect grows to 560% over the first decade after the opening, which reflects the gradual expansion of the new college. To illustrate how much the new student population increases the human capital base of highly skilled workers in the region, we use in column (2) the student population as a share of high-skilled employees in the region. The college opening may thus increase the share of high-skilled workers in the region by more than 50% over the first decade (see column (2) of table 2). As such, the college openings imply a substantial positive shock to high-skilled labor supply in the local economy.

Yet, a local expansion in the student population does not need to translate into more high-skilled employment in the local economy. If most students leave the region after they finish their college degree to work and live in other regions, a college opening would have little permanent impact on the local skill structure or the local economy more broadly. To see whether the college opening has a lasting effect on the human capital base of the local workforce, we estimate the event study from equation (1) where the outcome is now full-time employment of college graduates between the ages of 20 and 29 (in logs). Figure 3 shows that the employment of young high-skilled workers moves in parallel in treatment and control districts before the opening of the new college. The relative size of young high-skilled labor starts to diverge between event and control regions three years after the college opening, when the first cohort graduates and enters the labor market. The difference widens until about seven years after the opening and then levels off. The timing of the increase in local high-skilled employment supports our identification assumption of no differential shock or growth in the demand or supply of high-skilled workers in treatment districts relative to control districts *prior* to the opening.

The employment of young high-skilled has increased by a sizable 13% in event districts six to eleven years after the opening (see column (3) of table 2).[12] Overall, the evidence on the

the event.

[12]The new colleges have on average 900 students five years after the opening, which would be equivalent to a

student population and high-skilled employment shows that the college opening results indeed in a permanent increases in the human capital base of the local economy.

4.2 Regional Employment and Wages

We just showed that the college opening generated a permanent growth in the local supply of high-skilled labor. This permanent growth in the human capital base might benefit the local economy through several channels. First of all, the growth creates a thicker labor market for skilled workers and thus reduces the search and hiring costs for employers and employees. This reduction in costs could raise wages and employment of high-skilled workers. In addition, highly skilled workers might have positive spillover effects on older skilled workers or less skilled workers. The availability of high-skilled labor could also encourage firms to locate in the regions or invest in capital and technology thus raising labor productivity for all workers.

We might see few effects on regional employment or wages, in turn, if young high-skilled workers simply replace older or less-skilled workers with few spillovers on the productivity of those workers. On the labor supply side, an influx of young college graduates could induce some workers to leave the region or labor market: older workers with more elastic labor supply might leave full-time employment for early retirements schemes, for instance (Dustmann et al. 2016). If the new college graduates simply replace older or less-skilled workers or these workers drop out of the labor market in response, we would observe that a college opening reduces the employment of other skill or age groups with few net effects on total employment.

To trace the average effect of a college opening on the local economy, we estimate variants of our model in equation (2) where the dependent variables are total employment in the local economy and employment for less- and highly-skilled workers (in logs). The first three columns in table 3 reveal that a college opening has few effects on regional employment. Neither does total employment increase (column (1) of table 3), nor is there an effect on the employment of high-skilled (columns (2)) or less-skilled workers (column (3) of table 3). While the coefficients for high-skilled employment overall are positive they do not reach statistical significance at conventional levels.

The same pattern can be seen in figure 4 where we show the year-by-year estimates based on equation (1). The increase in overall high-skilled employment in figure 4 mirrors the growth in young high-skilled employment in figure **??**: employment rates between event and control

32% increase in high-skilled employment in the pre-event year. Suppose all of the 900 students have graduated eight years after the opening. In that case, more than 50% of the student population show up in local social security employment. This calculation does not include graduates who take up a job in the treatment district outside the social security system as self-employed or civil servant. It also does excludes graduates and dropouts who leave the region to find a job inside or outside the social security system in another district.

regions start to diverge from the opening year until about seven years later and then level off. Note that the growth in overall high-skilled employment is much smaller than the growth in young college graduates, which indicates that college graduates do replace some older high-skilled workers close to retirement.[13] Also, there is little movement in the employment share of less skilled workers neither before nor after the opening of the college in the region. Hence, we do not see a simple upskilling of the workforce where employers just replace less-skilled workers with new college graduates.

Rather than employment effects, we might observe an effect on local wages. We would expect that the large increase in the supply of young, high-skilled workers at least temporarily reduces high-skilled wages. High-skilled wages might increase in the long run if firms invest in technology or capital that complement high-skilled labor. Yet, the growth in the high-skilled workforce might also increase the wages of all workers in the presence of productivity or knowledge spillovers or if attracting high-productive firms to the area.

To investigate local wage effects, we re-estimate our model in equation (2) where the dependent variables are now the log mean daily wages of full-time workers. As for employment, we find no effect on the average wage in the local economy compared to control regions (see column (4) of table 3). One reason for the absence of a wage effect could be that wages of high-skilled workers decline while wages of groups that are complementary in the production process increase. Yet, columns (5) and (6) of table 3 suggest no offsetting effects. The coefficients on wages for high- and less-skilled workers are both positive in the post-period but fail to reach statistical significance.[14]

Our results imply that the new college had no effect on local wages of high-skilled or low-skilled workers. These findings stand in sharp contrast to two recent empirical studies that report a positive effect of a skilled supply shock on high-skilled wages: Beerli et al. (2021) show that high-skilled commuters increased the wages of high-skilled natives. Even closer to us, Carneiro et al. (2022) find that the opening of new colleges in Norway raised high-skilled wages in the region. The authors attribute this to the fact that employers invested purposefully in skill-biased technology after the college openings. Yet, we are not the only study where a growth in high-skilled workers has had little effect on the skill premium (see Beaudry and Green (2003)

[13]Splitting employment by age and skill together, we find no differential growth in employment between treatment and control regions. The only exception is, of course, young, high-skilled employment, for which the college opening has a large positive effect as shown in column (3) of table 2. We also find no population adjustments in the district. Hence, it is not the case that the new college graduates make older workers leave the region or the labor market.

[14]An analysis of wages differentiated by skill and age groups yields a very similar pattern. We find no downward pressure on wages of young high-skilled workers though their supply expands substantially following the college opening. Similarly, wages of older high-skilled workers or young less-skilled workers who might be substitutes or complements to young high-skilled workers remain unchanged as well.

for evidence from Germany and, more recently, Blundell et al. (2022) for the UK). How can we explain these very different results? Economic theory suggests that the response of the skill premium to a large shift in relative supply depends on the degree of substitutability between different types of workers, the type of technological change and potential investments in capital. We investigate these relationships in the next section.

4.3 Worker Substitutability, Technological Change and Capital

Despite the sizable growth in young high-skilled workers in the local economy, we observe neither an initial downward pressure on their wage, nor an increase later on.[15] If nothing else changed, we would expect a (temporary) decline in the local college premium after the new graduates enter the local labor market. One potential explanation for the absence of a short-run decline in the skill premium in response to the supply shock is that workers of different age and skill groups are very good substitutes. In the longer-run, firms might not respond to the growth in high-skilled labor by adjusting their production technologies; for instance. Such technology shifts could be due to profit-maximizing innovators' endogenous choice of research direction (Acemoglu 1998) or producers' selection of an optimal production technology from a given pool of alternatives (Beaudry and Green 2005; Blundell et al. 2022). A third explanation for the absence of a change in the skill premium could be that firms invested in physical capital instead, which raised the productivity of all workers with little impact on the skill premium (Beaudry and Green 2003).

To investigate what our findings imply about the substitutability between workers, the nature of technological change and potential capital responses, Appendix A outlines a theoretical framework linking local skill supplies to local wages, technology and capital. We start from a regional CES production function where the local good is produced by labor of different skill and age groups as in Card and Lemieux (2001). We further allow for factor-augmenting technological change that is potentially skill-biased. For the empirical implementation, we then relate local relative wages to relative shifts in local labor supply for different age and skill groups and other control variables.

In the first step, we estimate the elasticity of substitution across age groups using high-skilled wages of young workers relative to older workers (see equation (A.3) in Appendix A). As OLS estimates are likely biased due to reverse causality or omitted variables, we use the college opening as an instrument for the relative supply shift of young, high-skilled workers. All the estimations use the matched sample of treatment and control districts restricted to the period

[15] We will not observe a downward pressure on nominal wages if wages are downward rigid. Yet, we should still observe a relative decline in high-skilled wages compared to the skill group, for instance.

four years before and eleven years after the college opening. As shown in column (3) of table 2 and figure 3, the first stage is strong in the post-event period.

Appendix table A3 reports estimates of the age premium for three alternative samples: Column (1) compares young, high-skilled workers to all prime-aged and older workers with a college degree. As the substitutability might vary across age groups, we consider the relative wages of younger to older workers with a college degree and the relative wages of younger to prime-aged workers with a college degree separately in columns (2) and (3). Appendix table A3 shows that the OLS estimates (reported in Panel A) are small and positive suggesting that high-skilled workers belonging to different age groups are actually complements rather than substitutes. The IV estimates (shown in Panel B) are negative indicating some substitutability across age groups but the estimates fail to reach statistical significance. For both estimation approaches, the estimates do not change much whether we use older or prime-aged workers as comparison. Within the CES production function framework, the elasticity of substitution across age groups is the inverse of the reported coefficients. The IV estimates thus indicates a substitution elasticity of around six, which would explain why we do not find an effect of the college opening on the wages of prime-aged or older skilled workers.

It is important to stress that we identify the response of *local* relative wages to a *local* relative supply shift, which will be different than the elasticity of substitution estimated from a national production function. A large relative shift in local supply might not affect relative wages locally if many workers leave the local labor market or drop out of the labor force, for instance. As such, we should find a smaller elasticity of substitution than based on a national production function.[16].

In the next step, we estimate the substitutability across skill groups by relating the college premium to the relative supply of skilled workers and additional controls. Specifically, we estimate a version of equation (A.4) where we proxy skill-biased technological change by a linear trend that is allowed to vary in the pre- and post-event period (see Appendix A for details). The results using all age groups are reported in column (4); the estimates using only the skill premium of young workers are shown in column (5) of appendix table A3.

The OLS estimates for relative supply are again positive and statistically significant irrespective of which age group we use in the estimation (Panel A). The IV estimates, in contrast, are negative but only reach statistical significance in the full sample (Panel B). The sizable difference between OLS and IV estimates indicates some omitted variable or reverse causality issue

[16]For Germany, OLS estimates based on a national production function range from around seven to twenty indicating a strong substitutability across age groups (Bruell and Gathmann 2020; Fitzenberger and Kohn 2006; Glitz and Wissmann 2017)

biasing the OLS estimate upward. Based on the IV estimates, high- and less-skilled workers are (weak) substitutes with an elasticity of substitution of around 0.5. These estimates imply that a positive shock to high-skilled supply will have only a small impact on the skill premium, which is in line with the results we saw in table 3.

Interestingly, we find little support for the type of factor-augmenting technological change that favors skilled workers, which has been the focus in much of the literature on supply shifts and the skill premium. The coefficients on the linear trend variable in both the OLS and IV specifications are zero or negative and typically not statistically significant. Hence, if anything, technological change is either skill-neutral or even tends to reduce the college premium. We find a similar pattern if we restrict the specification to a common linear trend or allow for more flexible quadratic trends to capture the skill bias of technological change.

The weak substitutability across skill groups and absence of skill-biased technological change might be an artifact of the particular production function we used. The CES production function restricts technological change to be of factor-augmenting form and we have abstracted from adjustments in other inputs, especially physical capital. Yet, periods of rapid technological change might not simply raise the productivity of some production factor, but generate disruption through the arrival of new forms of production, which also require new modes of organization (see the discussion in Beaudry and Green 2003; Blundell et al. 2022). Moreover, plants might invest in additional physical capital, which could affect the skill premium if it is not factor neutral. Beaudry and Green (2003) have long pointed out that the skill premium has risen much faster in the U.S. than in Germany, in part because employers in Germany made sizable investments in physical capital.

To assess the role of capital and broader technological advances, we extend the regional production function in two ways. First, we include physical capital as an additional input that is traded in a national market. Second, we allow for flexible shifts in technology by using a first-order linear approximation to an arbitrary production function following Blundell et al. (2022). We then obtain an augmented specification for the skill premium (see equation (A.6) in Appendix A). The skill premium now depends on relative skill supplies as before, the regional capital intensity and technological shifts. We estimate this augmented equation by relating the college premium to relative skill supplies, capital intensity, general TFP growth and other technological change, which we proxy by a linear time trend that may differ before and after the college openings.

The results of this more general specification are shown in column (6) for all age groups and column (7) for young workers in appendix table A3. Focusing on the IV estimates, the coefficients on relative skill supplies again suggest some substitutability between skill groups. The implied substitution elasticity in this more general specification ranges from 0.7 to 1, which is quite in a similar range than the elasticities obtained from the CES production function.

General TFP growth seems to favor high-skilled workers in the full sample (column (6)) but not among young workers (column (7)). Instead, wages of young, high-skilled workers were pushed up by investments in capital intensity indicating that employers in event regions not only hired the new college graduates but also invested in additional physical capital. The linear time trend, which proxies for factor-augmenting technological change, is again zero or negative prior to the opening but turns slightly positive in the post-event period. Hence, the shock to high-skilled labor supply did not reduce the skill premium because of some offsetting capital investments and a modest technological change favoring young college graduates. Yet, the additional capital and shifts in technology are not sizable or long-lasting enough to push up high-skilled or average wages in the even regions in the long-run.

Overall, we show find strong evidence for weak substitutability across age and skill groups at the local level – independently of how we specify the labor demand side. That implies that even large shifts in relative supply have only a small or no impact on the age or college premium, which is consistent with the absence of local wage effects – overall and across age or skill groups. We see only limited evidence for skill-biased technological change; instead, capital investments seem to play an important role for the absorption of the new college graduates in the local economy. Before we investigate the channels of the local absorption, we first demonstrate the robustness of our main results.

4.4 Specification Checks

The dependent variable for all robustness checks is the log of young, high-skilled employment in the region. For ease of comparison, we report our baseline estimates from table 3 again in column (1) of appendix table A4.

A first-order concern with our event study approach in equation (2) is that the effects may be caused by differential trends in outcomes between treated and matched control regions or by unobserved confounders. As we demonstrated in table 1, our matching approach does balance not only levels of employment and wages, but also their growth rate. Nevertheless, potential confounding factors could be other changes in regional policies like local firm subsidies; or unobserved demand and productivity shocks that are unequally distributed across regions due to differences in the underlying local industry structure. We address these concerns in several ways. First, we control for unobserved region-specific shocks by including a separate linear (in column (2)) or quadratic trend (in column (3)) for each region. The results are very similar to the baseline in column (1). Our results might also be accounted by negative demand or supply shocks in control regions. The observed increase in young, high-skilled employment might then be explained by an employment decline in control districts rather than an expansion in treated regions. To check for confounding shifts in control regions, we run a placebo test: we match control regions to other untreated regions using the same matching approach and variables as for our main analysis (see Section 3.2). We then re-estimate our baseline model in equation (2). Column (4) of appendix table A4 shows negative coefficients – but they are never close to be statistically significant.

We next test the robustness of our results to the heterogeneity of the treatment estimates. The event study approach in equation (1) and the aggregate approach in equation (2) may not identify an average treatment effect on the treated (ATT) if effects are heterogeneous across regions or change dynamically over time. An emerging literature has demonstrated that the standard event study design with staggered adoption only identifies some weighted average of the treatment effects with weights that could be negative. To check for this possibility, we implement the re-weighting estimator of Sun and Abraham (2021) that identifies a proper ATT even in the presence of heterogeneous or dynamic treatment effects in column (5). The results are almost identical to the baseline estimates, which is perhaps less surprising if one considers that the college openings all occur within a decade and hence, a relatively short time window.

The matching approach might also give rise to concerns. Recall that we match on variables just before the college opening (in $\tau = -1$). If there are anticipation effects, the local economy might have started to adapt to the college opening, e.g. by changing its industry structure, which are part of our matching set. As an alternative, we repeat the matching using all variables measured three years before the opening ($\tau = -3$) instead. Column (6) shows statistically somewhat weaker effects for the post-period. Furthermore, our two-step estimation strategy controls for time-invariant regional confounders but does rely on a common trends assumption conditional on our matching step. An alternative approach is match not only on regional observable characteristics, but also on pre-treatment outcomes like employment directly. The synthetic control approach matches the pre-event trend in employment for each event region, and does therefore not rely on a common trend assumption between treated and (synthetic) control regions. Yet, the approach requires pre-event confounders to be mean independent of the outcome. Column (7) in appendix table A4 shows similar, albeit noisier estimates.

Finally, college openings might not only affect the district in which the new college is located, but rather spills over to neighboring districts. Such spillover effects could be important if the college draws in young people from the surrounding districts for studying and later supplies neighboring regions with high-skilled workers. It is important to note that our matching approach does not match event regions to any neighboring district. As such, our baseline results are not contaminated by control regions experiencing positive (or negative) spillover effects. Yet, in the presence of spillovers to neighboring regions, our baseline estimates would underestimate the true benefits of the college opening. To check for spillover effects in the broader region, we define the broader region as all neighboring districts sharing a border with an event (or control) district but exclude the event resp. control district. We then re-estimate equation (2) where the dependent variable is now log employment of young, high-skilled workers in all neighboring districts of an event resp. control region. The results in column (8) of appendix table A4 show only a muted response beyond the event district. As such, college openings seem to have mostly local effects with few spillovers beyond district boundaries.

Overall then, all specification checks demonstrate that our results are very robust to alternative matching approaches and assumptions in the first stage as well as alternative estimators and specifications in the second stage.

5 Local Absorption of the New College Graduates

Our evidence so far points to few local employment and wage effects in the local economy on average, while the production function approach indicates that employers have responded to the additional skilled labor by additional capital investments. We now explore where the new high-skilled labor is absorbed in the local economy and who benefited from the college opening.

5.1 Employment in Manufacturing vs. Services

We first ask whether the college graduates are mainly employed in manufacturing or services. Thus ,we re-estimate equation (2) where the dependent variables are total employment (columns (1) and (4)), high-skilled (columns (2) and (5)) and less-skilled (columns (3) and (6)) employment in the specified sector. Table 4 reveals that high-skilled labor in manufacturing increases by 16.6 percentage points, while there is little change in high-skilled employment in the service sector. We also checked whether we find any effect if we split the service sector into low- and high-skilled services. Yet, we do not find an employment effect for high-skilled services like insurance, consulting or finance sector, likely because these are typically located in the large urban centers, which are not in our sample.

Does the growth in high-skilled employment in manufacturing imply that less-skilled workers are replaced and hence, their employment declines after the college opening? Column (3) in table 4 shows a negative, albeit not significant coefficient for less-skilled employment. Hence, most college graduates find a job in local manufacturing where they replace some less-skilled manufacturing workers. As for total employment in the region, we find no effect on total employment in manufacturing (see column (1)) or services (see column (4)).[17]

To isolate the employment effect of college openings further, we split manufacturing into high-tech manufacturing – containing the chemical industry, machinery, electrical and transport equipment and some smaller manufacturing industries (see also Beerli et al. 2021) – and into other manufacturing. The results show that high-skilled employment increases mostly in high-tech manufacturing. Here, high-skilled employment grows by 28.7 percentage points within the first decade after the college opening (see column (7) in table 4). Interestingly, the long-run estimate for less-skilled workers in high-tech manufacturing is also positive (see column (8)) indicating that high-tech firms do not simply hire college graduates to replace less-skilled workers.

Given the sizable employment responses, we next turn to the development of wages in high-tech manufacturing. High-skilled wages do not grow in high-tech manufacturing after the college opening (see column (9) in table 4). The absence of a wage effect suggests that high-tech firms could satisfy their demand for skilled workers and hence, solve any labor shortages that might have existed in the region before the college opening.

The final column of 4 further shows that the additional hiring of skilled workers in high-tech manufacturing firms increased the wages of less-skilled workers by 5.6 percentage points within ten years after the college opening relative to high-tech firms in control regions. The wage effect across skill groups indicates that high-skilled workers raise the productivity of less-skilled workers. In turn, Section A.1 showed that additional capital investments and technological change did favor high-skilled workers, but not less skilled labor.

Overall then, high-tech firms in manufacturing definitely benefited from the college opening as the new graduates helped to fill vacancies. Another group that benefits from the college opening are less-skilled workers who work in high-tech manufacturing and benefit from sizable wage growth.

[17]Beyond these broader categories, we see few shifts in the employment composition of detailed industries. If the local supply shock is primarily absorbed through inter-regional trade, regions with a college opening would expand their skill-intensive industries and export more goods that use high-skilled workers more intensively compared to control regions. We do not see such a pattern, however.

5.2 Professionals, Managers and Engineers

We next investigate which occupations the new college graduates occupy in the local economy. To do so, we restrict the sample to workers in the age range from 20-29. We then re-estimate our model in equation (2) for four broad occupational groups: unskilled manual labor, skilled manual labor, semi-professionals and professionals. The results in columns (1)-(4) of table 5 reveal that new college graduates primarily enter professional occupations. In the first five years, professional employment among young workers increases by 6.2 percentage points; the cumulative effect five to ten years after the college opening has grown to 14.4 percentage points (see column (4)).

Are these additional professional jobs created in manufacturing or in the service sector? To answer this question, we study professional employment in each sector separately: columns (5) and (6) of table 5 show that professional employment grows in manufacturing by 15.4 percentage points, while we see little change in the service sector. Finally, we investigate which professional jobs the new college graduates obtain in manufacturing. In particular, we distinguish between managerial positions and engineering jobs. Columns (7) shows that a college opening does not change the number of managerial positions in the manufacturing sector. Instead, the growth of professional jobs in the manufacturing sector is concentrated among engineering jobs.

5.3 STEM Colleges and Innovation

As the college opening has the biggest effect in the high-tech sector with a strong growth in engineering jobs, the benefits of the college for the local economy might depend on the subjects the college offers. In particular, the effects might differ for colleges that focus more on STEM subjects and related areas and colleges that focus more on teaching business or architecture, for instance. A first reason why the type of subjects offered matters is that employers often face shortage in the supply of high-skilled occupations like engineers or other STEM subjects. Another reason could be that STEM workers create positive externalities through R&D activities, production or knowledge spillovers. To investigate the role of different study programs, we classify the colleges into those with a STEM focus and those with no STEM focus. We then re-estimate equation (2) by letting the coefficients on the college opening differ by college type. Panel A of in table 6 shows results for STEM colleges, Panel B for non-STEM colleges.

We find that total employment increases in regions where a STEM college was opened (see column (1)). Within the first five years, local employment increases by 11.6 percentage points in regions with a STEM college compared to the control regions, while there is no effect on local employment for non-STEM colleges. Even ten years after the college opening, the growth in local employment is still much stronger for STEM colleges (+17.5 percentage points) than for non-STEM colleges (+9.1 percentage points, which is not statistically significant). Column (2) further shows that the differential effect on total employment is not driven by a higher growth in high-skilled employment. For both STEM and non-STEM colleges, we observe little to no growth in total high-skilled employment in the region.

We next turn to the question whether STEM and non-STEM colleges also have a differential impact on local wages relative to the control regions. If graduates from STEM colleges create positive spillovers on other workers, for instance, the wages of workers whose productivity has increased through knowledge spillovers or whose demand increased because of production complementarities with STEM workers should increase. Columns (3) to (5) of table 6 show the results for the wages of less-skilled workers by age.

STEM colleges raise the wages for both young and older less-skilled workers by 1.1-1.6 percentage points relative to the control regions; we see no effect in regions that opened a college without a STEM focus. These spillover effects indicate that engineers and other graduates from STEM Colleges increase the productivity of less-skilled workers in the region.

Turning to high-skilled wages in columns (6)-(8), we find positive coefficients for all age groups in regions with STEM colleges (Panel A) but they do not reach statistical significance. For non-STEM colleges, Panel B shows that the increase in supply of young high-skilled workers reduces young, high-skilled wages initially by 2.4 percentage points (see column (6) in Panel B). That indicates that the supply of new college graduates exceeded the demand for high-skilled labor for regions with new colleges not focused on STEM subjects initially. In the long-run, the wage effect of young, skilled workers reverts to zero as employers absorb the new supply of college graduates into their workforce. We also find no statistically significant effects on high-skilled wages for prime-aged or older workers (see columns (7) and (8)).

Given the strong employment effect for engineering jobs, one might wonder whether the new engineers encourage innovation in the regions with a college opening – which could be another reason we find positive wage effects on less-skilled workers. To investigate this, we use information on patents filed in the region based on the address of the organization or person named in the patent documents as patent holder. We then use our baseline model in equation (2) to see whether patent activity goes up after a college opening; and whether there is any differential effect for regions in which a college with STEM focus was opened. Appendix table A6 shows the results: columns (1)-(3) report unweighted results, while columns (4)-(6) uses local employment in the pre-event period as weight. The dependent variable in all specifications is the total number of patents filed in the region. We first use the full sample (in column (1) and (4)) and then run separate analyses for STEM colleges (in columns (2) and (5)) and non-STEM colleges (in columns (3) and (6)). The main conclusion here is that we do not find any effect on patenting activity in regions with a college opening irrespective of whether the college has a STEM focus or not.

Overall then, the new graduates did not increase the innovative capacity of a region, to the extent that this can be measured by patents. The absence on any effect for patent also confirms that the new college did not themselves spur innovation through research and start-ups in the local area (as discussed in Section 2).

5.4 University Employment and Local Demand

We further investigate whether the new college itself has a direct effect on the local economy. The college creates jobs for different skill groups: on the one hand, the college needs faculty and practitioners to teach in the college. In addition, the college requires an administration and services like cleaning and maintenance. We focus first on total employment in higher education, which includes colleges and universities located in the region. As only two regions have a university prior to the college opening, employment in higher education will largely reflect additional jobs in the new colleges. Based on equation (2), appendix table A5 shows that there is no employment growth in higher education prior to the opening of the college in our sample. Within five years after the opening of the new colleges, total employment in higher education institutions has increased by almost 60 percentage points. In the long-run, employment in higher education has grown by 93.2 percentage points relative to control regions (see column (1)). Do colleges as employers hire more high- or rather less-skilled workers? Columns (2) and (3) show that both employment categories increase; yet, relative to the local workforce, the employment growth contributes only a small share to overall employment. Hence, it is not surprising that the impact of the college employment on the local labor market is limited.

A region might further benefit from the opening because the student body and university staff bring in additional income and raise the demand for local goods and services. The right-hand side of appendix table A5 shows that there is no effect on employment in the non-tradable sector: overall employment (in column (4)), high-skilled employment (in column (5)) and less-skilled employment (in column (6)) does not change after the college opening compared to control regions.[18] The absence of any effect on local goods and services suggests modest local multipliers in our setting, which is not surprising given that the new technical colleges are

[18]If we zoom in on the hospitality industry, we do see a transitory employment effect of about five percentage points, which is no longer statistically significant in the long-run (not reported).

relatively small.

6 Are College Openings an Effective Place-Based Policy?

The evidence thus far indicates that the opening of a college improves the local human capital base. While we find no boost for the overall economy in the region, the new college graduates were quickly absorbed into the labor market, esp. by high-tech manufacturing firms to alleviate local skill shortages. The growth in high-skilled employment created additional gains for less-skilled workers in high-tech manufacturing. We also saw that STEM colleges generate larger local benefits than colleges without a STEM-focus. In contrast, job creation by the college or through local multiplier effects are modest, in part because the colleges are themselves quite small.

Yet, do these results imply that opening new institutions of higher education could be a successful place-based policy tool – a kind of a golden bullet to help the economic development of declining regions or areas facing substantial structural transformation? We saw in Section 2 above that the regions in which a college opened were neither the most economically advanced urban centers nor the most backward regions. Do all of the regions benefit from a college opening or just some? It could well be that college openings only generate benefits for the region in economically dynamic regions; or, it could be that less vibrant regions benefit the most from a boost to the local human capital base. Knowing the answer to this question is important to guide policy-makers: if there are no benefits to economically declining regions, it makes more sense to open colleges in regions with more favorable economic conditions, for instance.

6.1 Estimation Approach

To answer the question which regions benefit, we split our sample into regions with a more dynamic labor market and those with less dynamic labor markets. We define regions as 'dynamic' if they had above median employment growth (15 percentage points on average) in the late 1970s. We define those regions with below median employment growth (just 3 percentage points) as 'stagnant'.

Comparing the two regions along observable characteristics in appendix table A7 suggests otherwise few observable differences: Dynamic and stagnant regions are very similar in their industry structure or the age and skill structure of their workforce. Further, dynamic and stagnant regions do not differ in wage levels or wage growth prior to the college opening. Reflecting their more favorable local labor market, dynamic regions have a somewhat lower unemployment rate (by 2 percentage points) than stagnant regions (see columns (1) and (3)). Dynamic and stagnant regions also have a very similar share of high-tech manufacturing industry and are equally likely to obtain a college with a STEM focus. Based on observables, it is a-priori not clear which of the two regions might benefit the most from a college opening.

To explore the heterogeneity, we augment our baseline approach in equation (2) by interacting the event variable with indicators whether the region was economically dynamic or stagnant. Specifically, we estimate variants of the following model:

$$\begin{aligned} Y_{r\tau t} = {} & \beta_B^{Dyn} Before_\tau * Opening_r^{Dyn} + \beta_T^{Dyn} Trans_\tau * Opening_r^{Dyn} + \beta_P^{Dyn} Post_\tau * Opening_r^{Dyn} + \\ & + \gamma_B^{Stag} Before_\tau * Opening_r^{Stag} + \gamma_T^{Stag} Trans_\tau * Opening_r^{Stag} + \gamma_P^{Stag} Post_\tau * Opening_r^{Stag} + \\ & \theta_\tau^{Dyn} + \theta_\tau^{Stag} + \delta_t + \alpha_r + \varepsilon_{r\tau t} \end{aligned} \tag{3}$$

where $Y_{r\tau t}$ are again regional employment or wages. As before, the subscripts r, t and τ denote region, calendar time and the period relative to the event, respectively. $Opening_r^{Dyn}$ is now an indicator equal to one if a college opened in a region with a dynamic labor market r. The variable $Opening_r^{Dyn}$ is zero for control districts or event districts that belong to a region with a stagnant labor market. Similarly, $Opening_r^{Stag}$ is an indicator equal to one if a district r had a college opening but is located in a stagnant local labor market; and zero for control regions and event regions with a dynamic labor market. We focus on this pooled estimation to increase statistical power as we only have twenty event regions. As in previous sections, $Before_\tau$ denotes the period before the actual opening ($-7 \leq tau \leq -1$), $Transition_\tau$ is an indicator equal to one in the years between the opening and the graduation of the first cohort of students ($0 \leq \tau \leq 5$) and $Post_\tau$ characterizes the long-run adjustment ($6 \leq \tau \leq 11$).

The specification in equation (3) allows dynamic and stagnant regions to have different employment trends before and after the college opening by allowing separate event time fixed effects for dynamic (θ_τ^{Dyn}) and stagnant local labor markets (θ_τ^{Stag}). All other variables are defined as before. Compared to estimating the equation (2) separately for dynamic and stagnant regions, we only require calendar time to affect both types of regions similarly; yet, we do allow for differences in employment levels and trends in the pre- and post-period. The estimates β_B^{Dyn} and γ_B^{Stag} show whether dynamic (or stagnating) regions that had a college opening exhibit a differential pre-trend than their respective control regions. The main coefficients of interest are β_T^{Dyn}, β_P^{Dyn}, γ_T^{Stag} and γ_P^{Stag}, which trace whether dynamic or stagnant regions have better labor market outcomes than their respective control regions in the medium- and long-run.

6.2 College Openings in Dynamic and Stagnant Labor Markets

We start out with the evolution of young high-skilled employment. Figure 6 plots the coefficients for the years before and after the college opening separately for dynamic and stagnant areas. The figure shows clear differences: the employment of new college graduates increases steadily in economically dynamic regions (the red line) compared to their control regions. The picture looks different for stagnant regions: here, there seems to be only a temporary growth in the employment of young high-skilled workers (the blue line). Five years after the opening, stagnant regions see a reversal of the growth and young high-skilled employment reverts toward it pre-opening level. The corresponding estimates (reported in column (1) of table 7) indicate that the growth in local employment of young high-skilled increases more than twice as much in dynamic regions (by 16.4 percentage points, see Panel A, column (1)) relative to control regions in comparison with the growth in stagnant regions (see Panel B, column (1)). These numbers indicate that some regions seem to be able to absorb and benefit from the new supply of high-skilled workers more than others.

One reason for the observed difference is that the regions vary in the size of the supply shock because the colleges opened in economically less vibrant regions are smaller than in more dynamic areas, for instance. Columns (2) and (3) of table 7 reveal, however, that dynamic and stagnant regions do not differ in their growth of the student population. In both regions, the student population increases by a factor of five to six (in column (2)) and the potential share of high-skilled in the region by 52-54 percentage points (see column (3)). Hence, the size of the new colleges is very similar in the two regions. The differential effect is also not explained by differences in the subject mix – in vibrant regions, four colleges opened with a STEM focus, while there were five colleges with STEM focus in stagnant regions.[19]

Are regions with a stagnating economy not able to retain the high-skilled workforce trained in the region after the college opening? To investigate this, we turn to population flows between districts, which provide a better picture of actual mobility than employment flows in the social security records. Outflows in the social security records are only recorded if a person was working in a job subject to social security contributions in the district in one year and is then observed in an employment relationship subject to social security contributions in a different district in a later year, for instance. Students might never be registered in the social security records of an event district if they leave the area before or immediately after graduation and obtain their first job elsewhere. And yet, the data on population flows also have limitations. Students might

[19] The differential dynamic is also not the explained by the fact that two out of the ten dynamic regions have already had a university or college. We still find the same patterns if we drop the two districts with a university or college prior to the opening.

not register with the municipality but remain registered at their parents' residence instead; or, they might never move to the district hosting the college but commute from neighboring districts.[20] In both cases, a student entering (or leaving) the college is not registered as an inflow (or outflow). The undercounting of students in their district of study introduces measurement error in the population flows. While there is no reason the issue should be worse in dynamic than in stagnant regions, it will make our estimates less precise.

We then re-estimate equation (3) where the dependent variable are now population inflows and outflows of individuals between the ages of 18 and 30 years. The estimates provide suggestive support that less vibrant regions experience sizable outflows of young people from the region after the college opening (see table 7, column (5) in Panel B), which is not compensated by increased inflows (see column (4) in Panel B). We observe the opposite pattern in dynamic local economies: here, we observe a reduced outflows of young people after the college opening (see table 7, column (5) in Panel A). It seems that less vibrant regions initially attract young people to the area, but cannot retain them in the region later on. In contrast, vibrant regions are able to keep most graduates trained in the new college resulting in a sustained and permanent boost to the local human capital base.

The sustained growth of the high-skilled workforce in economically dynamic regions could also impact how the local economy benefits from the college opening. An abundant supply of high-skilled workers might attract new firms to the region, for instance. To explore this, we investigate employment in incumbent firms versus employment in new firms, i.e. that were founded within the past five years. Finally, we also look at the number of firms exiting the market. We then re-estimate equation (3) where the dependent variables are now total or high-skilled employment in incumbent and entering firms. Table 8 shows several interesting patterns: in stagnant regions, the additional high-skilled workers are absorbed by incumbent firms (see column (2) in Panel B). As total employment in incumbent firms does not change (see column (1) in Panel B), this implies that incumbents up-skill their workforce by replacing less-skilled workers with high-skilled workers. Dynamic regions exhibit a very different pattern: here, the additional high-skilled workers are employed in new firms (see column (4) in Panel A). New firms create additional jobs and hence, increase their total employment (see column (3) in Panel A). There is no effect on firm exit.

These findings show that it matters in which economic environment a college is opened. Our evidence will disappoint policy-makers who wish to use the founding of new colleges to turn around the fate of economically declining regions. The results in this paper show that such

[20]Unfortunately, data on commuting flows is not available for the time period we analyze.

a policy is not beneficial for stagnant regions in the longer-run. At most, existing firms will benefit from the more abundant supply of high-skilled workers. Beyond that, the benefits for economically stagnant regions are modest and temporary. The situation looks much brighter for the more dynamic regions. New colleges, even if they are relatively small, can attract new firms to the region and create additional jobs – though these do not translate into employment or wage growth at the local labor market level (see appendix table A8).[21]

Our results are consistent with insights from EU structural funds that showed net gains in income and investment per capita only in regions with a favorable human capital base and governance structure (Becker et al. 2013). While the policies implemented differ, one lesson to take away is that economically backward and struggling regions benefit little from such place-based policies. Such policies do work best in regions that have a sound economic basis and governance structure, which enables them to gain from the proposed subsidy or infrastructure investment.

7 Discussion and Conclusion

We exploit the opening of new technical colleges in Germany during the 1980s and early 1990s to study their impact on the local economy. Our empirical strategy combines matching with an event study approach to find suitable control regions for the event districts with a college opening. We have four main findings. First, the opening of a college substantially increases the local student population. The opening further spurs a sizable growth in the share of high-skilled employment by 13% in the district where the college is located. Second, we find no effect on overall employment or wages suggesting few growth or productivity gains for the local economy on average. Third, we see that the new college graduates get absorbed by high-tech firms in manufacturing, mostly in engineering jobs, which also pushed up wages of less skilled workers in high-tech manufacturing. In contrast, we find few changes in the high- and low-skilled service sector. Finally, we document that the impact of a college opening depends on the local labor market condition: in dynamic labor markets, a college opening results in a sustained growth in the high-skilled workforce, which encourages firm entry and job creation. In less vibrant labor markets, in turn, the high-skilled share grows less and college graduates are largely absorbed by incumbent firms.

The insights from our analysis carry important lessons for regional policy. College openings

[21] Appendix table A8 shows that total employment increases by 3.3 percentage points (see column (1) in Panel B), while local employment in stagnating regions actually declines by 5 percentage points (see column (1) in Panel A), largely because less-skilled employment declines (see column (3) in Panel A). Yet, the standard errors also show that the estimates are noisy as none of them is statistically significant at conventional levels.

are an effective strategy to increase the skill level of the regional workforce. Yet, college opening need not benefit the whole local economy by raising average employment or wages, which could provide further justification for subsidizing tertiary education. Instead, the benefits are locally concentrated in some industries and professions with larger benefits from STEM colleges. And economically backward regions are less able to reap the benefits from a college openings than regions with a more vibrant labor market.

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A Appendix A: The Substitutability between Labor Inputs, Technological Change and Capital

A.1 Regional Production Function

Each region r produces a single output using labor. We abstract from capital and interregional trade for now. In Section A.4 below, we extend our framework to allow for capital adjustments; we also analyze the potential role of inter-regional trade in Section 5.1. Following Card and Lemieux (2001) and Card and Lewis (2007), aggregate labor is specified as a nested CES production function using two types of labor: Less-skill ed and skilled, which we denote by L_{rt} and S_{rt} respectively.

$$Y_{rt} = \left(\theta_{lt} L_{rt}^{\psi} + \theta_{st} S_{rt}^{\psi}\right)^{\frac{1}{\psi}}, \tag{A.1}$$

where $-\inf < \psi \leq 1$ is a function of the elasticity of substitution between college and non-college labor ($\psi = 1 - 1/\sigma_E$). The shares of different types of labor are represented by θ_{lt} and θ_{st}, which may evolve over time due to technological change, for instance. In equation (A.1), labor-augmenting technical change of high-skilled workers would result in an increase in θ_{st}; and similarly for less-skilled workers (θ_{lt}). Skill-biased technical change would imply an increase in $(\theta_{st}/\theta_{lt})$ over time.

Labor in each skill group consists of a CES-aggregate of the labor of workers in $j = 3$ different age groups:

$$L_{rt} = \left[\sum_{j=1}^{3} \alpha_{lj} L_{jrt}^{\phi}\right]^{\frac{1}{\phi}}, \qquad S_{rt} = \left[\sum_{j=1}^{3} \alpha_{sj} S_{jrt}^{\phi}\right]^{\frac{1}{\phi}} \tag{A.2}$$

where $-\infty < \phi \leq 1$ depends on the elasticity of substitution between age groups ($\phi = 1 - 1/\sigma_A$) and the α_j's are relative efficiency parameters for age-group j, which we take as constant over time.

The specifications in equations (A.1) and (A.2) imply that the elasticity of substitution between workers of different ages are the same for all skill groups and the elasticity of substitution of different skill groups is the same for all age groups. We test these restrictions with our data below. Workers of different ages are gross substitutes when $\sigma_A > 1$, and gross complements when $\sigma_A < 1$. If different age groups within a given skill level are perfect substitutes, $\sigma_A \to \infty$.

A.2 Elasticity of Substitution across Age Groups

We first study the age premium among skilled workers. Assuming perfect competition and hence, that labor is paid its marginal product, this age premium is defined as:

$$ln\left(\frac{w_{jrt}^S}{w_{1rt}^S}\right) = ln\left(\frac{\alpha_{sj}}{\alpha_{s1}}\right) - \left(\frac{1}{\sigma_A}\right) ln\left(\frac{S_{jrt}}{S_{1rt}}\right) + \varepsilon_{jrt} \tag{A.3}$$

where $j = 2, 3$ are prime-aged and older workers and $j = 1$ is the group of young, high-skilled workers. Equation (A.3) shows that rising supply of young workers may increase the wages of older high-skilled workers relative to young, high-skilled workers by $\frac{1}{\sigma_A} dlog\left(\frac{S_{jrt}}{S_{1rt}}\right)$. If young and older workers are perfect substitutes in their skill group $\sigma_A \to \infty$, however, there is no effect on the age premium.

College openings provide us with an exogenous shock to the local supply of young, high-skilled labor (S_{1rt}) in the treatment regions. Using the college openings, we can then identify the elasticity of substitution across age groups (σ_A) and the ratio of efficiency parameters $(\frac{\alpha_{sj}}{\alpha_{s1}})$ from a regression of relative wages of young and older high-skilled workers on age-specific relative supplies, age group dummies, matched pair fixed effects and year fixed effects interacted with a treatment indicator. The latter allow for differential trends in relative wages between treatment and control regions over time. Matched pair fixed effects ensure that we compare each event region to its respective control. The age group dummies absorb differences in the relative efficiency parameters ($\frac{\alpha_{sj}}{\alpha_{s1}}$). By normalizing one of the α_{sj}, we obtain estimates of the efficiency parameters of the two other age groups.

It is important to stress that we identify the response of *local* relative wages to a *local* relative supply shift, which will be different than the elasticity of substitution estimated within the framework of a national production function. A large relative shift in local supply might not affect relative wages if many workers leave the local labor market or drop out of the labor force. In that case, our estimates of the elasticity of substitution should be larger in absolute terms because we do not take into account movements across local labor markets.

The results of estimation equation (A.3) are shown in columns (1)-(3) of appendix table A3. The top panel shows results using OLS, while the bottom panel reports instrumental variable estimates where we use the college opening as instrument for the relative supply of young, high-skilled workers. Column (1) shows the pooled estimates for all three age groups together, while columns (2) and (3) report the results if we estimate it for older and prime-aged workers (relative to young workers) separately. The OLS estimates are positive, rather than negative indicating that among high-skilled workers, different age groups might be complements rather than substitutes. The IV estimates are negative but not statistically significant. The IV estimates would imply an elasticity of from $\widehat{\sigma_A} = 3$ to $\widehat{\sigma_A} = 10$. The fact that skilled workers of different ages are not good substitutes locally provides on rationale why we find few effects on the college opening on the employment or wages of older, high-skilled workers.

A.3 Elasticity of Substitution across Skill Groups

We next turn to the impact on the college premium and its determinants. Using our regional production function, relative wages of skilled to less-skilled workers, in age group j are defined as:

$$ln\left(\frac{w^S_{jrt}}{w^L_{jrt}}\right) = ln\left(\frac{\alpha_{sj}}{\alpha_{lj}}\right) + ln\left(\frac{\theta_{st}}{\theta_{lt}}\right) - \left(\frac{1}{\sigma_E}\right) ln\left(\frac{S_{rt}}{L_{rt}}\right) - \left(\frac{1}{\sigma_A}\right)\left[\ln\left(\frac{S_{jrt}}{L_{jrt}}\right) - ln\left(\frac{S_{rt}}{L_{rt}}\right)\right] \quad \text{(A.4)}$$

Equation (A.4) shows how changes in relative supply may affect the college premium. Abstracting from technological change for now, the direct effect of an increase in the supply of young, skilled workers on the skill premium of young workers is given by:

$$dln\left(\frac{w^S_{1rt}}{w^L_{1rt}}\right) = -\frac{1}{\sigma_A} dln\left(\frac{S_{1rt}}{L_{1rt}}\right) + \left(\frac{1}{\sigma_A} - \frac{1}{\sigma_E}\right) dln\left(\frac{S_{rt}}{L_{rt}}\right)$$

In the absence of technological change, a college opening reduces the college premium for young workers if the supply of skilled workers increases a lot and the elasticities of substitution across age and education groups are small. Given that our estimated elasticities across age groups are large, the college premium will only decline if there is large increase in the supply of skilled labor and a low elasticity of substitution across skill groups. If there is skill-biased technological change, i.e. an increase in $\frac{\theta_{st}}{\theta_{lt}}$ in event regions over time, the skill premium could rise for all age groups in response to the positive supply shock of skilled workers.[22]

We cannot estimate the parameters of equation (A.4) directly because of the unobservable aggregate skill supplies (S_{rt} and L_{rt}), which depend on the age-specific skill supplies and param-

[22]The college premium might also increase with relative changes in the age-specific efficiency units ($\frac{\alpha_{sj}}{\alpha_{lj}}$). We follow the literature here and abstract from that possibility here.

eters of the model (σ_A, α_{sj} and α_{lj}). However, we can use our estimates from equation (A.3) above to calculate aggregate skill supplies. If the efficiency parameters are the same across skill groups ($\alpha_{sj} = \alpha_{lj}$ for all j), estimation of equation (A.3) is sufficient to identify the efficiency parameters for all age and skill groups. The evidence indicates that the restricted version of uniform efficiency parameters is valid. Using our estimates of $\widehat{\sigma_A}$ and $\widehat{\alpha_{.j}}$, we can calculate the aggregate skill supplies (S_{rt} and L_{rt}) from equation (A.2).

It remains to make an assumption how the rate of relative skill-biased technological change ($\theta_l t$ and $\theta_s t$) evolves over time. The college opening will affect the relative skill supplies of young, skilled workers; moreover, it may raise the rate of skill-biased technological change in the event regions relative to control regions. Therefore, the college opening cannot serve as an instrument to separate the two channels. We start out with the assumption the skill-biased technological change follows a linear trend t according to $\frac{\theta_{st}}{\theta_{lt}} = d_0 + d_1 * t + d_2 * t^{After} + \vartheta_{rt}$ (Katz and Murphy 1992). This assumption implies that we can capture the impact of skill-biased technological change with linear time trends where the trends are allowed to differ after the college opening.

Columns (4) and (5) in appendix table A3 report the estimates for the skill premium allowing for factor-augmenting technological change. Column (4) uses the whole sample, while column (5) uses the skill premium for young workers only. The OLS estimates in Panel A are again positive, while the IV estimates in Panel B are negative. Based on the IV estimates, workers belonging to different skill groups are substitutes with an elasticity of substitution of 0.5. The linear trend is negative or zero suggesting little change in technology in response to the supply shock. Based on these estimates, we would expect that the relative supply shock reduces the skill premium a little.

A.4 Allowing for Adjustments in Capital and Flexible Technological Change

An alternative explanation why a sizable growth in skilled workers has little impact on relative wages is because of adjustments in capital (Beaudry and Green 2003; Beaudry et al. 2010), which we have abstracted from for now. If capital and skilled labor are complements (or become more complementary due to technological change), a decline in the skill premium induces firms to invest more in capital. In addition, the specification of the production function in equation (A.1) above is restrictive as it only allows for factor-augmenting technological change but not for disruptive shifts in technology and modes of organization as seen during the IT revolution, for instance (Blundell et al. 2022).

To investigate the role of capital and flexible technological change, we extend the regional production function according to $Y_{rt} = F(\theta_{st} S_{rt}, \theta_{lt} L_{rt}, K_t)$ where K_t denotes physical capital, which we assume to be traded in a national market. As before, S_{rt} and L_{rt} are the regional supplies of skilled and less-skilled workers, which combines the labor of different age groups according to the CES production function in equation (A.2) above. θ_{st} and θ_{lt} again denote the skilled and less-skilled labor-enhancing technological change parameters. Unlike in equation A.1, we do not specify a specific functional form for the production function in order to nest alternative models of technological change (Blundell et al. 2022). Rather, we only require the production function F(.,.,.) to be constant returns to scale.

Assuming competitive labor markets where each skill group is paid their marginal product, the first-order condition for skilled workers in age group j is:

$$w^S_{jrt} = \theta_{st} F_1 \left(\frac{\theta_s S_{rt}}{K_t}, \frac{\theta_l L_{rt}}{K_t}, 1 \right) \alpha_{sj} \left(-\frac{1}{\sigma_A} \right) \left(\frac{S_{jrt}}{S_{rt}} \right)$$

where F_1 denotes the first derivative with respect to skilled labor. Similarly, for less-skilled workers we obtain:

$$w^L_{rt} = \theta_{lt} F_2 \left(\frac{\theta_{st} S_{rt}}{K_t}, \frac{\theta_{lt} L_{rt}}{K_t}, 1 \right) \alpha_{lj} \left(-\frac{1}{\sigma_A} \right) \left(\frac{L_{jrt}}{L_{rt}} \right)$$

where F_2 denotes the first derivative with respect to less-skilled labor. Using a first-order linear approximation, we can write the wages of skilled workers belonging to age group j as:

$$lnw_{jrt}^S \approx ln\alpha_{sj} - \frac{1}{\sigma_A} ln\left(\frac{S_{jrt}}{S_{rt}}\right) + ln\theta_{st} + \delta_1 ln\left(\frac{\theta_{st}S_{rt}}{\theta_{lt}L_{rt}}\right) + \delta_2 ln\left(\frac{K_t}{\theta_{st}S_{rt}}\right)$$

and likewise for less-skilled workers:

$$lnw_{jrt}^L \approx ln\alpha_{lj} - \frac{1}{\sigma_A} ln\left(\frac{L_{jrt}}{L_{rt}}\right) + ln\theta_{lt} + \gamma_1 ln\left(\frac{\theta_{st}S_{rt}}{\theta_{lt}L_{rt}}\right) + \gamma_2 ln\left(\frac{K_t}{\theta_{lt}L_t}\right)$$

Concavity of the production function implies $\delta_1 - \delta_2 \leq 0$ and $\gamma_1 + \gamma_2 \geq 0$. The skill premium can then be written as:

$$\begin{aligned} ln\left(\frac{w_{jrt}^S}{w_{jrt}^L}\right) &= ln\left(\frac{\alpha_{sj}}{\alpha_{lj}}\right) + (\delta_1 - \delta_2 - \gamma_1) ln\left(\frac{S_{rt}}{L_{rt}}\right) - \frac{1}{\sigma_A}\left[ln\left(\frac{S_{jrt}}{L_{jrt}}\right) - ln\left(\frac{S_{rt}}{L_{rt}}\right)\right] \\ &+ (\gamma_2 - \delta_2) ln\theta_{lt} + (1 + \delta_1 - \delta_2 - \gamma_1) ln\left(\frac{\theta_{st}}{\theta_{lt}}\right) + (\delta_2 - \gamma_2)\left(\frac{K_t}{L_{rt}}\right) \end{aligned} \tag{A.5}$$

The first term denotes the evolution of the age-specific efficiency parameters of the skill group, which we will capture by age group fixed effects. The second term captures how the relative supply of skilled workers affects the skill premium, which under standard assumptions about technological change is governed by the elasticity of substitution across skill groups. The third term characterizes how the difference between the age-specific relative skill supply from the overall relative skill supply affects the skill premium, which is governed by the elasticity of substitution across age groups. The last three terms represent the impact of general productivity increases, additional skill-biased technological change and adjustments in capital intensity, respectively.

To estimate equation (A.5), we again need to make some assumption about the underlying productivity parameters θ_{st} and θ_{lt} as they are unobserved. We follow Beaudry and Green (2005) and Blundell et al. (2022) by assuming that general productivity increases are captured by TFP growth and include a linear time trend to capture any exogenous skill-biased productivity shifts.[23]

The specification for the skill premium, which extends equation (A.4), is now defined as:

$$\begin{aligned} ln\left(\frac{w_{jrt}^S}{w_{jrt}^L}\right) &= d_0 ln\left(\frac{\alpha_{sj}}{\alpha_{lj}}\right) + d_1 ln\left(\frac{S_{rt}}{L_{rt}}\right) + d_2\left[ln\left(\frac{S_{jrt}}{L_{jrt}}\right) - ln\left(\frac{S_{rt}}{L_{rt}}\right)\right] \\ &+ d_3\left(\frac{lnTFP_t}{sh_{lt} + sh_{st}}\right) + d_4 ln\left(\frac{K_t}{L_{rt}}\right) + d_5 * t + d_6 * t^{After} + \varepsilon_{jrt} \end{aligned} \tag{A.6}$$

where sh_{lt} and sh_{st} denote skill shares. The fact that TFP growth and capital have no regional subscript reflects the assumptions that technologies are available in all regions and that the capital market is national.

The coefficient d_1 in equation (A.6) reflects the elasticity of substitution between skilled and less-skilled labor just like in the CES production function framework, i.e. $d_1 = -\frac{1}{\sigma_E}$. Skill-biased technological change might show up as $d_3 > 0$ (if general TFP growth favors skilled workers) or as $d_5 > 0$ (if there is a positive time trend in the skill premium just as in the CES production function framework). If the estimated elasticity of substitution between skill groups is large when controlling for technological change then the effect of a shift in relative skill supply on the relative wage should be large and positive. The results of estimating equation (A.6) are shown in columns (6) and (7) of appendix table A3.

[23] Following the productivity literature, TFP growth can be approximated as $TFP_t \approx sh_{ht}ln\theta_{st} + sh_{lt}ln\theta_{lt}$.

The IV results again indicate a moderate degree of substitutability between high- and less-skilled workers. The elasticity of substitution ranges between 0.7 and 1 is therefore close to the elasticity based on the CES production function. As before, the linear trend is negative but turns slightly positive after the college opening – indicating that technological change exhibits some skill bias. General productivity gains favor high-skilled workers in the full sample (see column (6)) though the effect is not significant for the sample of young workers (see column (7)). Finally, young high-skilled workers benefit from additional capital investments. Overall then, the college opening would have decreased the skill premium but was offset by both capital investments and a moderate skill biased technological change.

Table 1: Comparison of Treatment and Control Regions

	Treated Districts	Other West German Districts	Control Districts	Difference Treated vs. All Districts		Difference Treated vs. Control Districts	
				Coeff.	S.E.	Coeff.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Matched Characteristics							
University or College in Region	0.100	0.354	0.100	-0.254***	0.073	0.000	0.098
Population per square km	349.19	1090.58	357.92	-741.390***	157.60	-8.73	93.05
Industry structure:							
Share in Agriculture and Fishing	0.010	0.008	0.008	0.001	0.001	0.001	0.001
Energy and Mining	0.026	0.018	0.012	0.007	0.015	0.014	0.016
Manufacturing	0.437	0.355	0.489	0.083**	0.032	-0.052	0.043
Construction	0.079	0.067	0.067	0.013***	0.004	0.012*	0.007
Trade	0.128	0.142	0.121	-0.014**	0.006	0.007	0.008
Transport and Communication	0.036	0.051	0.034	-0.015***	0.004	0.002	0.004
Financial services	0.026	0.043	0.026	-0.017***	0.004	0.000	0.002
Other Services	0.179	0.228	0.169	-0.049***	0.012	0.010	0.016
Non-Profit Organizations	0.019	0.025	0.018	-0.006*	0.003	0.002	0.003
Public Administration	0.060	0.063	0.056	-0.003	0.004	0.004	0.006
Panel B: Characteristics Not Matched							
Age structure:							
Ages 20-29	0.328	0.305	0.326	0.022**	0.009	0.001	0.011
Ages 30-44	0.406	0.406	0.392	0.000	0.009	0.014	0.012
Ages 45-59	0.267	0.289	0.282	-0.022**	0.009	-0.015	0.011
Education:							
High-skilled Share	0.056	0.092	0.062	-0.036***	0.006	-0.006	0.007
Less-skilled Share	0.944	0.908	0.938	0.036***	0.006	0.006	0.007
Other Regional characteristics:							
Unemployment Rate	8.201	8.558	7.298	-0.357	0.778	0.903	1.044
Employment	49,518	51,373	44,670	-1,855	6,797	4,848	9,686
Population (in Thousands)	282.52	396.34	252.35	-113.82	83.84	30.17	68.41
Employment Growth (past 5 years)	0.076	0.045	0.090	0.031	0.020	-0.015	0.030
Average Daily Wage	118.38	125.95	122.77	-7.572***	2.319	-4.39	4.03
Wage Growth (past 5 years)	0.050	0.052	0.071	-0.001	0.012	-0.020	0.023

Notes: The table compares characteristics between treatment regions (column (1)), the average region in West Germany (column (2)) and the matched control region (column (3)) in the pre-event period (t=-1). Columns (4)-(5) show the difference (and standard errors) between the treatment and average West German districts in observable characteristics, while columns (7) and (8) show the differences in observables between treatment and matched control regions. With the exception of employment and the indicator for the presence of another university in the district, all observations are weighted by district employment in the year just before the event ($\tau = -1$). The matched control regions are identified through Mahalonobis matching using the variables shown in Panel A in the pre-event period (t=-1). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: College Openings, the Student Population and the Supply of Young High-skilled Workers

	Number of Students (1)	Student to High-skilled Workers (2)	Young, High-skilled Employment (3)
Opening*Before	-0.173	-0.017	0.018
	(0.196)	(0.038)	(0.034)
Opening*Transition	4.500***	0.211***	0.055
	(0.523)	(0.059)	(0.034)
Opening*Post	5.603***	0.526***	0.128**
	(0.644)	(0.117)	(0.062)
Event Time Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes
Observations	760	760	760
R^2	0.917	0.924	0.979

Notes: The table shows estimates from the event study in equation (2). The dependent variables are the log number of students in the district (in column (1)), the ratio of students to the number of full-time workers with a university degree (in column (2)), and the log of full-time employees between the ages of 20 and 29 with a university degree (in column (3)). The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effects of a College Opening on Regional Employment and Wages

	Employment			**Wages**		
	Total	High-skilled	Less-skilled	Total	High-skilled	Less-skilled
	(1)	(2)	(3)	(4)	(5)	(6)
Opening*Before	0.002	-0.006	0.001	0.001	0.002	0.001
	(0.014)	(0.016)	(0.014)	(0.005)	(0.010)	(0.004)
Opening*Transition	-0.001	0.017	-0.002	0.006	-0.001	0.005
	(0.013)	(0.018)	(0.014)	(0.005)	(0.006)	(0.005)
Opening*Post	-0.008	0.027	-0.009	0.016	0.011	0.014
	(0.030)	(0.042)	(0.031)	(0.011)	(0.013)	(0.009)
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	760	760	760
R^2	0.992	0.991	0.991	0.961	0.951	0.960

Notes: The table reports estimates of the event study in equation (2). The dependent variables are the log of total employment (column (1)), employment of workers with a university or college degree (in column (2)) and employment of workers without a college or university degree (in column (3)). Column (4)-(6) shows estimates for the mean log daily wage overall (column (4)), high-skilled workers (column (5)) and less-skilled workers (column (6)) as dependent variables. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: College Openings and the Industry Composition of Employment

	Manufacturing			**Services**			**High-Tech Manufacturing**			
	Total Employment (1)	High-skilled Employment (2)	Less-skilled Employment (3)	Total Employment (4)	High-skilled Employment (5)	Less-skilled Employment (6)	High-skilled Employment (7)	Less-skilled Employment (8)	High-skilled Wages (9)	Less-skilled Wages (10)
Opening*Before	0.016	0.031	-0.002	-0.013	0.001	-0.019	0.050	0.020	-0.014	-0.015
	(0.021)	(0.034)	(0.022)	(0.017)	(0.034)	(0.017)	(0.077)	(0.037)	(0.020)	(0.009)
Opening*Transition	0.012	0.068	0.015	0.005	-0.014	0.007	0.091	0.002	-0.008	0.003
	(0.021)	(0.041)	(0.020)	(0.015)	(0.037)	(0.014)	(0.057)	(0.042)	(0.017)	(0.009)
Opening*Post	-0.026	0.166*	-0.023	0.011	-0.031	0.021	0.287*	0.043	0.037	0.056***
	(0.059)	(0.095)	(0.060)	(0.035)	(0.069)	(0.034)	(0.147)	(0.101)	(0.033)	(0.019)
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	760	760	760	760	760	760	760
R-squared	0.985	0.969	0.982	0.988	0.978	0.989	0.946	0.973	0.843	0.843

Notes: The table reports estimates of equation (2) where the dependent variable is the logarithm of employment (total, high-skilled and less-skilled) in manufacturing and services. High-tech manufacturing contains the chemical industry, machinery, electrical and transport equipment and some smaller manufacturing industries (see also Beerli et al. 2021). The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: College Openings and Employment by Occupation

	Employment of Young Workers				Professional Employment by Industry		Professional Occupations in Manufacturing	
	Unskilled Manual	Skilled Manual	Semi-Professional	Profess-ional	Manufac-turing	Services	Managers	Engineers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opening*Before	-0.117	0.003	0.011	0.026	0.000	-0.011	-0.027	0.043
	(0.083)	(0.016)	(0.024)	(0.032)	(0.034)	(0.025)	(0.031)	(0.063)
Opening*Transition	0.064	0.016	0.027	0.062*	0.068*	0.012	0.000	0.082
	(0.065)	(0.015)	(0.024)	(0.034)	(0.036)	(0.030)	(0.038)	(0.060)
Opening*Post	0.059	0.057	0.050	0.144***	0.154*	0.034	-0.012	0.252**
	(0.114)	(0.044)	(0.050)	(0.053)	(0.082)	(0.055)	(0.072)	(0.124)
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	760	760	760	760	760
R-squared	0.892	0.985	0.984	0.979	0.977	0.981	0.980	0.961

Notes: The table reports the estimates in equation (2). The dependent variable is the logarithm of employment in different occupations. Column (1) shows results for employees in unskilled manual occupations (such as agricultural workers or unskilled industrial workers); column (2) for skilled manual workers (such as mechanics or hairdressers); column (3) for semi-professional occupations (such as nurses or technicians); and column (4) for professionals (such as doctors, engineers or managers). The dependent variables are the logarithm of employment of professionals in manufacturing firms (column (5)) and in all other industries (column (6)). The last two columns separate professionals in manufacturing into employment of managers (column (7)) and employment of engineers (column (8)). The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Employment and Wage Effects in STEM and Non-STEM Colleges

	High-Skilled Employment		**Less-skilled Wages**			**High-skilled Wages**		
	Age 20-29	Total	Age 20-29	Age 30-44	Age 45-60	Age 20-29	Age 30-44	Age 45-59
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Colleges with STEM Focus				
Opening*Before	0.008	0.012	-0.001	-0.007	0.001	0.019	-0.013	-0.014
	(0.055)	(0.021)	(0.006)	(0.007)	(0.006)	(0.018)	(0.013)	(0.023)
Opening*Transition	0.116***	0.014	0.011*	0.003	0.007	0.015	0.010	-0.008
	(0.033)	(0.020)	(0.005)	(0.005)	(0.004)	(0.011)	(0.008)	(0.017)
Opening*Post	0.175**	0.017	0.018	0.007	0.016*	0.027	0.013	0.014
	(0.062)	(0.046)	(0.013)	(0.012)	(0.008)	(0.017)	(0.017)	(0.035)
Observations	342	342	342	342	342	342	342	342
R-squared	0.985	0.992	0.975	0.966	0.983	0.912	0.969	0.952
				Panel B: Colleges without STEM Focus				
Opening*Before	0.026	-0.005	-0.000	-0.002	-0.001	0.013	-0.011	0.021
	(0.043)	(0.020)	(0.006)	(0.004)	(0.005)	(0.012)	(0.009)	(0.019)
Opening*Transition	0.006	-0.013	0.002	0.002	0.001	-0.024**	-0.008	-0.001
	(0.050)	(0.018)	(0.008)	(0.007)	(0.009)	(0.010)	(0.009)	(0.017)
Opening*Post	0.091	-0.029	0.007	0.008	0.012	-0.006	-0.010	0.013
	(0.101)	(0.041)	(0.013)	(0.009)	(0.014)	(0.020)	(0.017)	(0.031)
Observations	418	418	418	418	418	418	418	418
R-squared	0.973	0.992	0.922	0.965	0.961	0.857	0.941	0.921
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the estimates of equation (2) when the sample is split between colleges with a STEM-focus and those without. The dependent variables are the log of employment of workers with a college or university degree aged 20 to 29, log employment of all workers with a college or university degree. Column (3)-(8) use log wages of workers by qualification and age group as dependent variables. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Students, High-Skilled Employment and Population in Dynamic and Stagnant Regions

	Number of Students (1)	Students to High-Skilled Workers (2)	Young, High-skilled Employment (3)	Population 18-30 Inflows p.c. (4)	Population 18-30 Outflows p.c. (5)
			Panel A: Dynamic Regions		
Opening*Before	-0.298	-0.072	0.027	-0.105	-0.076
	(0.275)	(0.060)	(0.042)	(0.066)	(0.087)
Opening*Transition	4.191***	0.223***	0.081**	-0.057	-0.070
	(0.775)	(0.059)	(0.038)	(0.074)	(0.069)
Opening*Post	5.379***	0.540***	0.169**	-0.082	-0.125
	(0.798)	(0.143)	(0.081)	(0.085)	(0.084)
			Panel B: Stagnant Regions		
Opening*Before	-0.049	0.038	0.009	0.000	-0.015
	(0.271)	(0.045)	(0.051)	(0.061)	(0.044)
Opening*Transition	4.811***	0.200*	0.028	0.032	0.056
	(0.696)	(0.103)	(0.047)	(0.047)	(0.045)
Opening*Post	5.832***	0.515***	0.084	0.035	0.088
	(1.002)	(0.186)	(0.077)	(0.086)	(0.077)
Observations	760	760	760	751	751
R-squared	0.918	0.925	0.981	0.939	0.913
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quadratic Time Trend	No	No	No	Yes	Yes

Notes: The table reports the estimates of heterogeneous treatment effects on employment and the student population according to equation (3). Column (1) shows estimates for the effect of a college opening on the log number of students, column (2) for the ratio of students to workers with a college or university degree, and column (3) for workers with a college or university degree aged 20 to 29. The last two columns use the log number of yearly in- and outmigration of individuals aged 18-30 per capita as dependent variable. Panel A contains the estimates for dynamic regions, panel B for stagnant regions where regions are split by the median employment growth between 1975 and 1980. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Employment in Incumbent and New Firms in Dynamic and Stagnant Regions

	Employment Incumbent Firms		**Employment New Firms**		**Exiting Firms**
	Total	High-skilled	Total	High-skilled	
	(1)	(2)	(3)	(4)	(5)
			Panel A: Dynamic Regions		
Opening*Before	-0.034	0.027	0.096	0.184	-0.050
	(0.026)	(0.037)	(0.107)	(0.238)	(0.067)
Opening*Transition	-0.017	-0.067*	-0.000	0.119	-0.055
	(0.024)	(0.039)	(0.114)	(0.263)	(0.081)
Opening*Post	-0.007	-0.118	0.311*	0.345	-0.014
	(0.056)	(0.092)	(0.181)	(0.344)	(0.093)
			Panel B: Stagnant Regions		
Opening*Before	0.028	0.001	-0.067	-0.175	0.000
	(0.021)	(0.032)	(0.080)	(0.188)	(0.049)
Opening*Transition	0.014	0.055*	0.010	-0.100	0.041
	(0.022)	(0.030)	(0.081)	(0.193)	(0.064)
Opening*Post	-0.000	0.131*	-0.156	-0.345	0.047
	(0.048)	(0.075)	(0.142)	(0.266)	(0.067)
Observations	760	760	760	760	760
R-squared	0.992	0.986	0.939	0.879	0.968
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quadratic Time Trend	No	No	No	Yes	Yes

Notes: The table reports the estimates of heterogeneous treatment effects on employment in incumbent firms and new firms as well as the number of exiting firms according to equation (3). Entering firms are defined as new firms entering within a five-year window (from t to t-4). Exiting firms are defined as the number of firms closing down in a given calendar year. The dependent variables are full-time employment in incumbent firms (in logs) in column (1) and full-time high-skilled employment (in logs) in incumbent firms in column (2). The dependent variables are full-time employment (in logs) in entering firms in column (3) and high-skilled employment (in logs) in entering firms. In column (5), the dependent variable is the number of firms exiting the region. Panel A contains the estimates for dynamic regions, panel B those for stagnant regions where regions are split by the median employment growth between 1975 and 1980. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Geographic Location of Treatment and Control Districts

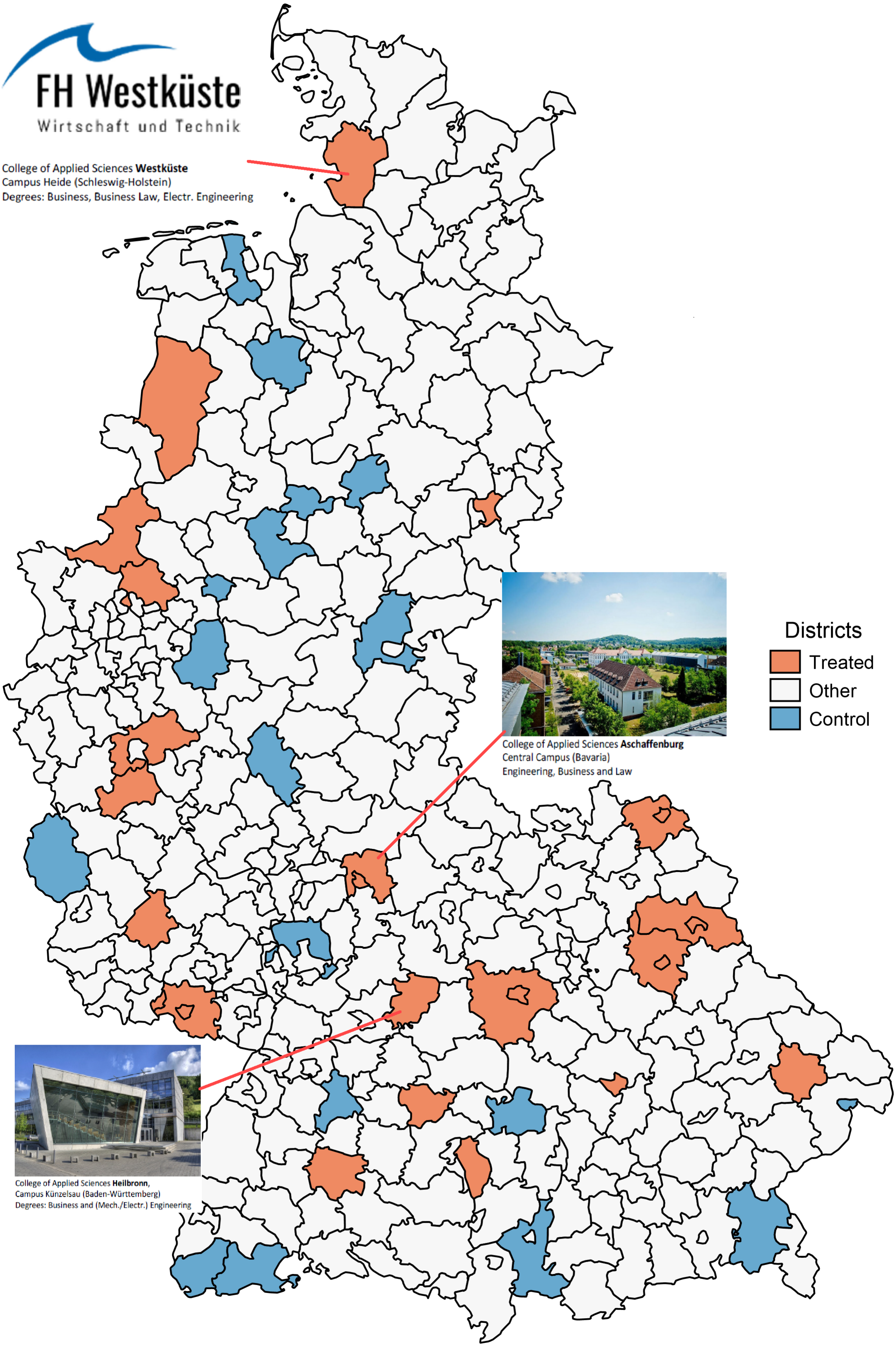
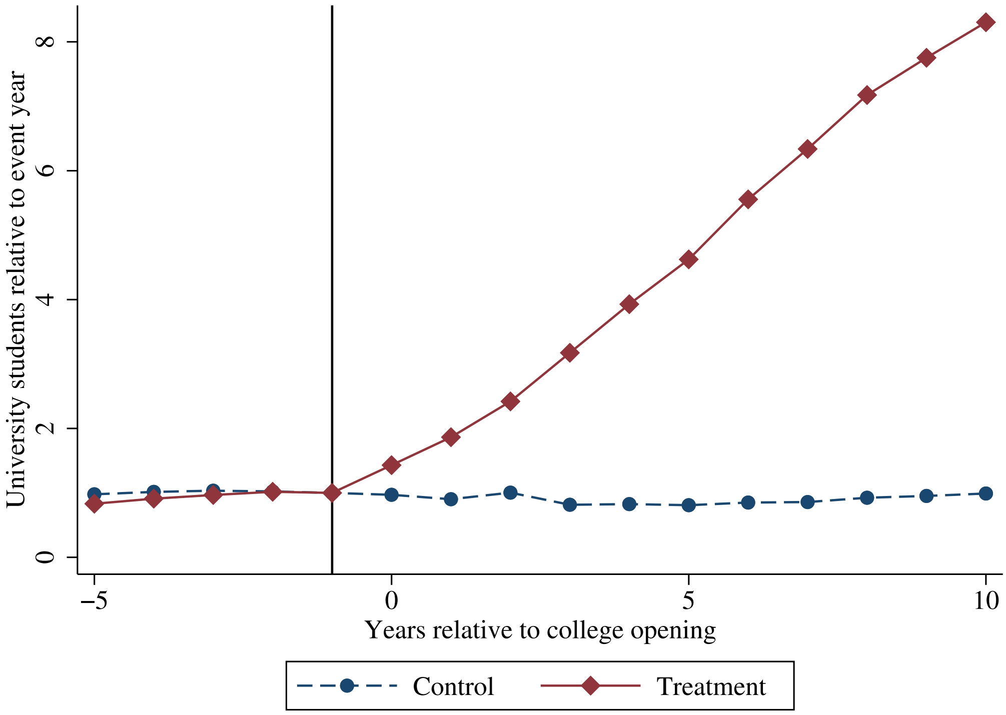
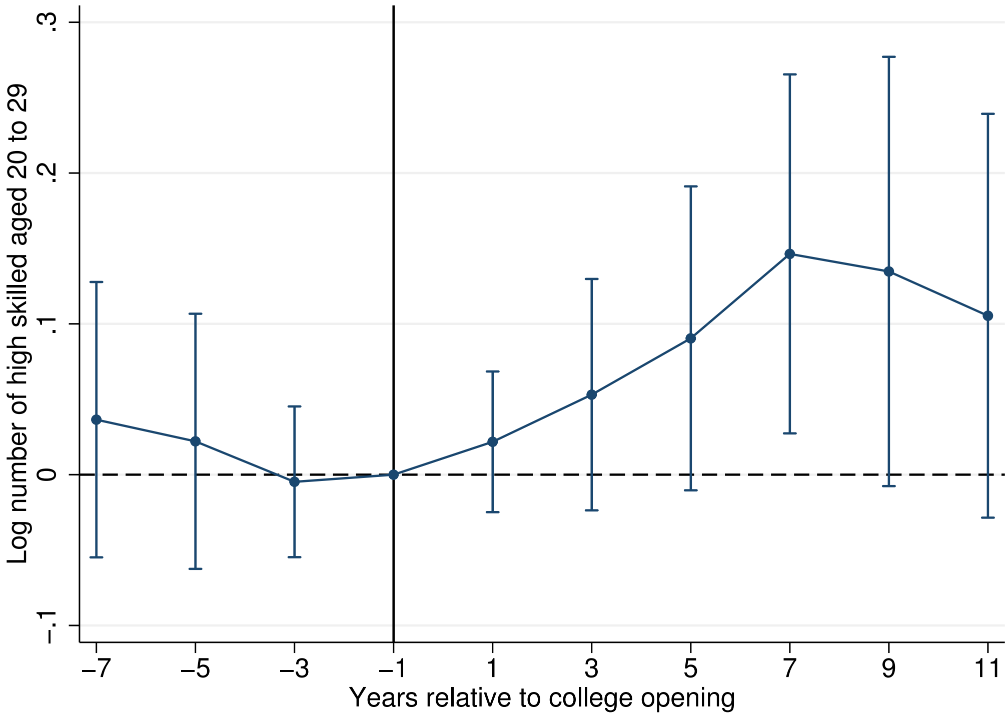


Figure 2: Number of Students in Treatment and Control Districts



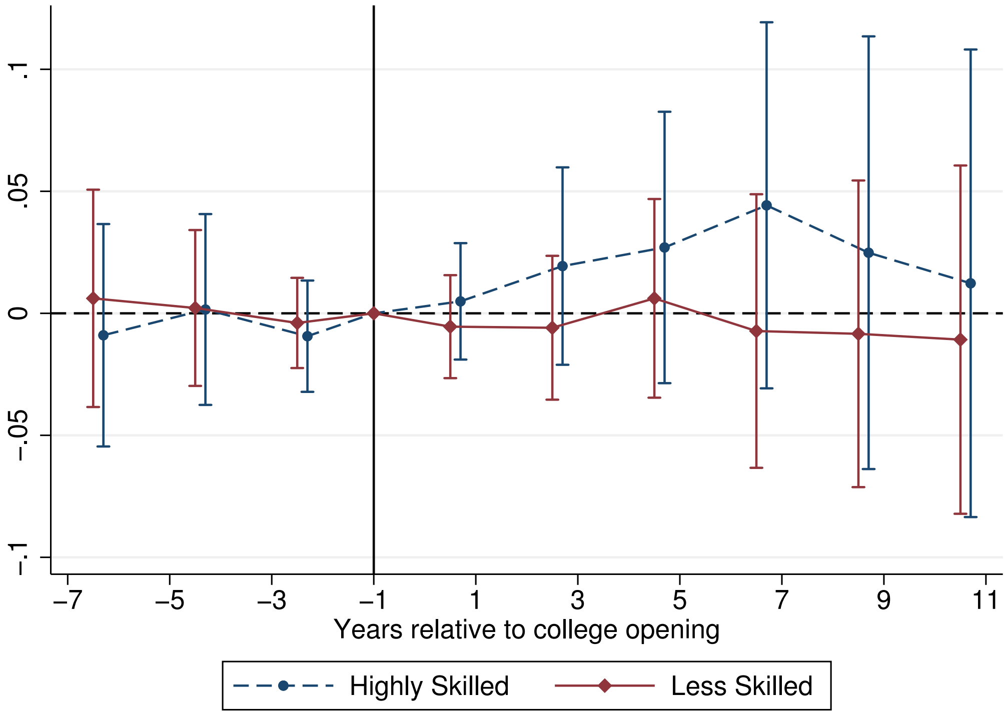
Notes: Average number of full-time students enrolled in universities of treatment and control districts. The year before the college opening is normalized to one.

Figure 3: College Openings and the Employment of Young High-Skilled Labor



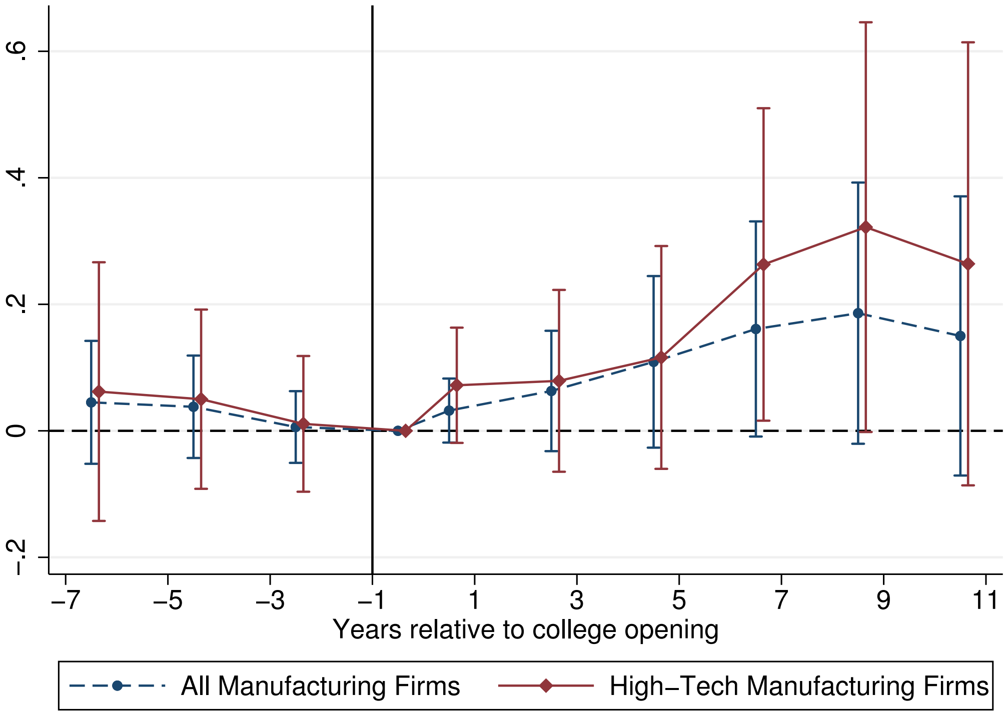
Notes: The figure reports the point estimates and 95% confidence intervals of the regression described in equation (1). The dependent variable is the logarithm of full-time employees between the ages of 20 and 29 with a college or university degree. The unit of observation is district-year. Standard errors are clustered at the district level.

Figure 4: College Openings and Employment of Less- and High-Skilled Workers



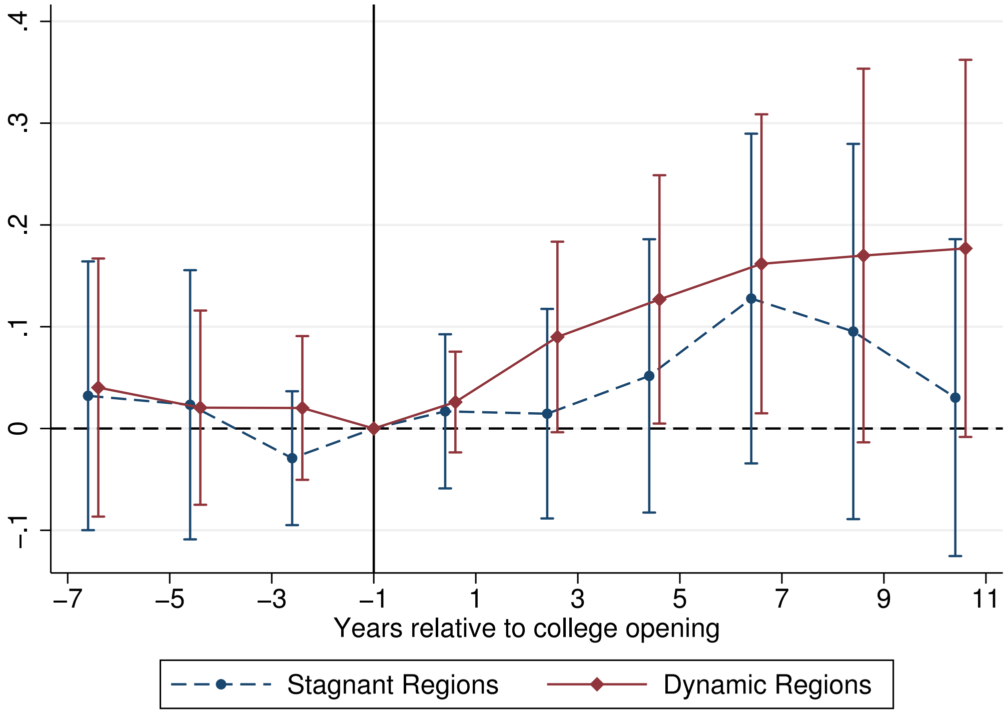
Notes: The figure reports the point estimates and 95% confidence intervals of the regression described in equation (1). The dependent variable is the logarithm of full-time employees by skill level. The unit of observation is district-year. Standard errors are clustered at the district level.

Figure 5: College Openings and High-Skilled Employment by Sector



Notes: The figure reports the point estimates and 95% confidence intervals of the regression described in equation (1). The dependent variable is the logarithm of full-time employees with a college or university degree in manufacturing firms or in high tech manufacturing firms. The unit of observation is district-year. Standard errors are clustered at the district level.

Figure 6: College Openings and Young High-Skilled Employment in Dynamic and Stagnant Regions



Notes: The figure reports the point estimates and 95% confidence intervals of the regression described in equation (3) separately for dynamic and stagnant regions. Regions are split by the median employment growth between 1975 and 1980. The dependent variable is the logarithm of full-time employees aged 20-29 with a college or university degree. The unit of observation is district-year. Standard errors are clustered at the district level.

Table A1: List of Treatment Colleges

College	City	Opening Year	5 Years after Opening Students	5 Years after Opening Employees
Hochschule Esslingen, Hochschule Nürtingen-Geislingen	Göppingen, Geislingen	1988	798	80
Hochschule Heilbronn	Künzelsau	1988	438	62
Hochschule Albstadt-Sigmaringen	Albstadt-Ebingen	1988	885	118
Westfälische Hochschule Gelsenkirchen	Bocholt	1992	626	62
FH Westküste	Heide	1993	601	92
FH Braunschweig-Wolfenbüttel	Salzgitter	1993	671	72
Hochschule Kaiserslautern	Zweibrücken	1994	1186	123
Technische Hochschule Ingolstadt	Ingolstadt	1994	863	94
Technische Hochschule Deggendorf	Deggendorf	1994	1121	132
Hochschule für angewandte Wissenschaften Hof	Hof	1994	792	106
FH Neu-Ulm	Neu-Ulm	1994	855	110
Hochschule Osnabrück	Lingen	1995	319	50
Hochschule Bonn-Rhein-Sieg	Sankt Augustin, Rheinbach	1995	1762	138
Westfälische Hochschule	Recklinghausen	1995	797	71
Ostbayerische Technische Hochschule Amberg-Weiden	Amberg	1995	476	108
Ostbayerische Technische Hochschule Amberg-Weiden	Weiden	1995	524	59
FH Aschaffenburg	Aschaffenburg	1995	762	112
Hochschule Trier	Birkenfeld	1996	1148	149
Hochschule für angewandte Wissenschaften Ansbach	Ansbach	1996	915	133
Hochschule Koblenz	Remagen	1998	1650	156

Table A2: Regional Determinants of College Adoption

	(1)	(2)	(3)	(4)
Tertiary institution in region	-0.004**		-0.004***	-0.004**
	(0.001)		(0.001)	(0.001)
Population (in 1000s) per sq km	-0.003***		-0.003*	-0.003**
	(0.001)		(0.001)	(0.001)
Share in Agriculture and Fishing	-0.192		-0.183	-0.166
	(0.109)		(0.110)	(0.102)
Energy and Mining	-0.014		-0.019	-0.008
	(0.046)		(0.047)	(0.044)
Manufacturing	-0.027		-0.025	-0.016
	(0.042)		(0.041)	(0.038)
Construction	-0.091		-0.089	-0.066
	(0.069)		(0.062)	(0.063)
Trade	-0.034		-0.028	-0.020
	(0.032)		(0.031)	(0.028)
Transport and Communication	-0.008		-0.005	0.007
	(0.046)		(0.034)	(0.039)
Financial services	-0.055		-0.056	-0.044
	(0.057)		(0.058)	(0.059)
Other services	-0.057		-0.055	-0.045
	(0.050)		(0.050)	(0.046)
Non-Profit Organizations	0.010		0.006	0.029
	(0.119)		(0.109)	(0.117)
Highly skilled share		-0.053**	0.006	
		(0.022)	(0.017)	
Share aged 20-29		-0.075	-0.055	
		(0.058)	(0.047)	
Share aged 45-59		-0.049	-0.052	
		(0.041)	(0.043)	
Urban region		-0.001	-0.001	
		(0.004)	(0.003)	
Urban neighboring region		-0.001	-0.001	
		(0.002)	(0.002)	
Population				-0.021
				(0.028)
Average daily wage				-0.029
				(0.040)
Highly skilled employment				0.014***
				(0.004)
Less skilled employment				-0.031
				(0.028)
Year fixed effects	Yes	Yes	Yes	Yes
Federal State FE	Yes	Yes	Yes	Yes
Observations	5088	5088	5088	5088
Adjusted R^2	0.006	0.005	0.005	0.006

Notes: The table reports the estimates of a linear probability model with college opening as the dependent variable for the years 1985-2000. The unit of observation is district-year. All explanatory variables are lagged by one year. Growth variables refer to the growth in characteristics between τ-6 and τ-1. Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Estimates of Production Functions and Elasticities

	Age Premium High-Skilled			Skill Premium			
	Pooled	Old/Young	Prime/Young	HS/LS All	HS/LS Young	HS/LS All	HS/LS Young
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS Estimates							
Relative Supply	0.062***	0.062***	0.041***	0.445***	0.811***	0.817***	0.572***
	(0.010)	(0.016)	(0.009)	(0.063)	(0.096)	(0.067)	(0.070)
Time Trend				-0.004*	-0.001	-0.012***	-0.004***
				(0.002)	(0.002)	(0.001)	(0.001)
Time Trend x Post				-0.002	-0.000	0.009***	0.003***
				(0.002)	(0.002)	(0.001)	(0.001)
Total Factor Productivity						0.249***	0.102
						(0.078)	(0.082)
Capital/LS Labor						-0.008***	0.010***
						(0.003)	(0.003)
Observations	1120	560	560	1680	560	1638	546
R Squared	0.854	0.873	0.725	0.883	0.481	0.885	0.459
Panel B: IV Estimates							
Relative Supply	-0.161	-0.339	-0.105	-2.194***	-2.412	-1.454***	-1.073*
	(0.144)	(0.393)	(0.069)	(0.593)	(1.597)	(0.525)	(0.619)
Time Trend				0.000	0.004	-0.005**	0.001
				(0.000)	(0.004)	(0.002)	(0.002)
Time Trend x Post				-0.001	0.003	0.009***	0.003**
				(0.003)	(0.004)	(0.001)	(0.001)
Total Factor Productivity						0.261***	0.107
						(0.101)	(0.115)
Capital/LS Labor						-0.002	0.013***
						(0.004)	(0.005)
Observations	1120	560	560	1680	560	1638	546
F-Statistic (1st Stage)	7.401	1.678	11.580	37.905	5.498	44.961	13.443
Match Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Age Group FE	Yes	No	No	Yes	No	Yes	No

Notes: The table reports the estimates of the production function linking relative wages across age or skill groups to relative supplies and controls for technology and capital. The unit of observation is district x year. The results in columns (1)-(3) are from estimating the regression in equation (A.3) where the dependent variable is the wage of older high-skilled workers relative to younger high-skilled workers (pooled estimates for older and prime-aged workers relative to young workers in column (1), separately for older and prime-aged relative to young workers in columns (2) and (3), respectively). The results in columns (4)-(5) are based on equation (A.4) where the dependent variable is the relative wage of high-skilled to less-skilled workers for all age groups in column (4) and for young workers only in column (5). The results in columns (6) and (7) are based on equation (A.6) where the dependent variable is again the skill premium for all workers in column (6) and for young workers in column (7). Panel A reports OLS estimates, Panel B instrumental variable estimates where the college opening is used as an instrument for the relative supply of young, high-skilled workers. All specifications include calendar year and matched pair fixed effects. Pooled estimates in columns (1), (4) and (6) also control for age group fixed effects. Columns (4)-(7) include a linear time trend that is allowed to differ between pre- and post-opening period. Columns (6)-(7) further control for TFP growth and capital intensity at the national level. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). *Before* denotes the period from $\tau = -7$ to $\tau = -2$, *Transition* the period from $\tau = 0$ to $\tau = 5$, and *Post* the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Specification Checks

	Baseline Estimates (1)	Linear trend (2)	Quadratic trend (3)	Placebo Estimates (4)	Heterogenous effects (5)	Matching in t=-3 (6)	Synthetic Control (7)	Spillovers Broader Region (8)
Opening*Before	0.018	0.012	0.012	-0.015	0.019	0.034	-0.008	-0.015
	(0.034)	(0.034)	(0.034)	(0.037)	(0.032)	(0.041)	(0.033)	(0.016)
Opening*Transition	0.055	0.061*	0.061*	-0.027	0,055*	0.029	0.032	0.026
	(0.034)	(0.031)	(0.031)	(0.037)	(0.032)	(0.040)	(0.032)	(0.020)
Opening*Post	0.128**	0.145***	0.145***	-0.057	0,128**	0.055	0.083	0.045
	(0.062)	(0.052)	(0.052)	(0.075)	(0.059)	(0.076)	(0.069)	(0.035)
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	722	760	760	760	760
R-squared	0.979	0.991	0.991	0.973	0.980	0.974	0.976	0.996

Notes: The table reports several robustness checks for log young, high-skilled employment. The baseline results are shown in column (1). Columns (2) and (3) contain estimates when a linear or quadratic regional trend are added to equation (2), respectively. Column (4) measures the placebo treatment effect by matching all control districts to other untreated districts. Column (5) provides estimates using the heterogeneous treatment effects estimator of Sun and Abraham (2021). The estimates in column (6) are based on a matched sample using the same variables but in $\tau = -3$. Column (7) presents estimates for a synthetic control estimator. Column (8) estimates the spillover effect of treatment into neighboring districts. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. Unless state otherwise, the estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Employment Effects in Higher Education and the Non-tradable Sector

	Employment in Universities			**Employment in Non-tradable sector**		
	Total (1)	High Skilled (2)	Less Skilled (3)	Total (4)	High Skilled (5)	Less Skilled (6)
Opening*Before	-0.116	0.009	-0.095	-0.007	0.002	-0.007
	(0.077)	(0.068)	(0.064)	(0.016)	(0.028)	(0.016)
Opening*Transition	0.593***	0.360**	0.450***	-0.001	-0.026	0.001
	(0.198)	(0.149)	(0.154)	(0.017)	(0.035)	(0.017)
Opening*Post	0.932***	0.692*	0.738***	-0.008	-0.047	-0.002
	(0.339)	(0.297)	(0.251)	(0.036)	(0.061)	(0.036)
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	760	760	760	760	760	760
R-squared	0.832	0.739	0.860	0.987	0.981	0.987

Notes: The table reports the estimates of equation (2) for employment in higher education and the non-tradable sector (i.e. public administration and all services excluding financial services). The dependent variables are the log of total employment (column 1), log employment of workers with a college or university degree (2) and workers without a degree (3) in higher education. Columns (4)-(6) present estimates equivalent to the first three columns for employment in the non-tradable sector. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: College Opening and Patent Activity

	Patents (Unweighted)			Patents (Weighted)		
	Total (1)	STEM (2)	Non-Stem (3)	Total (4)	STEM (5)	Non-Stem (6)
Opening*Before	-0.204	-0.142	-0.286	-0.245	-0.239	-0.259
	(0.237)	(0.355)	(0.304)	(0.193)	(0.276)	(0.275)
Opening*Transition	-0.107	-0.229	0.038	-0.098	-0.198	0.020
	(0.169)	(0.255)	(0.209)	(0.141)	(0.192)	(0.203)
Opening*Post	0.027	-0.049	0.116	0.045	-0.024	0.125
	(0.172)	(0.215)	(0.256)	(0.150)	(0.176)	(0.233)
Observations	760	418	342	760	418	342
R-squared	0.853	0.811	0.924	0.869	0.840	0.921
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the estimates of equation (2) on patent activity. The dependent variables are the log number of granted patents in a district (columns 1-3), and the log number of patents weighted by the number of people from a district on the patent application. Column (1) and (4) present estimates for all district, the other columns for a sample split based on college focus in STEM or non-STEM subjects. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Comparison between Treatment and Control Districts in Dynamic and Stagnant Regions

	Stagnant		Dynamic		Stagnant vs Dynamic Treatment Districts		Stagnant Treated vs. Control		Dynamic Treated vs. Control	
	Treated Districts	Control Districts	Treated Districts	Control Districts	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Matched Characteristics										
Institutions of higher education:										
Tertiary institution in region	0.000	0.000	0.200	0.200	0.200	0.133	0.000	0.000	0.000	0.189
Population per square km	389.39	384.05	306.17	328.079	-83.226	156.824	5.343	155.251	-21.912	94.596
Industry structure:										
Share in Agriculture and Fishing	0.008	0.008	0.011	0.009	0.003	0.002	0.001	0.002	0.002	0.002
Energy and Mining	0.043	0.014	0.008	0.009	-0.035	0.027	0.028	0.028	-0.002	0.002
Manufacturing	0.437	0.499	0.437	0.477	0.001	0.062	-0.062	0.072	-0.04	0.049
Construction	0.076	0.065	0.083	0.070	0.007	0.008	0.012	0.009	0.013	0.011
Trade	0.121	0.118	0.135	0.125	0.014	0.011	0.004	0.01	0.01	0.012
Transport and Communication	0.034	0.035	0.039	0.033	0.005	0.004	-0.001	0.007	0.006	0.004
Financial services	0.025	0.026	0.027	0.026	0.002	0.002	-0.001	0.002	0.001	0.002
Other services	0.179	0.162	0.179	0.177	0	0.023	0.016	0.025	0.002	0.019
Non-Profit Organizations	0.015	0.018	0.024	0.017	0.008	0.006	-0.003	0.003	0.006	0.006
Public Administration	0.062	0.056	0.058	0.055	-0.004	0.009	0.006	0.010	0.003	0.007
Panel B: Characteristics Not Matched										
Age structure:										
Age: 20-29	0.317	0.326	0.339	0.327	0.022	0.018	-0.009	0.012	0.012	0.018
Age: 30-44	0.411	0.392	0.400	0.392	-0.01	0.018	0.019	0.017	0.008	0.015
Age: 45-59	0.272	0.282	0.261	0.281	-0.011	0.019	-0.010	0.019	-0.020	0.013
Further regional characteristics:										
Unemployment rate	9.362	6.774	6.959	7.896	-2.403*	1.286	2.588	1.612	-0.938	0.795
Employment	51,195	47,634	47,841	41,706	-3,354	12,029	3,561	14,710	6,135	12,660
Population (in Thousands)	306.22	243.58	257.15	262.36	-49.07	116.85	62.64	103.97	-5.21	89.53
Education:										
Highly skilled share	0.053	0.068	0.059	0.054	0.006	0.008	-0.015	0.010	0.005	0.008
Less skilled share	0.947	0.932	0.941	0.946	-0.006	0.008	0.015	0.010	-0.005	0.008
Employment Growth (past 5 years)	0.049	0.096	0.104	0.085	0.055	0.037	-0.047	0.046	0.020	0.033
Average Daily Wage	116.01	126.49	120.92	118.518	4.918	3.85	-10.481	6.504	2.406	3.082
Wage Growth (past 5 years)	0.051	0.087	0.049	0.05	-0.002	0.025	-0.035	0.038	-0.003	0.019

Notes:The table compares mean characteristics between dynamic treatment regions (column (1)), their matched controls (column (2)) as well as stagnant treatment regions (column (3)) and their matched controls (column (4)) in the pre-event period (t=-1). Columns (5)-(6) show differences (and standard errors) between dynamic and stagnant treatment regions along observable characteristics. Columns (7)-(10) show differences in observables between dynamic or stagnant treatment regions and their respective matched control regions. With the exception of employment and the indicator for the presence of another university in the district, all observations are weighted by district employment in the year just before the event ($\tau = -1$). The matched control regions are identified through Mahalonobis matching using the variables shown in Panel A in the pre-event period ($\tau = -1$). Regions are divided into dynamic and stagnant based on a median split of their employment growth between 1975 and 1980. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Employment and Wages in Dynamic and Stagnant Regions

	Employment			**Average Wages**		
	Total	High-skilled	Less-skilled	Total	High-skilled	Less-skilled
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Dynamic Regions			
Opening*Before	-0.004	0.008	-0.004	0.001	0.002	0.001
	(0.017)	(0.017)	(0.018)	(0.007)	(0.010)	(0.007)
Opening*Transition	0.012	0.022	0.010	0.012	0.004	0.011
	(0.015)	(0.022)	(0.016)	(0.008)	(0.010)	(0.009)
Opening*Post	0.033	0.038	0.030	0.019	0.004	0.017
	(0.028)	(0.046)	(0.028)	(0.018)	(0.020)	(0.016)
			Panel B: Stagnant Regions			
Opening*Before	0.008	-0.019	0.007	0.001	0.003	0.000
	(0.021)	(0.025)	(0.022)	(0.006)	(0.017)	(0.005)
Opening*Transition	-0.014	0.011	-0.014	-0.001	-0.006	-0.000
	(0.018)	(0.026)	(0.019)	(0.005)	(0.007)	(0.005)
Opening*Post	-0.049	0.014	-0.047	0.012	0.017	0.011
	(0.038)	(0.056)	(0.039)	(0.010)	(0.014)	(0.010)
Observations	760	760	760	760	760	760
R-squared	0.994	0.993	0.993	0.963	0.956	0.963
Event Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic Time Trend	No	No	No	Yes	Yes	Yes

Notes: The table reports the estimates of heterogeneous treatment effects on employment and wages according to equation 3. Columns (1)-(3) present estimates for the effect of a college opening on log full-time employment (in column (1)), log of workers with college or university degree (in column (2)) and the log of workers without a tertiary degree (in column (3)). Columns (4)-(6) use the log of the average daily wage for the respective group as dependent variable. Panel A contains the estimates for dynamic regions, panel B those for stagnant regions according to employment growth in the decade prior to the college opening. The unit of observation is district x year. All regressions are weighted by employment in the year prior to the event ($\tau = -1$). $Before$ denotes the period from $\tau = -7$ to $\tau = -2$, $Transition$ the period from $\tau = 0$ to $\tau = 5$, and $Post$ the period from $\tau = 6$ to $\tau = 11$. The estimates are based on a matched sample comparing districts with a college opening to suitable control regions using Mahalonobis matching (see details in text). Standard errors are clustered at the district level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.