The Decline of Routine Tasks, Education Investments, and Intergenerational Mobility *

Patrick Bennett† Kai Liu‡ Kjell Salvanes§

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Abstract

How does a large structural change to the labor market affect education investments made at young ages? Exploiting differential exposure to the national decline in routine-task intensity across local labor markets, we show that the secular decline in routine tasks causes major shifts in education investments of high school students, where they invest more in college education and less in vocational-trades education. Our results highlight that labor demand changes impact inequality in the next generation. Low-ability and low-SES students are most responsive to task-biased demand changes and, as a result, intergenerational mobility in college education increases.

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†University of Liverpool. Email: Patrick.Bennett@liverpool.ac.uk

‡Faculty of Economics, University of Cambridge. Email: kai.liu@econ.cam.ac.uk

§Norwegian School of Economics. Email: Kjell.Salvanes@nhh.no

1 Introduction

The growth of professional, managerial, and technical occupations and the decline of production, operative, and clerical positions has caused fundamental changes to the task contents of jobs. Routine-biased technical change (RBTC) has led to more jobs requiring abstract (non-routine cognitive) tasks and fewer jobs requiring routine-intensive tasks (Autor et al., 2003; Goos et al., 2014). Despite the importance of education in driving future labor market outcomes and economic growth, little is known about the impact of RBTC on education investment decisions of young persons.[1]

We analyze how high school students respond to the task-biased demand changes by sorting into different education tracks. In addition to documenting the *quantity* of students shifting their education investments in response to RBTC, we also show that the *quality* of students sorting into different education tracks changes in response to the demand changes. Both quantity and quality shifts have important distributional implications for understanding the overall response to RBTC. Such changes matter for measures of equality in the education system such as intergenerational mobility (Black and Devereux, 2011; Bjorklund and Salvanes, 2011) as well as measures of labor market equality (Carneiro and Lee, 2011).

Using Norwegian administrative data and linking occupations to their task contents as in Autor and Dorn (2013b) and Deming (2017), we show that, similar to other developed economies, routine-intensive tasks have declined throughout the past four decades. The decline in routine-task intensity is accompanied by a rise in the share of youth choosing college education (which provides training in abstract-intensive tasks) and a decrease in the share of youth choosing vocational-trades education (which provides training in relatively routine-intensive tasks).

To identify the causal impacts of RBTC, we exploit differential exposure across commuting zones (CZs) to the secular change in tasks in the national labor market facing students when they choose different tracks in the first year of high school. Our task-biased labor demand shock is measured by the predicted local change in CZ employment share of occupations with a high routine task-intensity, holding the initial composition of occupations fixed. We find that the decline in routine-task concentration decreases rates of dropping out of high school, shifts young persons away from vocational-trades

[1] For evidence on the impact of RBTC on labor market, see Autor and Dorn (2009, 2013a); Acemoglu and Autor (2011); Cortes (2016).

education and into academic education, and increases subsequent enrollment in college education.[2] Our results are robust to a battery of specification checks, including placebo tests that exclude any pre-existing differential trends and other recent advances in the Bartik literature (Goldsmith-Pinkham et al., 2020). When interpreted using standard models of human capital investments, our estimates imply a positive and sizable elasticity of choice of college education with respect to expected earnings.

We find that the changes in education investments are heterogenous by both student ability and parental education levels, suggesting that there are important distributional implications of the task-biased demand change. For instance, increases in college enrollment are driven by low-ability students (measured by GPA before high school) and those from low-educated families. For students of high-ability and from high-educated families, declines in routine tasks only lead to shifting into STEM fields from non-STEM fields, with overall college enrollment unchanged. Within low-SES families, girls shift to college education at higher rates than boys, while boys also shift within vocational education, away from vocational-trades towards vocational-services. RBTC shifts the sorting of students into college, and we identify marginal students, who are more likely to be low-SES and girls within those families, whose education investments adapt.

Finally, we leverage parent-child linkages at the individual level to show that RBTC increases upward mobility in college education. Our estimates reveal that RBTC decreases the intergenerational persistence in education by 18% from 2003–2013, relative to the overall decline over this period. While non-college educated parents are adversely impacted by RBTC, children of low-educated parents can adapt to new conditions by increasing college enrollment. Our results suggest that RBTC can be one potential driver for absolute upward education mobility.

We contribute to the understanding of how labor markets adjust to RBTC. In particular, our evidence suggests that certain individuals adapt to technological change by adjusting their education choices, implying that labor markets could adjust more favorably to technological change than previously understood. Our findings complement Cortes (2016), who find that workers who switch from routine to non-routine cognitive jobs have significantly higher wage growth than stayers eventually.[3] Accounting for the individual-level adjustment to technological changes may further explain why we

[2]Vocational education is prominent across the OECD: 37% of students enroll in vocational high school (Figure A.1), with slightly higher enrollment for males (41%) than females (31%). Norway is comparable with the OECD average.

[3]Edin et al. (2019) find that workers cope when demand for their occupation declines, in part through successful occupational switching.

do not see large job losses from technological changes as many experts predict (e.g. Arntz et al., 2017).

This paper is also related to a set of papers understanding how education investments are affected by local economic conditions, including labor market conditions (Betts and McFarland, 1995; Black et al., 2005), housing market (Charles et al., 2018), industry composition (Tuhkuri, 2022; Whitaker, 2023), and openness to trade (Atkin, 2016; Greenland and Lopresti, 2016). Using U.S. decadal census and a shift-share approach, Chuan and Zhang (2021) find that the decline in routinization increases college enrollment for women but not for men. We analyze a broader range of education decisions, including education tracks in high school and college majors, and leverage the granularity of our data to examine the implications of RBTC on inequality and intergenerational mobility in education. We also show that the quantity adjustments are accompanied by changes in quality. Furthermore, we follow multiple cohorts from the time of entering high school (age 16). This alleviates concerns about geographic mobility and potential endogeneity of local task changes (due to endogenous supply changes), especially relative to existing papers that exploit cross-sectional correlations between local labor market exposures and education choices as sources of identification.[4]

Finally, our paper relates to a handful of papers estimating the elasticity of demand for schooling (including field of study) with respect to expected earnings. While Abramitzky et al. (2022) find that young adults are responsive to changes in the returns to schooling, Beffy et al. (2012) and Wiswall and Zafar (2014) find limited response in the choice of college major. Our elasticity estimates are based on long-run relative changes in college wage premia induced by RBTC, representing a large and likely permanent structural change to the labor market. One limitation is that our elasticity estimates are based on ex-post earnings changes, which only coincides with perceived changes under the strong assumption that people have rational expectations.

2 Data and Empirical Strategy

We use detailed Norwegian administrative data, combining data across multiple sources. First, the central population register provides information on municipality of residence, demographics, and unique

[4]For instance, Tuhkuri (2022) measures the share of all 16–19-year-old residents of the CZ who are high school dropouts, which, by definition, excludes dropouts who previously enrolled in a local high school but migrated out of the area. We measure individual's exposure to RBTC using local task compositions measured at area of residence at age 16, before they enter the labor market.

personal identifiers that can be linked with other register data. We follow Gundersen and Juvkam (2013) and match municipalities to their relevant CZ, resulting in 160 CZs, each of which represents a distinct labor market (Akerman et al., 2015, 2022). We also link children to their parents (and parental characteristics) to assess the intergenerational importance of changes in education investments in response to changing tasks. Our primary sample focuses on cohorts born from 1987–1997.

Second, the employment register contains detailed data on employment, pre-tax labor earnings, occupation, and industry for the entire working-age population. We map a worker's detailed four-digit occupation, with 356 occupations, to the O*NET data following Deming (2017).[5] We construct the distribution of task intensities within each CZ between 2003 and 2018. For sensitivity analysis, we also use the 1980 population census data to construct changes in task-specific labor demand back to 1980. This allows us to measure task intensity for each CZ over a 20+ year period, providing a longer-run perspective on the importance of shifts in education investments in response to changing tasks.

Finally, the education register provides annual data on an individual's level of completed education and any ongoing study. Academic tracking begins at the start of high school, where students choose between an academic and vocational track. The academic track lasts three years and is geared towards preparing students to attend college.[6] We focus on completion of high school across different fields—where we separate high school into academic, vocational-services, and vocational-trades degrees as in Bertrand et al. (2021)—and enrollment in college education. In addition, we separate college into STEM fields—defined as science, technology, engineering, math, and medicine—and non-STEM fields. As a proxy for the "quality" of students, we also make use of the middle school GPA data, which is the sum of the final-year grades in 11 different subjects.

2.1 Empirical Strategy

Our empirical strategy exploits differential exposure across CZs to the secular change in tasks in the national labor market. Our measure of changes in local labor market demand is the CZ-specific

[5] See Appendix B for details.

[6] We refer to college education as any tertiary educational program after high school. Appendix C provides further detail of data sources and the education system, including the grading system for middle school GPA.

projected change in routine-intensive tasks between year t and initial year t_0:

$$\Delta RSH_{mt} = \sum_{j=1}^{J} \frac{L_{mjt_0}}{L_{mt_0}} \times (lnL_{jt} - lnL_{jt^0}) \times \mathbf{1}[RTI_j > RTI^{p66}] \tag{1}$$

where $\mathbf{1}[RTI_j > RTI^{p66}]$ is an indicator equal to one for an occupation j with a routine-task intensity greater than the 66$^{\text{th}}$ percentile (as in Autor and Dorn, 2013b), $lnL_{jt} - lnL_{jt^0}$ is the national growth in employment for occupation j, and the fraction $\frac{L_{mjt_0}}{L_{mt_0}}$ is the share of employment in occupation j in CZ m's total employment, as measured in the initial year $t_0 < t$.[7] The index of routine task-intensity, RTI_j, is defined by

$$RTI_j = \ln R_j - \ln M_j \tag{2}$$

where R_j and M_j are, respectively, the intensity of routine and math task input of occupation j, measured on a 0 to 10 scale as in Deming (2017). This measure is rising/falling in the relative importance of routine/math tasks within an occupation.

Compared to Autor and Dorn (2013b), equation (2) differs in two ways. First, while we define "math" tasks from O*NET, Autor and Dorn (2013b) define "abstract" tasks from the Dictionary of Occupational Titles. However, there exists considerable overlap between occupations which specialize in both tasks. Second, Autor and Dorn (2013b) include "manual" tasks in their measure. Our results are robust to the inclusion "services" as a third factor in equation (2), which overlaps strongly with manual tasks.

The projected change in routine-intensive tasks in equation (1) corresponds to a Bartik shift-share method (Bartik, 1991; Hershbein and Kahn, 2018; Autor et al., 2019; Blair and Deming, 2020). As in Autor et al. (2013), the Bartik shock in (1) measures the predicted change in CZ employment share of occupations with a high routine task-intensity holding constant the initial composition of occupations.[8] The Bartik shock is calculated, by year, using data on the entire working population aged 18–54. We choose 2003 as the base year in most analyses, since this is the first year when the occupational data become available; Section 3.1 assesses how this choice of base year affects the results, using census data

[7]Since we link occupations in Norway to the U.S., systematic differences in the level of tasks between the two countries are a potential concern. In defining routine-intensive occupations by whether an occupation has RTI above a threshold, any systematic differences in RTI levels become irrelevant as long as the relative ranking of occupations above/below the threshold is similar.

[8]The level of RTI^{p66} is indicated by the dashed vertical line in Figure 1b. Results using the change in the average RTI are similar.

to define $t_0 = 1980$.

Figure 1 describes the relationship between the RTI index and education investments over time.[9] As math and routine tasks growth and decline in importance respectively, the index is declining over time. Corresponding with the declining RTI index is the growth of enrollment in college education and the declining importance in vocational-trades education (panel a). Importantly, the growth of college education leads to occupations which are among the least RTI dominant (panel b). While the most common occupation group among the college educated is executive officers in administration, business, social work, and entertainment, the most common occupation group among the vocational-trades educated is metal and machinery workers.[10] Over 70% of those enrolled in college are eventually employed in occupations with a *negative* RTI; in contrast, over 75% of occupations from vocational-trades education have a *positive* RTI. As routine tasks become increasingly less in demand in the labor market, students are increasingly investing in education which is less routine dominant and decreasingly investing in vocational-trades degrees dominated by routine tasks.

To understand the sources of declining routine tasks, Figure D.2 shows that high-skilled occupations grow considerably from 2003–2015, driven by growth among professionals and technicians. This growth comes at the expense of declines in middle-skilled occupations such as plant operators, clerks, and trade workers. Figure E.1 describes the initial employment shares in high RTI jobs across industries and education. Consistent with the shifts in occupations, nearly 50% of manufacturing jobs are high RTI, compared to just 20% for non-manufacturing jobs. Differences by education are similar: while less than 10% of college educated workers are in high RTI jobs, over 30% of non-college educated are. As such, children from low-educated families are considerably more likely to have a parent adversely affected by local demand shocks.[11]

Table E.1 reports the correlation between different economic factors and the change in RTI_j. We find that CZs with larger initial manufacturing shares and those that are more affected by automation see larger declines in RTI. There exists little correlation between changing imports from China as in Balsvik et al. (2015) and the RTI measure, suggesting manufacturing decline isn't itself the dominant factor in our RTI measure. This suggests that our RTI measure captures the importance of technological

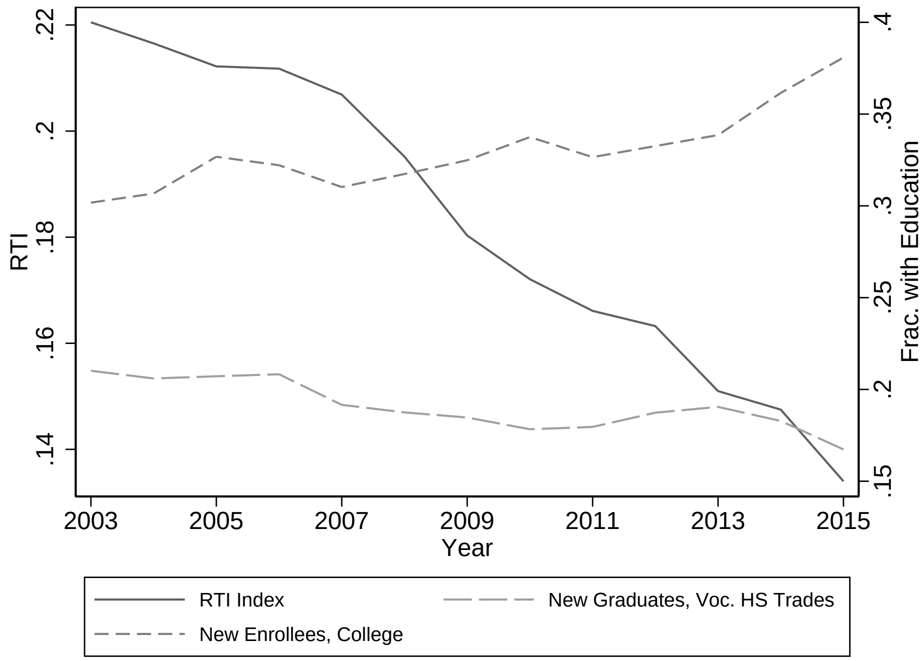
[9] Figure D.1 presents the change in RTI back to 1980. Similar to the U.S., there is a stark decline from 1980–2000 in routine relative to nonroutine (analytical) tasks.

[10] Appendix D describes common occupations for different fields in further detail.

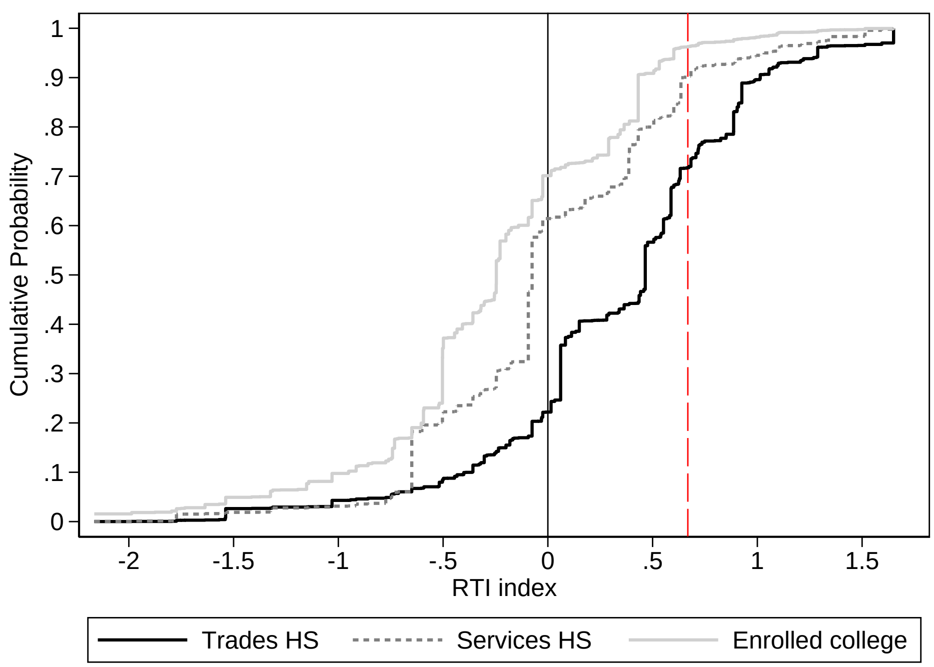
[11] Figure E.2 shows large earnings gaps between low/high RTI jobs which expand over the sample period.

Figure 1: The Relationship Between RTI Index and Education Investments

(a) RTI Index and Education of New Graduates/Enrollees Over Time



(b) RTI Index Across Fields of Study



Notes: Panel (a) plots the RTI index and growth of new graduates across fields of study. RTI index measured for all private workers aged 18–54; new graduation and enrollment in vocational-trades high school and college education measured for those aged 21. Panel (b) plots the cumulative density of RTI index across two vocational high school degrees, trades and services, and enrollment in college for those born in 1985. The dashed line corresponds to the level of RTI index where occupation is classified as high RTI. Linkage between field of study and RTI index is defined in Appendix D.

change over time, but there are also strong correlations between technological change and other key CZ-level factors.

3 Local Demand Changes and Education Investments

To estimate the causal relationship between task-specific demand and education investment, we exploit between-cohort and cross-CZ variations in routine tasks. Specifically, we estimate the following regression model:

$$\Delta Y_{mc} = \beta_{0c} + \beta_{1c}\Delta Z_{mc} + \boldsymbol{\beta}'_{2c}\boldsymbol{X}_m + \varepsilon_{mc} \tag{3}$$

The dependent variable, ΔY_{mc}, is the difference in education investment between cohort c, who resided in CZ m at age 16, and the base cohort (the 1987 birth cohort), who resided in the same CZ at age 16.[12] ΔZ_{mc} is the predicted change in local routine-intensive tasks between cohort c and the base cohort, measured when they are at age 16 (when they are about to start high school), defined by

$$\Delta Z_{mc} = \frac{\Delta RSH_{mc+16}}{\Delta \overline{RSH}_{c+16}},\ c + 16 \in \{2004, \ldots, 2013\} \tag{4}$$

ΔZ_{mc} corresponds to the Bartik shock, defined in Equation (1) evaluated in the year when cohort c turns age 16 ($t = c{+}16$) and scaled by the aggregate predicted change over the same period ($\overline{RSH}_{c+16}$).

The parameter β_{1c} captures the causal relationship between local changes in routine-intensive tasks and education investment. It is a reduced-form parameter. In Section 3.3, we combine the estimated β_{1c} with earnings data to infer the elasticities of education with respect to expected earnings, under the assumption that people have rational expectations (the expected earnings changes from changing tasks coincide with realized earnings changes).

We use ΔZ_{mc} instead of actual changes in local task-intensity in equation (3), because actual changes in local task-intensity might capture local labor demand shocks as well as other CZ-specific shocks. For instance, a local fiscal shock could affect both local task compositions and spending on schools (and hence schooling decisions). In addition, actual task-intensity growth at the CZ level may be measured with error, while the Bartik measure allows for more precision.

Equation (3) is estimated separately for each of the 10 successive cohorts ($c = 1988, \ldots, 1997$); the

[12] Education outcomes are measured at age 21, when most have completed high school and started to enroll in college.

estimated parameters vary flexibly by cohort. Our empirical strategy compares two cohorts within the same area to ask how areas with differential exposure to the shock experience differential changes in education. The constant term, β_{0c}, absorbs the overall change in education in the absence of the demand shock. The coefficient β_{1c} is identified from geographic differences across CZs in the predicted changes in routine-intensive tasks, conditioning on changes at the national level. The regression is weighted by cohort size in CZ's in the initial year. In Section 3.2, we also estimate the same regression separately by students' ability groups and parental education groups, allowing the parameters in Equation (3) to vary flexibly across groups and removing time-invariant factors that are specific to each group.

Our key identifying assumption is that there is no pre-existing unobserved differential trend that is correlated with ΔZ_{mc}, conditional on the initial differences across CZs (X_m) described below. Section 3.1 provides placebo tests for the presence of pre-existing trends, finding no evidence of differential trends. By specifying the regression in differences, we allow for level differences across CZs and remove CZ-level permanent characteristics that may have affected education decisions and tasks at the same time. In the regression, we additionally control for a set of CZ-level characteristics ($\boldsymbol{X}_m$)—the share of employment in manufacturing, employment-to-population ratio, the fraction of the population over 40, initial specialization in high school fields (the fractions specializing in trades and academic), and the initial specialization in college fields (the fraction specializing in STEM college)—measured using overall population data from 18–54 just prior to the initial base year from, 2000–2002. To the extent that these characteristics are correlated with a pre-existing CZ-specific trend in education, these controls help adjust for differences across CZs in their preexisting trends before the base cohort.

We interpret ΔZ_{mc} as exogenous local demand shocks to routine-intensive tasks (conditional on a set of covariates), and conduct a range of tests to justify this assumption in Section 3.1. Importantly, we measure local routine-intensive tasks facing youth cohorts when they are at age 16, prior to their entry to the labor market. This has important advantages to alternative research designs where market-level changes in education attainment are correlated with changes in tasks, in which case changes in education attainment may affect local routine-task concentration either through a direct supply effect, through an indirect demand effect, or both.[13] Instead, our measure is not affected by the education decision of youth cohorts.

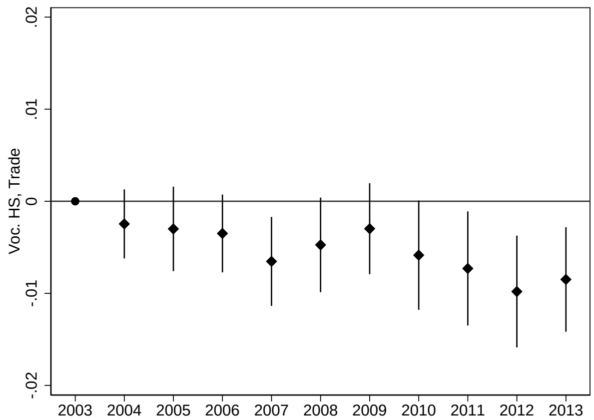
[13]For instance, increasing education may change the task-specific labor demand at the local level as firms adapt their technological inputs in production to local skill levels (Carneiro et al., 2023).

Figure 2 presents how local changes in task-intensity lead to considerable shifts in investments in education. Students shift away from investing in vocational-trades education, a field dominated by high RTI occupations and the most exposed to changing tasks. The shift away from specialization in vocational-trades, as predicted by the average Bartik shock from 2003–2013, corresponds to 0.8 percentage point (ppt) decline, 8% relative to the average in the initial period. Within vocational high school, there is some evidence that students shift towards investing in services (panel b), though such increases are not statistically significant. Importantly, the declining importance of routine tasks leads not just to changes in specialization within high school, but also to increases in the fraction of students investing in education, as high school dropout rates are significantly lower (panel c). Students who shift away from vocational high school primarily shift towards academic high school: changes in local demand mainly decrease dropout through large increases in academic high school (see Figure F.1). Increases in academic high school are important, as there is a strong connection between academic high school and further investments in college education: nearly all of the 43% of the base cohort who graduate from academic high school enroll in college by 21.

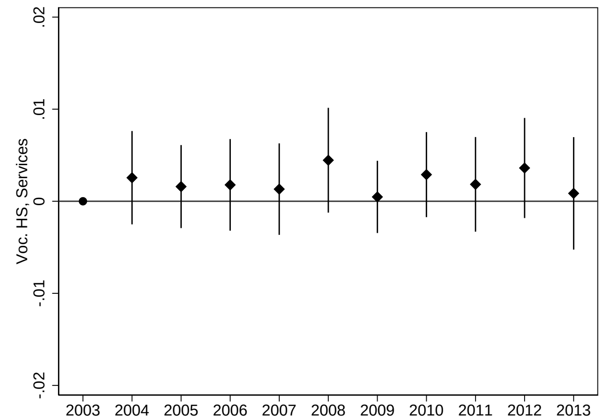
Increasing investments in high school education among students affected by negative demand shocks also translate to significant increases in enrollment in college education at age 21 (panel d). Such gains correspond to a 1.2 ppt increase by 2013 (3.3% increase), and suggest that students on the margin of shifting from vocational toward academic high school have a strong willingness to invest in higher education. Panels e & f reveal that while there is some increase in enrollment in non-STEM fields in the short-run, enrollment in STEM fields is especially large, and increases by 12% by 2013. Given the large labor market return to science, engineering, and medical fields (Altonji et al., 2016; Kirkeboen et al., 2016), the increase in STEM resulting from changes in demand is particularly important. While most cohorts are too young to follow enrollment to graduation, Appendix G reveals minor declines from enrollment to graduation by age 27, among cohorts for whom graduation is observable. Such a finding is crucial, as increases in college enrollment come at the expense of youth employment, and not in education, employment, or training (NEET) remains unchanged at age 21 (Figure F.2).

Figure 2: The Effect of Local Demand Changes on Education Investments

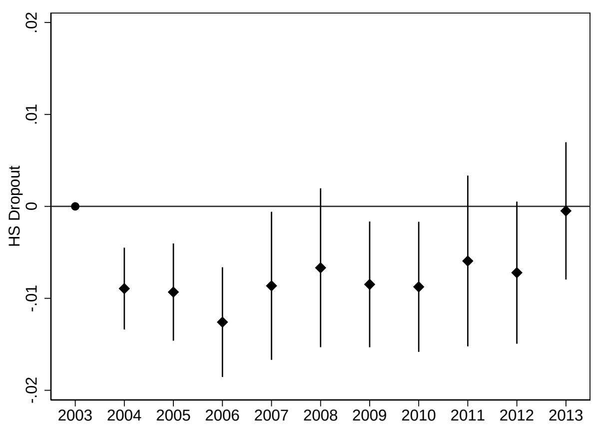
(a) Voc. HS, Trades



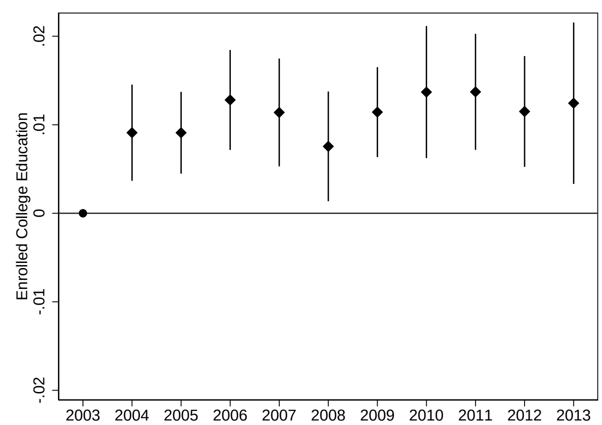
(b) Voc. HS, Services



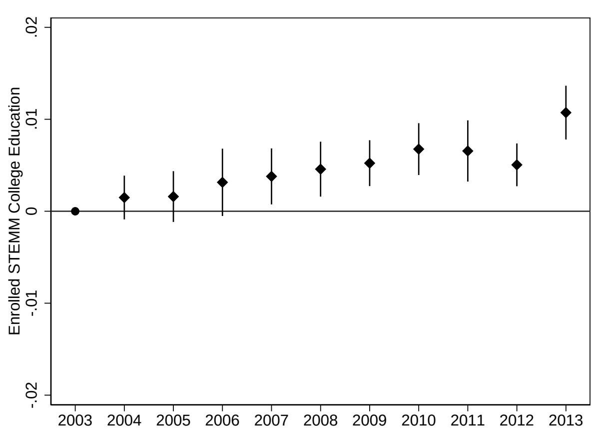
(c) HS Dropout



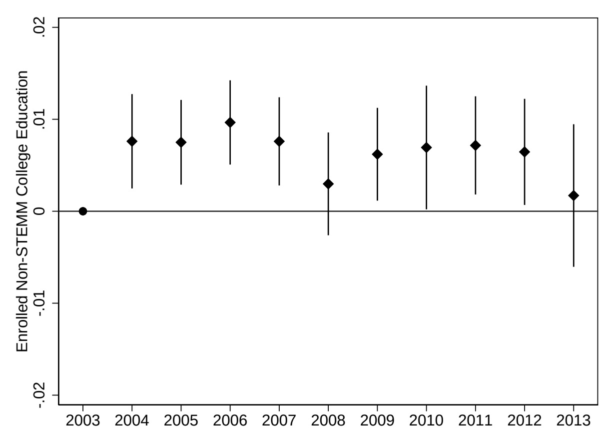
(d) Enrollment in College Education



(e) Enrollment in College Education, STEM



(f) Enrollment in College Education, Non-STEM



Notes: Figure plots estimates of β_{1c} from Equation (3). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16 for cohorts born 1987–1997. Average values of reference group across six outcome variables measured at age 21: 11%, 11.2%, 34.5%, 38.2%, 9.0%, & 29.2% respectively. 95% confidence intervals plotted.

3.1 Validating Identifying Assumptions and Robustness Checks

We conduct several specification checks to investigate the robustness of these results. A major concern with Equation (3) is that places that are more/less affected by the change in demand may have differential trends in education prior to the shock, as emphasized by Goldsmith-Pinkham et al. (2020) and Borusyak and Hull (2020). Figure H.1 reports results from placebo regressions, which regress changes in education between the 2003 cohort and cohorts just *prior* (those aged 16 from 1997–2002) on the predicted (future) changes in local demand from 2003–2013, conditional on the same set of covariates X_m. As these changes from 2003–2013 are yet to occur for cohorts who have already invested in education, their investment decisions should be unaffected, provided there are not differential pre-trends between areas that are more/less exposed in the future. Figure H.1 shows that the estimated coefficients on the predicted future changes in demand are small in magnitude and generally not significantly different from zero, suggesting that areas which are more/less affected by the change in demand are on similar trends prior to such changes.

To further understand the occupations which generate the differential exposure across CZs in our reduced form specification, we conduct additional tests as in Goldsmith-Pinkham et al. (2020). Table H.1 calculates Rotemberg weights to assess the importance of specific occupations in our Bartik measure. The top five occupations account for 48% of the total weight. Results are insensitive to excluding these occupations, suggesting that unobserved shocks to these large weight occupations do not drive the results (Figure H.2). Results are also robust to using the initial "share" of jobs in 1980, $\frac{L_{mj1980}}{L_{m1980}}$ from Equation (1), but keeping the "shift" in employment relative to 2003, $(lnL_{jt} - lnL_{j2003})$ (Figure H.3).[14] The similarity of the results using different initial shares further supports the validity of the Bartik design.

An alternative design estimates the long-run impact of local demand changes on education, comparing the education investments of the 1980 cohort to those of students over 20 years later (Figure H.4). Using 1980 values for the initial share and a long-run shift component over 20 years in equation (1) shows similar impacts over a longer time horizon: local demand shocks shift education investments away from trades education and towards college enrollment. Importantly, these long-run differences also follow students to graduation, and the estimated increases in enrollment are nearly identical to

[14] Results using initial 1980 share are also robust to dropping occupations with large weights.

graduation by age 30.

Results are robust to alternative definitions of the Bartik shock, such as including services in RTI_j in Equation (2) (Figure H.5) and calculating the "leave-one-out" Bartik shock (Figure H.6). Results are unchanged both when including services, which have also become increasingly important over time, and when excluding the influence of the local CZ itself in national demand change.

To ensure that the Bartik shocks capture exogenous demand changes but not changes in supply, Figure H.7 shows that our results are robust to controlling for the effect of the expansion of the European Union in 2004 and the resulting increase in immigration of Baltic workers (Bratsberg and Raaum, 2012). One might be also concerned that parents may choose to relocate in anticipation of or in response to local demand shocks (Greenland et al., 2019). Figure H.8 shows that using a student's birth CZ produces almost identical results to those using a student's CZ at age 16, suggesting that any geographic mobility from birth to age 16 is not driving our results.

Figure H.9 assesses the importance of large urban areas, where work has evolved differently over time (Autor, 2019). Results excluding large cities are similar, although the increases in college education are roughly 25–50% smaller in magnitude, suggesting that the availability of local options to invest in higher education are important as universities are overwhelmingly located in urban areas.

3.2 Unequal Responses by Student Achievement and Family Background

We assess heterogeneity of the shifts in education investments, focusing on whether investments respond differently by students' achievement (middle school GPA) and parental education. Just 5% of students in the bottom GPA quartile enroll in college, compared to 77% in the top GPA quartile. Similarly, there are large gaps in college enrollment of 24ppt between students with college/non-college educated fathers.[15]

We estimate Equation (3) separately by subgroups defined by student achievement and parental education levels, removing any time-invariant factors specific to these groups. We define students as high-/low-ability if they are in the top/bottom quartile of middle school GPA in their cohort. Similarly, we use parental education as a proxy for SES, defined as whether a student's father is college educated.[16]

[15] Appendix I reports results for maternal education. Results are similar when considering heterogeneity by maternal education, with slightly larger impacts on college education for both college and non-college educated families.

[16] Although there exists some overlap between measures of ability and SES, the correlation is far from perfect (see Appendix J.1).

Table 1 reveals that changes in local demand primarily impact the education investments of low-ability and low-SES students.

Focusing on differences by GPA, columns (1)–(2) and (5)–(6), reveals four key findings. First, declining investments in trades education are driven by low-ability students—who are 1.5 ppt (10%) less likely to graduate from trades degrees—with no observed change among high-ability students. Second, low-ability students shift within vocational education to invest in services degrees, which increase by 0.8 ppt (9%). Third, enrollment in college increases among low-ability students by 1.1 ppt (20%). Finally, there is an increase in STEM degrees for both high- and low-ability students. While high-ability students increasingly enroll in STEM degrees at the expense of non-STEM degrees, whose decline mirrors the increase in STEM degrees, low-ability students increasingly invest in both STEM and non-STEM degrees. Indeed, non-STEM degrees matter considerably for low-ability students, which increase by 0.7 ppt (24%).

For low-SES children, investments in trades degrees decline significantly while investments in services degrees increase significantly. Dropout also decreases among low-SES students. These shifts in investment in high school also translate into significant increases in enrollment in both STEM and non-STEM college degrees. However, in contrast to high-ability students, those from high-SES families also shift their education investments in response to changes in labor demand: investment in trades decreases significantly, while both high school dropout and college enrollment remain unchanged. As with high-ability students, those from high-SES families also substitute away from non-STEM college to STEM college, and total college enrollment remains unchanged.

Overall, low-ability/SES students increase enrollment in college education considerably more relative to high-ability/SES students. Tables K.1 and K.2 show that within low-ability/SES students, girls are considerably more likely to enroll in college: enrollment of girls increases by 1.5ppt while enrollment of boys increases by roughly half this amount. While some low-ability/SES boys shift to college, such boys also shift within vocational high school, away from vocational-trades to vocational-services degrees, with no change in vocational-services among low-ability/SES girls. This suggests there is a gender disparity responding to the task-specific demand changes in the different margins of adjustment.

Table 1: The Effect of Local Demand Changes on Education Investments by Ability & Parental Education, 2003–2013

	GPA		Father's Education		GPA		Father's Education	
	Top (1)	Bottom (2)	High (3)	Low (4)	Top (5)	Bottom (6)	High (7)	Low (8)
	Panel A: Voc HS, trades				*Panel B: Voc HS, services*			
point estimate, 2003-2013	-0.000	-0.015***	-0.005**	-0.007***	-0.003	0.008***	-0.001	0.004**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
% of mean	[-0.3]	[-9.8]	[-5.4]	[-4.8]	[-3.1]	[8.6]	[-1.7]	[3.5]
	Panel C: HS dropout				*Panel D: enrollment in college*			
point estimate, 2003-2013	0.001	-0.003	0.001	-0.004*	0.002	0.011***	0.007	0.015***
	(0.002)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
% of mean	[1.0]	[-0.4]	[0.6]	[-1.1]	[0.2]	[19.6]	[1.3]	[5.0]
	Panel E: enrollment in college, STEM				*Panel F: enrollment in college, Non-STEM*			
point estimate, 2003-2013	0.013***	0.004**	0.017***	0.006***	-0.012***	0.007***	-0.011**	0.009***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.003)
% of mean	[7.1]	[15.3]	[12.2]	[10.5]	[-2.0]	[23.5]	[-2.9]	[3.8]

Notes: Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. Table shows estimates of β_{1c} from Equation (3). Point estimate calculated as a percent of the mean of the initial cohort reported in brackets. Estimation period is 10 year difference from 2003–2013 for cohorts born 1987 and 1997. 7.2% of sample missing data on middle school GPA. High-ability in columns (1) & (5) defined as student in the top 25% of middle school GPA distribution. Low ability in columns (2) & (6) defined as student in the bottom 25% of middle school GPA distribution. High-educated in columns (3) & (7) defined as student whose father is a college graduate. Low-educated in columns (4) & (8) defined as student whose father is non-college educated. Sample of 160 CZs. Estimating equation: $\Delta Y_{gmc} = \beta_{0gc} + \beta_{1c}\Delta Z_{mc} + \beta_{2c}X_m + \varepsilon_{gmc}$, where g corresponds to each of the GPA/father's education groups.

Table 2: The Relative Elasticity of College and Vocational-Trades Education, 2003–2013

	(1) Gap in 2003	(2) Estimated Change, Bartik 03-13	(3) % Change	(4) Relative elasticity, college & voc.-trades
Relative earnings, $ln(college) - ln(trades)$	0.063	0.010***	15.2%	–
		(0.003)		
Relative education, $college - trades$:	*Panel (a): overall sample*			
Overall Sample	0.273	0.025***	9.2%	0.61
		(0.007)		
	Panel (b): bottom & top of GPA			
GPA, Bottom	-0.095	0.030***	32%	2.11
		(0.009)		
GPA, Top	0.668	-0.001	-0.1%	-0.01
		(0.006)		
	Panel (c): high & low father's education			
Father's Education, Low	0.154	0.024**	15.8%	1.04
		(0.009)		
Father's Education, High	0.414	0.014	3.5%	0.23
		(0.010)		

Notes: Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. Table shows estimates of relative earnings and education between college and vocational-trades education. Earnings are measured as annual earnings from employment. Column (1) presents the average gap between college & trades earnings/education prior to the Bartik shock in 2003. Column (2) estimates the impact of the Bartik shock on relative earnings/education, as specified below. Column (3) reports the percentage change from 2003–2013 due to the Bartik shock estimated in column (2). Column (4) reports the relative elasticity, dividing the percentage change in relative education by the percentage change in relative earnings. The estimation sample for relative education is cohorts born in 1987 and 1997. 7.2% of sample missing data on middle school GPA. Relative education choices between college and vocational-trades education reported in panels (a)–(c). Panel (a) reports estimates from overall sample, panel (b) reports estimates separately by student ability level, and panel (c) reports estimates separately by parental education level. High/low ability in panel (b) defined as student in the top/bottom 25% of middle school GPA distribution. High/low-educated in panel (c) defined as student whose father is college/non-college educated. Sample of 160 CZs. Estimating equation for column (2): $\Delta Y_{gmc} = \beta_{0gc} + \beta_{1c}\Delta Z_{mc} + \beta_{2c}X_m + \varepsilon_{gmc}$, where g corresponds to each of the GPA/father's education groups in panels (b) and (c). Y_{gmc} in relative earnings regression is $ln(college) - ln(trades)$, where *college* & *trades* are the average pre-tax labor earnings from all workers 18–54 who have a minimum earnings level greater than 1 pension qualifying amount in 2003 & 2013. Y_{gmc} in relative education regression is $college - trades$, where *college* & *trades* are the average fraction of students who invest in type of education in 2003 & 2013.

3.3 Elasticities of Education with Respect to Expected Earnings

In standard models of education investment (Becker, 1975; Willis and Rosen, 1979), students acquire additional education comparing the marginal benefit of increasing lifetime earnings to the marginal cost, including tuition, psychic costs, and the opportunity cost of foregone earnings. In Norway, education at all levels, including college, is free. We thus postulate that the local demand change only affects marginal benefits and the opportunity cost of schooling. Indeed, as reported in the first row of Table 2, we find that the marginal benefit of college education increases relative to vocational-trade education, as the decline in RTI from 2003–2013 widens the relative earnings gap between college and vocational-trade educated workers. In addition, declines in RTI reduce the average earnings of vocational-trade-educated workers, suggesting that the opportunity cost of college attendance also declines. Therefore, the standard model predicts an increase in college enrollment as routine tasks decline, consistent with our findings above.

Panel (a) of Table 2 estimates the relative elasticities of education choice with respect to expected earnings. In particular, we assess how 10-year changes in local demand affect the relative earnings premia of college to vocational-trades education, and how the same demand change differentially affects education investments at age 16.[17] A one-unit change in the Bartik shock, corresponding to the average 10-year change, increases the relative earnings gap by 1 ppt (15.2% relative to the initial gap in 2003). The same Bartik shock increases college education relative to vocational-trades by 2.5ppt, (9.2%). These two changes correspond to a relative elasticity between college and vocational-trades education of 0.61. Therefore, we find a positive and sizable elasticity of choice of education with respect to expected earnings.

Relative elasticities between college and vocational-trades education differ considerably by students' characteristics: the relative elasticity is considerably larger for low-ability students and close to 0 for high-ability students (panel b). Similarly, the relative elasticity among low-SES students is considerably greater than the elasticity for high-SES students (panel c). Although demand changes do not eliminate the large initial enrollment gaps, they lead to considerable catching up among disadvantaged students.[18]

[17] Earnings are measured as annual pre-tax labor earnings for all workers aged 18-54. Table 2 reports the change in earnings from 2003–2013. As mentioned earlier, we infer the elasticities using realized earnings, which is only equivalent to the elasticities at the time of making education decisions if individuals have rational expectations.

[18] The large increase in college attendance for low-ability students is consistent with an extended model of human capital investment where the psychic costs from college education are decreasing in students' ability (see Charles et al., 2018). Such a model implies a threshold ability beyond which students will choose college education. As the returns from college

4 Local Demand Changes and Intergenerational Mobility in Education

Table 3 shows how local demand changes affect the intergenerational persistence in college education from fathers to their children (both girls and boys). We use the following individual-level regression model to investigate whether the (local) intergenerational persistence in education changes more over time in areas with larger demand shocks (defined by 10-year projected change in routine-intensive tasks, ΔZ_{m2013}):[19]

$$\begin{aligned} college_{imc} = & \gamma_0 + \gamma_1 college^f_{imc} + \gamma_2 1(c = 2013) + \gamma_3 college^f_{imc} \times 1(c = 2013) \\ & + \gamma_4 college^f_{imc} \times \Delta Z_{m2013} \times 1(c = 2013) + \gamma_5 \Delta Z_{m2013} \times college^f_{imc} \\ & + \gamma_6 \Delta Z_{m2013} \times 1(c = 2013) + \gamma_7 \Delta Z_{m2013} + \boldsymbol{\gamma}'_x \boldsymbol{X}_m + \varepsilon_{imc}. \end{aligned} \tag{5}$$

The pair-wise regression takes two cohorts, $c = 2003, 2013$, and estimates the change in the intergenerational persistence due to the Bartik shock, where $college_{imc}$ indicates whether child i of cohort c has enrolled in college, $college^f_{imc}$ indicates whether the child's father f has completed college, and $\boldsymbol{X}_m$ includes the same set of CZ-level characteristics. γ_1 identifies the intergenerational persistence in the base 2003 cohort, γ_2 corresponds to the overall change in college enrollment from 2003–2013, and γ_3 represents the national-level change in the intergenerational persistence in the absence of a demand shock (i.e. holding $\Delta Z_{m2013} = 0$). The triple interaction coefficient γ_4 identifies how differential exposure to the demand shock, ΔZ_{m2013}, affects the intergenerational persistence in education over time. Finally, γ_5, γ_6, and γ_7 correspond to the difference in intergenerational persistence across areas affected by ΔZ_{m2013} in the base cohort, the change in college enrollment in affected areas, and the difference in college enrollment across areas affected by ΔZ_{m2013} in the base cohort respectively. While previous regressions were estimated at the area-level, we estimate Equation (5) using individual level data and cluster the standard errors at the CZ level.

Results in Table 3 reveal that local demand shocks lead to a significant decline in the intergenera-

attendance become larger, this will reduce the threshold for college education and push marginally low-ability students into college.

[19] Similar approaches are taken in Pekkarinen et al. (2009); Bütikofer et al. (2022) for intergenerational mobility in earnings.

tional persistence of college, or equivalently, an increase in intergenerational mobility. In the absence of the demand shock, there is an overall decline in the intergenerational persistence by 0.039 (γ_3). A one-unit change in ΔZ_{m2013} (corresponding to the national average demand shock) leads to an additional decline of intergenerational persistence by 0.007 (γ_4), or 18% decline relative to the overall decline in the absence of any demand shocks. Given the unequal responses by family background where students from low-educated families increasingly enroll in college, task-specific demand changes increase intergenerational mobility in college education.

5 Conclusion

How does a large structural change to the labor market affect education investments of young persons? We show that changing job tasks, as measured by the predicted decline in the intensity of routine tasks, affect education investments decisions from high school through to college. Students shift away from vocational-trade high school towards college education. We document changes in the quality of new graduates and identify the marginal students whose education choices respond to changes in labor demand. Low-ability and low-SES students respond the most to such changes. Within low-SES families, girls shift towards college at higher rates while boys shift within vocational education, from vocational-trades to vocational-services.

Although task-biased technological change has led to increasing inequality, it levels up enrollment in college education among those yet to enter the labor market. As low-SES students overwhelmingly shift their education investments in response to changes in labor demand, they are able to close gaps in college enrollment with their more advantaged counterparts. Intergenerational mobility in college education increases, and children of low-educated parents increasingly enroll in college in contrast to their fathers who are negatively affected by declining demand. Our findings have important distributional implications for understanding inequality in education and the labor market going forward: as young students join the labor market, both the quantity and quality of new graduates are an important factor of adjustment in understanding the long-run implications of task-biased demand change.

Table 3: The Effect of Local Demand Changes on the Intergenerational Persistence in College, 2003–2013

	(1) child college
father college (γ_1)	0.273***
	(0.007)
2013 (γ_2)	0.078***
	(0.006)
father college $\times$ 2013 (γ_3)	-0.039***
	(0.008)
ΔZ_{m2013} $\times$ father college $\times$ 2013 (γ_4)	-0.007***
	(0.003)
ΔZ_{m2013} $\times$father college (γ_5)	0.008***
	(0.003)
ΔZ_{m2013} $\times$ 2013 (γ_6)	0.013***
	(0.002)
ΔZ_{m2013} (γ_7)	0.011***
	(0.004)
Constant (γ_0)	-0.076
	(0.103)
Observations, individuals	114673

Notes: Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. Estimation period is 10 year difference from 2003–2013 for cohorts born 1987 and 1997. Reported observations corresponds to the number of students from these cohorts. ΔZ_m2013 measures the area-level shock from 2003-2013 as defined in Equation (4). Individual level sample of cohorts born 1987 and 1997. Estimating equation: Equation (5).

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The Decline of Routine Tasks, Education Investments, and Intergenerational Mobility

Online Appendix

Patrick Bennett* Kai Liu† Kjell Salvanes‡

*University of Liverpool. Email: Patrick.Bennett@liverpool.ac.uk
†Faculty of Economics, University of Cambridge.Email: kai.liu@econ.cam.ac.uk
‡Norwegian School of Economics. Email: Kjell.Salvanes@nhh.no

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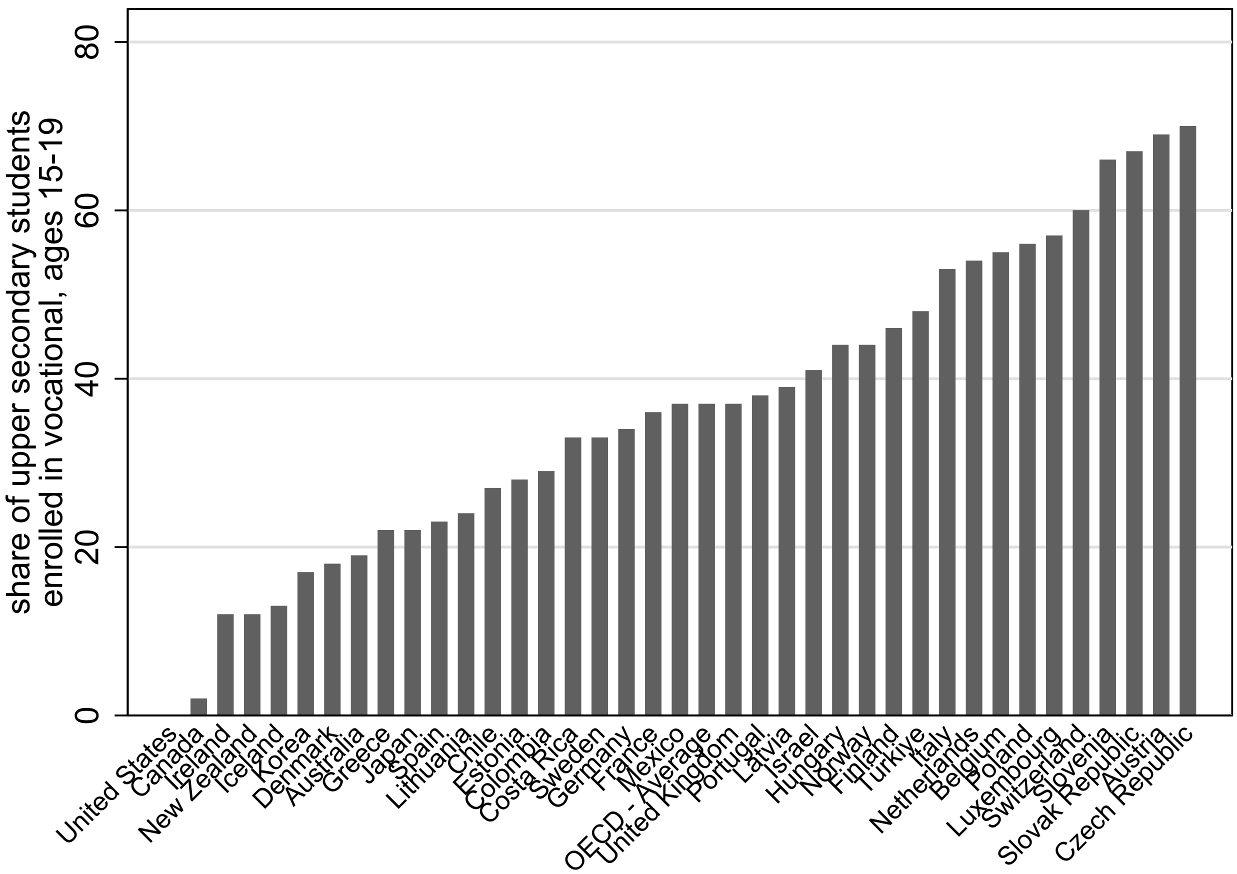
A Vocational Education Across the OECD

Figure A.1: Enrollment Among Students 15–19 in Vocational Education, 2019



Notes: Figure plots fraction of students aged 15–19 enrolled in upper secondary education who are enrolled in vocational education. OECD data defines general and vocational education for the sample of OECD countries in 2019. Data source: "Enrolment by gender, programme orientation, mode of study and type of institution" from OECD "Education at a Glance". OECD average: 37%.

B Norwegian Register Data: Additional Details

The papers uses Norwegian Register data from 2003–2018, combining data from across multiple registers. The data covers all Norwegian residents with 100% coverage.

Employment Data, Occupational Data, & Occupational Classification System Employment status is measured in the third week of November. The employment data covers all residents aged 16–74. When calculating the Bartik measures, we focus on workers aged 18–54. If an individual has multiple jobs, we focus on an individual's primary job. Due to data limitations, we focus on private sector occupations as public sector occupations are not well measured at the start of the data period.[1]

Occupations are measured according to the STYRK1998 (Standard for Yrkeklassifisering, Norwegian standard of occupational classification) classification created by Statistics Norway. Such classification closely follows the European classification system ISCO-88 (European International Standard Classification of Occupations 1988), with some very minor differences to accommodate mior differences in structure of work. There are 356 possible occupations in the STYRK1998 classification standard.

We match occupations in the Norwegian classification system to measures of task intensity as follows. We extract raw O*NET data from O*NET 2000, and follow Deming (2017) in measuring tasks. In our primary specification, which measures $RTI_j = lnR_j - lnM_j$ for each occupation j, we make use of data on tasks for routine and math respectively. As in Deming (2017), routine tasks are measured by responses to the following questions: (i) the level of automation of this job and (ii) how important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job. Math tasks are measured by responses to the following questions: (i) the ability to understand and organize a problem and then to select a mathematical method or formula to solve the problem; (ii) knowledge of numbers, their operations, and interrelationships including arithmetic, algebra, geometry, calculus, statistics, and their applications; and (iii) using mathematics to solve problems. In a robustness check, we include service tasks into this measure of RTI_j. Service tasks are measured by responses to the following questions: (i) providing assistance or personal care to others and (ii) actively looking for ways to help people.

[1] Occupational data is collected starting in 2003 and due to data limitations, occupational data on public sector workers is largely unavailable at the start of the period, when roughly one in four public sector workers have an occupation classified. While there is considerable growth in the share of jobs in the public-sector *prior* to 2000, the public sector employment share is stable throughout our sample period.

As the values measured in O*NET have no inherent meaning, these values are rescaled to have the range of 0–10 as in Deming (2017), where 10 is the occupation with the highest task intensity and 0 is the occupation with the lowest task intensity. This O*NET data provides measures of tasks for each 6 digit SOC occupation.

To match Norwegian occupations to tasks using O*NET data on the task intensity of occupations in the US, we develop a linkage between the Norwegian occupation standard and the US Standard Occupational Classification (SOC). The mapping proceeds as follows. First, 4 digit occupations in the Norwegian standard are matched manually to the closest 6 digit occupation in the SOC.[2] Direct matches where 1 Norwegian occupation matches to 1 US occupation represent 60% of occupations. This is due to the fact that the US system is much more detailed than the Norwegian system: while there are 356 unique occupations in the Norwegian standard, there exist 821 unique occupations in the US standard.

Second, all occupations which do not have one-to-one matches are matched to multiple occupations in the US standard. One-to-two matches represent 25% of occupations in the Norwegian standard. One-to-three matches represent another 7%. In practice, when one Norwegian occupation maps to multiple occupations in the US SOC, these occupations often fall within the same group in the SOC standard. For occupations in the Norwegian standard which map to multiple occupations in the US standard, the average of the US occupations is taken and assigned to the unique Norwegian occupation.

The three occupations in the Norwegian system with the highest routine intensity are Sewing-machine operators, Stenographers and typists, and Shoemaking- and related machine operators. For math intensity, the three highest ranked occupations are Mathematicians and related professionals, Physicists and astronomers, and Chemical engineers.

Education Data Data on education is extracted from the education register. Such data is high-quality, and schools have a legal mandate to report any information on student enrollment and graduation to Statistics Norway. The data includes information on the exact qualification attained including information on field of study. Additionally, any ongoing education is also recorded for each student, including information on field of study. The completion of educational qualifications and ongoing student status are measured at the start of October.

[2] Matches are created based on the description of tasks in both standards, as well as relevant occupation titles.

Income Data From the tax and earnings register, we extract data on annual income. The measure of income comprises total labour income, including any income earned from self-employment, as well as any taxable benefits received during the year including parental leave, unemployment, and sickness benefits.

1980 Census Data Data from the 1980 census has near 100% coverage of all resident in Norway at the start of November in the census year. Employment status is measured for the 12 months preceding the census. Occupations in the 1980 census are classified according to NYK1965 (Nordisk Yrkeklassifisering-1965, Nordic Classification of Occupations), a measure which closely follows the European ISCO-58 standard. Using a crosswalk, we match occupations in the NYK1965 standard to the nearest possible occupation using the STYRK1998 standard described above.

C The Norwegian education system

The Norwegian education system consists of four levels, primary school (grades 1–7), middle school or lower secondary school (grades 8–10), high school or upper secondary school (three years), and then higher education. Norwegian compulsory education starts at age six, lasts for 10 years and consists of primary school and lower secondary school. Norwegian municipalities operate schools to provide compulsory education, and the vast majority (98%) of pupils attend public, local schools during compulsory schooling. At the elementary school level, all pupils are allocated to schools based on fixed school catchment areas within municipalities. With the exception of some religious schools and schools using specialized pedagogic principles, parents are not able to choose the school to which their children are sent (except by moving to a different neighborhood). There is a direct link between elementary school attendance and attendance at middle or lower secondary schools (ages 13–16/grades 8–10), in that elementary schools feed directly into lower secondary schools. In many cases, primary and lower secondary schools are also integrated.

The high schools have two main tracks, vocational and academic. High schools are administered at the county level (above the level of municipalities) and attendance is not mandatory, although since the early 1990s everybody graduating from middle schools has been guaranteed a slot in high school. Admissions procedures differ across counties for upper secondary schools. In some counties, pupils can freely choose schools, while in others children are allocated to schools based on well-defined catchment areas, or high school zones. Within schools, there is no systematic sorting of students into classes.

About 95% of students moving into high school enroll in the year they finish compulsory education. About 45% enroll in the academic track, which qualifies for higher education. The rest of the students enroll in the vocational track, and there are several subject fields for this track. There is an option also for students coming from the vocational track to enroll in university, but that requires some extra coursework. Admission at different universities and in different majors at universities is based on high school GPA. This is a combination of non-blind grading by local teachers and the results of the final-year exams, which are prepared centrally by the Directorate for Education (a branch of the Ministry of Education) and are subject to blind grading. The high school GPA is not normalized at the school level.

C.1 Teacher grading and exam grading at middle school (Middle school GPA)

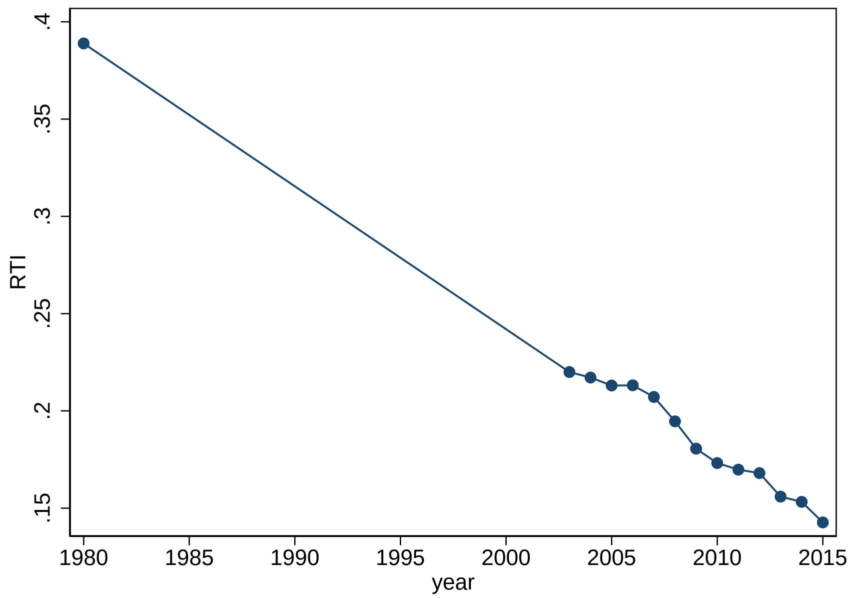
At the end of middle school, students are evaluated both non-anonymously by their teachers for 11 subjects taught in school, and in addition anonymously in 2 nationally administered exit exams, which are graded by external examiners (who are not students' teachers). The subjects for the national exit exams are randomly selected for each student among the 11 subjects in which they are also evaluated by their teachers. The assessment for Norwegian and English consists of both oral and written exams. For the rest of the subjects, the assessment consists of only written exams. In each assessment, the grade ranges between 1 and 6. The final grade of a subject is determined by a simple average between the grades by the teacher and grades from the national exam in the final year, if present. The middle school GPA is not standardized at the school level so they are not grading to the curve.

The final-year middle school GPA used by post-reform high school admission is the sum of final grades across 11 subjects, for students who had grades in at least 3 subjects, hence it ranges between 3 and 66 (i.e. 6×11). Note that the algorithm for calculating the final-year GPA changed in the school year 2006/2007. Instead of summing up the grades in 11 subject, the final-year GPA is determined by first taking a simple average across all subjects and then multiplied by 10.

Grading principles are set by the Education Act of 1998 ("Opplæringslova"). In the Prescript to the Education Act of 1998 (Forskrift til opplæringslova) it is stated that teacher evaluations are to be based on the degree to which students have achieved the competence goals stated by the subject-specific centrally set “Learning goals,” which are stated in each topic. For each subject, the final teacher evaluation grade is given in April and is set based on the performance in the final year of middle school. Notably, it is specifically stated that student behavior (“orden og oppførsel”) is not to be reflected in grading, and (of course) that student background should not count in grading (“Prescript to Education Act”). Effort is allowed to be included in grading in gymnastics. Teacher grades are given *before* the grading of national exams, and hence teachers are not aware of the student’s national exam score at the time when teacher assessment is given.

D Linking Fields of Study to Tasks

Figure D.1: Change in RTI from 1980–2015



Notes: Figure plots the RTI index measured for all private workers aged 18–54 from 1980–2015.

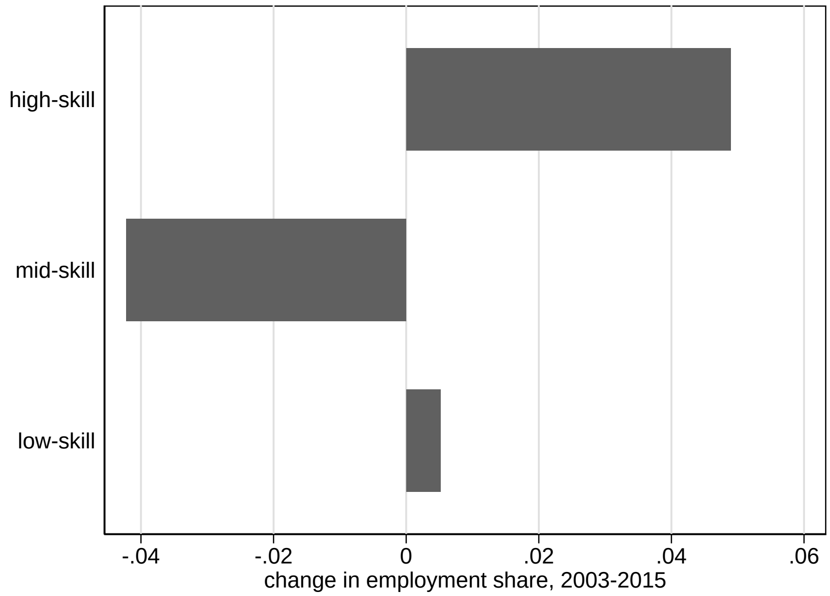
In order to measure the changes in tasks as predicted by shifts in educational investments, we create a measure of RTI for each degree as follows. First, we use data on the 1985 birth cohort, those who are aged 16 in 2001 and before our sample period. Second, we match their initial field of study at age 21—(i) high school dropout, (ii) vocational-trades, (iii) vocational-services, (iv) academic, (v) enrolled in STEM, and (vi) enrolled in non-STEM—to the occupation which they are employed in at age 30. While high school dropouts may return to graduate from education between 21–30 (see Bennett et al., 2020, for details), we measure only their initial educational choices at age 21. Similarly, those enrolled in STEM/non-STEM college may not necessarily graduate by age 30. We create a measure of tasks for each of these 6 degrees by taking the median measure of RTI across all the occupations which people in these different education levels perform. Table D.1 reports the three most common fields of study across different levels of education.

Table D.1: Most Common Occupations Among Different Fields of Study

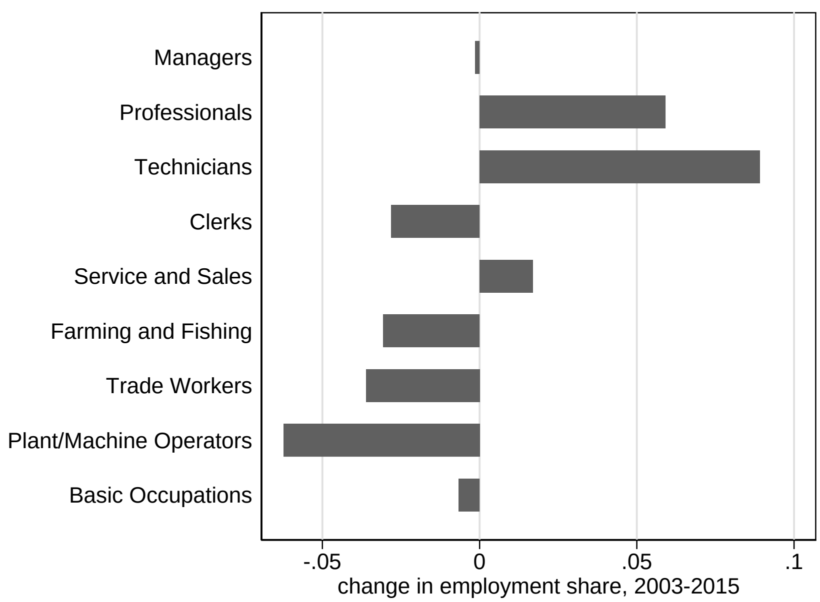
Rank:	Level of education:
	High School Dropout
1	Personal care and related workers (9.8%)
2	Salespersons and demonstrators (7%)
3	Building frame and related trades (2.6%)
	Vocational-Trades
1	Building frame and related trades (11%)
2	Engineering science technicians (9.9%)
3	Electricians, electrical, and electronic (9.8%)
	Vocational-Services
1	Personal care and related workers (24.1%)
2	Salespersons and demonstrators (8.7%)
3	Housekeeping and restaurant service (5.1%)
	College, STEM
1	Engineering science technicians (15.5%)
2	Architects and engineers (13.4%)
3	Health professionals (12.2%)
	College, non-STEM
1	Nursery and registered nurses for mentally challenged (8.2%)
2	Primary education teaching (7.7%)
3	Finance and sales associates (6.5%)

Figure D.2: Change in Occupational Employment Shares, 2003–2015

(a) Skill Groupings as in Autor (2019)



(b) Detailed 1-digit Occupations



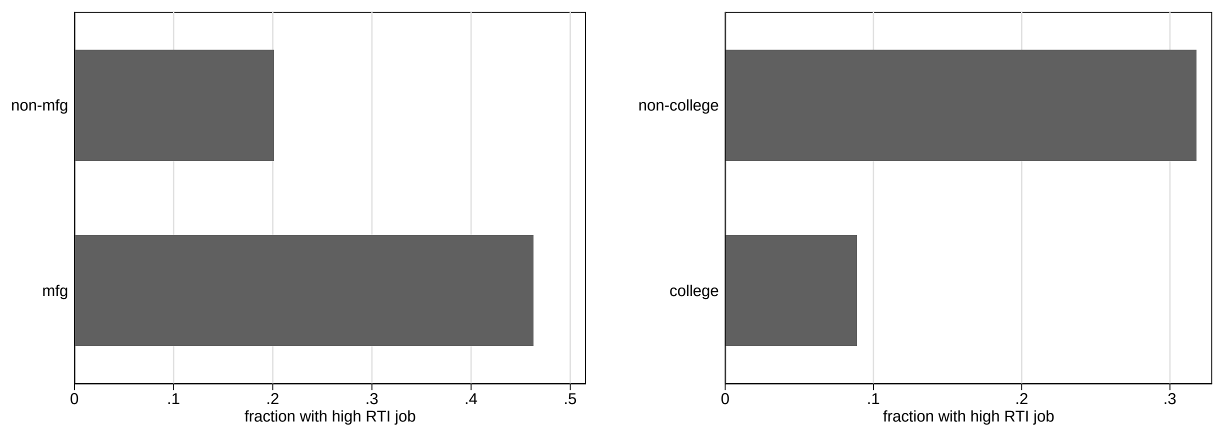
Notes: Figure plots the change in the employment share of different occupations. Panel a groups occupations by skill as in Autor (2019), while panel b reports 1 digit occupation groupings. High-skill corresponds to Managers, Professionals, and Technicians. Mid-skill corresponds to Clerks, Trade Workers, and Plant/Machine Operators. Low-skill corresponds to Basic Occupations and Service and Sales.

E What are High RTI Jobs and What Correlates with Their Decline?

Figure E.1 plots the fraction of jobs which are classified as high RTI occupations across different industries (panel a) and education levels (panel b). Manufacturing industries are dominated by high RTI jobs, as nearly 50% of jobs in manufacturing are high RTI occupations. In contrast, just 20% of non-manufacturing jobs are high RTI. As with manufacturing industries, work among non-college educated is dominated by routine occupations, as over 30% of these jobs are high RTI comapred to less than 10% of college jobs.

Figure E.1: Employment Shares in high RTI Jobs by Industry and Education

(a) Manufacturing/Non-manufacturing (b) College/Non-college



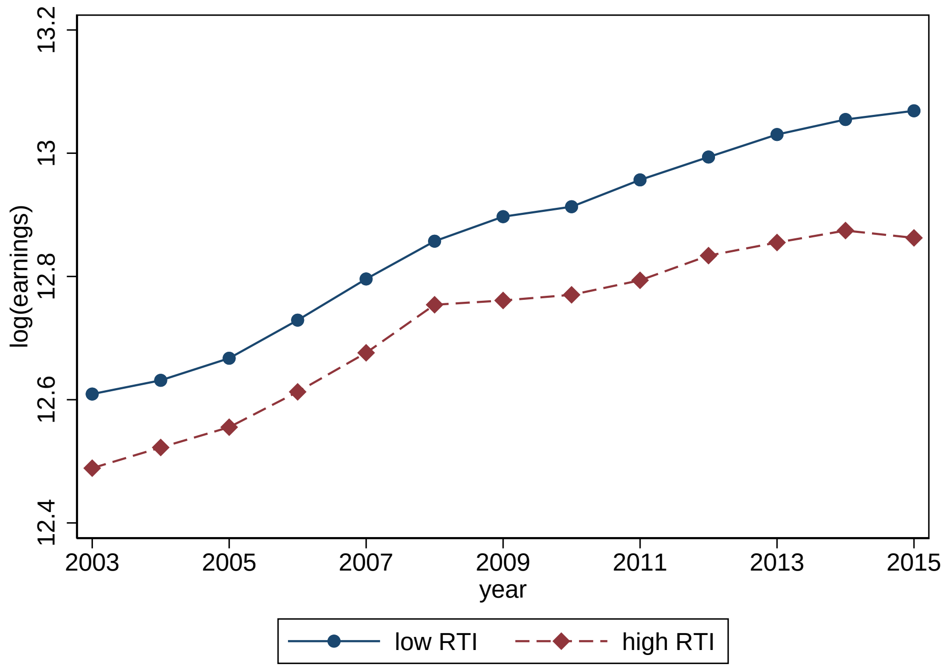
Notes: Figure plots the employment shares of high RTI jobs separately by industry (panel a) and education (panel b). Employment shares calculated for all workers aged 18–54 in the base year 2003. High RTI defined as in Section 2.1.

Figure E.2 plots the average earnings of workers employed in high/low RTI jobs from 2003–2015. In the initial year 2003, workers employed in low RTI occupations have higher earnings, a gap which roughly doubles by 2015.

Table E.1 reports the factors which are correlated with the change in the RTI index over different time periods. Time periods are from 2003–2015. Initial manufacturing share (column 1) is strongly correlated with declining routine task intensity. The negative sign suggests that areas with higher manufacturing specialization experience significantly stronger declines in routine tasks.

Automation is also significantly correlated with the change in the RTI index from 2003–2015 (column 3). The negative sign suggests that areas with more automation, measured as industrial robots per

Figure E.2: Earnings Growth over Sample Period by low and high RTI Occupations



Notes: Figure plots the average log of annual labor earnings for all workers aged 18–54 from 2003–2015. High RTI defined as in Section 2.1.

1000 workers in Norway, see larger decreases in routine task specialization.

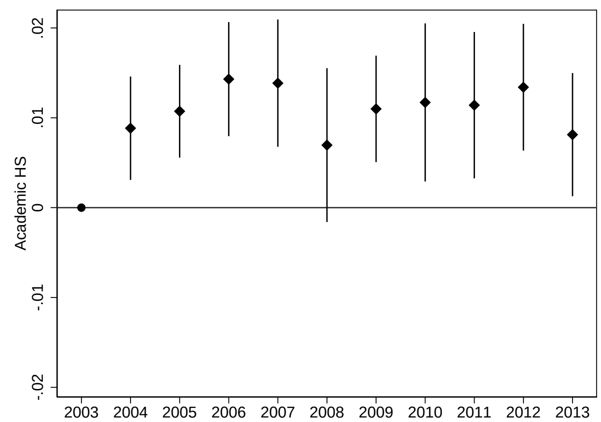
Table E.1: The Correlates with Changing Routine Task Intensity

	(1) Δ RTI, 03–15	(2) Δ RTI, 03–15	(3) Δ RTI, 03–15	(4) Δ RTI, 03–07
initial manufacturing share, 2003	-0.171***			
	(0.050)			
Δ mfg. share		0.249		
		(0.160)		
Δ industrial robots			-0.003***	
			(0.001)	
Δ Chinese imports, 2003–2007 (billions NOK)				0.001
				(0.002)
Constant	-0.013**	-0.028***	-0.014**	
	(0.006)	(0.006)	(0.005)	
N	160	160	160	160

Notes: Table reports estimates from regressing the change in the RTI index over different time period on different factors reported in the table. Column (1) measures the initial fraction of jobs employed in manufacturing in 2003. Column (2) measures the change in the manufacturing share from 2003–2015. Column (3) measures the change in industrial robots from 2003–2015, the number of robots per 1000 workers allocating robots to each CZ in Norway using their initial industry share. Column (4) measures the change in Chinese imports from 2003–2007 as in Balsvik et al. (2015). ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively.

F The Impact of Local Demand Shocks on Academic High School and Labor Market Outcomes at Age 21

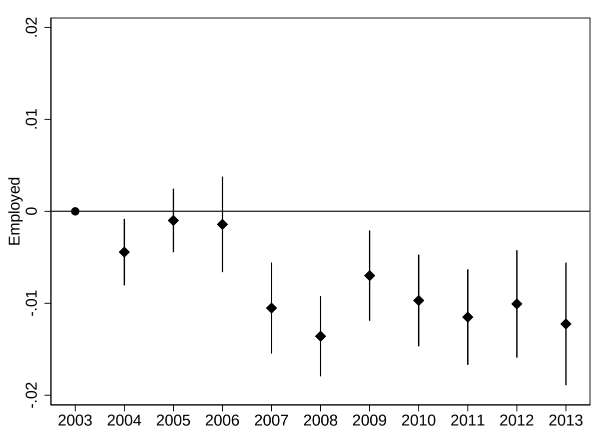
Figure F.1: The Effect of Local Demand Shocks on Academic High School



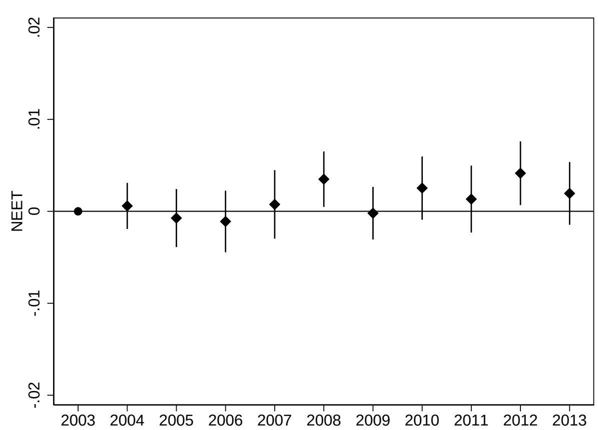
Notes: Figure plots estimates of β_{1c} from equation (3). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Outcome variable: graduation from academic high school at age 21. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

Figure F.2: The Effect of Declining Routine Task Intensity on Labor Market Outcomes at Age 21

(a) Employed



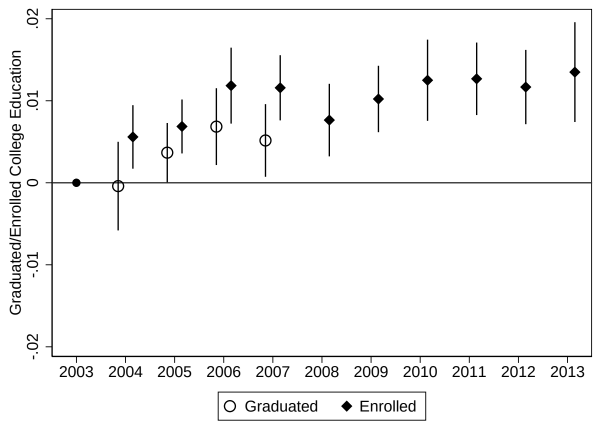
(b) NEET



Notes: Figure plots estimates of β_{1c} from equation (3). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Outcome variables: employment (panel a) and not in education, employment, or training (panel b) at age 21. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

G Graduation from Higher Education by Age 27

Figure G.1: The Effect of Declining Routine Task Intensity on Graduation from Higher Education by Age 27, By Ability



Notes: Figure plots estimates of β_{1c} from equation (3). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Outcome variables: graduation from higher education at age 27 and enrolled in higher education at age 27. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

H Robustness of Baseline Results

Here we address numerous challenges to the Bartik identification. We examine the sensitivity of the results to the definition of key variables, sample selection, different measures of the Bartik shock, additional control variables, and recent advances in the Bartik literature. In addition, we assess whether places which are more/less affected by the change in demand may have differential trends in education prior to the shock.

First, Figure H.1 performs a placebo regression, asking whether education is already changing prior to the demand shock in areas that will be affected in the future. A concern with the Bartik approach of equation (3) is that places which are more/less affected by the change in demand may have differential trends in education prior to the shock. We perform this placebo regression by regressing changes in local demand from 2003–2013 on the change in education of cohorts prior to the change. We use cohorts who are aged 16 from 1997–2002 and measure the change in education between them and the 2003 birth cohort. By doing so, we ask whether there are differential trends in education between areas that are more/less exposed prior to the changes in demand.

Second, Section H.2 addresses the importance of different "large weight" occupations for the results, as in Goldsmith-Pinkham et al. (2020), and further examines the validity of assuming that initial occupation shares are exogenous at the area-level. Table H.1 calculates Rotemberg weights inthe Bartik measure, and Figure H.2 assesses the robustness to dropping these occupations one by one. Figure H.3 examines the robustness of the results to to using the initial share of jobs in 1980, that is, changing only the *share* of initial jobs from 2003 to 1980 ($\frac{L_{mj1980}}{L_{m1980}}$ from equation (1)). By only using this initial share in 1980, the *shift* in employment remains relative to 2003, i.e. $(lnL_{jt} - lnL_{j2003})$. Figure H.4 examines how sensitive the Bartik demand shock is to the choice of the initial period, moving the initial period from 2003 to over 20 years earlier in 1980. The exercise establishes the robustness of the results using a change in demand measured from 1980–2004, making use of the 1980 census data to understand how a longer time horizon, as well as a change of the initial period from 2003 to 1980, affects the results. That is, Figure H.4 changes the *share* of initial jobs from 2003 to 1980 and also changes the *shift* of national changes in the composition of jobs from $2003 - t$ for $t = 2004, ...2013$ to 1980–2004.

Third, Figure H.5 includes a third factor in the RTI index, altering equation (2) to include services. While routine and mathematical tasks are important, services have also changed considerably, becoming more prominent in the labor market over time.

Fourth, Figure H.6 examines the robustness of the results to calculating the Bartik shock as a "leave-one-out" approach. Doing so excludes the influence of the local CZ itself in national changes in demand, which creates a shift measure of employment which is arguably more exogenous as the shift in the local area itself is endogenous.

Fifth, Figure H.7 designs a robustness check to account for the expansion of the European Union in 2004. Following the inclusion of additional states into the European Union, there was a large influx of Polish and Baltic workers who immigrated to Norway to work, primarily, in unlicensed construction jobs (Bratsberg and Raaum, 2012). This expansion was a large shock for the Norwegian labor market, and given that the timing coincides with our sample period, it is important to exclude the confounding influence of changes in immigration at the local level, which could also potentially affect educational investments.

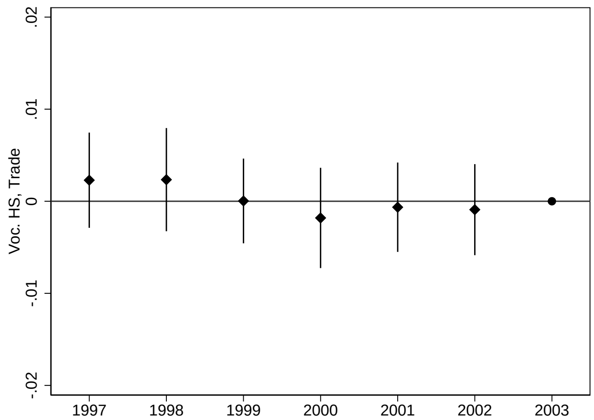
Sixth, Figure H.8 changes the area of residence from where the student resides from age 16 to using the area of birth. Roughly 10% of those who have a CZ defined at age 16 do not have data on CZ of birth. Such a sample restriction disproportionately excludes migrants from the sample as the cannot have a CZ of birth in Norway by definition.

Finally, Figure H.9 assesses the importance of large urban areas for the baseline results. Large urban areas are five major cities in Norway, Oslo, Bergen, Stavanger, Trondheim, Kristiansand, and Tromsø. Figure H.9 excludes these 5 CZs from the estimation sample, reducing the sample size from 160 to 155. Doing so assesses the importance of urban areas for the results, but also tests how important local opportunities for higher education are as universities are overwhelmingly located in these large urban areas.

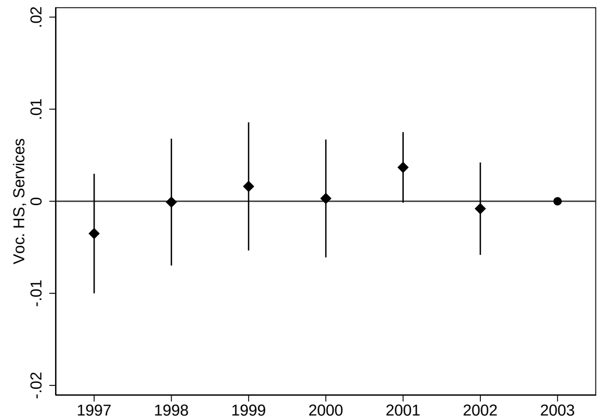
H.1 Examining the Importance of Diverging Trends Prior to Bartik Period

Figure H.1: Placebo Regression Estimating Trends in Education Prior to Bartik Shock Period

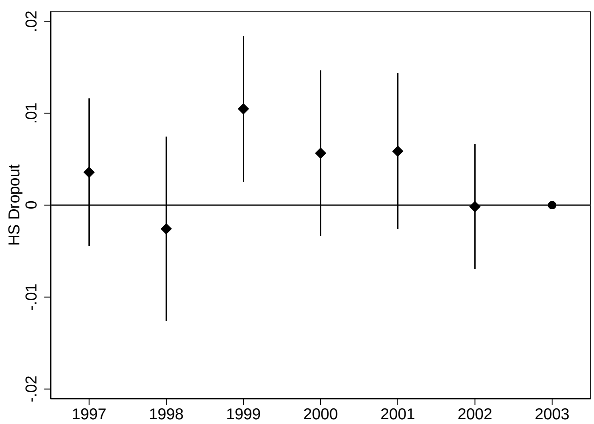
(a) Voc. HS, Trades



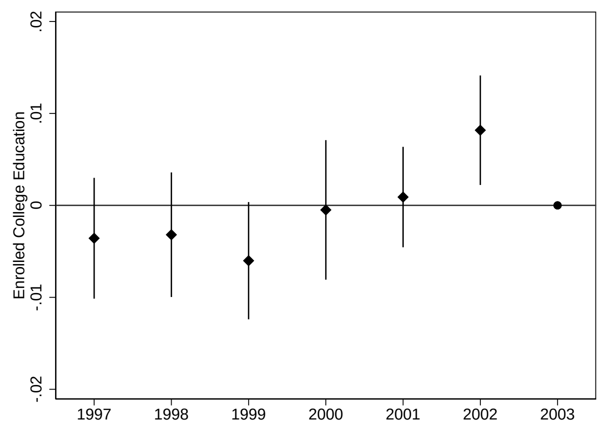
(b) Voc. HS, Services



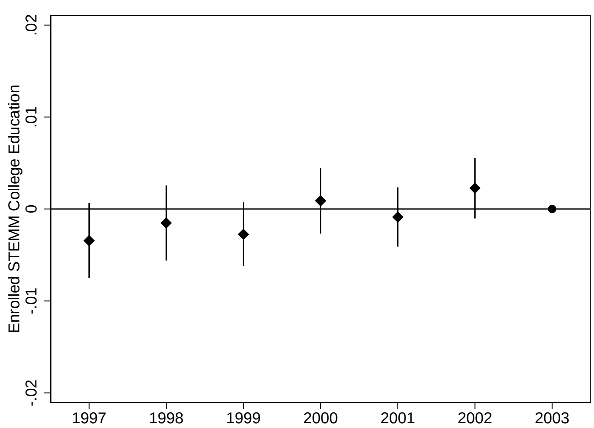
(c) HS Dropout



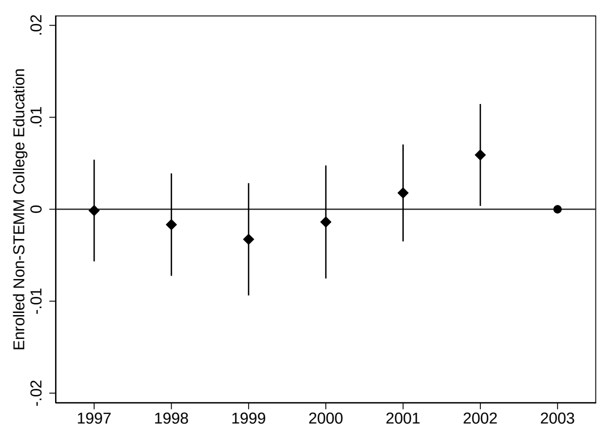
(d) Enrollment in College Education



(e) Enrollment in College Education, STEM



(f) Enrollment in College Education, Non-STEM



Notes: Figure plots estimates of β_{1c} from equation (3), fixing ΔZ_{mc} to the change in RSH from 2003–2013 and using cohorts born prior to the shock. Outcome variable is measured as the different in education relative to the initial cohort (1987 cohort aged 16 in 2003), using cohorts born prior to 1987 from 1982–1986. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock from 2003–2013. 95% confidence intervals plotted.

H.2 Diagnostics as in Goldsmith-Pinkham et al. (2020)

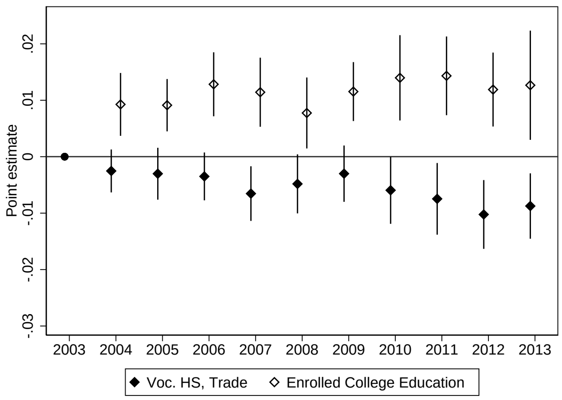
Table H.1: Summary of Rotemberg Weights & Occupations Underlying Bartik Measure

	sum	mean
Panel a: summary of weights		
Rotemberg Weights	1	0.0032
	$\hat{\alpha}$	
Panel b: occupations with highest weights		
Fishery	0.213	
Air traffic controller	0.081	
Ships' machine crew	0.073	
Shoemaking machine operator	0.070	
Chimney sweep	0.041	
Power plant operator	0.030	
Ships' engineer	0.028	
Agricultural, fishery, and related labourers	0.025	
Protective services N.E.C.	0.024	
Textile machine operator N.E.C.	0.021	

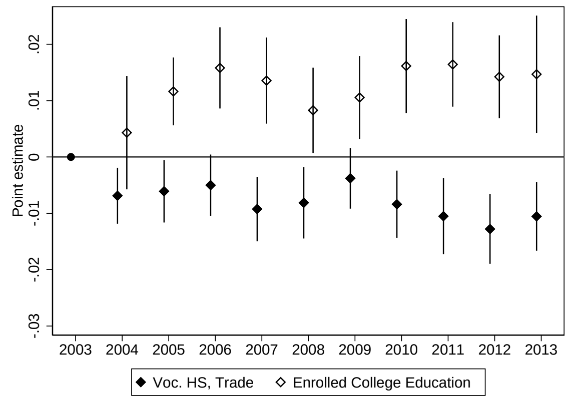
Notes: Table reports the summary of all occupations' Rotemberg weights (panel a) and the top 10 occupations with the highest weight which contribute to the Bartik (panel b) as in Goldsmith-Pinkham et al. (2020).

Figure H.2: The Importance of High Rotemberg Weight Occupations

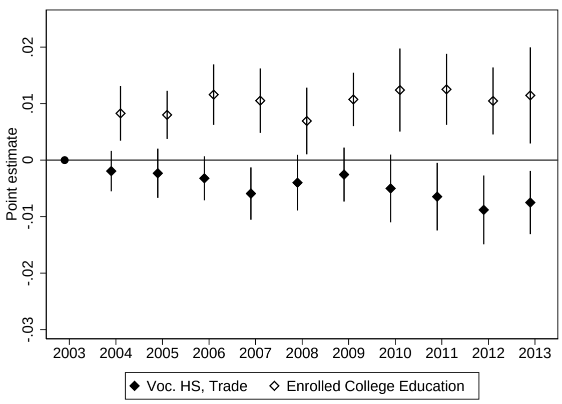
(a) Fishery



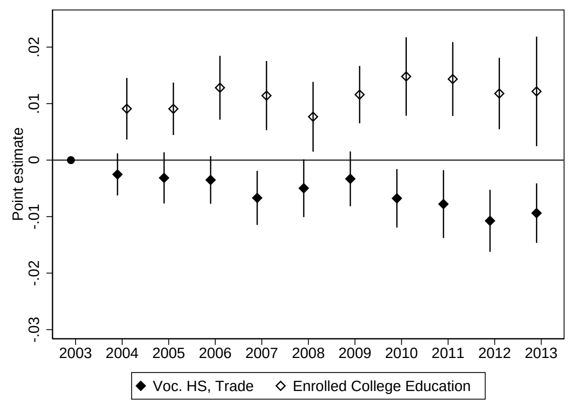
(b) Air traffic controller



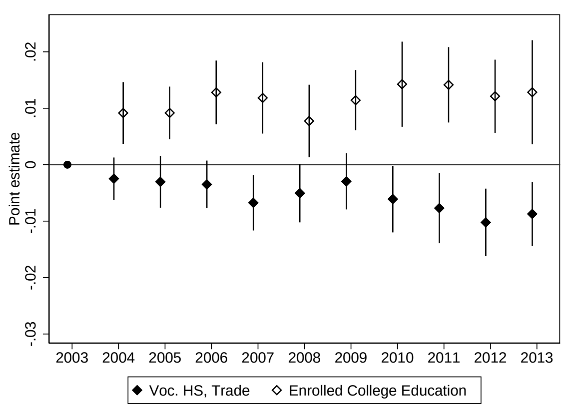
(c) Ships' machine crew



(d) Shoemaking machine operator



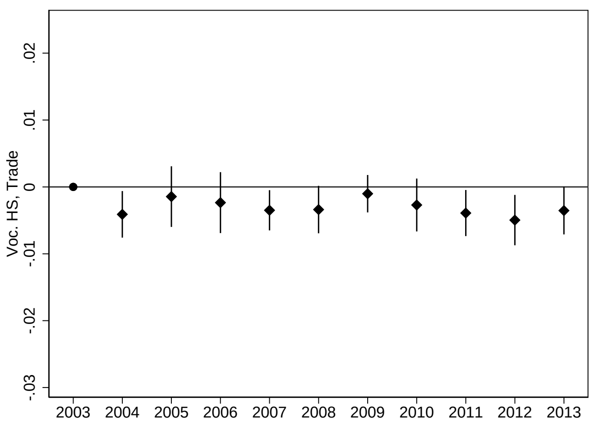
(e) Chimney sweep



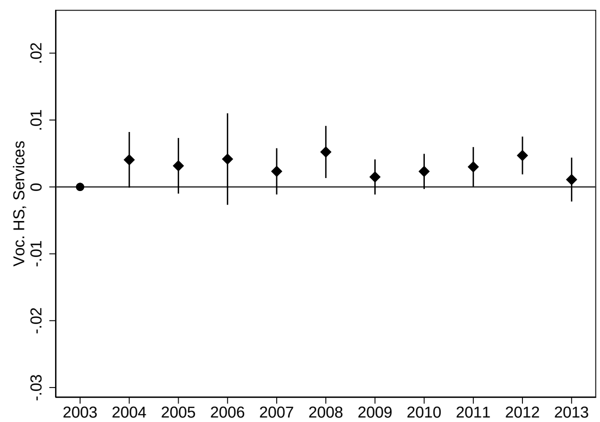
Notes: Figure plots estimates of β_{1c} from equation (3), excluding the top 5 occupations one by one from panels (a)–(e) calculating Rotemberg weights as in Goldsmith-Pinkham et al. (2020). Outcome variable is measured as the different in education relative to the initial cohort (1987 cohort aged 16 in 2003). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. 95% confidence intervals plotted.

Figure H.3: The Effect of Declining Routine Task Intensity on Educational Investments, 1980 Area-level Occupational Share

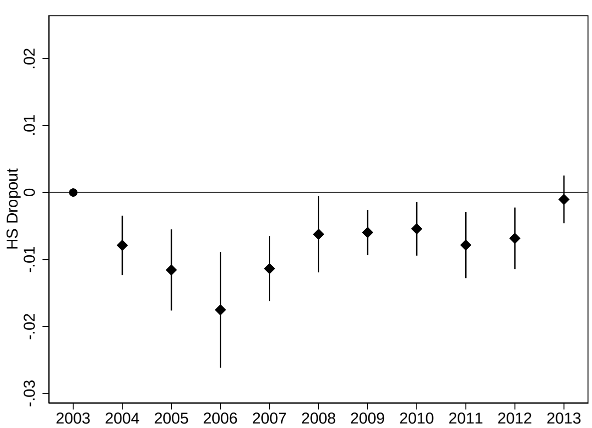
(a) Voc. HS, Trades



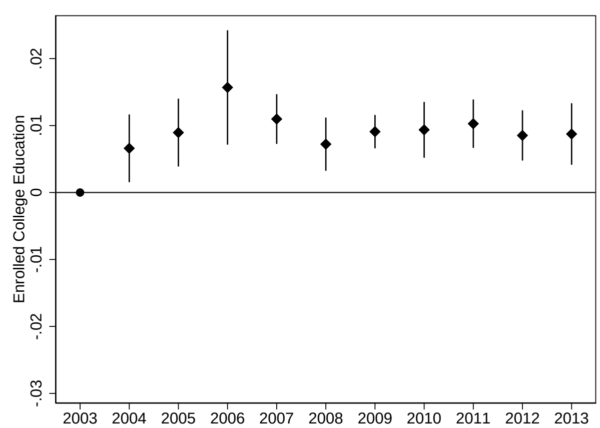
(b) Voc. HS, Services



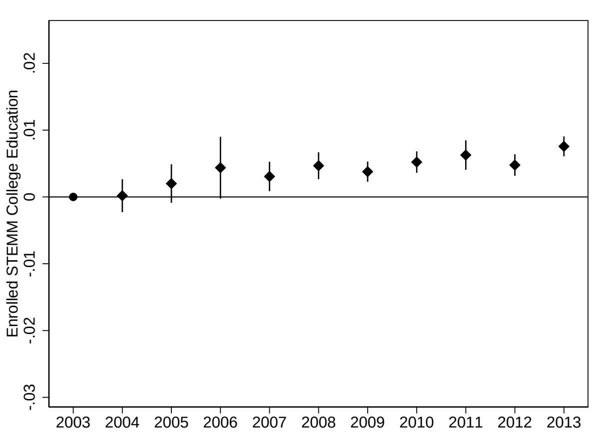
(c) HS Dropout



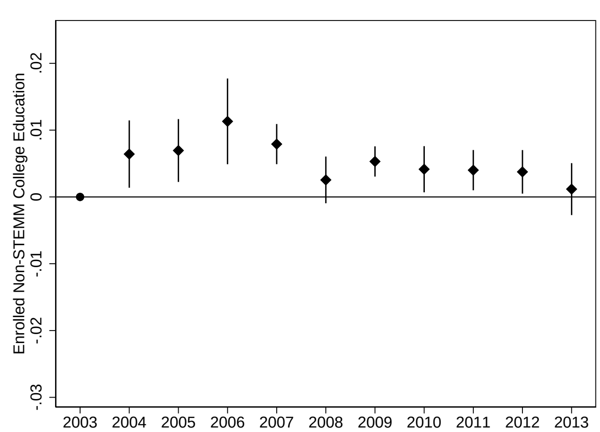
(d) Enrollment in College Education



(e) Enrollment in College Education, STEM

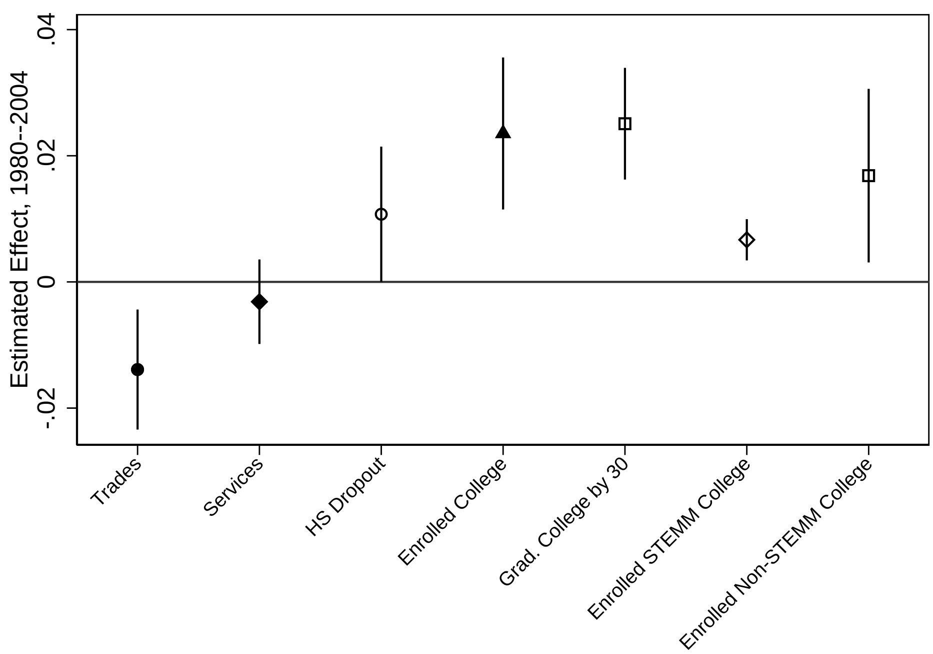


(f) Enrollment in College Education, Non-STEM



Notes: Figure plots estimates of β_{1c} from equation (3), altering the measure of ΔRSH_{mc+16} by defining $\frac{L_{mj1980}}{L_{m1980}}$ from equation (1). Bartik defined using the 1980 share and shifts in the 2000s relative to 2003 as: $\Delta RSH_{mt} = \sum_{j=1}^{J} \frac{L_{mj1980}}{L_{m1980}} \times (lnL_{jt} - lnL_{j2003}) \times \mathbf{1}[RTI_j > RTI^{p66}]$. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

Figure H.4: The Long Run Impact of Labor Demand Shocks on Educational Investments, from 1980–2004

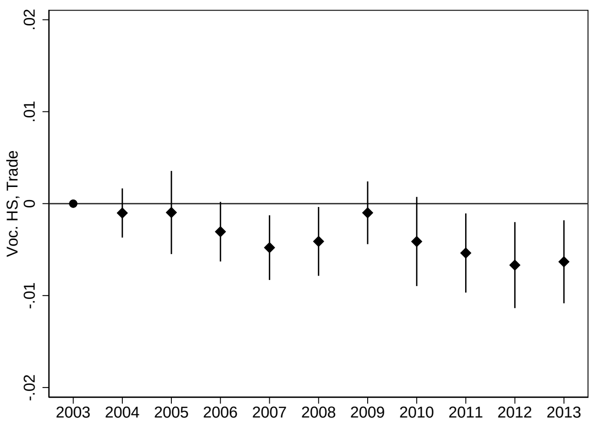


Notes: Figure plots estimates of β_{1c} from equation (3), changing base cohort from 1987 (age 16 in 2003) to 1964 cohort (age 16 in 1980). Plotted coefficients are the long-run difference from 1980–2004, comparing the educational investments of the 1964 birth cohort to the 1988 birth cohort. Bartik defined using the 1980 share and shifts from 1980–2004 as: $\Delta RSH_{mt} = \sum_{j=1}^{J} \frac{L_{mj1980}}{L_{m1980}} \times (lnL_{j2004} - lnL_{j1980}) \times \mathbf{1}[RTI_j > RTI^{p66}]$. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

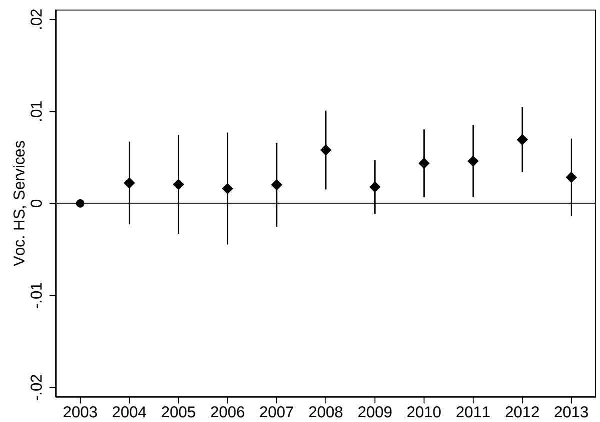
H.3 Including Services in RTI Measure

Figure H.5: The Effect of Declining Routine Task Intensity on Educational Investments, Including Services into Measure of RTI

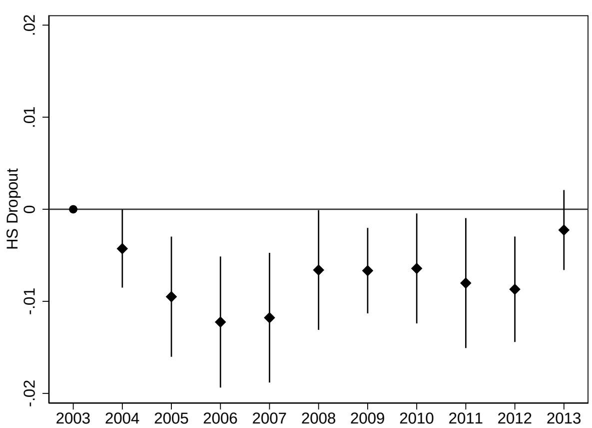
(a) Voc. HS, Trades



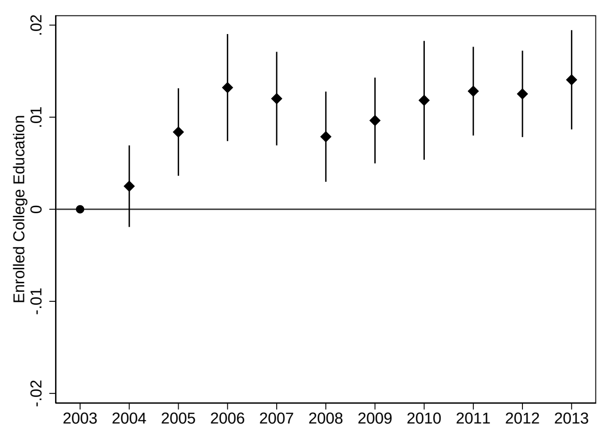
(b) Voc. HS, Services



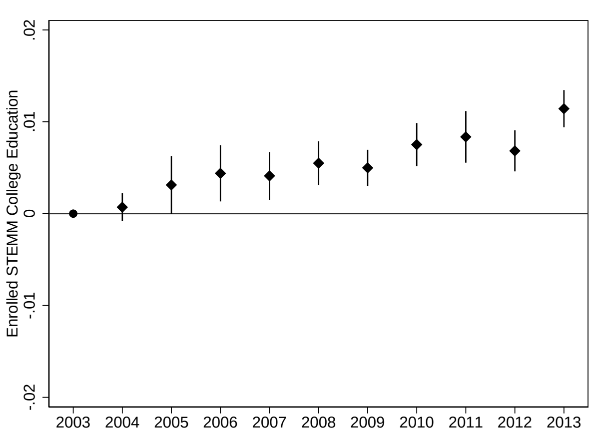
(c) HS Dropout



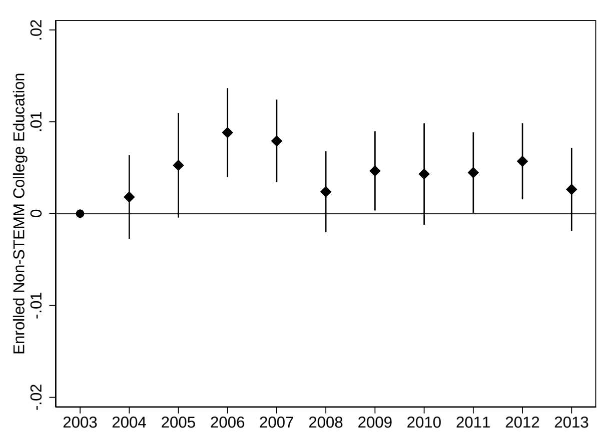
(d) Enrollment in College Education



(e) Enrollment in College Education, STEM



(f) Enrollment in College Education, Non-STEM

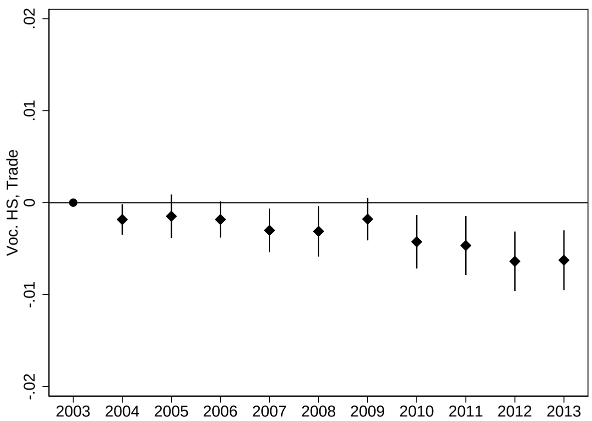


Notes: Figure plots estimates of β_{1c} from equation (3), changing measure of ΔRSH_{mc+16}. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. RTI measure including services defined as: $RTI_j = lnR_j - lnM_j - lnS_j$, where $R_j, M_j, andS_j$ correspond to routine, math, and services respectively. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

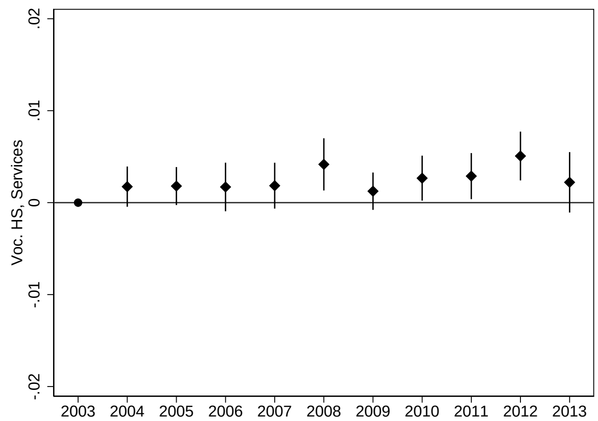
H.4 Leave-One-Out Design

Figure H.6: The Effect of Declining Routine Task Intensity on Educational Investments, Leave-One-Out Bartik

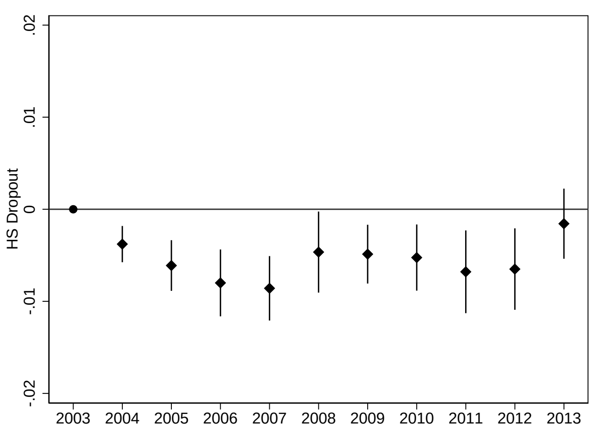
(a) Voc. HS, Trades



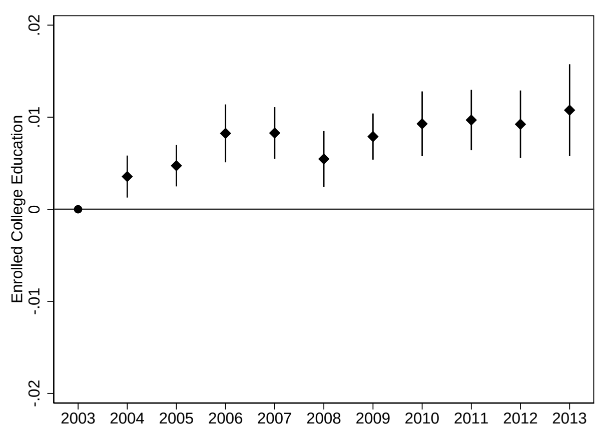
(b) Voc. HS, Services



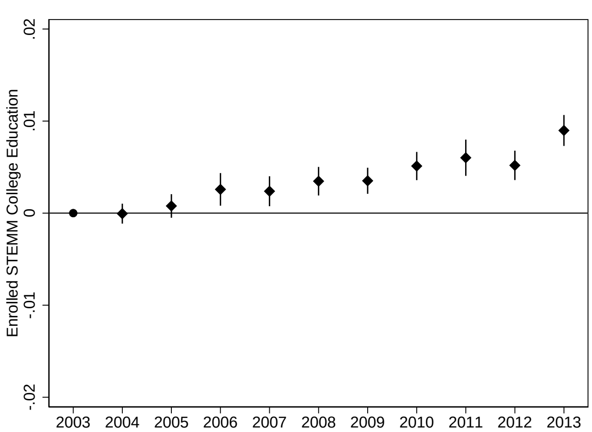
(c) HS Dropout



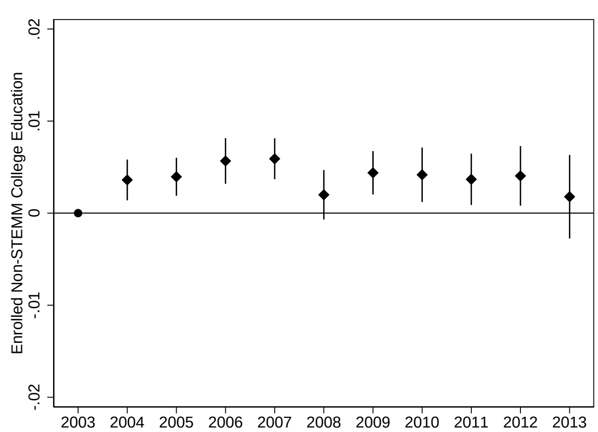
(d) Enrollment in College Education



(e) Enrollment in College Education, STEM



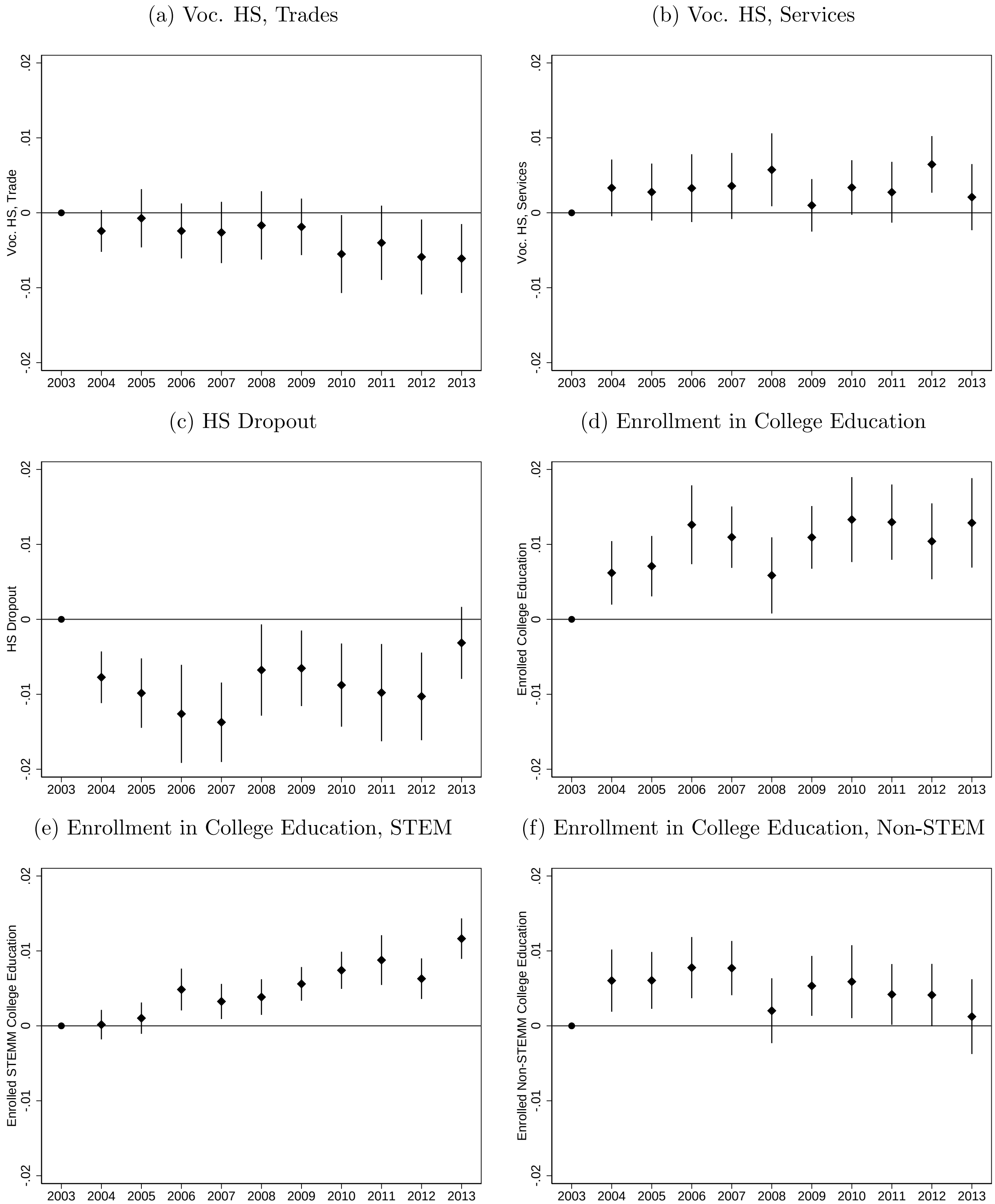
(f) Enrollment in College Education, Non-STEM



Notes: Figure plots estimates of β_{1c} from equation (3), changing definition of Bartik shock to calculate ΔRSH_{mc+16} excluding the CZ itself from $(lnL_{jt} - lnL_{jt^0})$ in equation (1). Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

H.5 Controlling for Change in Immigration in Each Year

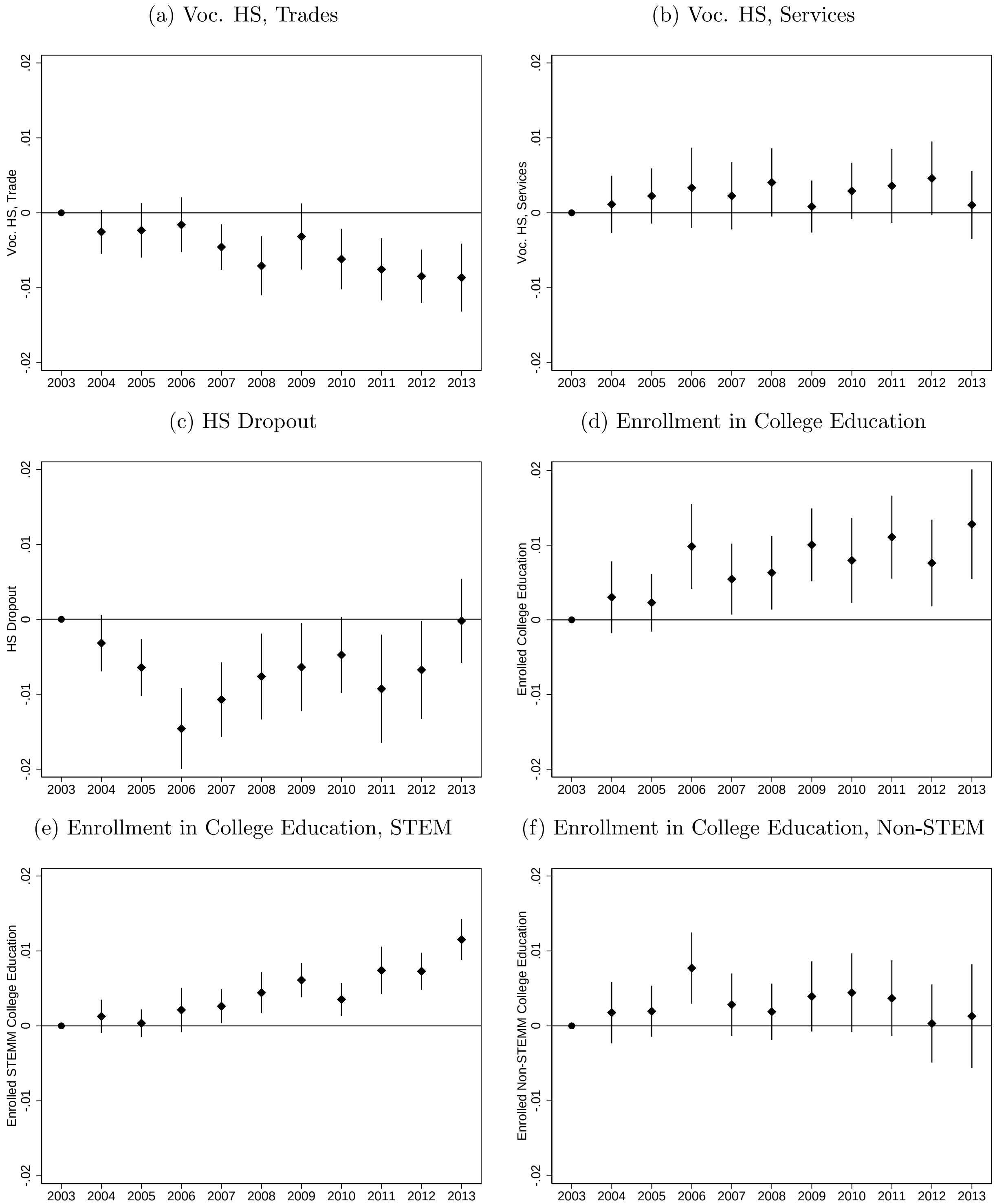
Figure H.7: The Effect of Declining Routine Task Intensity on Educational Investments, Controlling for Change in Immigration



Notes: Figure plots estimates of β_{1c} from equation (3), including the change in share of Poles residing in each CZ to account for the expansion of the EU in 2004 where a large influx of Polish workers immigrated to Norway. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

H.6 Using CZ of Birth

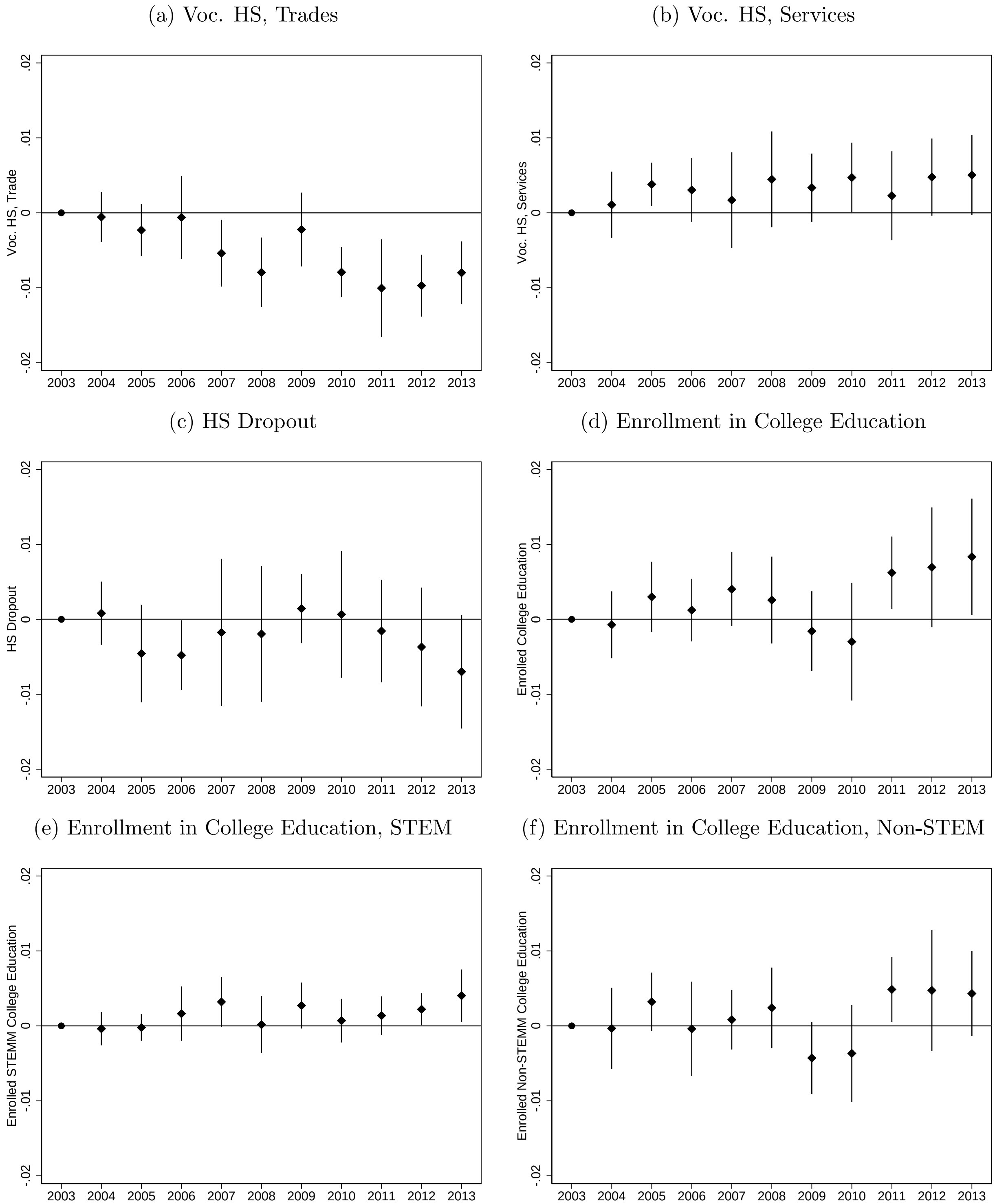
Figure H.8: The Effect of Declining Routine Task Intensity on Educational Investments, Using CZ of Birth



Notes: Figure plots estimates of β_{1c} from equation (3), changing the CZ from the CZ of residence at age 16 to the CZ of birth among those born in Norway for whom data on birthplace is available. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted.

H.7 Excluding Large Urban Areas

Figure H.9: The Effect of Declining Routine Task Intensity on Educational Investments, Excluding Large Urban Areas



Notes: Figure plots estimates of β_{1c} from equation (3), changing estimation sample to exclude large urban areas. Year plotted on x-axis corresponds to the year a birth cohort faces the RTI shock at age 16. Coefficients are scaled by average change in the Bartik shock in each year. 95% confidence intervals plotted. Sample excludes the CZs of Oslo, Bergen, Stavanger, Trondheim, Kristiansand, and Tromsø.

I The Effect of Local Demand Changes on Education Investments by Maternal Education, 2003–2013

Table I.1: The Effect of Local Demand Changes on Education Investments by Ability & Parental Education, 2003–2013

	GPA		Mother's Education		GPA		Mother's Education	
	Top (1)	Bottom (2)	High (3)	Low (4)	Top (5)	Bottom (6)	High (7)	Low (8)
	Panel A: Voc HS, trades				*Panel B: Voc HS, services*			
point estimate, 2003-2013	-0.000	-0.015***	-0.010***	-0.005**	-0.003	0.008***	-0.000	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
% of mean	[-0.3]	[-9.8]	[-8.5]	[-3.4]	[-3.1]	[8.6]	[-0.1]	[2.1]
	Panel C: HS dropout				*Panel D: enrollment in college*			
point estimate, 2003-2013	0.001	-0.003	0.006**	-0.008***	0.002	0.011***	0.009**	0.016***
	(0.002)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
% of mean	[1.0]	[-0.4]	[3.0]	[-2.0]	[0.2]	[19.6]	[1.8]	[5.6]
	Panel E: enrollment in college, STEMM				*Panel F: enrollment in college, Non-STEMM*			
point estimate, 2003-2013	0.013***	0.004**	0.018***	0.006***	-0.012***	0.007***	-0.008**	0.010***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.003)
% of mean	[7.1]	[15.3]	[14.2]	[10.8]	[-2.0]	[23.5]	[-2.1]	[4.3]

Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. *Notes:* Table shows estimates of β_{1c} from equation (3), scaled by average change in the Bartik shock. Point estimate calculated as a percent of the mean of the initial cohort reported in brackets. Estimation period is 10 year difference from 2003–2013. High ability in columns (1) & (5) defined as student in the top 25% of middle school GPA distribution. Low ability in columns (2) & (6) defined as student in the bottom 25% of middle school GPA distribution. High-educated in columns (3) & (7) defined as student whose mother is a college graduate. Low-educated in columns (4) & (8) defined as student whose mother is non-college educated. Sample of 160 CZs. Estimating equation: $\Delta Y_{gmc} = \beta_{0gc} + \beta_{1c}\Delta RSH_{mc} + \beta_{2c}X_m + \varepsilon_{gmc}$, where g corresponds to each of the GPA/mother's education groups.

J The Relationship Between Father's Education & Child GPA

Figure J.1: Distribution of Middle School GPA by Father's Education Level

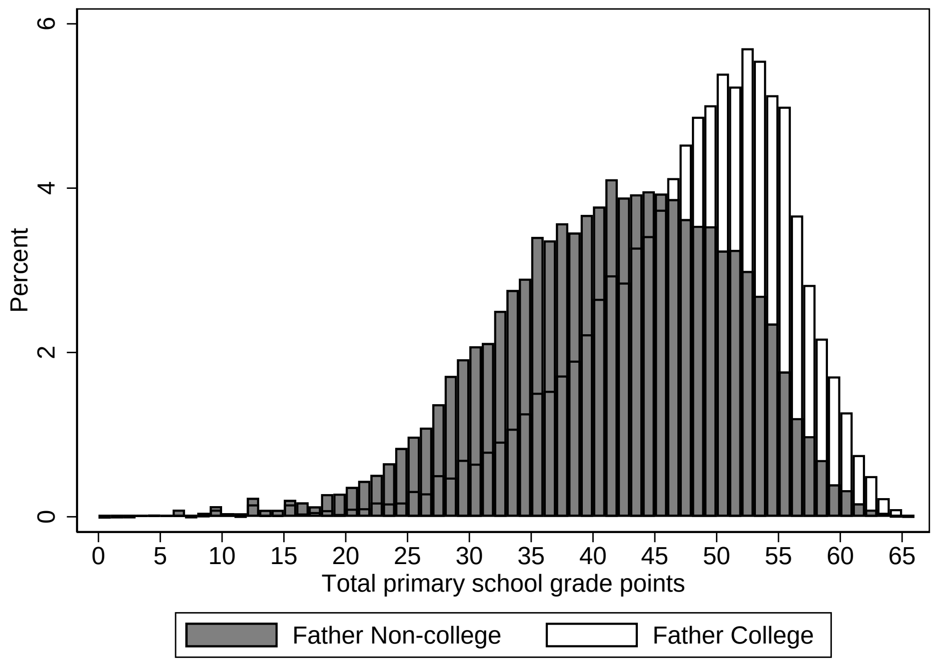


Figure plots the distribution of middle school GPA for birth cohort 2003 separately by those with a high and low educated father. Each bar corresponds to a 1 unit difference in GPA, measured from 0–66. High/low ability father defined as whether or not father graduated from college.

K The Effect of Declining Routine Task Intensity on Educational Investments, Separately by Gender

K.1 Separately Analyzing Girls and Boys, by Father's Education and GPA

Table K.1: The Effect of Local Demand Changes on Education Investments by Ability & Parental Education for Boys, 2003–2013

	GPA		Father's Education		GPA		Father's Education	
	Top	Bottom	High	Low	Top	Bottom	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Voc HS, trades				*Panel B: Voc HS, services*			
point estimate, 2003-2013	-0.004	-0.018***	-0.004	-0.017***	-0.004	0.009***	-0.002	0.008***
	(0.005)	(0.004)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
% of mean	[-2.7]	[-8.3]	[-2.7]	[-6.4]	[-9.0]	[22.6]	[-5.0]	[16.7]
	Panel C: HS dropout				*Panel D: enrollment in college*			
point estimate, 2003-2013	-0.001	0.001	0.001	0.006	0.013**	0.008***	0.014*	0.008**
	(0.003)	(0.005)	(0.007)	(0.005)	(0.007)	(0.003)	(0.008)	(0.004)
% of mean	[-0.7]	[0.2]	[0.3]	[1.4]	[1.8]	[15.0]	[3.4]	[3.9]
	Panel E: enrollment in college, STEM				*Panel F: enrollment in college, Non-STEM*			
point estimate, 2003-2013	0.023***	0.005***	0.022***	0.005*	-0.010	0.002	-0.008	0.003
	(0.007)	(0.002)	(0.005)	(0.003)	(0.007)	(0.002)	(0.006)	(0.004)
% of mean	[7.5]	[16.9]	[13.2]	[6.0]	[-2.2]	[12.2]	[-3.4]	[2.6]

Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. Table shows estimates of β_{1c} from Equation (3), estimated for sample of boys. Point estimate calculated as a percent of the mean of the initial cohort reported in brackets. Estimation period is 10 year difference from 2003–2013 for cohorts born 1987 and 1997. High-ability in columns (1) & (5) defined as student in the top 25% of middle school GPA distribution. Low ability in columns (2) & (6) defined as student in the bottom 25% of middle school GPA distribution. High-educated in columns (3) & (7) defined as student whose father is a college graduate. Low-educated in columns (4) & (8) defined as student whose father is non-college educated. Sample of 160 CZs. Estimating equation: $\Delta Y_{gmc} = \beta_{0gc} + \beta_{1c}\Delta Z_{mc} + \beta_{2c}X_m + \varepsilon_{gmc}$, where g corresponds to each of the GPA/father's education groups.

Table K.2: The Effect of Local Demand Changes on Education Investments by Ability & Parental Education for Girls, 2003–2013

	GPA		Father's Education		GPA		Father's Education	
	Top (1)	Bottom (2)	High (3)	Low (4)	Top (5)	Bottom (6)	High (7)	Low (8)
	Panel A: Voc HS, trades				*Panel B: Voc HS, services*			
point estimate, 2003-2013	0.002	-0.005*	-0.001	-0.002	-0.003	0.005	-0.009*	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.005)	(0.004)
% of mean	[10.6]	[-45.1]	[-2.5]	[-6.4]	[-2.3]	[2.5]	[-7.4]	[-0.3]
	Panel C: HS dropout				*Panel D: enrollment in college*			
point estimate, 2003-2013	0.003	-0.011	-0.006	-0.007	-0.008	0.015***	-0.002	0.015**
	(0.003)	(0.011)	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)
% of mean	[4.6]	[-1.4]	[-3.8]	[-2.1]	[-1.0]	[35.4]	[-0.3]	[3.8]
	Panel E: enrollment in college, STEM				*Panel F: enrollment in college, Non-STEM*			
point estimate, 2003-2013	0.008**	0.003***	0.010**	0.004***	-0.016**	0.012**	-0.012*	0.011
	(0.004)	(0.001)	(0.004)	(0.001)	(0.007)	(0.006)	(0.007)	(0.007)
% of mean	[6.1]	[165.3]	[8.2]	[11.0]	[-2.4]	[28.9]	[-2.3]	[3.1]

Standard errors reported in parentheses clustered at the commuting zone (CZ) level. ***, **, and * correspond to significance at the 1%, 5%, and 10% levels respectively. Table shows estimates of β_{1c} from Equation (3), estimated for sample of girls. Point estimate calculated as a percent of the mean of the initial cohort reported in brackets. Estimation period is 10 year difference from 2003–2013 for cohorts born 1987 and 1997. High-ability in columns (1) & (5) defined as student in the top 25% of middle school GPA distribution. Low ability in columns (2) & (6) defined as student in the bottom 25% of middle school GPA distribution. High-educated in columns (3) & (7) defined as student whose father is a college graduate. Low-educated in columns (4) & (8) defined as student whose father is non-college educated. Sample of 160 CZs. Estimating equation: $\Delta Y_{gmc} = \beta_{0gc} + \beta_{1c}\Delta Z_{mc} + \beta_{2c}X_m + \varepsilon_{gmc}$, where g corresponds to each of the GPA/father's education groups.

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