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Summary

The US financial sector has become a magnet for the brightest graduates in the science, technology, engineering and mathematical fields (STEM). We provide quantitative bases for this anecdotal fact for the US, over the period 1980-2019 and with a specific focus on the last decade where information on major fields of study is available. First, we show that long-run educational upgrading of finance was biased towards STEM graduates, especially for postgraduates, and accelerated in the last decade. Second, the STEM.upgrading also occurs within finance and business occupations, matching a task reorientation towards mathematics in those occupations. Third, STEM reallocation towards finance is more pronounced among experienced workers peaking at prime age. Fourth, the reallocation of STEM is associated with large wage premia in finance, which are heterogeneous across occupations, age groups, degrees and along the wage distribution. Returns to STEMs are higher than returns to other degrees in finance and become very high in finance and managerial occupations at the top of the distribution, especially for postgraduates.

Keywords: finance industry, finance occupations, STEM labour markets, reallocation, technological change

JEL Classification: E24, G28, I26, J24, J31

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Finance and the Reallocation of Scientific, Engineering and Mathematical Talent *

Giovanni Marin† Francesco Vona‡

Abstract

The US financial sector has become a magnet for the brightest graduates in the science, technology, engineering and mathematical fields (STEM). We provide quantitative bases for this anecdotal fact for the US, over the period 1980-2019 and with a specific focus on the last decade where information on major fields of study is available. First, we show that long-run educational upgrading of finance was biased towards STEM graduates, especially for postgraduates, and accelerated in the last decade. Second, the STEM-upgrading also occurs within finance and business occupations, matching a task reorientation towards mathematics in those occupations. Third, STEM reallocation towards finance is more pronounced among experienced workers peaking at prime age. Fourth, the reallocation of STEM is associated with large wage premia in finance, which are heterogeneous across occupations, age groups, degrees and along the wage distribution. Returns to STEMs are higher than returns to other degrees in finance and become very high in finance and managerial occupations at the top of the distribution, especially for postgraduates.

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1 Introduction

Over the past four decades, the financial sector has become a magnet for graduates in the science, technology, engineering and mathematical fields (STEM henceforth), possibly causing skill shortages and higher costs to tech-intensive sectors (Murphy et al., 1991). For instance, almost 1/3 of the 33,000 employees working full-time at Goldman Sachs are engineers and programmers, and roughly 1/5 of new physics graduates accept a job in the financial sector, which is more than those who go to work in high-tech industries.[1] Highly talented STEM graduates, in particular, have been increasingly attracted to careers in finance by the spectacular earnings rise in the financial sector (Kaplan and Rauh, 2010; Philippon and Reshef, 2012; Bell and van Reenen, 2014). Two flagship examples of top scientists working in the financial industry are James Simons, the mathematician founder of the hedge fund Renaissance Technologies and Ryan Buckingham, a top particle physicist, who recently joined Goldman Sachs.[2] According to James Weatherall, the author of bestselling book "*The Physics of Finance*," Renaissance Technologies is "*the best physics and mathematics department in the world*" (Lewis, 2014).

These patterns are also evident in the data. Goldin and Katz (2008) and Kedrosky and Stangler (2011) find that the share of Harvard and MIT graduates, respectively, entering the financial sector increased substantially in more recent cohorts compared to less recent ones. Shu (2016) finds that finance is the most popular industry for MIT STEM graduates entering the labour market, but does not systematically attract the best prepared graduates. Celerier and Vallee (2019) show that the share of graduates from top French engineering schools employed in finance increased from 2% in 1986 to 8% in 2011. Using US census data over a century, Philippon and Reshef (2012) find that wages and skills increased tremendously in the financial sector since the 1980s. The authors also document a robust increase in the use of math skills by the financial sector compared to the rest of the economy.[3]

Empirical evidence on the reallocation of STEM graduates towards finance is mostly limited to the case of top schools, but the broader trends and the characteristics of this reallocation remains largely unexplored. Our paper fills this gap in the literature by uncovering a series of stylized facts that are associated with the reallocation of STEM graduates towards finance. Key to our analysis and results is to exploit variation in the use of STEM graduates both across sectors, as in Philippon and Reshef (2012), and occupations, a novel aspect of our study. Following recent contributions of the task-based literature (Atalay et al., 2020; Deming and Noray, 2020), we also examine the STEM-biasedness at the occupational level by assessing within-occupation changes in both the use of STEM graduates and math task requirement (the main STEM skill) in STEM and non-STEM occupations, including finance occupations.

The main data source used in this project is the American Community Survey (ACS), which contains information on the workers' degrees by major fields of study and thus allows to retrieve the distribution of

[1] For more anecdotal evidence on this, see: http://uk.businessinsider.com/goldman-sachs-has-more-engineers-than-facebook-2015-4 and http://www.cityjobs.com/cityblog/2015/05/06/banks-physics-maths-grads/.

[2] See http://www.telegraph.co.uk/finance/10188335/Quants-the-maths-geniuses-running-Wall-Street.html and http://news.efinancialcareers.com/uk-en/141013/goldman-sachs-hires-particle-physicist-from-the-large-hadron-collider. See also the interesting debate between Robert Shiller and Vivek Wadwha, http://wadhwa.com/2014/04/04/the-economist-goldman-versus-google-a-career-on-wall-street-or-in-silicon-valley/.

[3] Boustanifar et al. (2018) provide the first international evidence on the evolution of wages and skills in finance confirming the upskilling trend, although with substantial exceptions.

STEM graduates across sectors and occupations. These data are available only for the period 2009-2019, which is the main focus of our analysis. However, to compare our findings with those of Philippon and Reshef (2012), we also examine a longer time span, covering the period where finance started becoming more intensive in human capital, i.e. since the 1980s. In doing so, we complement the ACS dataset with data of the decennial Census for the period 1980-2000. Since in the Census we can only observe STEM workers and their general educational attainments, including post-graduate education, we reconstruct the time series of STEM graduates over the period 1980-2008 by assigning the average occupation-by-industry level of STEM graduate intensity in 2009-2019 to the previous decades and carefully assess the validity of this procedure (see next section for details).

Our analyses shed light on five issues. First, we document a long-term reallocation of the hours worked by STEM graduates towards finance and away from other sectors. STEM reallocation exceeds the well-known reallocation of the hours worked by any other graduates towards finance. Concomitantly, finance has become more STEM-intensive than other sectors. Thus, the long-term skill upgrading in finance displayed a pronounced bias toward STEM graduates (STEM-biasedness henceforth), especially for STEM graduates with postgraduate education. This finding qualifies the well-known skill upgrading in finance found in the previous literature (see, e.g., Goldin and Katz, 2008; Philippon and Reshef, 2012; Shu, 2016).

Second, the STEM upgrading pattern accelerates in the last decades for which data on degree fields are available. Moreover, STEM upgrading occurs mostly within-finance and non-STEM high-skilled occupations. In the spirit of the race between technology and education (Goldin and Katz, 2009), we observe a pronounced task reorientation towards math in finance and business occupations, which is associated with a change in the types of education required in these occupations. These findings also speak to the literature on within occupation task changes (Atalay et al., 2020; Deming and Noray, 2020) by looking at both the educational upgrading and task reorientation. Autor et al. (2002) describe how the set of tasks performed by bank tellers became more complex following the introduction of digital check imaging. Dillender and Forsythe (2019) generalize this finding for white collar occupations that are more exposed to routinization. Consoli et al. (2019) find that clerical occupations become less routine task intensive than other occupations in the last three decades. However, none of these papers look at high-skilled occupations and STEM skills specifically.[4]

Third, STEM reallocation towards finance is more pronounced among experienced workers, but not uniformly so. The attractiveness of finance peaks at prime age STEMs aged between 35 and 45, and declines afterwards. Deming and Noray (2020) show that, at the beginning of the career, STEM graduates earn relatively more in STEM occupations. At later stages, however, the experience-earning profile in STEM positions flattens because of skills obsolescence, which is stronger in technological-intensive occupations requiring a continuous skill upgrading to develop and operate new technologies. Such upgrading is much easier for younger workers who are directly enrolled in new vintages of training and educational programs (Violante, 2002). We complement these findings by showing that STEM graduates who get

[4]Finally, these findings resonate with the recent analysis of Grinis (2019), who also uses job vacancy data to show that there are STEM-intensive jobs that are not classified as STEM jobs in standard occupational classifications.

older earn significantly more by going to work in finance. In particular, the earning premium in finance exhibits a clear jump for prime age workers.

Fourth, we find a large earning premium of STEM graduates working in finance relative to the rest of the economy and to most of the other degrees except business ones, which help explain the reallocation of STEM graduates towards finance. Our analysis shows that the finance wage premium is highly heterogeneous within the financial sector across occupations and age groups. On average, STEM graduates earn significantly more in finance in managerial and STEM positions. Such premia increase for graduates older than 35 in non-STEM occupations.

Finally, the returns to STEM graduates and even more postgraduates working in finance and managerial occupations are extremely skewed towards the top of the wage distribution. This identifies a clear typology of winners among the privileged top 1%: STEM postgraduates working in finance and managerial positions. Further research is required to quantify the extent to which such astonishing premia for STEMs in finance occupations reflects the increasing math-intensity of asset management tasks or the sorting of highly talented STEMs into rent-seeking activities.

These empirical patterns are associated with profound technological changes affecting the financial industry more than the rest of the economy. Finance is an information-intensive industry that benefited from improvements in information and communication technologies (ICT) more than other industries did. The STEM biasedness in the demand of college graduates is consistent with the complementarity between ICT technologies and STEM graduates documented elsewhere (Stephan, 1996; Peri et al., 2015; Barth et al., 2016; Harrigan et al., 2020). Moreover, STEM graduates are the key input to adopt and develop innovative financial solutions: from the simplest task of computing financial fees and mortgage interest rates to far more complicated tasks such as automated trading, risk management and cybersecurity.

Recent studies discuss particular types of technological innovations in finance that can be motivated by rent-seeking and facilitate various speculative activities, i.e. investments in speed (Pagnotta and Philippon, 2018) and in big data processing (Glode and Ordonez, 2020). At the macro-level, Philippon and Reshef (2013) and Greenwood and Scharfstein (2013) highlight the puzzling fact that the benefits of technological change were not passed on to end users through reductions in the costs of financial services, suggesting an increase of the rents extracted by incumbents. Recently, however, the emergence of fintech companies brought new destructive players into the market that challenged the incumbents' rents (Philippon, 2016). While these new players introduced efficiency-enhancing technologies that reduced the costs of financial services through automation, they also contributed to the success of highly speculative activities, such as cryptocurrencies. At the same time, fintech developments proved to boost the demand for specific skills. In a recent work by Jiang et al. (2021), empirical evidence points to a substantial up-skilling in fintech-exposed jobs, with an increase in 'finance' and 'software' skills, higher education attainment and work experience.

Against this backdrop, technological change in finance appears a double-edged sword as it is directed towards both productivity-enhancing and rent-seeking tasks. As long as STEM talents are a key input in both tasks, the demand of STEM will increase more than the demand of other talents in finance. According to both the productivity-enhancing and rent-seeking explanations, STEM talents are attracted by (and contribute to) a very large finance wage premium (Philippon and Reshef, 2012), thus the ultimate causes of STEM talents' reallocation towards finance are very difficult to disentangle. In the first case, finance attracts the best talents because new technologies make talents more productive there relative to the rest of the economy. In the second case, the best talents purely capture the rents extracted by the financial sector (Murphy et al., 1991), also by means of technological innovation.[5]

Empirical research struggles to provide convincing support to any of those explanations, with two recent exceptions that take advantage of accurate measures of talents and longitudinal data that allow to control for unobserved heterogeneity and talents' self-selection.[6] Celerier and Vallee (2019) filter graduates' talent using the quality of French engineering schools attended. The authors show that the large and increasing earning premium in finance is associated with the strong complementarity between scale and talent relative to other sectors, which conjures a sort of superstar effect (Rosen, 1981). In contrast, using a general measure of talents based on military aptitude tests, Böhm et al. (2018) document that the finance wage premium is unrelated to individual talents, raising concerns about the size of rents in finance. To reconcile these contrasting findings, Celerier and Vallee (2019) note that rent-seeking and increasing efficiency are both important in explaining the finance wage premium, which highlights the ambiguous role of technological innovation in this sector.

Although the data used in this paper do not allow to discern the determinants of the finance wage premium, we contribute to this literature by shedding light on the heterogeneity of the finance wage premium across degrees, occupations and along the wage distribution. Incidentally, our findings also speak to the literature of top income inequality (Piketty and Saez, 2003; Alvaredo et al., 2013), as we precisely identify a subset of winners: STEM post-graduates working in non-STEM occupations at the top of the earning distribution. While the finance wage premium contributes to explain top income inequality in general (Kaplan and Rauh, 2010; Philippon and Reshef, 2012; Celerier and Vallee, 2019), it matters even more for STEM graduates or postgraduates working in finance and managerial occupations. Finally, in shedding light on the heterogeneity of the finance wage premium, we contribute to the literature on returns to major fields of study (Altonji et al., 2016). This literature shows that STEM fields stand out as the best paid ones, and that there is a complementarity between field of study and occupation-specific tasks, thus STEM graduates earn more in STEM jobs.[7] We show that, in the spirit of the race between technology and education, these complementarities may change over time so that STEM skills can pay more in non-STEM jobs whose math intensity increased over time.

The paper is organized as follows. Section 2 describes the dataset and the measures of STEM input. Section 3 provides evidence on the reallocation of STEM graduates, both across sectors and occupations. Section 4 focuses on the earning premium for STEM graduates in finance and the link with STEM reallocation. Section 5 summarizes the main findings of the paper and offers some policy insights.

[5]The rent sharing mechanism is discussed in several theoretical contributions (see, e.g., Axelson and Bond, 2015; Glode and Lowery, 2016; Bolton et al., 2016). Other explanations of the finance wage premium are related to preferences and non-pecuniary factors influencing occupational choices. For instance, higher wages in finance compensate for stress and long working hours. See the discussion in Celerier and Vallee (2019).

[6]Other important papers are Oyer (2008), Kaplan and Rauh (2010), Philippon and Reshef (2012) and Bell and van Reenen (2014).

[7]See, e.g, Robst (2007); Nordin et al. (2010); Lemieux (2014); Lindley and McIntosh (2015); Kinsler and Pavan (2015).

2 Measuring STEM input

The main sources of information about the importance of STEM skills used in this project are the individual-level data from the US Decennial Censuses (years 1980, 1990 and 2000) and the American Community Survey (ACS, years 2000-2019), which is available in IPUMS (Integrated Public Use Microdata Series, see Ruggles et al., 2015). The data from the decennial censuses cover a 5-percent sample of the US population, while the ACSs cover a 1-percent sample of the US population.[8] We focus our attention on employed individuals in working age (16-64 years old, or 22-64 when we consider the sub-sample of college graduates). These data sources are standard in labour research, but a few aspects related to the measuring of STEM skills are worth to be discussed here.

The number and the intensity of STEM graduates in a particular industry are our variables of interest. Ideally, we would like to have information on the use of STEM graduates for the four decades covered in our analysis. This information is available in the ACS data from 2009 till 2019, when ACS data started including systematic information on the field of study for graduate and postgraduate workers. Table 1 illustrates the definition of STEM degrees used in this article by listing the STEM major fields of study grouped by discipline, namely, computer science, mathematics, engineering and technology, science. Compared to other definitions of STEM majors used in the literature (e.g., Peri et al., 2015), we exclude health-related and medical STEM majors, which are clearly unrelated with the skill set that finance may need.

Table 1: Definition of STEM degrees (for ACS 2009-2014, based on *degfield* variable)

Science degrees:	**Computer related degrees:**
Physical Sciences	Computer Engineering
Astronomy and Astrophysics	Mathematics and Computer Science
Atmospheric Sciences and Meteorology	Communication Technologies
Chemistry	Computer and Information Systems
Geology and Earth Science	Computer Programming and Data Processing
Geosciences	Computer Science
Oceanography	Information Sciences
Physics	Computer Information Management
Materials Science	Computer Networking and Telecommunication
Multi-disciplinary or General Science:	
Neuroscience	**Math degrees:**
Cognitive Science and Biopsychology	Mathematics
Biology	Applied Mathematics
Biochemical Sciences	Statistics and Decision Science
Botany	
Molecular Biology	**Engineering degrees:**
Genetics	All engineering degrees
Microbiology	
Pharmacology	
Physiology	
Zoology	
Neuroscience	
Miscellaneous Biology	

[8]The main issue of using such data over a long time frame is that occupational and industry classifications are often revised and are not always comparable at the most disaggregate level of detail. Following other similar contributions (e.g. Autor et al., 2013; Autor and Dorn, 2013), we use more aggregated classifications that are consistent over time. More specifically, occupations (333) defined according to the *occ1990* classification are aggregated into 323 *occ1990dd* occupations and industries (223) defined according to the *ind1990* classification are aggregated into 207 *ind1990dd* industries (Dorn, 2009). Both classifications are fully balanced over the period 1980-2019. For the analysis on more recent data (2009-2019), however, we take advantage of the more detailed classification of occupations based on the SOC (*occsoc* variable in ACS) occupational classification.

Because the ideal degree-based measure is not available before 2009, we should rely on an alternative measure to examine the STEM dynamics for a longer time span. To this aim, we predict the use of STEM graduates by sector backward through the period 1980-2008 by exploiting the rich set of dimensions (education, industry, occupation) reported in Census and ACS data.[9] In doing so, we note from the most recent ACS data that the use of STEM graduates is largely occupation and sector specific, e.g., being significantly higher in certain STEM-intensive occupation-sector pairs. To illustrate, in Table C1 in Appendix C we report the top 20 occupations in terms of STEM graduates contribution in finance, accounting for about 70% of the STEM graduates in finance. The interesting facts here are: i. top occupations in terms of STEM graduates' intensity belong to several occupational groups (finance, STEM, managerial and other occupational groups), beyond STEM occupations; ii. if we take the ratio between the contribution of each occupation to total number of STEM graduates in finance and the contribution of the same occupation to STEM graduates in all industries (i.e. a Balassa index) as an indicator of cross-industry differences in the STEM intensity of occupations, we observe important divergences from 1 (e.g., equal intensity), which implies that STEM graduates intensity of occupations is highly industry-specific.

Taking stock from this evidence, we compute the share of STEM graduates among college graduates workers for each occupation-industry cell (average 2009-2019)[10] and project them backwardly to the period 1980-2008.[11] By keeping fixed the share of STEM graduates among college graduates within a very detailed occupation-industry cell, the change in STEM intensity in broader industry groups (i.e., "finance", see Table B1 in Appendix B) over the period 1980-2008 is then driven by changes in the industry-occupation composition and by changes in the share of college graduates within the same industry-occupation cell.

We validate our imputation with a decomposition analysis (see Appendix A), showing that over the period 2009-2019 about 87% of the time variation of STEM is driven by compositional changes (between-occupation and incidence of college graduates within-occupation) that can be consistently measured since 1980. To the extent to which the share of STEM graduates increases in finance more than proportionally than in other sectors within all occupations among college graduates (that is what actually happened in 2009-2019, see section 3.1 below), our imputation slightly understates the STEM educational upgrading in finance before 2009. For this reason, we do not perform a detailed analysis of the evolution of STEM graduates by decades, but we either consider the very long-run (1980-2019, in this section) or the last decade (2009-2019, from the next section on).

Besides measuring the allocation of the hours worked by STEM graduates across sectors, we are also interested in looking at within-sector changes in STEM intensity. STEM intensity is correlated with technological change, thus it is directly related to the broad explanation of the STEM-biased human capital upgrading in finance. Following Philippon and Reshef (2012), our generic measures $y_{j,t}^{STEM}$ of

[9]STEM input's intensity in sector j at time $t < 2009$ is defined as $y_{j,t}^{STEM} = \sum_o \sum_e y_{j,o,e,t=2009-2019}^{STEM} \times \phi_{j,o,e}$ where $y_{j,o,e,t=2009-19}^{STEM}$ is the share of hours worked by STEM graduates in industry j, occupation o and education level e (two categories: less than college, college or more) in years 2009-2019 and $\phi_{j,o,e,t}$ is the share of hours worked in occupation o, with education level e over total hours worked in industry j in year t.

[10]In Appendix A, we show that using different combinations of years to compute the occupation-industry-education share of STEM does not affect the precision of the backward projection. However, the measure used here gives the most accurate fit, e.g. see Table C2.

[11]For post-graduates, we consider the share of STEM graduates by occupation-industry in 2009-2019 for the sub-set of workers with post-graduate education before 2009.

the STEM input's intensity in sector j at time t are built as follows:

$$y_{j,t}^{STEM} = \frac{\sum_{i \in j} \phi_{i,t} h_{i,t} I_{i \in STEM,t}}{\sum_{i \in j} \phi_{i,t} h_{i,t}}, \tag{1}$$

where $h_{i,t}$ and $\phi_{i,t}$ are hours worked multiplied by sample weights, respectively, and $i \in j$ denotes that the individual i works in sector j. $I_{i \in STEM,t}$ is equal to one if individual i holds a STEM degree as defined in Table 1.[12] Cross-sectoral differences in this measure would capture the extent to which each sector uses STEM inputs relative to other inputs and thus benefits from public and private investments in STEM education.

In most of our analysis, we differentiate between post-graduates and graduates. The focus on post-graduates is particularly important as they account for a large and growing share of the college wage premium (Eckstein and Nagypal, 2004). We define postgraduate education as 17 or more years of education, as in Lindley and Machin (2016). The idea is that a college post-graduate working as a STEM is more likely to perform the most complex tasks within the range of tasks performed by an equivalent STEM worker. Thus, the focus on STEM post-graduates allows to get closer to a reliable measure of STEM talents.

Along the paper, we compare the allocation and labour market outcomes of STEM graduates in different sectors and occupations. Concerning the sectors, we define "finance" following Philippon and Reshef (2012), thus including: banking; savings institutions, including credit; credit agencies n.e.c.; securities, commodity brokerage, and investments; and insurance (see Table B1 in Appendix B). We compare finance with both the rest of the economy and other key employers of STEMs, especially knowledge-intensive business sectors (KIBS henceforth) and high-tech manufacturing sectors (HT henceforth), which are also defined in the Table B1 in Appendix B. Concerning the occupations, we compare the labour market outcomes of STEM workers in four possible occupational groups: finance occupations, STEM occupations, managerial occupations and other business-related occupations. Note that these occupation-graduate combinations can only be observed in the period 2009-2019, where we can also use the detailed SOC classification to define occupational groups (which is much more detailed than the *occ1990dd* classification used before 2009). Managers are defined as all SOC-11 (Management Occupations), except financial managers (SOC 11-3031). STEM occupations include SOC-15 (Computer and Mathematical Occupations), SOC-17 (Architecture and Engineering Occupations), SOC-19 (Life, Physical, and Social Science Occupations, with the exception of SOC 19-3 Social Scientists and Related Workers). Finance occupations include occupations in SOC-13-2 group (Financial Specialists) plus Financial Managers (11-3031), while all other business occupations include SOC 13-1 Business Operations Specialists and SOC 19-3 Social Scientists and Related Workers. These occupational groups are summarized in Table B2 in Appendix B.

[12] Following previous discussion, STEM degrees are observed for the period 2009-2019, while they are predicted at the occupation-by-industry cell among college graduates for the period 1980-2008 STEM degrees.

3 Allocation of STEM graduates across sectors and occupations

3.1 Industry-level analysis

We begin this section by describing the cross-sectoral reallocation of STEM graduates into finance over the period 1980-2019. In doing so, we compute the share of hours worked by STEM graduates in finance as the number of hours worked by STEM graduates working in finance over the total number of hours worked by STEM graduates in the entire US economy. For sake of brevity, we often refer to the share of STEM graduates in what follows, but the correct meaning is always the share of hours worked by STEM graduates.

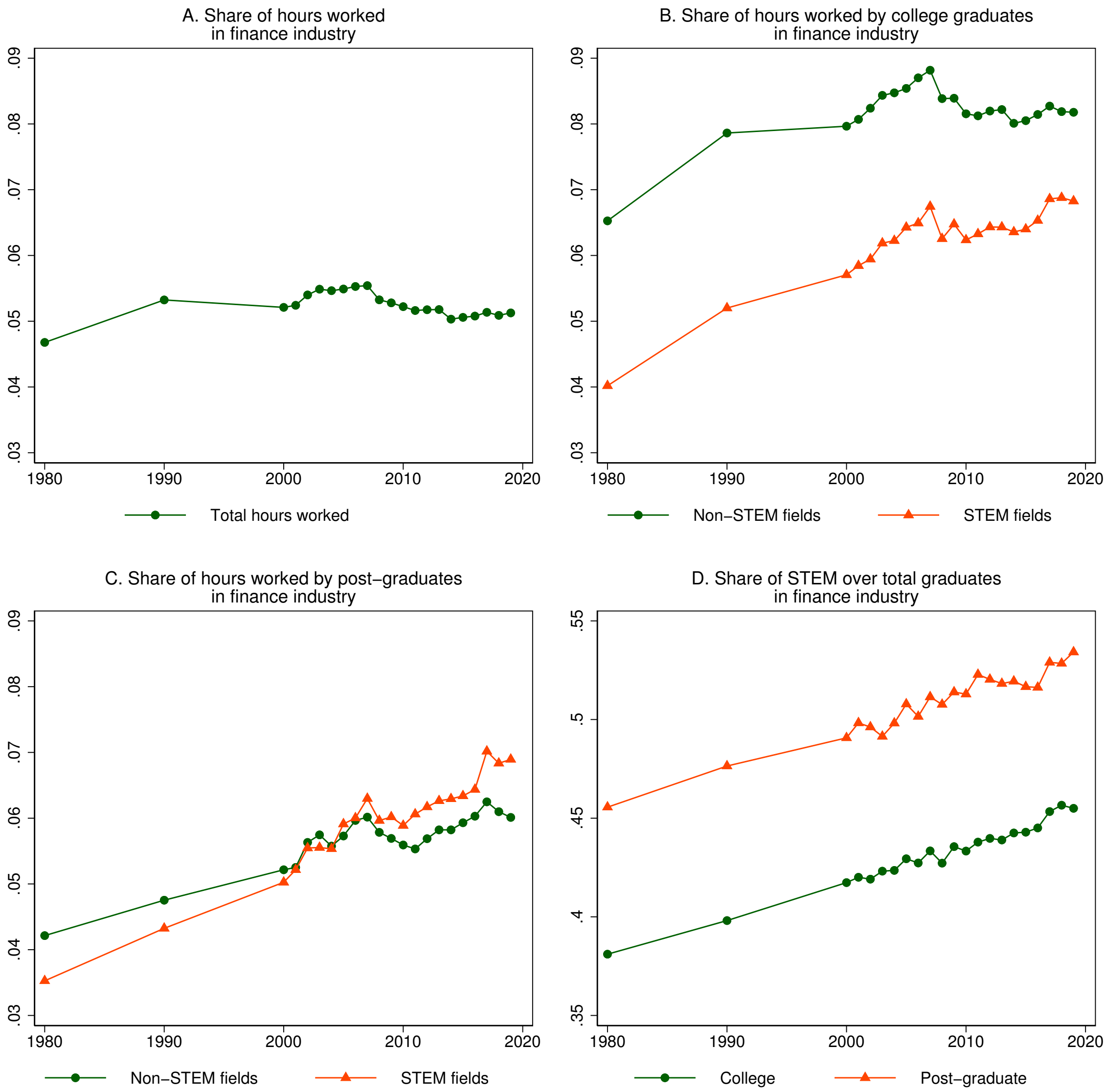
Figure 1 summarizes the reallocation patterns of STEM and non-STEM graduates towards finance. To give context, panel A reports the evolution of the share of employment in finance. Over the four decades of our analysis, the share of hours worked in the financial sector remains constant around 5%, with a modest upward trend before the Great Recession of 2008 followed by a modest downward trend afterwards. Panel B contrasts the long-term evolution of the share of STEM graduates with the long-term evolution of the share of non-STEM graduates in finance.[13] Here, we appreciate the well-known human capital upgrading for both STEM and non-STEM education (Philippon and Reshef, 2012). However, the probability that a STEM graduate works in finance increases by 69.9% (from 4% to 6.8%) between 1980 and 2019, which is substantially more than the concomitant increase in the probability that a non-STEM graduate works in finance (+25.3%, from 6.5% to 8.2%). This pattern is even more striking for postgraduates. While finance becomes an increasingly popular choice between both STEM and non-STEM postgraduates, the two trends are clearly divergent as visually highlighted by the crossing of the two lines in panel C.[14] To the extent to which postgraduate education is a filter for talent, this finding suggests that the finance may have attracted the best STEM talents.[15] The last panel shows directly the STEM-biasedness of the graduates hired in finance by plotting the share of STEM graduates over all graduates and the share of STEM postgraduates over all postgraduates. In both case, we observe a marked upward trend reinforcing the claim that the skill upgrading in finance has been highly STEM-biased in the last four decades.

[13] To visually spot the bias in interpolating STEM graduates backwardly, we plot both the effective and the predicted shares of STEM graduates after 2009.

[14] The probability that a STEM postgraduate works in finance increases from 3.5% in 1980 to 6.9% in 2019 (+95.5%). The concomitant change for non-STEM graduate is only from 4.2% in 1980 to 6% in 2019 (+42.6%).

[15] In Figure C1 in Appendix C we replicate panels B and C of Figure 1 using alternative assumptions on the backward interpolation. Interestingly, while it does not matter much whether the average occupation-industry specific intensity of STEM graduates was measured as the average value 2009-2019 (our favourite), in 2009 or in 2019, some substantial difference is found (in the levels) when just considering occupation-specific STEM intensity. In this latter case, there is poor overlap even for years 2009-2019. Finally, when considering occupation and industry specific linear trends in 2009-2019 to extrapolate back to 1980 (i.e. having a time-varying trends in STEM intensity within each occupation-industry pair), evidence suggests that our favourite choice represents a lower bound of the long run growth in STEM intensity in finance.

Figure 1: Finance industry vs total US economy



Notes: Share of hours worked in finance industries over total hours worked (person weights multiplied by hours worked) in the whole US economy (total and by category of worker). Own elaboration on Decennial Census (1980, 1990, 2000) 5% sample and ACS (2001-2019) 1% sample from IPUMS.

To be sure that the STEM-biasedness is a peculiarity of the financial industry, in Appendix C we replicate the same analysis for non-finance industries (Figure C2) and for the other two main employers of STEM workers, high-tech manufacturing (Figure C3) and KIBS (Figure C4). These Figures confirm that only finance experienced a STEM-biasedness skill upgrading in the last four decades.

From Figure 1, it is straightforward to infer that, combined with a constant share of total employment, the cross-sectoral reallocation of STEM graduates towards finance leads to a substantial increase in the STEM intensity of the financial sector. To fix this fact, Table 2 reports STEM intensities in 1980 and 2019 as well as the long-term growth rate over the four decades 1980-2019. Each column of the table represents a different sector (finance, HT manufacturing, KIBS and the rest of the economy except these three sectors), while each panel a different measure of STEM graduates intensity.[16]. The key takeaway is again that the upward trend in skill upgrading in finance was highly STEM-biased and even more so when compared to other main employers of STEM graduates. Quantitatively, while the cumulative growth rate in STEM graduate intensity is 196.3% in finance (column 1, panel A), the concomitant increase is only 144% in HT manufacturing, 54.8% in KIBS and 63.7% in the rest of the economy (columns 2-3-4, panel A). As usual, similar but more marked patterns are observed in the sub-sample of postgraduates (panels C and D). When looking at other fields of study, finance is still outperforming KIBS and other sectors, but it is lagging behind HT manufacturing. When combining these data (panels E and F), it is evident that the share of STEM graduates (or postgraduates) over total graduates declined in the rest of the economy and remained more or less constant in HT manufacturing and KIBS. In contrast, it increases by more than a quarter in finance. Overall, these results reinforce and confirm the first main finding of our paper: the long-term skill upgrading in finance displayed a pronounced biased toward STEM skills.

Table 2: STEM and non-STEM and math intensity by sector in 1980 and 2019

A. Share of workers with college degree in STEM fields				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.030	0.079	0.220	0.028
2019	0.089	0.192	0.341	0.046
Cumulative % growth rate	196.31%	143.97%	54.75%	63.70%
B. Share of workers with college degree in non-STEM fields				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.220	0.078	0.229	0.161
2019	0.486	0.208	0.385	0.296
Cumulative % growth rate	120.63%	166.25%	68.35%	84.09%
C. Share of workers with college degree in STEM fields with post-graduate educ				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.013	0.038	0.125	0.014
2019	0.036	0.082	0.138	0.018
Cumulative % growth rate	166.31%	117.32%	10.20%	27.37%
D. Share of workers with college degree in non-STEM fields with post-graduate educ				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.066	0.027	0.118	0.077
2019	0.131	0.066	0.128	0.111
Cumulative % growth rate	97.33%	148.58%	8.38%	43.70%
E. Share of workers with college degree in STEM fields over total workers with college degree				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.118	0.490	0.489	0.182
2019	0.153	0.484	0.472	0.153
Cumulative % growth rate	28.88%	-1.22%	-3.37%	-16.01%
F. Share of workers with post-graduate educ in STEM fields over total workers with post-graduate educ				
	Finance	Manuf HT	KIBS	Other sectors
1980	0.164	0.572	0.516	0.223
2019	0.209	0.556	0.528	0.187
Cumulative % growth rate	27.87%	-2.75%	2.47%	-16.27%

Notes: Statistics weighted with person weights multiplied by hours worked. Own elaboration on Decennial Census (1980) 5% sample and ACS (2019) 1% sample from IPUMS and O*NET. Math skills are computed using the time-invariant occupation-specific (*occ1990dd*) value for 2009.

[16]The measures are: STEM graduate intensity for graduates and postgraduates, non-STEM graduate intensity for graduates and postgraduates, the share of STEM graduates over total graduates also computed for postgraduates.

3.2 Occupation-level analysis

This section investigates the process of STEM workers' reallocation towards finance after the Great Recession, the subsequent regulatory changes, notably the Dodd-Frank Act (see Krainer, 2012) and the emergence of the fintech industry. As mentioned in section 2, the advantage of using the ACS data after 2009 is that we can track the change in STEM intensity both within- and across-occupations. The within-occupation margin is particularly important to capture the race between technology (i.e., the changes in task performed by an occupations) and education (i.e., the changes in the type of education required to perform new tasks) where it mostly occurs.

We begin by quantifying the contribution of the within-occupation margin to the overall increase of STEM graduates in finance that we documented in the previous section. With this aim in mind, panel A of Figure 2 shows the result of a standard within-between decomposition analysis where we explicitly distinguish the contribution of STEM and non-STEM occupations.[17] According to the discussion of the introduction, some non-STEM occupations in finance, such as financial analyst, become more STEM intensive over time due to the rapid diffusion of ICT technologies in this sector.

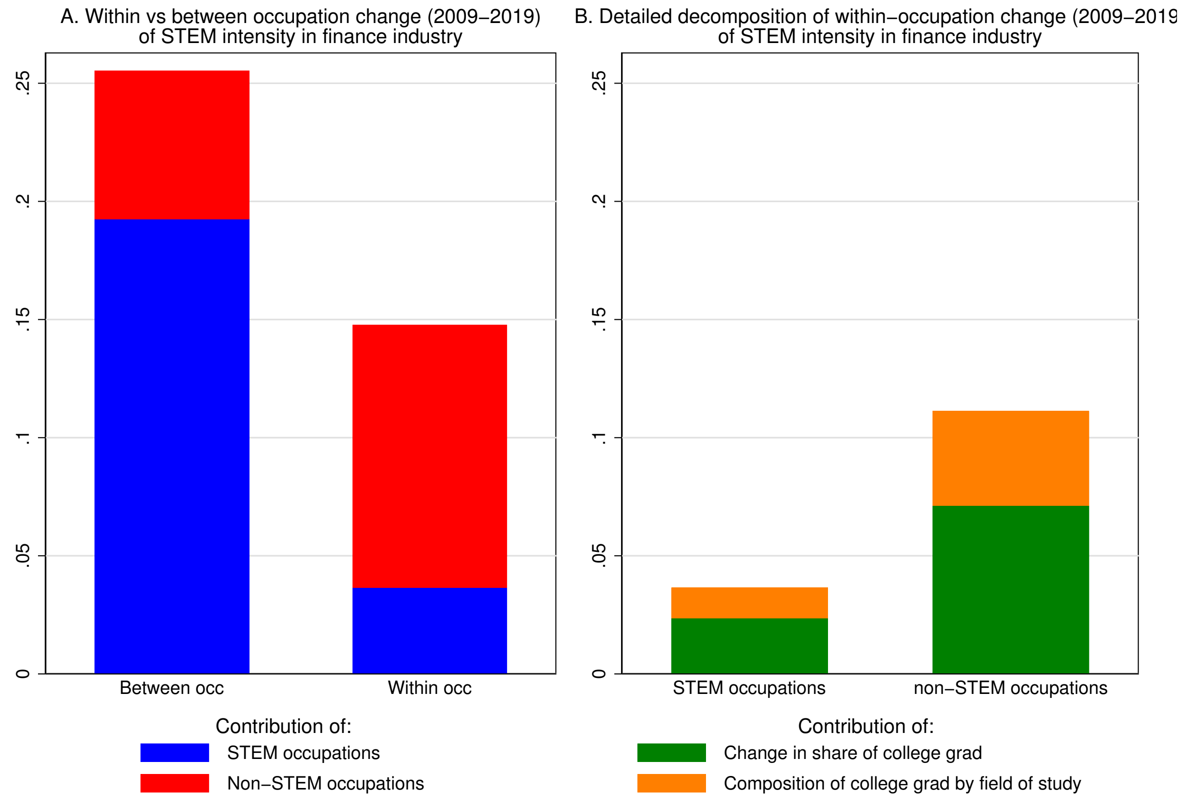
It is important to begin noting that the marked STEM biasedness in finance accelerated substantially in the last decades. More specifically, the share of hours worked by STEM graduates in finance increases from 6.35% to 8.9%, which represents almost half of the increase in STEM skill intensity in finance over the last four decades. When decomposing this 41% increase, we find that slightly more than 1/3 is explained by the within-occupation component, while the remaining 2/3 is due to compositional shifts in the occupational structure towards STEM-intensive occupations. The within-occupation increase in the use of STEM is primarily concentrated in non-STEM occupations, which contribute to as much as 92.7% of total employment in finance. Thus, non-STEM occupations attract an increasing share of STEM graduates in finance. In panel B of Figure 2, we decompose the within component that is the result of two forces: a change in the composition of field of study towards STEM fields (orange bars) and an increase in the share of all graduates regardless of the field (green bars). Both contribute to the increase in STEM intensity in non-STEM occupations, but the latter is quantitatively more important.

As for the between component, it is interesting to note that the increase in STEM intensity due to changes in the occupational composition (both across the two macro-groups, STEM and non-STEM, and within each macro group but across occupations) is mostly attributable to what happens to STEM occupations, even though these occupations only employ a relatively minor share of employment in finance (7.3% on average, 6% in 2009 and 9.3% in 2019). This is due to their systematically larger

[17] The change in the intensity of STEM graduate in finance between 2009 and 2019 ($y^{STEM}_{j=fin}$) is defined as:
$\triangle y^{STEM}_{j=fin} = \sum_o y^{STEM}_{j=fin,o,t=2019} \times \omega_{j=fin,o,t=2019} - \sum_o y^{STEM}_{j=fin,o,t=2009} \times \omega_{j=fin,o,t=2009}$,
where $y^{STEM}_{j=fin,o,t}$ is the share of hours worked by STEM graduates in finance industry and in occupation o over total hours worked in finance in occupation o in finance and $\omega_{j=fin,o,t}$ is the share of hours worked in occupation o in finance over total hours worked in finance. The within-occupation change is defined as:
$Within = \sum_o \left[(y^{STEM}_{j=fin,o,t=2019} - y^{STEM}_{j=fin,o,t=2009}) \times (\omega_{j=fin,o,t=2009} + \omega_{j=fin,o,t=2019})/2\right]$.
On the other hand, the between-occupation change is defined as:
$Between = \sum_o \left[(\omega_{j=fin,o,t=2019} - \omega_{j=fin,o,t=2009}) \times (y^{STEM}_{j=fin,o,t=2009} + y^{STEM}_{j=fin,o,t=2019})/2\right]$.
The split of the between component for STEM and non-STEM occupations pools together two sources of variation. The between component attributed to STEM occupations considers both the contribution to the increase in STEM intensity due to the change in employment in all STEM (resp. non-STEM) occupations and the contribution of changes in employment in each STEM (resp. non-STEM) occupation.

intensity of STEM skills compared to non-STEM occupations: on average, 52.7% (on average; 50.9% in 2009 and 52.9% in 2019) of employees in STEM occupations in finance hold a STEM college degree, while just 9.3% (on average; 8.2% in 2009 and 9.6% in 2019) of employees in non-STEM occupations in finance hold a STEM college degree.

Figure 2: Decomposition of changes in STEM graduates share in finance industry over 2009-2019



Notes: Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

In Figure C6 of the Appendix C, we provide further information on the changes in STEM intensity across occupations and in comparison with other degree fields. This Figure allows to see how the matching of degrees to occupations changed over time in finance. The bottom line is that the increase in the share of STEMs is widespread across all occupations, but in relative terms is more pronounced in finance and other business occupations than in STEM occupations, which, however, remain four-to-eight times more STEM-intensive than other high-skilled occupations. Again, the STEM-biasedness is evident also when comparing STEM degrees and other degrees, including in business major fields.[18] For all occupational groups the growth in the hours worked by STEM graduates is larger than the growth rate in the hours worked by non-STEM graduates.[19]

A key issue is whether the non-STEM occupations in finance become more STEM intensive simply because finance attracts the brightest talents (i.e., by paying very high wages) or because technological

[18]Business fields include the fields ‘Business’ and ‘Social Sciences’.

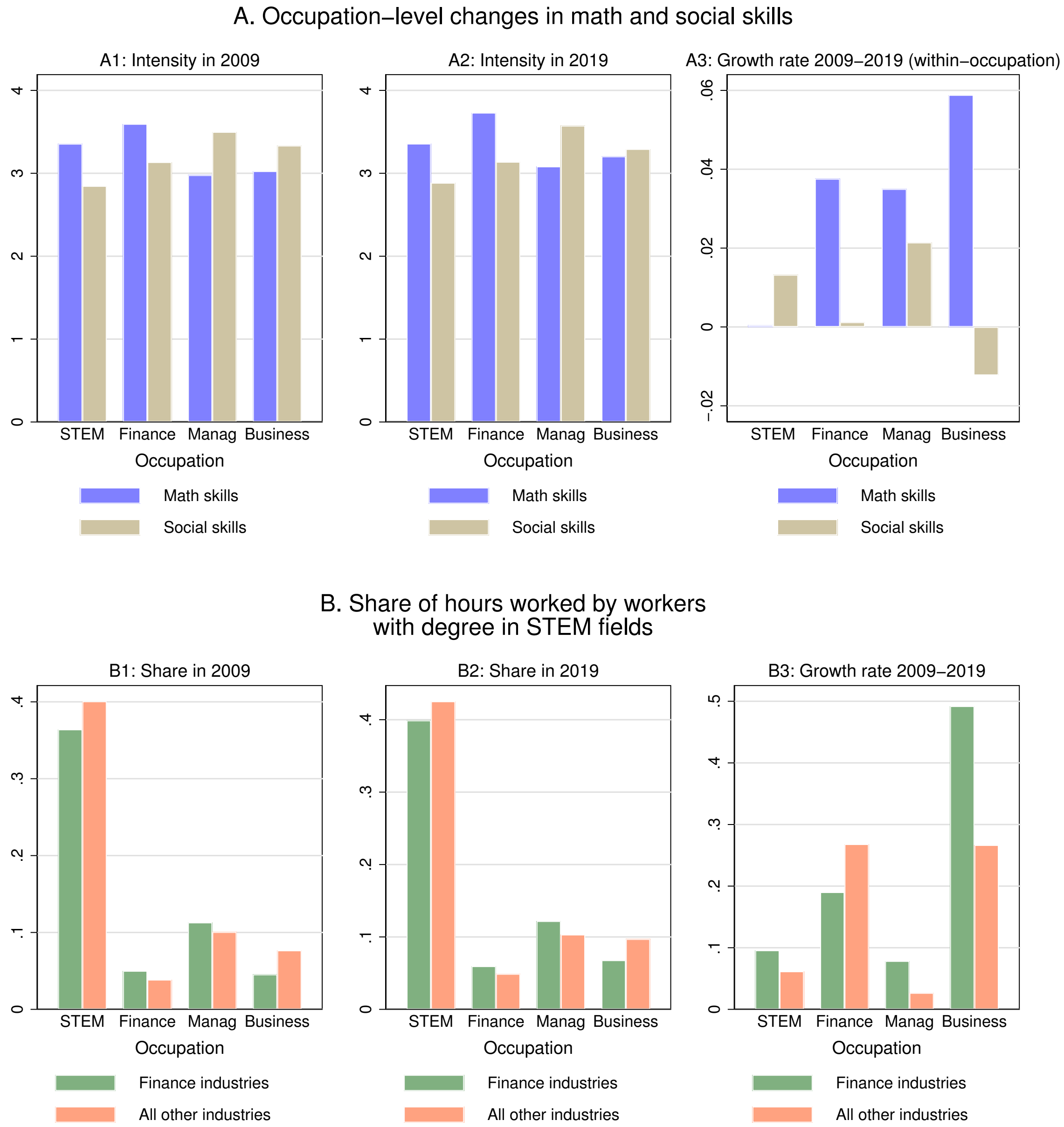
[19]For instance, in finance occupations STEM graduates’ intensity increases by 19%, while business’ and other fields’ intensities by 3% only. This difference is even larger for other business occupations (+49% for STEM vs. +6% for other fields).

change modifies the task content of these occupations towards typical STEM tasks. To start examining this issue, we exploit information contained in the occupational information network (O*NET), particularly the measure of the mathematical aptitude that previous research identifies as the key skill that involves STEM use (Deming, 2017). In panel A1 and A2 of Figure 3, we report the level of math and social skills intensity for macro-occupational groups in 2009 and 2019, respectively.[20]. **What emerges is that finance occupations are the most math-intensive ones followed by STEM occupations, while social skills are more important in business and managerial occupations. This ranking does not change over the decade covered by our analysis. In the third panel (A3), we compute the within-occupation task variation by keeping employment shares of detailed occupations within each macro-group at their initial level.** Because variation in task intensity is bounded upward in O*NET, it is remarkable to observe that the finance occupations, the most math intensive occupational group already in 2009, further specialize in mathematical tasks in 2019. In contrast, task reorientation towards social skills is much less pronounced in all groups, particularly in finance and business occupations.

Overall, using the metaphor of the race between technology/tasks and education/skills at the occupation level (Acemoglu and Autor, 2012; Vona and Consoli, 2015), we can conclude that changes in the demand of STEM tasks and the changes in the supply of STEM skills go hand-in-hand especially in non-STEM (business and finance) occupations. Panel B of Figure 3 reinforces this claim showing the evolution of STEM intensity in selected high-skilled occupations in finance with that of the rest of the economy. In particular, it shows the levels and decennial change of share of STEM graduates for the same high-skilled occupations in finance industry and in the rest of the economy. In line with previous descriptive statistics, the long-term growth rate of STEM input is substantially higher in the financial sector than in other sectors across all occupations, except finance occupations that, however, remained more STEM-intensive in finance than in other sectors. As for previous results, these patterns are more pronounced for postgraduates (see Figure C7 in Appendix C).

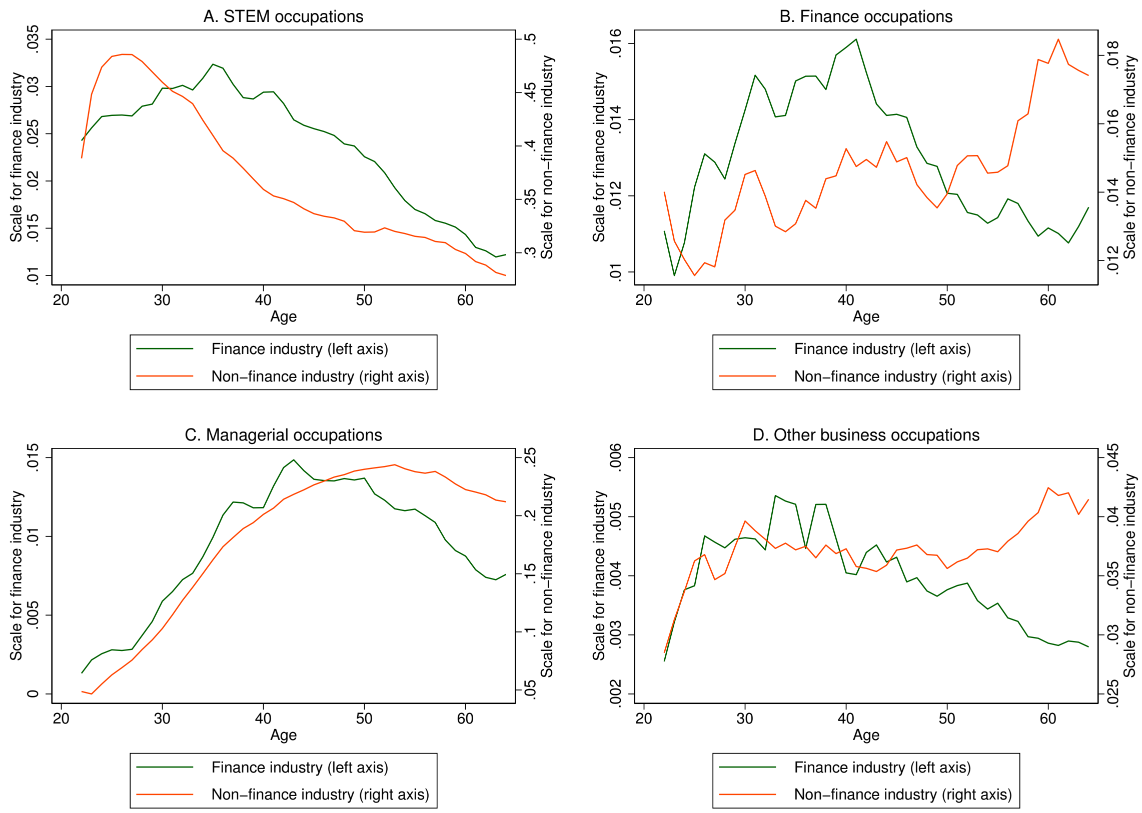
[20]Following Deming (2017), we use the average of the following O*NET items: mathematical reasoning (1A1c1) and mathematics (2C4a and 2A1e). We also follow Deming (2017) in building the measure of social skills. We use O*NET 14.0 for 2009 and O*NET 24.0 for 2019. O*NET scores are normalized to vary between 0 and 1

Figure 3: Within-occupation changes in STEM, math skills and social skills



Notes: Within-occupations level and change in STEM intensity, math skills and social skills. Statistics weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS and O*NET data.

Figure 4: Share of STEM graduates by industry and occupation over total STEM graduates (by age)



Notes: Statistics weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

Finally, we conduct an analysis of the age-profile of occupational choices of graduates in STEM major fields.[21] In Figure 4, we plot the probability that a STEM graduate works in a certain macro-occupational group in finance and in the rest of the economy. Panel A shows the well-known decline in the probability that a STEM graduate remains in a STEM occupation, which has been explained by the rapid depreciation of STEM skills (Deming and Noray, 2020). This declining pattern is, however, less pronounced in finance than in the rest of the economy. Interestingly, the financial sector exhibits an inverted U-shaped relation in the probability that a STEM graduate is employed in a STEM occupation, with a peak for prime age STEM graduates. Such inverted U-shaped pattern also emerges for STEM in other occupations in finance, thus appearing a specificity of the financial sector with respect to the rest of the economy. While in general non-STEM occupations become more popular as STEM graduates get older, the attractiveness of finance both increases and decreases earlier than other sectors, and it is concentrated among prime age workers. Summing up, these results add to Deming and Noray (2020) by showing that STEM graduates may escape the skill depreciation in STEM occupations by moving first to finance in non-STEM positions and then to other sectors, also in non-STEM positions. We will see in the next section that the age-profile of these changes are also reflected in the wage-age profile of STEM graduates.

[21]Figure C8 in Appendix C replicates the same results for college graduates with post-graduate education, showing very similar patterns.

4 Wage premium of STEM graduates in finance

4.1 A first look at reallocation and wages

In this section, we assess the main explanation of the reallocation of STEM graduates towards finance: earning differentials. As in related papers (Böhm et al., 2018; Celerier and Vallee, 2019), we use annual wages to measure earnings.[22] The analysis is conducted using individual-level data to investigate the heterogeneity of the finance wage premium for STEM graduates.

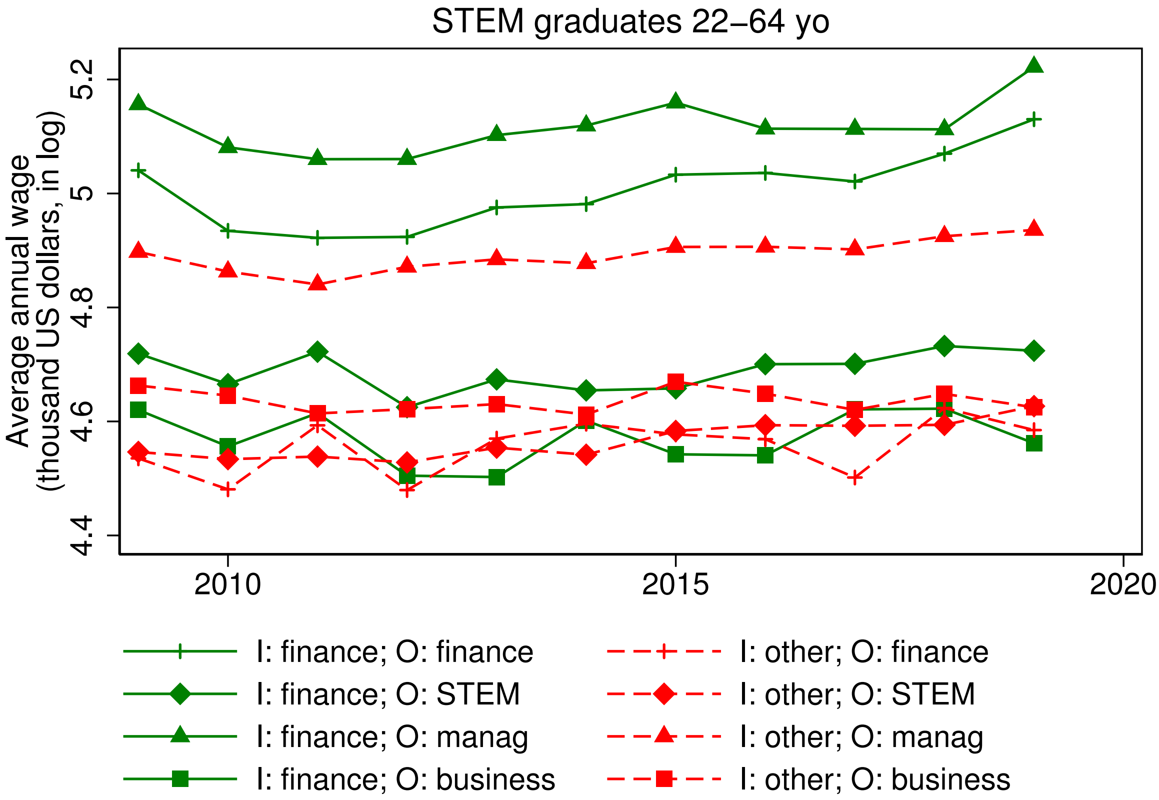
Monetary incentives are the most obvious and testable explanation of STEM reallocation towards finance. In Figure 5, we plot the log of annual wages in eight occupations (managers, finance, STEM, other business)-by-sector (finance or other sectors) pairs, for all the years between 2009-2019 in order to detect possible trends. Consistent with the reallocation of STEM graduates documented in the previous section, the highest returns to STEM education are in finance. However, the striking fact emerging from this Figure is that returns are much higher for STEM graduates working in non-STEM occupations, i.e. managers and, although to a less extent, finance occupations than for STEM graduates working in STEM occupations in finance. The differences are striking, also because a large portion of finance earnings are equity-based, cash and deferred bonuses (Lemieux et al., 2009; Bell and van Reenen, 2014), which cannot be measured with precision using ACS data.[23] The wage premium for a STEM working in finance as a manager (or in a finance occupation) is approximately 20 log points larger relative to the next best outcome for a STEM graduate, i.e. being a manager elsewhere.[24] Finally, it is worth noting that there are no strong trends, although the earning for STEM in finance tends to decline until 2014 and recovers afterwards. This justifies stacking all the years together in the econometric analyses of next section. Taking stock from these findings, the remainder of this section study the finance wage premium using standard wage regressions.

[22]The use of annual wages instead of hourly wages limits the presence of outliers and mitigates possible measurement errors related to the assessment of average hours worked at the micro level. All our results are confirmed when using hourly wages, see Table D5 in Appendix D.

[23]Indeed, beside wages, ACS reports a measure of interests, dividends and rental income (*INCINVST*). This is defined as "*how much pre-tax money the respondent received or lost during the previous year in the form of income from an estate or trust, interest, dividends, royalties, and rents received*". However, several of the bonuses offered to workers in finance (e.g. stock options) are recorded as income only once the option is sold or used.

[24]The difference between the two winners (i.e. STEM graduates in managerial and finance occupation in finance) and the rest of STEMs is again larger for postgraduates, as shown in Figure C9 in Appendix C.

Figure 5: Annual wages paid to STEM graduates in different occupation-industry pairs



Notes: Average annual wages paid to workers in log US Dollars (deflated to 2015 prices using CPI) weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

4.2 Estimating the finance wage premium

The rich ACS dataset allows to explore the structure of the finance wage premium and its variation across occupations, age groups and degrees. With respect to the previous section and to Figure 5, we use individual-level microdata and control for a standard set of intervening factors to mitigate the concern that the finance wage premium for STEMs is mostly driven by differences in observable individual characteristics correlated with both earnings and the probability of obtaining a STEM degree. This approach represents an imperfect soluton of the self-selection problem, thus our estimates should be interpreted as correlations describing how the finance wage premium varies across occupations and degrees. Moreover, in light of this limitation, our study is unable to discern the two main explanations of the finance wage premium: rent seeking vs. skill-biased technological change. The first explanation posits that the most talented STEM individuals work in finance to capture rents, but they would have been equally productive in other jobs (Böhm et al., 2018). The second is related to the fact that market forces magnify the effect of technology adoption on the productivity of finance workers, generating a talent-scale complementarity effect, especially for workers involved in tech-intensive tasks (Celerier and Vallee, 2019). In addition to these limitations, the fact that, in finance, STEM-intensive innovations can be used either for extracting rents or to improve productivity making even more difficult to assess the importance of these two explanations.

As in most previous studies (Celerier and Vallee, 2019; Böhm et al., 2018), we begin by estimating the STEM graduate wage premium in finance by exploring only the sector dimension of such premium. We slightly extend the standard speficification of such studies by differentiating between the returns specific to STEM graduates and the returns to other graduates in finance. Observing a similar return to STEM graduates and other graduates, or even high-school graduates, in finance relative to other sectors would uncover a wage premium that is not specific to STEM skills and thus more likely to reflect rent sharing (Böhm et al., 2018) (although this is still not enough to conclude that the rent sharing explanation is the prevalent one). To fix the idea, we fit the following pooled cross-sectional regression model over the period 2009-2019:

$$\begin{aligned} \log(w_{it}) &= \alpha_t + X_{it}'\theta + \phi HS_{it} + \pi OTH_{it} + \xi STEM_{it} + \omega BUS_{it} + \rho FIN\_I_{it} + \\ &+ FIN\_I_{it} \times (\zeta HS_{it} + \kappa OTH_{it} + \eta STEM_{it} + \lambda BUS_{it}) + \varepsilon_{it}. \end{aligned} \tag{2}$$

The dependent variable is the log of annual wages of individual i at time t, α_t are year dummies, ε_{it} is the error term and X_{it} is a vector of standard controls in wage equations.[25] Our coefficients of interest are those of the interaction between the dummy variable FIN_I_{it} and the series of indicator dummies for different levels and types of education (i.e. high-school graduates HS_{it}, STEM graduates $STEM_{it}$, graduates in business majors BUS_{it} and all other college graduates OTH_{it}).

Next, we move to our main specification that, in line with our descriptive analyses, exploits also the occupational variation of the STEM finance wage premium. More specifically, we compare the wage of a STEM graduate in occupations where math skills are more important (finance and STEM occupations) with the wage of a STEM graduate in occupations where other high skills, i.e. social ones, are also required, i.e. managers and other business occupations (Deming, 2017), both within the finance industry and comparing the finance industry and the rest of the economy. In formula, this specification reads as:

$$\begin{aligned} \log(w_{it}) &= +\alpha_t + X_{it}'\theta + \beta STEM_{it} + \rho FIN\_I_{it} + \sum_k \eta_k OCC_{it}^k + \sum_k \delta_k OCC_{it}^k \times STEM_{it} + \\ &+ \sum_k \phi_k OCC_{it}^k \times FIN\_I_{it} + \pi STEM_{it} \times FIN\_I_{it} + \\ &+ \sum_k \xi_k OCC_{it}^k \times STEM_{it} \times FIN\_I_{it} + \varepsilon_{it}, \end{aligned} \tag{3}$$

where notation is as in equation 2. Since the focus is on returns to STEM college graduates, we consider the sub-sample of college graduates only. We also run the model for different age groups taking stock from the descriptive evidence of section 3.2. **Importantly, because the descriptive analysis shows little variation over time in the returns to STEM graduates in different occupations and sectors, the coefficients of interest in equations 2 and 3 are estimated exploiting variation**

[25]That is: 2-years bins of age interacted with gender, 2-digit NAICS dummies, metro-area dummy, dummy for married individuals, dummy for black individuals, dummy for other non-white individuals, dummy for foreign-born individuals, a dummy for individuals with post-graduate education, occupation-level importance of math skills and social skills as defined in the previous section (O*NET). Regressions are weighted using person sampling weights.

across individuals in degree fields, occupation and/or sector of employment.[26]

The ideal thought experiment to estimate the returns to STEM through equation 3 would consist in randomly assigning talents to each occupation-sector combination, conditional on the set of controls X_{it}. Conditional random assignment is however implausible in this case. Talents of all sorts are attracted by the rents that a sector like finance can offer, thereby inflating the returns to STEM in finance. However, the comparison of the returns to STEM across high-skilled occupations in finance, conditional on a bunch of controls, mitigates problems of talents' self-selection as talents of all types are attracted by high rents in finance. To further delimit the notion of STEM talents, we conduct our regression analysis of the returns to STEM graduates for postgraduate only and at different percentiles of the wage distribution by means of Recentered Influence Function (RIF) regressions (Firpo et al., 2009). Quantile regressions allow to analyse whether larger returns to STEMs are concentrated at the top of the distribution and how returns in different occupations vary along the distribution.

Obviously, quantile regressions or sample restrictions do not fully solve the problem of talents' self-selection. Three sources of bias plague our estimates of the returns to STEM talents in both specifications. First, returns to STEM estimated through equations 2 and 3 are upper bounds because of talents' self-selection. As the literature on returns to major fields has shown (Altonji et al., 2016), sorting of talents into majors can explain as much as 50% of the returns to major and STEM graduates have, on average, higher abilities than non-STEM graduates. Nonetheless, Altonji et al. (2016) find that already controlling for the average SAT score of the occupation, as we partly do by controlling for the O*NET math and social skill scores of the occupation, helps alleviate the self-selection bias. Second, individuals need to be compensated for working in occupations that are more stressful than others or have a negative social image. Therefore, part of the finance wage premium is linked to a compensation for stress and other undesirable characteritics of finance occupations. Finally, because equity-based, cash and deferred bonuses such as stock options are a larger component of earnings in finance than in other sectors (Lemieux et al., 2009; Bell and van Reenen, 2014), our estimate represents a lower bound of the true finance wage premium.[27] The estimated reallocation elasticities of previous section suggest that this source of bias may be particularly important. Overall, the fact that the three sources of bias go in different directions and are mitigated by including occupation-level controls does not ensure that returns to STEM in different occupations are precisely estimated, but at least lends credibility to our findings regarding the heterogeneity in the STEM finance wage premium across occupations.

4.3 Estimation results

We begin by presenting the results of regressions based on equation 2. The estimated coefficients are shown in Table 3. To contextualize our analysis, it is worth emphasizing first that a STEM degree ensures a premium that is significantly larger than the premium for other degrees and, although to a less extent,

[26]We checked, however, that results remain robust by estimating the coefficient of interest for different time windows. Results are available upon request by the author.

[27]Using detailed UK data on earnings, Bell and van Reenen (2014) report that the bonus share on total earnings is larger in finance than in other sectors along the entire earning distribution and is particularly large (above 30%) at the top of the distribution.

to business degrees (row 3 of the Table).[28] This gap increases in the financial sector for both STEM degrees and business degrees. Again, the finance wage premium for STEMs and business majors are not statistically different from zero, while workers graduating in other majors are not getting any additional return to work in finance. The evidence is therefore mixed regarding the existence of a STEM-specific wage premium in finance. Although the finance wage premium is not unique to STEM graduates, only those with a business major are able to take a share of rents and/or productivity improvements similar to the that of STEM graduates (Philippon, 2016).

Table 3: Wage premia of STEM graduates in finance industry - regressions results

Dependent variable: log annual wage	(1)
High-school (dummy)	0.224***
	(0.00625)
College nor STEM or business fields	0.250***
	(0.0105)
College STEM fields	0.384***
	(0.00951)
College business fields	0.314***
	(0.00599)
High-school x Finance ind	0.0306
	(0.0222)
College nor STEM or business fields x Finance ind	0.0174
	(0.0154)
College STEM fields x Finance ind	0.109***
	(0.0190)
College business fields x Finance ind	0.104***
	(0.0156)
Observations	13154440

Notes: OLS regression weighted with sampling weights. Sample: all workers aged 22-64. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control variables: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET).

The specificity of the STEM finance wage premium can be analysed at a more granular level in our data, by comparing the returns of STEM and non-STEM graduates performing different tasks and across age cohorts. Table 4 summarizes the results of five regressions that use equation 3, for all graduates (column 1) and four age groups (columns 2-5). For sake of space, we report here only the combined returns to STEM education in STEM occupations in other sectors (i.e. the natural match, in the first row) and the difference in the returns relative such benchmark (second part of each panel) for different high-skill occupations in the finance sector. The full set of estimated coefficients for all the key variables are shown in Tables D1 in Appendix D.

Table 4 shows that, compared to the benchmark category of STEM graduates in STEM occupations outside of finance, STEM graduates earn more if they work in finance. The additional premium for STEM graduates in finance is concentrated in managerial and STEM occupations, not in finance or other business occupations. The STEM wage premia are generally lower when conditioning on observable characteristics compared to unconditional differences (e.g. Figure 5), indicating that our controls do a good job in reducing the expected self-selection bias.[29] The magnitude of the wage differences remains

[28]The confidence intervals of the coefficients do not overlap denoting a statistically insignificant difference.

[29]The largest reduction is obtained when adding the math and social task requirements of the occupation and a dummy

however large. Even if we take the ultraconservative approach of cutting the returns to STEM in finance by half (thus using the upper bound of the self-selection bias found in the literature on fields of study), we still have that a STEM graduate working as a STEM worker earns 14% more in finance than elsewhere.[30] Finally, the STEM premium increases with age only in the financial sector. In particular, while the returns to STEM decline with age in STEM occupations outside finance, they increase with age in finance, managerial and STEM positions in finance.[31] Therefore, moving to finance appears as a way to escape the human capital depreciation that STEM graduates experience in other sectors (Deming and Noray, 2020). Quantitatively, the largest earning jump is for prime age workers (35-44) compared to the youngest workers (22-34), which is consistent with the descriptive analysis of the STEM-age profile in Figure 4.

These results lend support to a technological explanation of the finance wage premium as STEM graduates appear to earn more in doing math intensive tasks in STEM occupations, such as designing algorithms and managing new technologies in fintech companies. This does not necessarily imply that combining social and math skills is not paying off in finance. Still, a STEM graduate earns significantly more in managerial position in finance than as a STEM worker outside finance. Overall, it remains extremely difficult to quantify the importance of the technological explanation of the finance wage premium.

Quite surprisingly, at least given the increased math intensity of finance occupations and the anecdotal evidence discussed in the introduction, we do not observe any additional reward for STEM working as brokers, i.e. in finance occupations. While brokerage activities in finance occupations become more math intensive, this task reorientation may have been particularly concentrated in top positions where the use of sophisticated mathematical models is required to deal with the increased size of in the average portfolio (Celerier and Vallee, 2019). Therefore, the returns of STEM graduates working in finance occupations can be very heterogeneous across the talent distribution.

for post-graduate education. Notice the large and statistically strong effect of post-graduate education and social skills (and, to a lesser extent, math skills) in Table D1 in Appendix D.

[30] From Table 4, the estimated coefficient for STEM working in STEM occupations in finance is 0.265. Dividing by 2 is 0.133, which corresponds to 14% ($0.14 = e^{0.133} - 1$).

[31] To test the statistical significance of the difference in the returns to STEM in different positions as depending on age, we also estimate the equation 3 for all age group together, with a full set of interactions between all independent variables and age group dummies. The main result is that differences in wage premia across age groups, while relevant in magnitude, are generally not statistically significant. However, we estimate significant differences for wage premia of STEM graduates in managerial occupations in finance industry for age categories 45-54 and 55-64 with respect to the younger cohort (22-34), the former difference with a p-value$<$0.1 and the latter difference with a p-value$<$0.01. Results remain available upon request.

Table 4: Estimated wage premia for different categories of workers (college graduates)

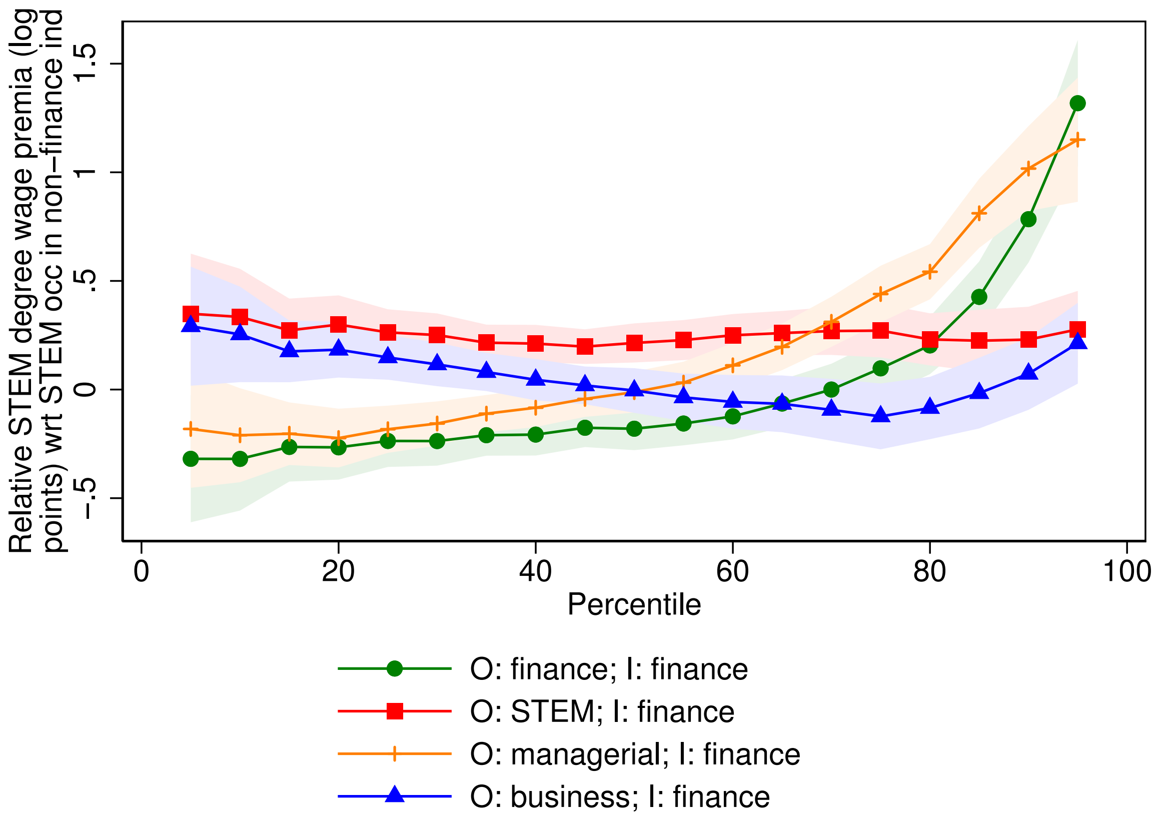
	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM graduates in STEM occ in non-Finance ind wrt other college graduates	0.383***	0.417***	0.363***	0.37***	0.352***
	(0.0234)	(0.0440)	(0.0397)	(0.0407)	(0.0544)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	0.053	-0.001	0.084	0.081	0.091
	(0.0650)	(0.1027)	(0.1033)	(0.1152)	(0.1410)
STEM field in STEM occ in Finance industry	0.265***	0.234***	0.281***	0.281***	0.331***
	(0.0592)	(0.0861)	(0.0846)	(0.1082)	(0.1331)
STEM field in Managerial occ in Finance ind	0.196***	0.088	0.202***	0.22**	0.289***
	(0.0625)	(0.0919)	(0.0926)	(0.1166)	(0.1411)
STEM field in Business occ in Finance ind	0.074	0.040	0.123	0.071	0.093
	(0.0627)	(0.0952)	(0.0929)	(0.1161)	(0.1385)

Notes: Wage premia (in log points) of different combinations of field of study, occupation and industry. Regression results are reported in Table D1 in the Appendix D. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

To tackle this issue, we examine whether STEM graduates obtain a differential wage premium at different quantiles of the wage distribution by means of Recentered Influence Regressions (RIF henceforth) (Firpo et al., 2009). RIF allows to compare the effect of STEM education on wages in different occupations at various percentiles of the wage distribution. This adds another dimension of heterogeneity to the wage analysis by discriminating between the wage premium of highly talented versus normally talented STEM graduates as ranked by their position in the wage distribution. Note that the interpretation of the estimated coefficients does not change compared to OLS. In particular, we still compute the returns of a STEM graduate working in occupation k relative to the benchmark, but such returns are specific to workers at different percentiles of the wage distribution. Figure 7 plots the returns to STEM graduates estimated through equation 3 as well as the associated confidence intervals (95%) for each vigintile of the distribution. As usual, we report the returns relative to the natural match STEM-STEM outside finance. We find that the return of STEM graduates working in STEM occupations is flat along the wage distribution. This supports the idea that the wage premium is due to the technological skills that STEM education brings rather than to the relative talent of those that obtained these skills. In contrast, the managerial premium to STEM graduates in finance increases along the distribution, crossing the STEM-STEM return at around the 7^{th} decile.[32] Similarly, the insignificant wage premium to STEM graduates in finance jobs in finance industry masks negative (additional) premia for most workers that select into the very first deciles, but a very large premium above the 8^{th} decile. Note that the returns to STEM in finance and managerial positions skyrocket up to about 3.3 times the base category in the last vigintile.

[32]Recall that managers include top and chief executives which are over-represented at the top of the distribution and an outlier in terms of earnings.

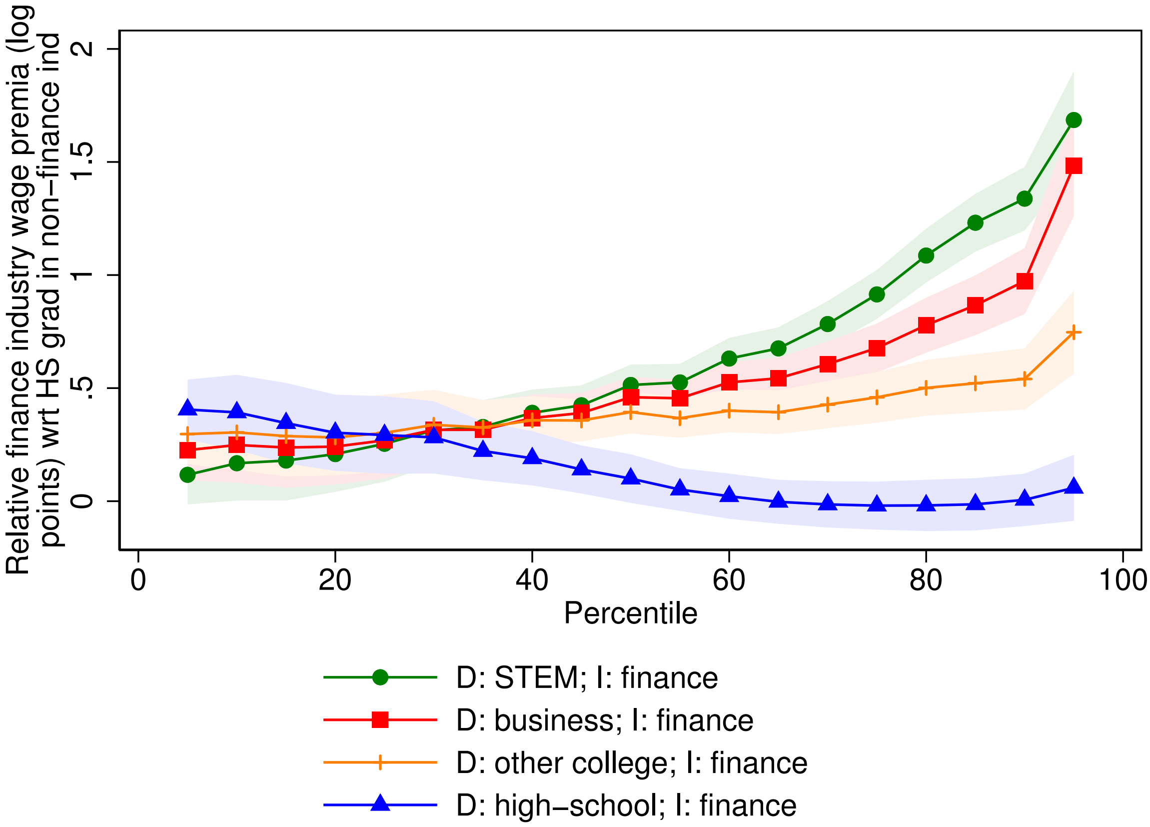
Figure 6: Wage premia for STEM graduates by occupation and industry -recentered influence function regressions



Notes: Results from selected interactions based on recentered influence regressions. Regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Shaded areas refer to 95% confidence intervals.

The very large returns to STEM graduates in finance and managerial positions at the top of the distribution highlights a compensation for talent that is probably more important than the compensation for their STEM skills. However, it is again difficult to assess the importance of generic talent vs. STEM-specific skills in this setup. Particularly for finance occupations, the best explanation appears a talent-skill complementarity that is magnified at the top of the distribution. As shown in the descriptive part, “quant” tasks are increasingly important in finance occupations, but probably they become extremely important only in top positions where the large funds are managed. Therefore, only top talents with STEM skills are able to perform these tasks sorting into highly paid asset management activities.

Figure 7: Wage premia for finance workers by degree field - recentered influence function regression



Notes: Results from selected interactions based on recentered influence regressions. Regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Shaded areas refer to 95% confidence intervals.

For sake of completeness, Figure 7 presents the same RIF regression for equation 2. Interesting, the returns to different degrees in finance diverge substantially along the percentiles of the wage distirbution. Returns to high-school graduates in finance exhibit a decreasing pattern, while returns to all majors are increasing along the distribution, in line with previous research (Böhm et al., 2018; Celerier and Vallee, 2019). The most important finding, however, is that the increasing pattern is quite heterogeneous across major fields, being steeper for STEMs and business graduates than for other graduates.

This figure makes it also transparent our contribution to the literature on inequality at the top of the distribution (e.g. Piketty and Saez, 2003; Alvaredo et al., 2013). The finance wage premium, which plays an important role in explaining the rise of top-1% inequality, is highly heterogeneous within finance, both across occupations (Figure 6) and types of degree (Figure 7). STEM graduates working in non-STEM occupations, especially finance and managerial ones, are among the main winners of the growing cake for the ultra rich.

The takeaway from this section is that the wages of STEM graduates are significantly higher in the financial sector and highly heterogeneous across occupations, age groups and along the earning distribution. Our analyses lend credibility to a technological explanation of the STEM wage premium in finance, but it is inconclusive regarding the ultimate reason (i.e., rent extraction or productivity improvement) for adopting new technologies in finance. The dynamics of the wage premiums along the distribution suggest that finance is able to attract the best STEM graduates and that the brightest among them likely work in managerial and math-intensive finance occupations.

4.4 Robustness checks

In the Appendix D, we report the results of a series of robustness checks. As for the rest of the paper, we conduct a devoted analysis on the subset of college graduates with post-graduate education. We re-estimate equation 3 for postgraduates using both OLS and RIF regressions. The main takeaway is the very large increase in returns to STEM postgraduates in finance occupations. This is evident on average (Table D2, row 2), but even more so at the top of the wage distribution (Figure D1). In the last vigintile of the distribution, STEMs working in finance occupations earn (statistically) significantly more than STEMs working as managers. To the extent to which postgraduate education and quantile regressions are good filters of talents within the STEM graduate groups, these results indicate that wage premia for STEM working in finance are larger for the most talented especially in non-STEM occupations.

Next, we check the robustness of our main results (Table 4) to different specifications and to alternative dependent variables. First, we consider the presence of pre-trends in wages and hours worked for narrowly defined cells.[33] Results are in line with the main ones and shown in Table D3. Second, we try to capture the role played by non-wage remuneration in finance by considering both wage and capital income earned in the year by the worker (Table D4 in Appendix D). Results of both robustness checks are qualitatively similar to those contained in the main Table 4. Finally, we decompose the effect on annual wages by considering either hourly wages or total hours worked as dependent variables (Tables D5 and D6, respectively). In general, the differences in hourly wages drive the main results, except for business and, to a less extent, STEM occupations. In business occupations, the additional premium with respect to the natural STEM-STEM match outside finance is fully driven by differences in hours worked.

5 Conclusions

This paper provides quantitative bases to a fact widely discussed in the public debate: the US financial sector attracts an increasing fraction of graduates in the science, technology, engineering and mathematical fields (STEM). We examine STEM reallocation towards finance over four decades (1980-2019), with a specific focus on the last decade where information on major fields of study is available. Our analysis sheds light on five facts. First, we show that long-run educational upgrading of finance was biased towards STEM graduates, especially for postgraduates, and **seems to accelerate** in the last decade. Second, the STEM-upgrading also occurs within finance and business occupations, in parallel with a task reorientation towards mathematics in these occupations. Third, STEM reallocation is more pronounced among experienced workers, peaking for prime aged ones. Fourth, the reallocation of STEM is associated with large wage premia in finance, but such premia are highly heterogeneous across occupations, age

[33]Gender, occupation (STEM occ, Finance occ, Managerial occ, Other business occ, Other occ), industry (Finance ind, KIBS, Manufacturing high-tech industry, Other industries), age (22-34, 35-44, 45-54, 55-64).

groups and degrees. Fifth, returns to STEMs are higher than returns to other degrees (except business degrees) in finance and become astonishingly high in non-STEM occupations (particularly finance and managerial occupations) at the top of the distribution. Again, this pattern is more pronounced for post-graduates. The latter finding indicates that talent sorting represents an important part of the finance wage premium at the top of the distribution and that the best STEM graduates probably end up working in the financial sector in non-STEM positions.

We conclude our paper by offering some general and speculative policy insights inspired by our findings. The key question is whether the brain drain of (especially top) STEM talents towards finance can be of concern for policy makers seeking to boost innovation and productivity growth. Seminal studies emphasized the fact that finance is an unproductive activity focused on rent seeking and creating negative spillovers to the rest of the economy associated with talents' poaching (Baumol, 1990; Murphy et al., 1991). A modern view focuses the key role of an efficient financial sector for economic development (Levine, 2005).[34] Roughly speaking, the challenge to understand the effect of a larger financial sector on economic growth is to quantify all the external economies and diseconomies created by finance to the rest of the economy.

As suggested by the literature on misallocation of talents (Baumol, 1990; Murphy et al., 1991), the STEM-reallocation channel studied in this paper can have negative effect on the rest of the economy (higher wages, skill shortages, missing productivity improvements etc.). Lockwood et al. (2017) proposes a theoretical framework in which income taxation is used as a Pigouvian tax to tackle the positive and negative externalities that may be generated by different professions/tasks in the rest of the economy. Their findings suggest that high-tech sectors create the largest net external benefits for the rest of the economy, while finance is ranked among the lowest. If a STEM employed in finance generates fewer positive externalities than a STEM employed in lower-paying high-tech jobs, the first-best option would be to issue a tax equivalent to the marginal social damage (in terms of forgone productivity improvements) that a STEM graduate employed in finance creates. However, it is extremely difficult in practice to estimate the size of these externalities.

On the other hand, however, there can be also a positive effect of employing STEMs in finance. Finance is an enabling sector, thus an increase in efficiency of finance may have large effect on the rest of the economy. For instance, fintech companies need STEM workers to develop software that reduce the costs of financial services. The productive specialization of one country also affects the benefits of having a strong and quantitatively-oriented financial sector. It is well known that having a comparative advantage in activities that rely on a similar set of capabilities increases the chances of further reinforcing this comparative advantage and creating new ones in related activities (Hidalgo et al., 2007). The particular specialization of the US economy in both global financial services and software development, digital technologies and semiconductor industries can be essential to increase the incentives to be enrolled in STEM majors and, even more important, to attract the most talented foreign STEM

[34]Levine (2005) identifies five main channels through which finance can positively affect the real economy: i) the production of information about investment opportunities and capital allocation; ii) the mobilization and pooling of household savings; iii) the monitoring of firms; iv) the financing of trade and consumption; and v) risk management and the provision of liquidity and diversification.

graduates.[35]

To conclude this broad discussion, it is not obvious that STEM reallocation towards finance is slowing down innovation and productivity growth in the rest of the economy. More research is needed to understand the extent to which a comparative advantage in high-tech is reinforced by the presence of a strong financial sector, as both attract workers with similar skills. Surely, however, subsidizing STEM education can be highly regressive by disproportionately benefiting top earners, especially given the extremely high cost of an engineer education compared to other majors (Altonji and Zimmerman, 2017). In presence of inequality aversion, these large distributional effects should be a part of a fully-fledged welfare evaluation of the subsidies to STEM education. Finally, to boost innovation in non-finance sectors, governments can design STEM tax credits and subsidies to STEM education conditioning them to the fact of working, at least at the beginning of the career, in activities that mitigate widely accepted and well-known externalities, such as climate change. This is particularly important because the low-carbon energy transition requires an intensive use of engineering and technical skills (Vona et al., 2018).

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[35] On the increasing importance of STEM immigrants in the US economy, see Hanson and Slaughter (2016) and Jaimovich and Siu (2016). Not only part of the substantial immigration of STEM talents to the US may have been driven by the large rewards in finance, but the perspective of escaping skill depreciation may have played a role in long-term career choices of foreign STEM graduates.

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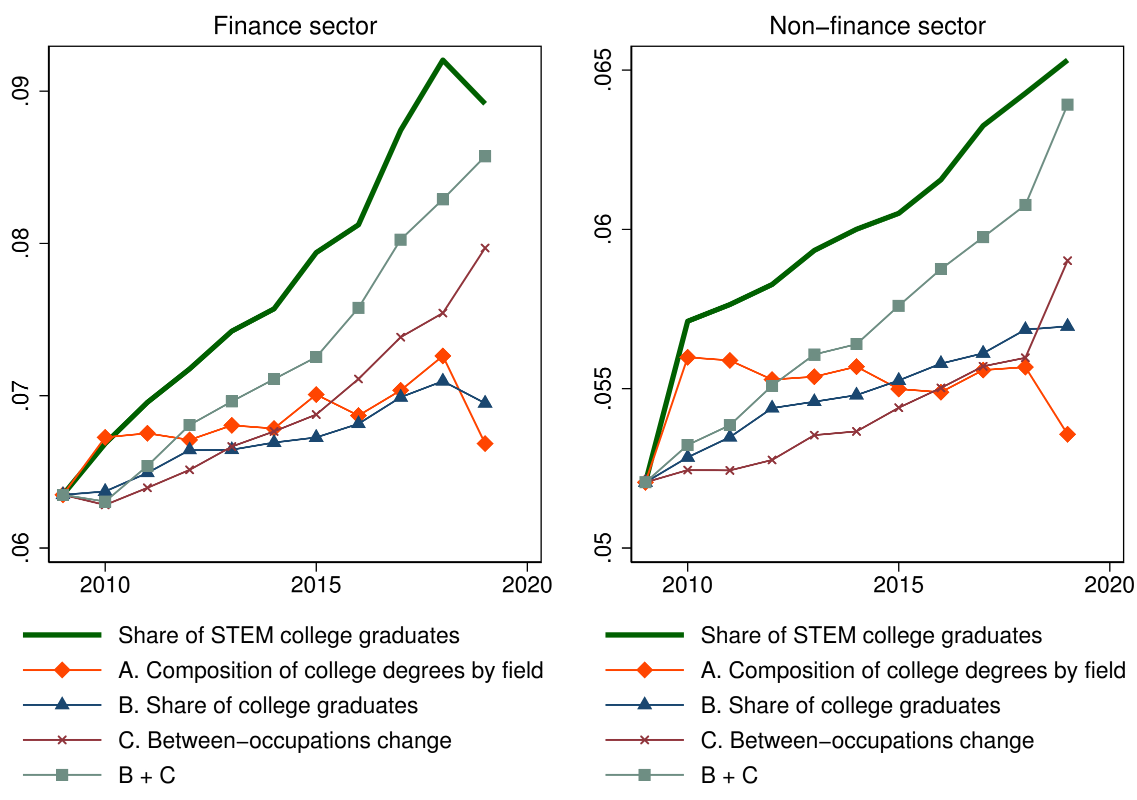
APPENDICES (FOR ONLINE PUBLICATION ONLY)

A Validating our STEM graduate measure

Our measure of STEM intensity for 1980-2008 is based on the assumption that the share of STEM graduates within each cell occupation-industry-education (respectively, *occ1990dd*, *ind1990dd* and college vs post-graduate) is time-invariant and equal to its average value over 2009-2019 (when it is observable). This means that the variation within each industry *ind1990dd* is driven by changes in the share of college graduates and college post-graduates within each occupation (industry-specific) and by changes in the relative importance of occupations within the same industry. What we cannot measure is the variation in the share of STEM graduates over total graduates within each occupation-industry cell. Based on data for 2009-2019, we decompose the total change in STEM intensity for the finance industry and for all other industries into a first component considering the share of STEM graduates over total graduates (A), a second component accounting for the change in the share of college graduates over total employees within the same occupation (B), a third component related to between-occupation changes in the composition of each industry (C). Components B and C can be measured for the whole period 1980-2019, while component A can only be measured for 2009-2019.

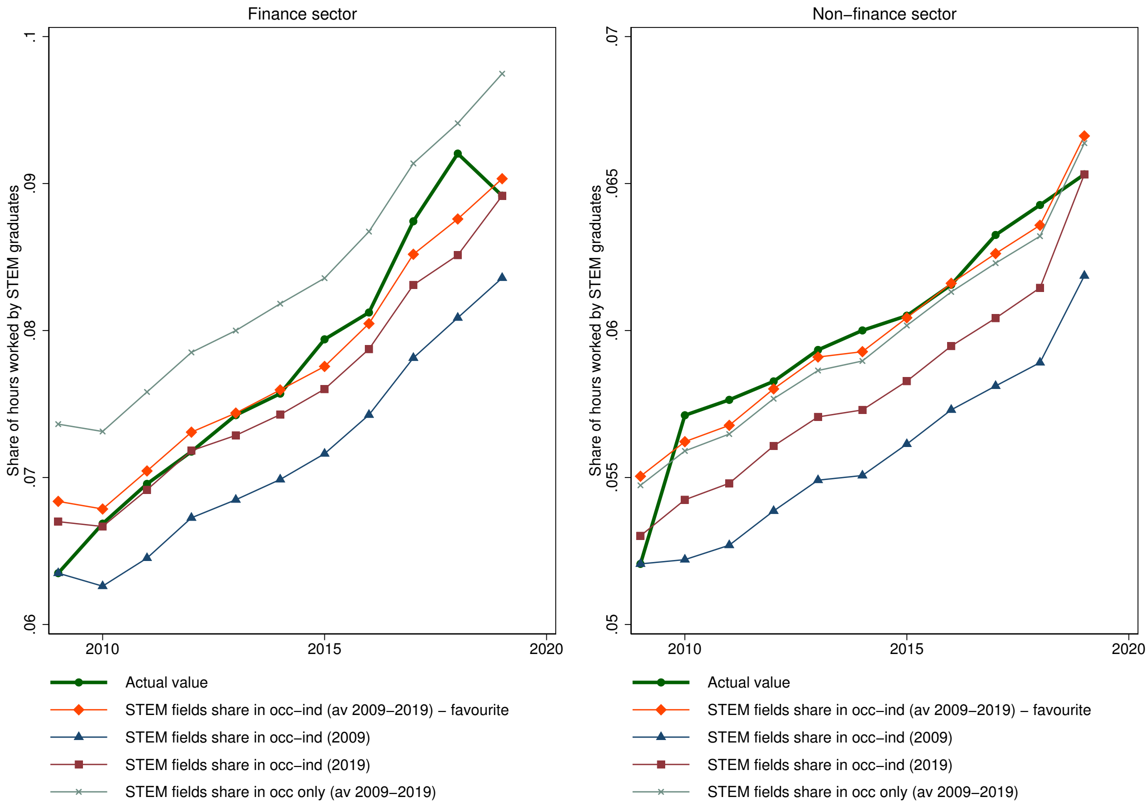
Figure A1: Decomposition of STEM degrees intensity (2009-2019)



Results are shown in Figure A1. Overall, over a rather long time-frame (11 years, 2009-2019), we observe that components B and C explain, together, as much as 86.5% of the change in the total share of STEM graduates in the finance industry (89.4% for non-finance industries).

To further validate the robustness of our measure, in Figure A2 we show alternative possible ways of estimating STEM intensity: STEM intensity of occupation-industry in 2009, STEM intensity of occupation-industry in 2019, STEM intensity of occupation (only) 2009-2019. Our favourite measure (orange line) appears to be the closest in level and trend to the true value (green line).

Figure A2: Alternative measures of STEM degrees intensity (2009-2019



B Sectoral and occupational classifications

Table B1: Definition of finance industry, KIBS, high-tech manufacturing (based on *ind1990dd*)

Finance industry
Banking
Savings institutions, including credit
Credit agencies, n.e.c.
Security, commodity brokerage, and investments companies
Insurance
Knowledge Intensive Business Services (KIBS)
Computer and data processing services
Engineering, architectural, and surveying services
Research, development, and testing services
High-tech manufacturing
Drugs
Computers and related equipment
Machinery, except electrical, n.e.c.
Machinery, n.s.
Household appliances
Radio, TV, and communication equipment
Motor vehicles and motor vehicle equipment
Aircraft and parts
Ship and boat building and repairing
Railroad locomotives and equipment
Guided missiles, space vehicles, and parts
Cycles and miscellaneous transportation
Scientific and controlling instruments
Medical, dental, and optical instruments and supplies

Table B2: Definition of occupational group (based on *occsoc*)

Finance occupations
13-2 Financial Specialists
11-3031 Financial Managers
Managerial occupations
11 Management Occupations (except 11-3031 Financial Managers)
STEM occupations
15 Computer and Mathematical Occupations
17 Architecture and Engineering Occupations
19 Life, Physical, and Social Science Occupations (except 19-3 Social Scientists and Related Workers)
Other business occupations
13-1 Business Operations Specialists
19-3 Social Scientists and Related Workers

C Additional descriptive analysis

C.1 Top STEM occupations in finance

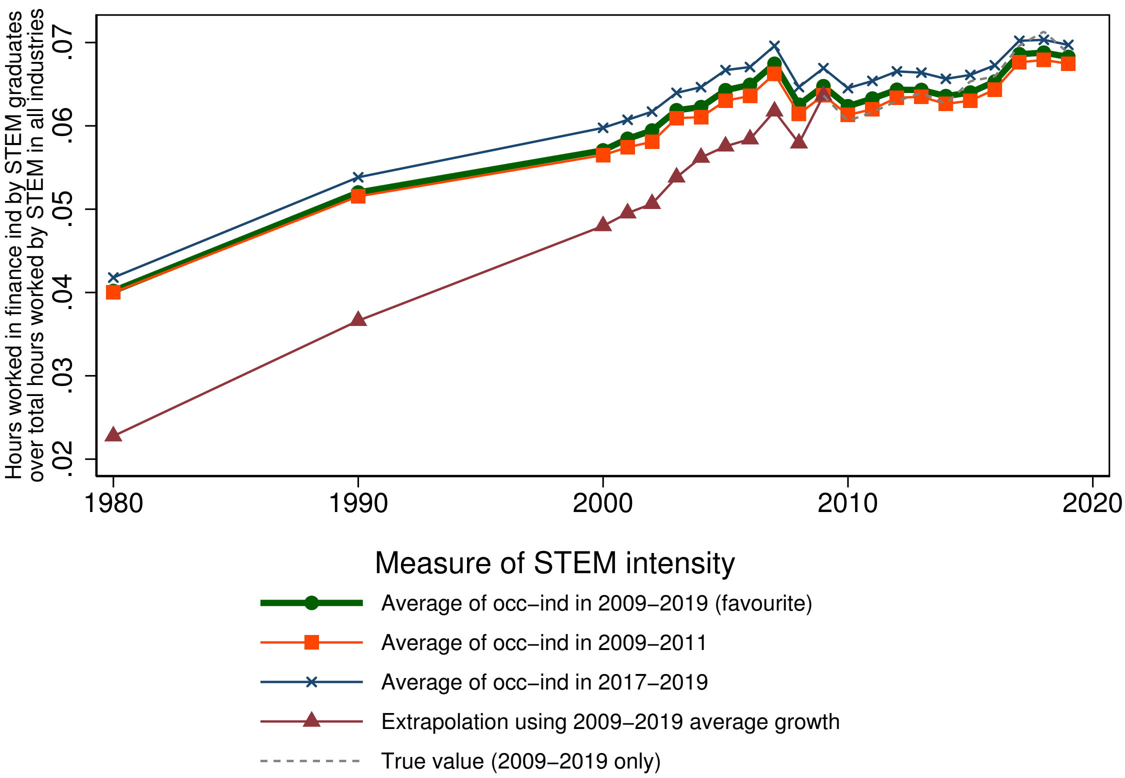
Table C1: Top 20 occupations in terms of contribution to STEM input in finance

Occupation	Macro-occ group	Share of STEM over total STEM in finance industry	Share of STEM over total STEM in all industries	Balassa index (ratio between first and second column)
113031 - Financial Managers	Finance	0.080	0.007	11.329
15113X - Software Developers, Applications and Systems Software	STEM	0.077	0.047	1.652
113021 - Computer and Information Systems Managers	Manag	0.051	0.022	2.320
132052 - Personal Financial Advisors	Finance	0.046	0.003	15.945
151131 - Computer Programmers	STEM	0.043	0.016	2.700
119XXX - Miscellaneous Managers	Manag	0.038	0.041	0.941
413031 - Securities, Commodities, and Financial Services Sales Agents		0.038	0.002	18.284
411012 - First-Line Supervisors of Non-Retail Sales		0.037	0.009	4.059
413021 - Insurance Sales Agents		0.033	0.002	18.379
151252 - Software Developers	STEM	0.033	0.017	1.901
1110XX - Chief Executives and Legislators	Manag	0.028	0.012	2.270
151121 - Computer Systems Analysts	STEM	0.027	0.009	3.036
132011 - Accountants and Auditors	Finance	0.026	0.011	2.418
151199 - Computer Occupations, All Other	STEM	0.026	0.011	2.404
152011 - Actuaries	STEM	0.025	0.002	14.398
132051 - Financial Analysts	Finance	0.022	0.002	9.877
131111 - Management Analysts	Other business	0.020	0.011	1.872
131030 - Claims Adjusters, Appraisers, Examiners, and Investigators	Other business	0.018	0.001	17.127
132070 - Credit Counselors and Loan Officers	Finance	0.015	0.001	16.634
1191XX - Other Managers	Manag	0.014	0.015	0.961
	Total top 20	0.698	0.241	2.896

Notes: Top-20 occupations (*occsoc* classification) in terms of hours worked by STEM graduates in the finance industry (average for 2009-2019). Own elaboration on ACS (2001-2019) 1% sample from IPUMS.

C.2 Alternative interpolations

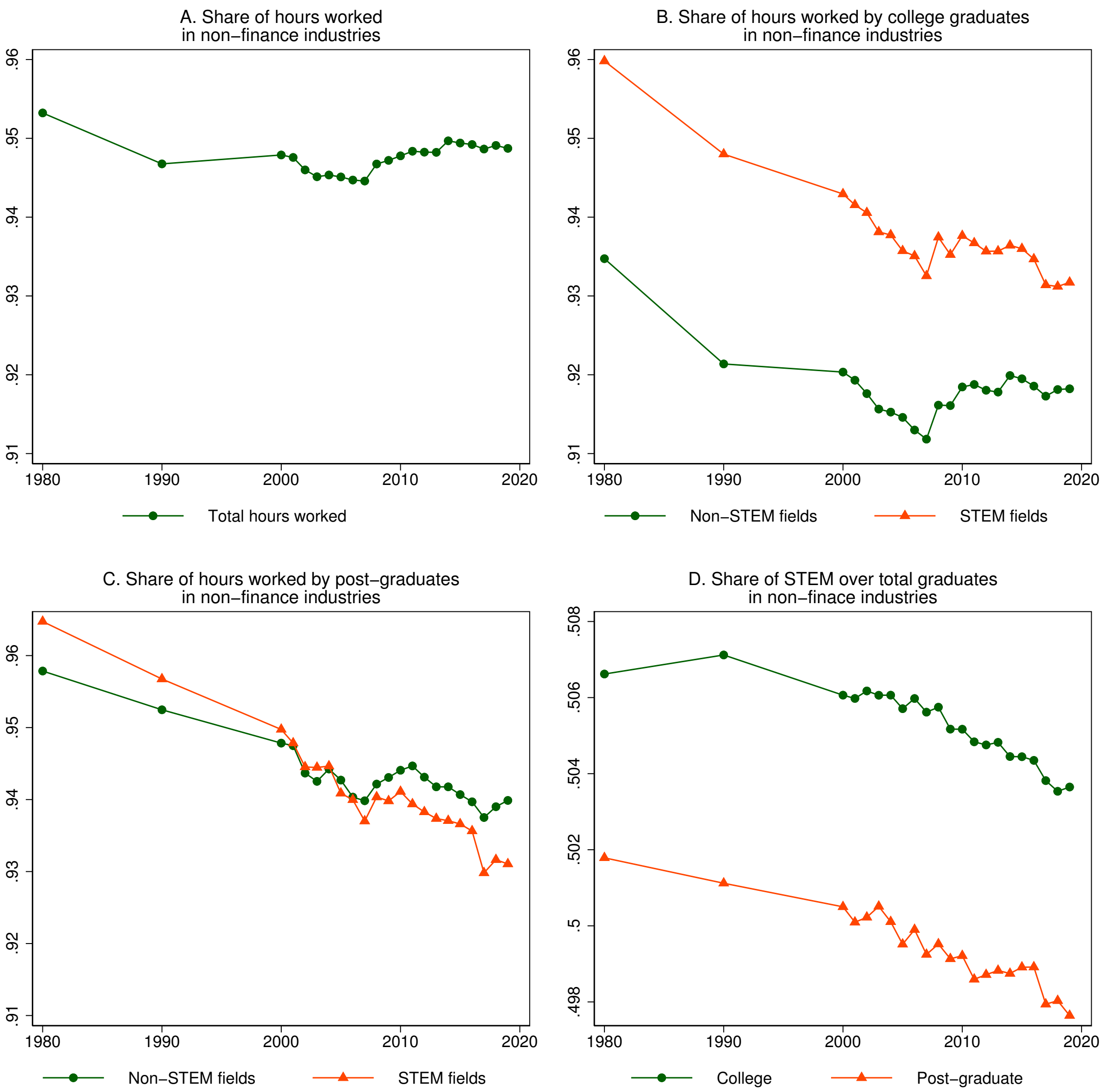
Figure C1: Share of hours worked in finance industries over total US economy using alternative interpolations



Notes: Share of hours worked in non-finance industries over total hours worked (person weights multiplied by hours worked) in the whole US economy (total and by category of worker). Own elaboration on Decennial Census (1980, 1990, 2000) 5% sample and ACS (2001-2019) 1% sample from IPUMS. As for the extrapolation using 2009-2019 average growth, we ran a linear regression on the balanced panel of occupation (o) by industry (i) pairs over 2009-2019 estimating the equation: $STEM_{iot} = \gamma_i + \theta_o + \delta_o t + \phi_i t + \rho College_{iot}$, where $STEM_{iot}$ is the STEM intensity of occupation o, industry i and time t, γ_i and θ_o are, respectively, industry and occupation dummies, t is a linear trend (which is assumed to be specific for both occupation and industry) and $College_{iot}$ is the share of college graduates in occupation o, industry i and time t. We then estimated the predicted values out-of-sample for 1980-2008.

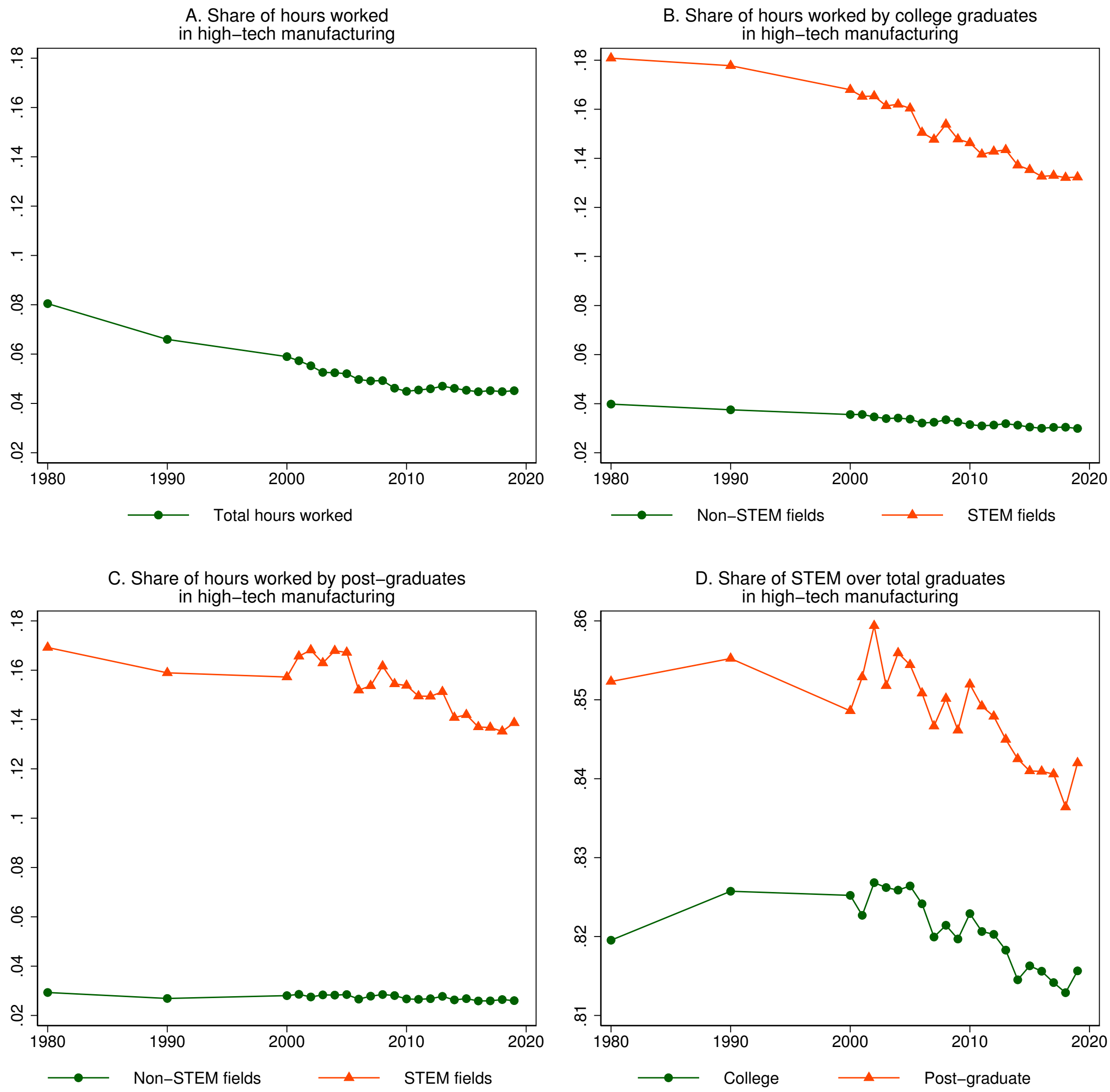
C.3 Reallocation of STEM graduates in non-finance industries

Figure C2: Share of hours worked in non-finance industries over total US economy



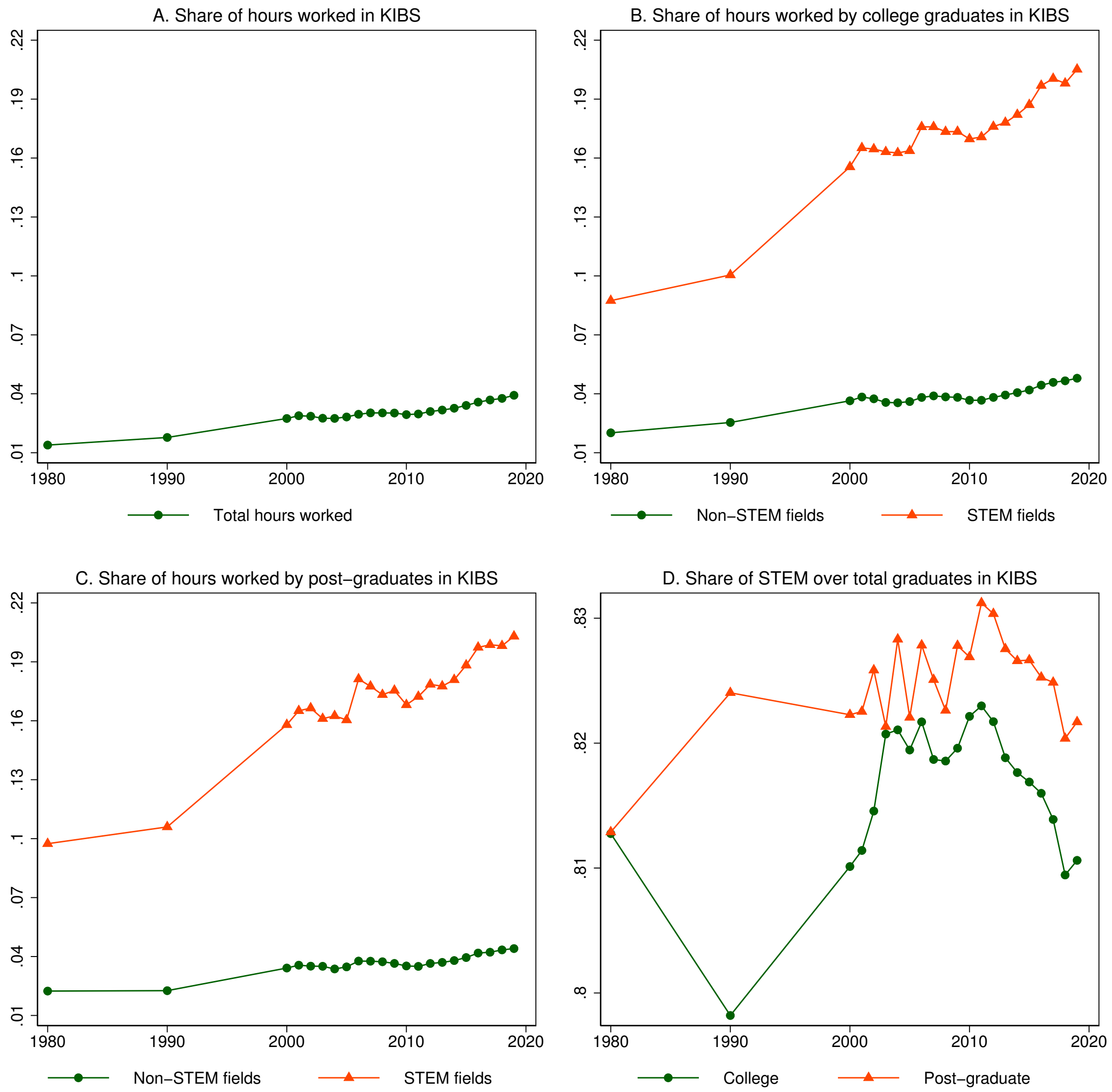
Notes: Share of hours worked in non-finance industries over total hours worked (person weights multiplied by hours worked) in the whole US economy (total and by category of worker). Own elaboration on Decennial Census (1980, 1990, 2000) 5% sample and ACS (2001-2019) 1% sample from IPUMS.

Figure C3: High-tech manufacturing industries vs total US economy



Notes: Share of hours worked in high-tech manufacturing industries over total hours worked (person weights multiplied by hours worked) in the whole US economy (total and by category of worker). Own elaboration on Decennial Census (1980, 1990, 2000) 5% sample and ACS (2001-2019) 1% sample from IPUMS.

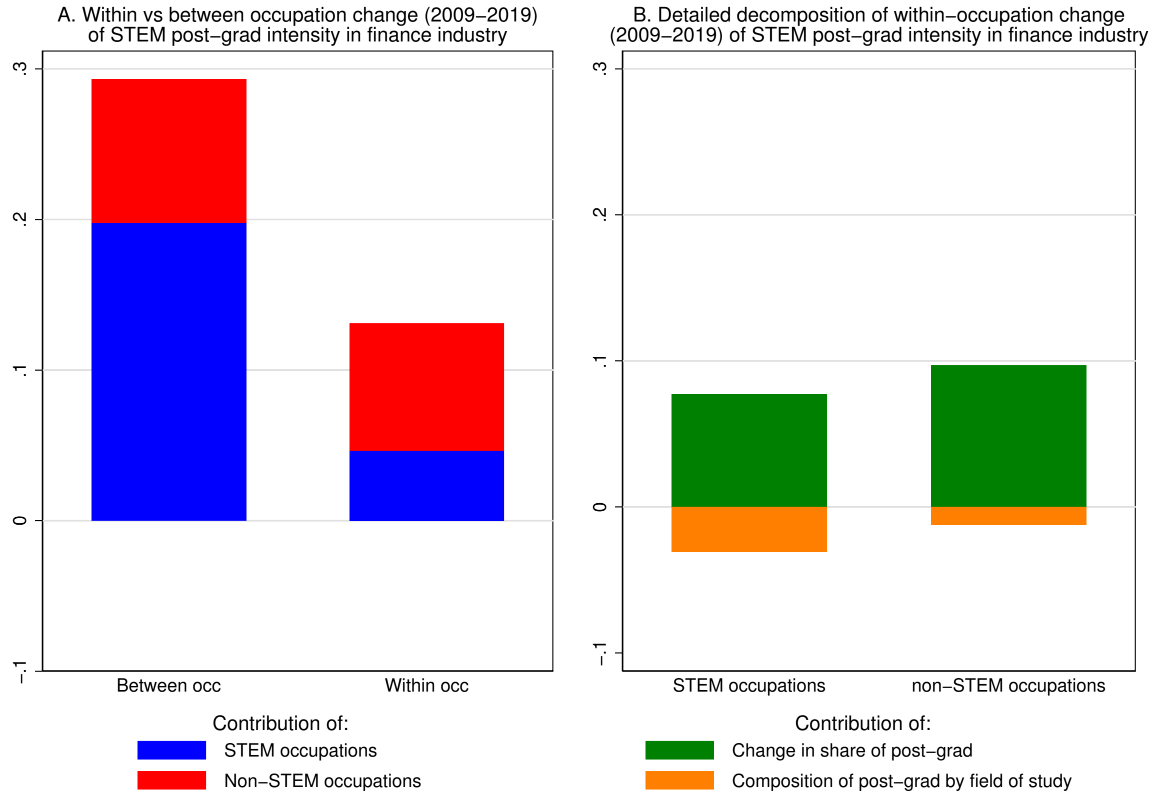
Figure C4: Knowledge-intensive business sectors (KIBS) vs total US economy



Notes: Share of hours worked in knowledge-intensive business sectors (KIBS) over total hours worked (person weights multiplied by hours worked) in the whole US economy (total and by category of worker). Own elaboration on Decennial Census (1980, 1990, 2000) 5% sample and ACS (2001-2019) 1% sample from IPUMS.

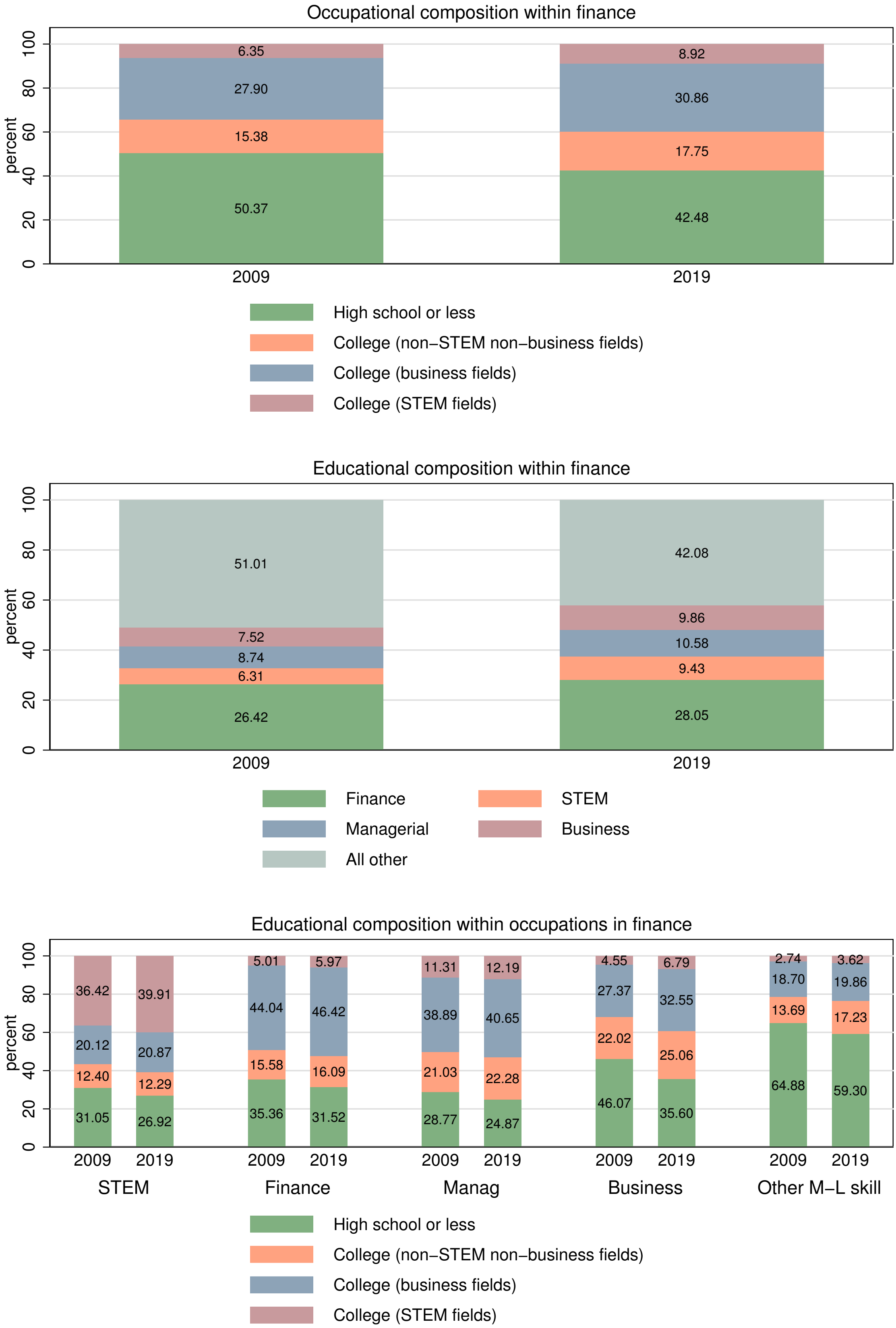
C.4 Details on the composition of STEM in finance

Figure C5: Decomposition of changes in STEM post-graduate share in finance industry over 2009-2019



Notes: Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

Figure C6: Composition of finance industry by educational attainment, occupation and education/occupation



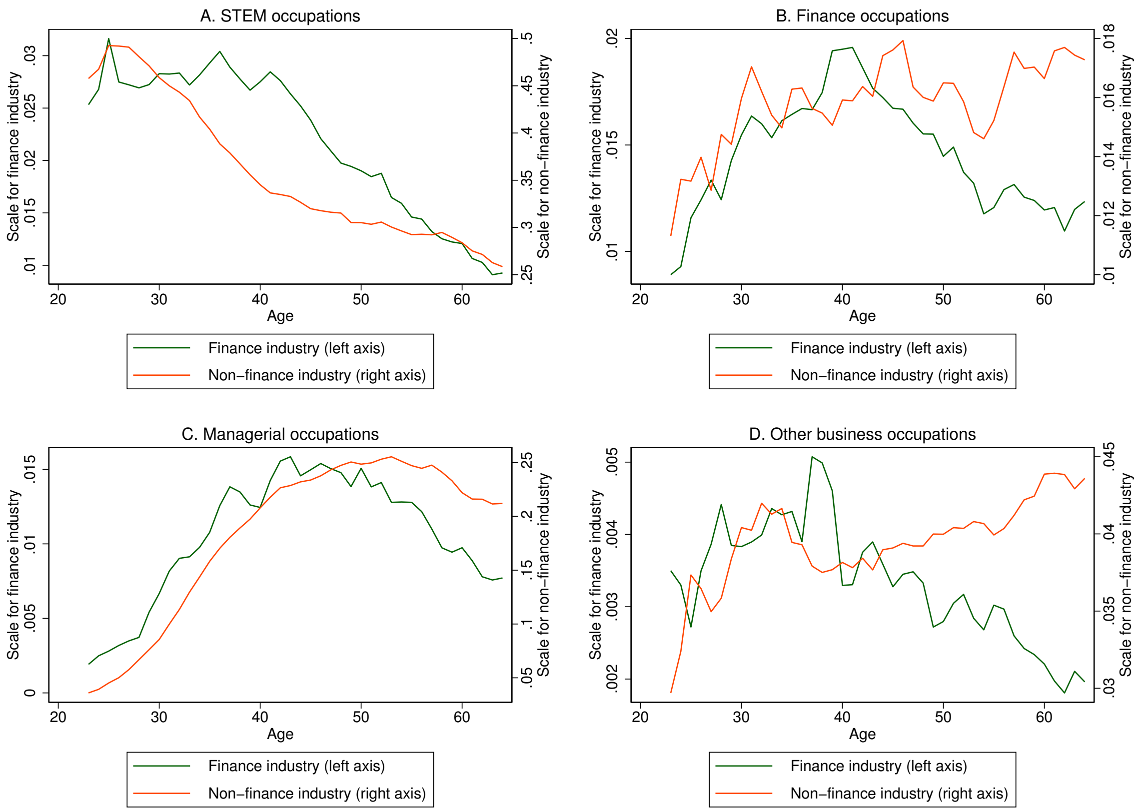
Notes: Percentages weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

C.5 Additional results for college graduates with post-graduate education

Figure C7: Within-occupation changes in STEM for college graduates with post-graduate education

Notes: Within-occupations level and change in STEM intensity. Statistics weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

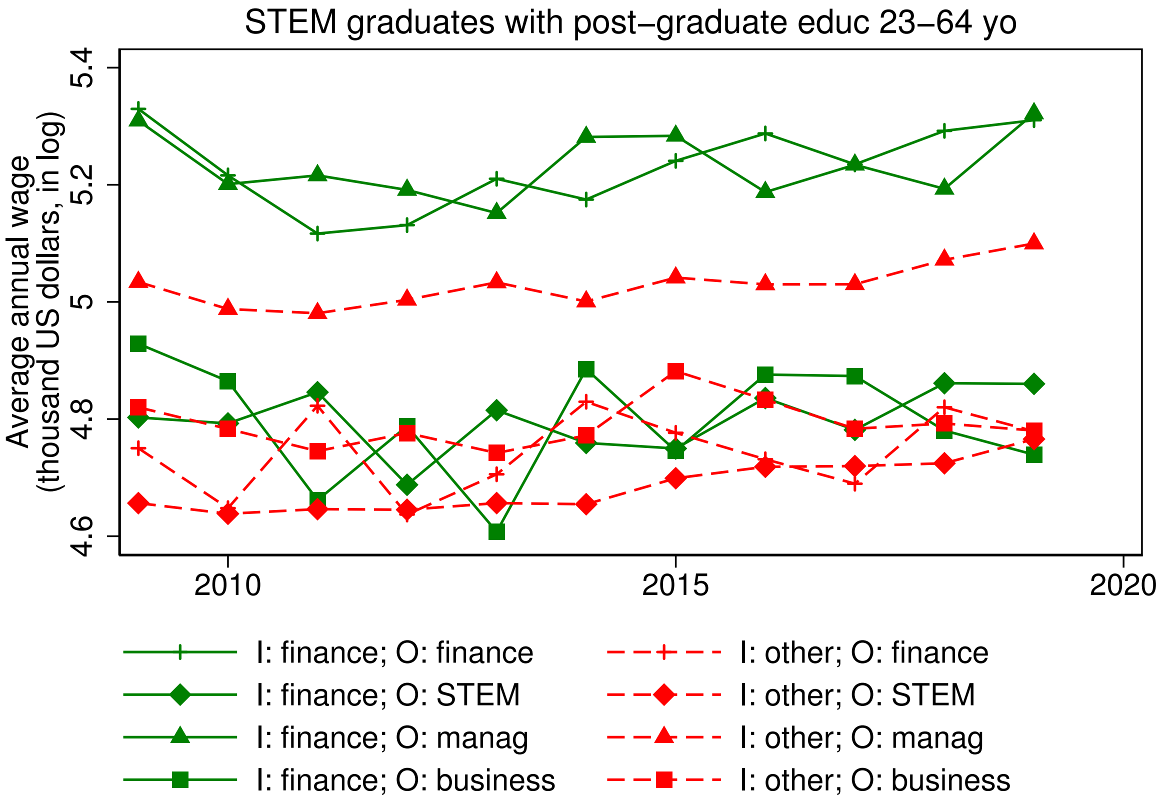
Figure C8: Share of STEM graduates with post-graduate education by industry and occupation over total STEM graduates (by age)



Notes: Statistics weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

C.6 Additional descriptive evidence for wage premia in finance for post-graduates

Figure C9: Annual wages paid to STEM graduates in different occupation-industry pairs - postgraduates



Notes: Average annual wages paid to workers in log US Dollars (deflated to 2015 prices using CPI) weighted weighted by person weights multiplied by hours worked. Own elaboration on ACS (2009-2019) 1% sample from IPUMS.

D Additional tables for wage regressions

Table D1: Full table with wage regressions: workers with college degree

Dependent variable: log annual wage	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Math skills (O*NET)	0.500***	0.457***	0.530***	0.528***	0.507***
	(0.0258)	(0.0371)	(0.0475)	(0.0542)	(0.0665)
Social skills (O*NET)	0.230***	0.240***	0.220***	0.220***	0.243***
	(0.0179)	(0.0334)	(0.0340)	(0.0346)	(0.0453)
Post-graduate education	0.262***	0.170***	0.301***	0.311***	0.261***
	(0.0152)	(0.0202)	(0.0290)	(0.0309)	(0.0344)
STEM field	0.0606***	0.0145	0.0774***	0.0807***	0.105***
	(0.0115)	(0.0169)	(0.0218)	(0.0255)	(0.0264)
Finance occ	0.187***	0.183***	0.191***	0.217***	0.171**
	(0.0252)	(0.0455)	(0.0453)	(0.0471)	(0.0682)
STEM occ	0.208***	0.153***	0.208***	0.259***	0.275***
	(0.0228)	(0.0426)	(0.0411)	(0.0415)	(0.0529)
Managerial occ	0.208***	0.117***	0.187***	0.244***	0.287***
	(0.0199)	(0.0341)	(0.0362)	(0.0395)	(0.0502)
Business occ	0.196***	0.214***	0.200***	0.187***	0.133***
	(0.0205)	(0.0367)	(0.0318)	(0.0346)	(0.0496)
STEM field x Finance occ	-0.143***	-0.0387	-0.147***	-0.169***	-0.282***
	(0.0253)	(0.0269)	(0.0342)	(0.0566)	(0.0698)
STEM field x STEM occ	0.114***	0.250***	0.0776**	0.0302	-0.0271
	(0.0193)	(0.0319)	(0.0363)	(0.0376)	(0.0404)
STEM field x Managerial occ	0.0447***	0.113***	0.0139	0.00836	-0.0187
	(0.0157)	(0.0263)	(0.0280)	(0.0309)	(0.0321)
STEM field x Business occ	0.0290	0.0890**	0.0103	0.0423	-0.0295
	(0.0219)	(0.0429)	(0.0353)	(0.0370)	(0.0413)
STEM field x Finance ind	-0.00951	0.0955*	-0.0183	-0.0721	-0.131**
	(0.0263)	(0.0504)	(0.0481)	(0.0443)	(0.0510)
Finance ind x Finance occ	-0.00817	-0.0175	-0.0359	-0.0162	0.0536
	(0.0405)	(0.0832)	(0.0711)	(0.0581)	(0.0731)
Finance ind x STEM occ	0.150***	0.247***	0.0843	0.102*	0.140**
	(0.0338)	(0.0690)	(0.0630)	(0.0563)	(0.0653)
Finance ind x Managerial occ	0.109***	0.113*	0.0579	0.101*	0.124**
	(0.0317)	(0.0644)	(0.0592)	(0.0520)	(0.0546)
Finance ind x Business occ	-0.00493	0.00546	-0.0525	0.0172	0.0727
	(0.0379)	(0.0662)	(0.0729)	(0.0724)	(0.0855)
STEM field x Finance ind x Finance occ	0.157***	0.0513	0.149**	0.187***	0.303***
	(0.0374)	(0.0573)	(0.0615)	(0.0726)	(0.0921)
STEM field x Finance ind x STEM occ	-0.0676**	-0.236***	-0.0145	0.0278	0.0982
	(0.0321)	(0.0633)	(0.0575)	(0.0529)	(0.0602)
STEM field x Finance ind x Managerial occ	-0.0253	-0.0759	0.0165	0.00415	0.0510
	(0.0310)	(0.0591)	(0.0550)	(0.0517)	(0.0592)
STEM field x Finance ind x Business occ	-0.00659	-0.0892	0.0396	-0.0372	0.0714
	(0.0359)	(0.0750)	(0.0602)	(0.0583)	(0.0698)
N	4784504	1464943	1183008	1168336	968217

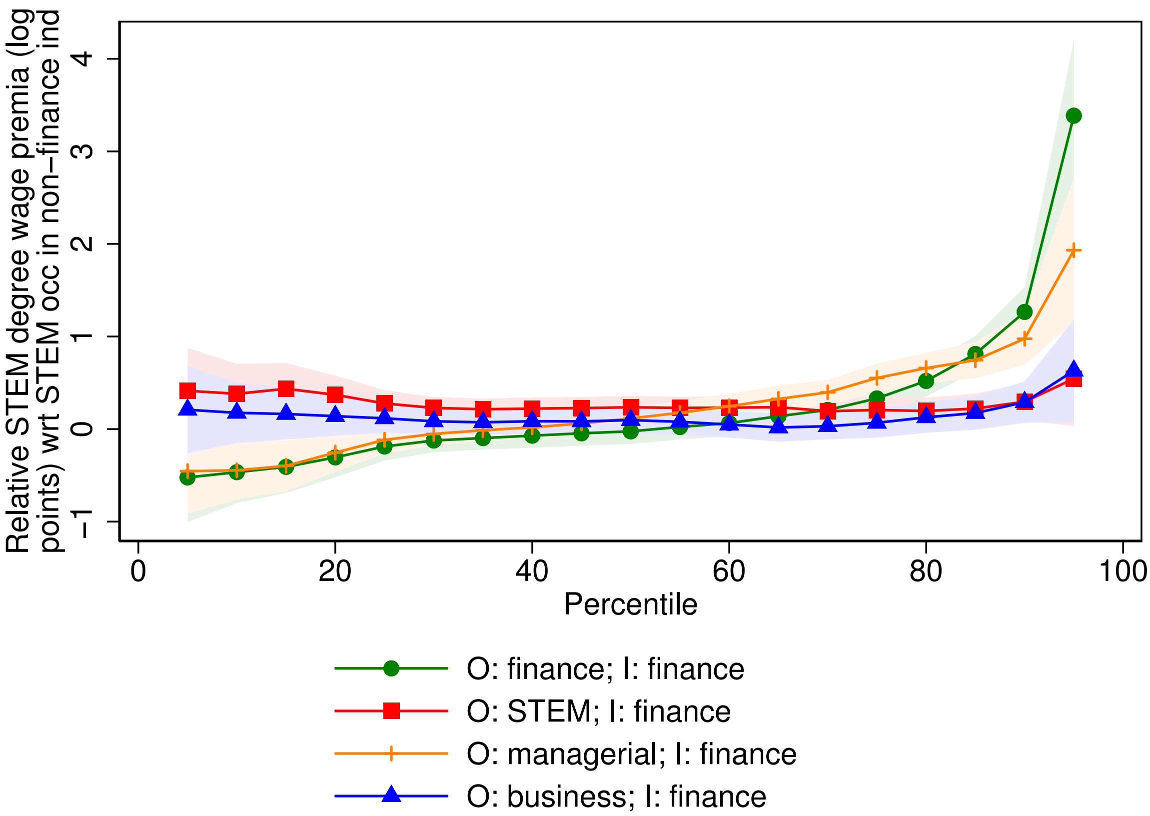
Notes: OLS regression weighted with sampling weights. Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control variables: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math intensity of occupation in 2009 (O*NET), post-graduate education dummy.

Table D2: Estimated wage premia for different categories of workers (college graduates with post-graduate education)

	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM post-graduates in STEM occ in non-Finance ind wrt other post-graduates	0.296***	0.361***	0.25***	0.283***	0.264***
	(0.0363)	(0.0639)	(0.0565)	(0.0610)	(0.0882)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	0.168**	0.087	0.232**	0.199	0.172
	(0.0774)	(0.1225)	(0.1167)	(0.1452)	(0.1786)
STEM field in STEM occ in Finance industry	0.279***	0.261***	0.291***	0.269**	0.336**
	(0.0695)	(0.0970)	(0.0997)	(0.1315)	(0.1627)
STEM field in Managerial occ in Finance ind	0.188**	0.076	0.194*	0.248*	0.251
	(0.0761)	(0.1133)	(0.1120)	(0.1452)	(0.1794)
STEM field in Business occ in Finance ind	0.135*	0.071	0.197*	0.094	0.219
	(0.0746)	(0.1166)	(0.1095)	(0.1429)	(0.1683)

Notes: Wage premia (in log points) of different combinations of field of study, occupation and industry. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regression results are available upon request.

Figure D1: Selected results from recentered influence function regression - college graduates with post-graduate education



Notes: Results from selected interactions based on recentered influence regressions. Regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Shaded areas refer to 95% confidence intervals.

Table D3: Estimated wage premia for different categories of workers - controlling for pre-trend in employment and wages

	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM graduates in STEM occ in non-Finance ind wrt other college graduates	0.387***	0.357***	0.356***	0.421***	0.354***
	(0.0236)	(0.0481)	(0.0392)	(0.0398)	(0.0556)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	0.068	0.055	0.046	0.116	0.077
	(0.0555)	(0.0943)	(0.0935)	(0.0967)	(0.1077)
STEM field in STEM occ in Finance industry	0.282***	0.306***	0.241***	0.305***	0.334***
	(0.0481)	(0.0730)	(0.0716)	(0.0924)	(0.1170)
STEM field in Managerial occ in Finance ind	0.214***	0.025	0.189**	0.23**	0.301***
	(0.0519)	(0.0730)	(0.0716)	(0.0924)	(0.1170)
STEM field in Business occ in Finance ind	0.072	-0.114	0.087	0.037	0.059
	(0.0522)	(0.0730)	(0.0716)	(0.0924)	(0.1170)

Notes: Wage premia (in log points) of different combinations of field of study, occupation and industry. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). We additionally control for employment and wage pre-trend (2000-2007) within the cell: gender, occupation (STEM occ, Finance occ, Managerial occ, Other business occ, Other occ), industry (Finance ind, KIBS, Manufacturing high-tech industry, Other industries), age (22-34, 35-44, 45-54, 55-64). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regression results are available upon request.

Table D4: Estimated wage premia for different categories of workers - wage + capital income

	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM graduates in STEM occ in non-Finance ind wrt other college graduates	0.401***	0.419***	0.376***	0.399***	0.393***
	(0.0249)	(0.0442)	(0.0412)	(0.0446)	(0.0591)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	0.027	0.003	0.073	0.028	0.020
	(0.0555)	(0.0943)	(0.0935)	(0.0967)	(0.1077)
STEM field in STEM occ in Finance industry	0.269***	0.236**	0.289**	0.291*	0.341
	(0.0481)	(0.0744)	(0.0771)	(0.0872)	(0.0956)
STEM field in Managerial occ in Finance ind	0.221**	0.098	0.219*	0.252	0.307
	(0.0519)	(0.0924)	(0.0788)	(0.0935)	(0.1087)
STEM field in Business occ in Finance ind	0.080	0.045	0.133	0.079	0.097
	(0.0522)	(0.0990)	(0.0816)	(0.1013)	(0.1034)

Notes: Wage premia (in log points) of different combinations of field of study, occupation and industry. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regression results are available upon request.

Table D5: Estimated wage premia for different categories of workers - hourly wages

	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM graduates in STEM occ in non-Finance ind wrt other college graduates	0.317***	0.338***	0.299***	0.309***	0.287***
	(0.0186)	(0.0331)	(0.0325)	(0.0338)	(0.0409)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	0.051	-0.004	0.085	0.076	0.065
	(0.0487)	(0.0754)	(0.0901)	(0.0926)	(0.0998)
STEM field in STEM occ in Finance industry	0.198***	0.158**	0.223***	0.213**	0.238***
	(0.0424)	(0.0621)	(0.0737)	(0.0840)	(0.0915)
STEM field in Managerial occ in Finance ind	0.18***	0.091	0.177**	0.197**	0.244**
	(0.0458)	(0.0659)	(0.0801)	(0.0910)	(0.1014)
STEM field in Business occ in Finance ind	0.014	0.006	0.049	0.010	-0.016
	(0.0479)	(0.0734)	(0.0819)	(0.1002)	(0.0980)

Notes: Wage premia (in log points) of different combinations of field of study, occupation and industry. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regression results are available upon request.

Table D6: Estimated differences in hours worked for different categories of workers

	All college graduates 22-64	College graduates (22-34)	College graduates (35-44)	College graduates (45-54)	College graduates (55-64)
Benchmark: Premium of STEM graduates in STEM occ in non-Finance ind wrt other college graduates	0.0643***	0.0752***	0.0635***	0.0606***	0.0563**
	(0.0118)	(0.0245)	(0.0179)	(0.0164)	(0.0252)
Additional premium relative to the benchmark (log points):					
STEM field in Finance occ in Finance industry	-0.009	0.002	-0.009	-0.003	-0.013
	(0.0280)	(0.0548)	(0.0500)	(0.0455)	(0.0694)
STEM field in STEM occ in Finance industry	0.0751***	0.079	0.066	0.0799*	0.1128*
	(0.0265)	(0.0505)	(0.0485)	(0.0441)	(0.0608)
STEM field in Managerial occ in Finance ind	0.026	0.000	0.036	0.034	0.050
	(0.0268)	(0.0515)	(0.0494)	(0.0458)	(0.0648)
STEM field in Business occ in Finance ind	0.0765***	0.047	0.0893*	0.0779*	0.1368**
	(0.0262)	(0.0488)	(0.0477)	(0.0460)	(0.0611)

Notes: Differences (in log points) across different combinations of field of study, occupation and industry. All regressions include the following control variable: interaction between gender and age dummies (2-year bins), 2-digit NAICS dummies, metro-area dummy variable, married dummy, black dummy variable, non-white dummy variable, foreign born dummy variable, math skills and social skills intensity of occupation in 2009 (O*NET). Standard errors clustered by industry, occupation and age group in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regression results are available upon request.

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