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Finance and the Misallocation of Scientific, Engineering and Mathematical Talent

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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 well-known fact and illustrate its consequences for the productivity growth in other sectors over the period 1980-2014. First, we find that the share of STEM talents grew significantly faster in finance than in other key STEM sectors such as high-tech, and this divergent pattern has been more evident for STEM than for general skills and more pronounced for investment banking. Second, this trend did not reverse after the Great Recession, and a persistent wage premium is found for STEM graduates working in finance and especially in typical financial jobs at the top of the wage distribution. Third, the brain drain of STEM talents into finance has been associated with a cumulative loss of labor productivity growth of 6.6% in the manufacturing sectors. Our results suggest that increasing the number of STEM graduates may not be enough to reignite sluggish economic growth without making their employment in finance more costly.

KEY WORDS

Finance, skills, STEM workers, brain drain, productivity.

JEL

Q52, Q48, H23, D22.

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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) who would otherwise be able to carry out research activities in the real economy. For instance, almost 1/3 of the 33,000 employers 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 Renaissance Technologies, the world's best performing hedge fund, 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*".

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 younger cohorts compared to older ones. Celerier and Vallee (2015) 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) document that wages and skills increased dramatically in the financial sector since the 1980s. Although their focus was not on STEM skills, the authors also document a robust increase in the use of math skills by the financial sector compared to the rest of the economy. Boustanifar et al. (2016) provide the first international evidence on the evolution of wages and skills in finance confirming the upskilling trend, although with substantial exceptions.

The first contribution of this paper is to extend the influential study of Philippon and Reshef (2012) with a dedicated focus on STEM workers. We believe that this extension is of paramount importance given that STEM competences are fundamental for innovation and economic growth. We study the crucial 1980-2014 period, during which financial sector deregulation took place and automation in finance has accelerated. In doing so, we compare the evolution of the share of STEM workers in finance with that of other large employers of STEM professionals, such as the high-tech manufacturing sector. We use two main data sources: i. the decennial Census, in which we can only observe STEM workers and their general educational attainments, is used to carry out a long-term analysis; ii. the 2009 to 2014 releases of the American Community Survey, which also contains information on the workers' degrees by fields of study and thus on the distribution of STEM graduates across sectors. Re-

[1] For more 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/.

gardless of the dataset used, we document that conditional on educational attainment, demographic characteristics and proxies of technology adoption, the share of STEM talents employed in finance has grown significantly faster than in other key sectors, especially in the 1980s and the early 2000s. Compared to Philippon and Reshef (2012), we find that the divergence between finance and other key sectors is more pronounced for STEM than for standard measures of human capital. Moreover, using recent waves of the American Community Survey, which contains information on degree field, we find that STEM graduates are paid significantly more in financial jobs, especially at the top of the wage distribution.

The second contribution of this paper regards the implications of such STEM reallocation into finance for productivity growth and technological progress in the real economy. These implications have so far remained relatively unexplored with the distinct exception of Kneer (2013b). Two forces make it difficult to predict the impact of such STEM reallocation. First, given that STEM talents are a key input of research, development and innovation activities, the concern is that the brain drain of STEM talent to finance may reduce a country's capacity to sustain long-term growth, which ultimately depends on technological progress.[3] On the other hand, a well-consolidated literature has found a positive relationship between a country's financial development and growth (e.g. Levine, 2005), although this relationship becomes negative at high levels of financial development (Law and Singh, 2014). Among the explanations of this reversal, the absorption of talent into finance has played a central role in the recent debate (Kneer, 2013b; Cecchetti and Kharroubi, 2015). To tackle this issue at the sectoral level, we estimate a standard productivity equation augmented for STEM human capital and compute counterfactual productivity changes in the absence of the reallocation of STEM talent to finance. We find that the reallocation of STEM talents into finance has been *de facto* a misallocation, especially in the manufacturing sector. We estimate a counterfactual impact that is relatively small for the whole economy (approximately 1.1% in terms of lower cumulative productivity growth) but modestly large for the manufacturing sector (approximately 6.6% in terms of lower cumulative productivity growth reaching 9.7% in high-tech sectors), which also experienced the largest decline of STEM input.

The theoretical literature on talent's misallocation and growth is a source of inspiration for our empirical analysis. Key in this literature is the distinction between productive and unproductive activities (Baumol, 1990). If a productive activity (i.e., entrepreneurship) is rewarded less than an unproductive activity (i.e., rent seeking), growth slows down because the best talents opt for careers in unproductive activities.[4] The classical analysis of Murphy et al. (1991) suggests that the rewards of entrepreneurship relative to those of rent seeking

[3] This concern was loudly voiced in the public press in the aftermath of the Great Recession. For instance: "The new players in the financial markets, the kingpins of the future who had the capacity to reshape those markets, were a different breed: the Chinese guy who had spent the previous ten years in American universities, the French particle physicist from FERMAT lab; the Russian aerospace engineer; the Indian PhD in electrical engineering. "There were just thousands of these people," said Schwall. "Basically all of them with advanced degrees. I remember thinking to myself how unfortunate it was that so many engineers were joining these firms to exploit investors rather than solving public problems." See Lewis (2015, p. 121).

[4] A classical and empirically well-documented example is that of the natural resource curse. In the presence of weak institutions, a windfall of natural resources may induce talented individuals to spend most of their time in activities related to the exploitation of these resources

are positively affected by the size and the contestability of the market and by the protection of property rights. Their cross-country regressions confirm that while rent-seeking is harmful for economic growth, entrepreneurship has a positive effect on growth.[5] More recently, Philippon (2010) studied an economy with explicit career choices and in which engineer-entrepreneurs need financiers because of borrowing constraints. The optimal policy can be to either tax or subsidize the financial sector depending on whether external economies are more sensitive to the aggregate level of investment (thus, relaxing the borrowing constraint is growth enhancing) than to the number of entrepreneurs (thus suggesting that finance should be taxed to prevent a brain drain of talents). Lockwood et al. (2017) propose a theoretical framework in which progressive taxation is seen as a sort of Pigouvian tax to tackle the externalities generated in different professions. If higher-paying industries such as finance generate fewer positive externalities than lower-paying ones, progressive taxation can be efficiency enhancing. Finally, an active strand of literature builds models of talent misallocations to explain the extent to which the astonishing rise in finance earnings premiums, especially in top positions, is a pure rent or is associated with a change in the skill distribution within the financial sector (Axelson and Bond, 2015; Glode and Lowery, 2016; Bolton et al., 2016).[6] While we provide new evidence of a wage premium for STEM graduates working in finance compared to other key sectors, we also evaluate how the reallocation of STEM talent affects the performance of the real economy.

Both the nature of jobs and the workforce composition within sectors have changed significantly in past four decades, and finance is no exception. Two facts are well documented by an active strand of the literature on the impact of new technologies on the labor market.[7] First, a large fraction of tasks performed within each job becomes more complex and less routinized, meaning that non-engineering and technical jobs may also require advanced analytic skills. Second, because digital and computer technologies are general purpose technologies, all sectors started automating and robotizing their production processes, hence requiring a larger share of high-skill workers with a strong technical and scientific

(i.e., patronage, bribe, etc.) rather than in activities characterized by increasing returns to scale or positive externalities (i.e., innovation). See, e.g., Sachs and Warner (1995), Mehlum et al. (2006), Robinson et al. (2006). Yet another strand of the literature examines the misallocation associated with gender and ethnic discrimination, the removal of which explains a large fraction of US productivity growth over the past 50 years (Hsieh et al., 2013).

[5] Interestingly, the idea that STEM workers are drivers of economic growth is incorporated in their measure of entrepreneurship, which is the share of college enrollment in engineering as opposed to rent seeking as measured by the share of college enrollment in law. Engineering studies allow one to obtain a comparative advantage in complex mathematical and problem solving tasks that can be then used to develop new technologies. In turn, law studies enable one to master language, rhetoric and communication skills, which are essential in successful exploitation of existing technologies.

[6] The empirical literature on finance and inequality at the top of the distribution is too extensive to be reviewed here. See, e.g., Kaplan and Rauh (2010), Philippon and Reshef (2012) and Bell and van Reenen (2014). Bell and van Reenen (2014) emphasize the importance of having good data on all types of compensation received by bankers. The recent papers of Celerier and Vallee (2015) and Bohm et al. (2015) have the advantage of using a very precise measure of engineering talent (the school where an engineer graduated and standardized test scores, respectively) and thus are particularly suitable for disentangling the role of skills and moral hazard in explaining the finance wage premium.

[7] Refer, among others, to the classical works of Katz and Murphy (1992), Acemoglu (1998), Autor et al. (1998), Autor et al. (2003), Acemoglu and Autor (2011), Goos et al. (2014), Beaudry et al. (2016).

backgrounds to operate these technologies. These two trends imply a fiercer sectoral competition for the workers endowed with STEM skills that could have contributed to substantially altering the allocation of STEM talent between jobs and sectors.

The financial sector is a perfect case study for understanding the nuances of the reallocation of STEM talent in the presence of the large-scale adoption of general purpose technologies and asymmetric sectoral shocks, such as trade shocks. First, it is well known that global imbalances increased the market size for US financial products, while the entry of China in the WTO induced a reduction of employment in US manufacturing (Acemoglu et al., 2016). Because technological development is positively related to market size (Romer, 1986; Murphy et al., 1989) and new technologies require skilled workers (Bartel et al., 2007), in recent decades, finance may have attracted more STEM talent than the manufacturing industry.

Second, the financial sector not only is a heavy adopter of information technologies but has also gradually become active in developing IT-related applications in fields such as data mining, information security and algorithmic trading. These innovations have shifted the nature of the tasks performed in financial jobs towards a more intensive use of STEM skills. The influential work by Autor et al. (2002) describes how the set of tasks performed by bank tellers became more complex following the introduction of digital check imaging. While this initial task-shift mainly pertained clerical jobs, recent innovations have substantially changed the nature of top financial occupations such as financial analysts. For example, tasks such as high-frequency and automated trading require extremely high proficiency in math, coding and problem solving, which are skills typically possessed by postgraduate workers in science and engineering. To track changes in the nature of financial jobs, we use recent waves of the American Community Survey, which contain information on degree field to document how, in typical financial jobs, the prevalence and the earnings of STEM talent have changed.

Finally, the services of the financial sector are needed by the entire economy, and thus, an increase in efficiency of finance may have large spillovers on the real economy. 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. Theoretically, one should expect these spillovers to be magnified following the deregulation of several financial activities, such as the removal of interest rate ceilings in the 80s and the repeal of the Glass-Steagall Act on the separation of investment and commercial banks in 1999. As a key driver of efficiency improvements, skill upgrading in finance should favor the reallocation of capital to more productive uses. Unfortunately, on top of the astonishing increase in financial sector wages, the two deregulation waves of the 80s and 2000s have been associated with a productivity slowdown in the real economy (Fernald, 2015). This central role of the financial sector suggests that what happened there and the massive STEM reallocation to finance in particular could contribute to explaining this productivity slowdown. Our paper seeks to provide support to the brain drain explanation put forward in a cross-country setup by Kneer (2013a) and Cecchetti and Kharroubi (2015) focusing on the types of competencies that are more likely to be misallocated to finance, i.e., scientific, technical and engineering skills.

The paper is organized as follows. Section 2 describes the dataset and the measures of STEM skills. Section 3 documents the long-term evolution of STEM workers across sectors, while Section 4focuses on the post-crisis period, for which we have a better measure of STEM input. Section 5 analyses the effect of the reallocation of STEM workers to finance on productivity in the real economy. Section 6 concludes with a discussion of the policy implication of our analysis.

2 Data and measures

Our main sources of information about the importance of STEM workers in the workforce are individual-level data from the decennial censuses (years 1980, 1990 and 2000) and the American Community Survey (ACS, years 2009-2014), 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.

[Table 1 about here]

The ideal measure of the sectoral intensity of STEM inputs is the share of workers with a STEM degree over the total number of employees of the sector. 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. To fix the ideas, Table 1 lists the STEM fields of study grouped by field, namely, computer science, mathematics, engineering and technology, science. However, such a degree-based measure is only available for the period 2009-2014, when ACS data started including systematic information on the field of study for graduate and postgraduate workers, while no information on the field of study was collected in previous ACS waves and in decennial censuses. Provided that the increase in the use of STEM workers by the financial sector occurred well before this period, we should rely on alternative measures to examine the STEM dynamics for a longer time span.

[Table 2 about here]

A first natural alternative is to use the share of workers in STEM occupations because occupations are defined in a consistent way across different censuses and ACSs (*occ1990* classification). Table 2 defines the main occupational grouping used throughout the paper. Our preferred occupation-based measure of STEM input includes math, statistics and computer science occupations but not engineering occupations (column 3) because these *core STEM jobs* represent more than 95% of STEM employment in the financial sector. Further, core STEM jobs are those that are complementary to innovative financial activities that intensively use ICT technologies, such as high-frequency trading and asset management.

Notice that the demand of STEM inputs has changed in finance both because financial companies have offered more STEM positions and because the tasks performed in typical financial positions, such as financial analyst (see Table 2), became more math-oriented. Using the share of workers in core STEM occupations captures only the first type of change but does not allow for a proxy of effective STEM education allocated to finance. Our second and third measures overcome this shortcoming by taking the share of workers in a core STEM job with a degree or a postgraduate degree, respectively. The focus on postgraduates is particularly important as they account for a large and growing share of the college wage premium (Eckstein and va Nagypl, 2004).[8] Arguably, given the highly specific skill requirements of STEM occupations, a graduate worker in a STEM occupation should hold a degree in a STEM-related discipline.[9]

The fourth measure exploits information contained in the Dictionary of Occupations and Titles (DOT), particularly the measure of the mathematical aptitude required for an occupation. Aggregated at the sectoral level, this measure captures the aggregate math input used by a sector but not the specific contribution of highly skilled workers, such as STEM professionals, to this input.

Following Philippon and Reshef (2012), our generic measures $y^{stem}_{j,t}$ of the STEM input's intensity in sector j at time t are as follows:

$$y^{stem}_{j,t} = \frac{\sum_{i \in j} \lambda_{i,t} h_{i,t} I_{i \in stem,t}}{\sum_{i \in j} \lambda_{i,t} h_{i,t}}, \tag{1}$$

where $\lambda_{i,t}$ and $h_{i,t}$ are sample weights and hours worked, respectively, and $i \in j$ denotes that the individual i works in sector j. $I_{i \in stem,t}$ is a dummy indicating that the individual i works in a STEM job. When our measure of STEM input takes education into account as well, $I_{i \in stem,t}$ is a dummy variable that is equal to one if i works in a STEM job and is a graduate or postgraduate. When our measure of STEM is math aptitude from the DOT, we replace $I_{i \in stem,t}$ with the DOT math score, which varies between 1 and 5 in equation 1. Finally, for the analysis of the sectoral distribution of STEM degrees for 2009-2014, $I_{i \in stem,t}$ is equal to one if individual i holds a STEM degree as defined in Table 1.

[Table 3 about here]

Concerning the sectoral breakdown, we aggregate finance and other key industries based on the harmonized classification *ind1990* that is available both in the decennial censuses and in ACS. The sectors, based on *ind1990*, are described in detail in Table 3. Regarding finance, we follow Philippon and Reshef (2012) and include banking; savings institutions, including credit; credit agencies n.e.c.; securities, commodity brokerage, and investments; and insurance. In Table 3, we also define a set of key sectors that are the main employers of STEM talent and thus are used throughout the paper as the main comparison group. These sectors can be divided into seven groups: knowledge-intensive business sectors (KIBS henceforth), health, education, utilities, mining and quarrying, high-tech manufacturing sectors (HT henceforth) and low-tech manufacturing sectors.

[8]We define postgraduate education as 17 or more years of education, as in Lindley and Machin (2016).

[9]A detailed discussion about the overlap between degree field and occupation is conducted in Section 3.2

3 STEM workers in finance, 1980-2014

This section illustrates the long-term evolution of STEM human capital and wages in the financial sector compared to other sectors. In line with the focus on the allocation of STEM talents among alternative uses, we mostly consider pairwise comparisons between finance and the two main employers of STEM talents; that is, the HT manufacturing sectors and KIBS. This comparison allows us to compare the capacity of finance to attract talent with respect to sectors that were not only early and extensive adopters of ICT but are also important engines of sustained productivity growth, thus representing a "productive" entrepreneurial use of scientific talents as opposed to an "unproductive" one (Baumol, 1990). The next sub-section illustrates the unconditional differences between finance and other sectors in the use of STEM skills, while in sub-section 3.2, we depurate these differences from observable proxies of technology, education and the initial level of STEM skills.

3.1 Unconditional differences: finance vs. selected sectors

Table 4 describes the distribution of STEM and core STEM jobs across different sectors in 1980 and 2014. Two salient facts emerge. First, KIBS and the financial sector absorbed the bulk of the well-documented increase of core STEM workers in the US economy between 1980 and 2014.[10] Although KIBS were employing only 18% of science, math and computer science workers in 1980, this share almost doubles in 2014. At the same time, the financial sector becomes the second-largest employer of core STEM workers, reaching 11.5% of total STEM employment in 2014.[11] Comparing the share of core STEM and STEM workers (including engineers), it becomes apparent that core STEM job represent the bulk of STEM employment in the financial sector. This observation justifies our focus on core STEM workers in the remainder of the paper. Second, high- and low-tech manufacturing industries experienced an impressive decline in their capacity to attract core STEM employment relative to other sectors. Such large changes in the sectoral distribution of STEMs may have had a significant effect on the productivity growth of manufacturing in as much as STEMs represent a key input of knowledge creation and innovation.

[Table 4 about here]

Large shifts in the distribution of STEM across sectors also reflect changes in the weight of each sector in the US economy. The decline of manufacturing employment may have thus mechanically driven down the number of STEM workers employed in HT manufacturing relative to other sectors. To account for the long-term decline in US manufacturing employment, a better measure is the share of STEM workers within a given sector as it informs us on the extent to which the incidence of STEM skills increases in the sectoral input mix.

[Figure 1 about here]

[10] According to our calculations, the share of hours worked by STEM jobs has increased from 2.8% of the total in 1980 to 4.8% of the total in 2014. When focusing on core STEM jobs, their share grew from 1% in 1980 to 3.2% in 2014.

[11] Interestingly, a recent study of the UK Commission for Employment and Skills shows that finance is the top employer of STEM graduates in the UK with 20% of total STEM workers (UKCES, 2015)

The top three panels of Figure 1 depict the evolution of the share of core STEM jobs within a sector as described by equation 1. For our three main measures of STEM skills (the share of core STEM workers, share of core STEM workers with a college degree and share of core STEM workers with a postgraduate qualification), the growth rate is remarkably higher in the financial sector compared to HT and KIBS. Interestingly, the divergent pattern is concentrated in the last 15 years after the acceleration in financial sector deregulation, which has been considered the main driver of wage and skill changes in finance by the influential paper of Philippon and Reshef (2012). To ensure that the these trends are not simply driven by the general boost of wages and human capital in finance, the bottom three panels of Figure 1 show the evolution of average hourly wages, share of college graduates and share of postgraduates in the same sectors. Compared to the finding of Philippon and Reshef (2012), the clear message is that at least in the period 1980-2014, the financial sector performs better than HT manufacturing only in terms of STEM input and that the average hourly wage paid to core STEM workers follows the same differential trend in the two sectors. Indeed, between 1980 and 2014, the share of college graduates and postgraduates grew faster in HT manufacturing than in finance.

[Figure 2 about here]

The fact that the tremendous acceleration in the use of STEM by the financial sector represents the most salient difference with respect to other sectors is also evident when using the routine vs. non-routine task constructs proposed by Autor et al. (2003).[12] Figure 2 shows that the financial sector becomes less routine intensive (top-left panel) than other key sectors by increasing the use of both non-routine abstract tasks (i.e., math) and interactive tasks (i.e., DCP) tasks compared to routine cognitive tasks (i.e., set standards).

[Table 5 about here]

Figure 1 illustrates the differences in STEM growth between finance and the rest of the economy but does not actually compare the levels of STEM intensity. The faster growth in the use of STEM in finance may merely reflect a catching-up phenomenon that is also evident when looking at the evolution of 'other sectors' but not HT and KIBS in Figure 1. Table 5 reports the level of core STEM intensity in the key macro-sectors and confirms the strong acceleration in STEM intensity in financial sectors compared to other key sectors. What is striking is that in finance (and compared to other sectors), the intensity of core STEM workers increases significantly more than the intensity of STEM workers.[13]

[Figures 3 and 4 about here]

[12]Task scores are taken from the 1991 (revised fourth) edition of the Dictionary of Occupations and Titles (DOT). More information on how this task constructs are built see (Autor et al., 2003). The RTI index is built as the logarithm of the ratio between the importance of routine tasks (finger dexterity and set limits, tolerances and standards) and non-routine abstract and interactive tasks (respectively, math and DCP - direction and planning). A value of 0 means that routine and non-routine tasks have the same importance for the occupation.

[13]For the sake of space, we do not report results for different financial sectors. As expected, investment banking experienced an even more pronounced increase in STEM inputs than other financial sectors. These results are available upon request by the authors.

To make these trends visually evident, Figure 3 plots the relative STEM intensity of finance compared to high-tech manufacturing, i.e., the ratio of STEM intensity in finance over STEM intensity in HT. Although starting from a substantially lower point in 1980, the level of STEM skills and wages in finance eventually reached or even passed that of HT manufacturing. This observation confirms that the documented skill upgrading of the US financial sector mostly pertained to STEM rather than general skills. When comparing finance with KIBS (Figure 4), we observe that even though the share of STEM and postgraduates in general remained significantly lower in finance than in KIBS, a substantial catching-up between 1980 and 2014 is found for both STEM, especially STEM postgraduates, and non-STEM measures of skills.

3.2 Conditional differences: finance vs. selected sectors

A more rigorous assessment of the sectoral differences in the use of STEM skills requires accounting for both the different exposure to (routine-replacing) technical change and for differences in the initial share of STEM talent to capture catching-up dynamics. In doing so, we fit simple regressions of the decennial change in various measures of sector-level STEM skills and human capital against the initial STEM level, a set of explanatory variables and a dummy variable for financial sector. The set of explanatory variables is intended to control for observable characteristics of the sector that naturally affect the demand of STEM workers. More specifically, we estimate the following equation:

$$\triangle y_i = \alpha + \phi y_{i,t-10} + \beta FIN\_I_i + X'_{i,t-10}\gamma + \varepsilon_i \qquad (2)$$

where the dependent variable y_i is the 10-year (7-year for the two sub-periods in the 2000s) difference in our measures of STEM inputs in industry i; FIN_I_i is our variable of interest and equals one for the financial sector and is zero otherwise; $y_{i,t-10}$ is included to control for initial differences in STEM inputs; ε_i is the idiosyncratic error term. The vector of lagged controls $X'_{i,t-10}$ includes i. the index of routine intensity proposed by Autor and Dorn (2013) to account for the scope of ICT diffusion across different sectors[14]; and ii. the logarithms of the average years of schooling and the average age of the workforce, which capture the intensity in the use of general human capital and the natural rate of worker's replacement, respectively. To tighten our comparison, we estimate equation 2 only for the sub-set of 97 sectors (*ind1990* classification) that are the main employers of STEM workers (see Table 3). While these 97 sectors represent only approximately 45% of the US economy, they employ more than 70% of the US STEM workers. The coefficient associated with the dummy FIN_I_i thus captures the conditional difference in the evolution of STEM skills between finance and other STEM-intensive sectors.

[Table 6 about here]

Table 6 reports the estimation of equation 2 by decade. Panel A clearly highlights that compared to other key employers of core STEM workers, the

[14]Recall that the index of routine intensity has been used as a proxy for the scope of ICT adoption within a sector and thus accounts for routine replacing technical change that disproportionately affects those sectors, such as finance, that use intensively standardized clerical tasks (Autor et al., 2003).

positive differential growth of STEM skills in finance is quantitatively important. Three accelerations are observed in the decades 1980 and 1990 and after the Great Recession (2007-2014). In the 80s, the share of core STEM workers grew 0.72 percentage points more in finance than in other key sectors. Compared to the observed growth of the share of core STEM workers in other key sectors over the same period (0.83 pp), the conditional growth in finance has been 87% faster. The difference in the growth of the share of core STEM workers between finance and other key sectors remained significantly different from zero but slowed down substantially in the 90s. Quite surprisingly, during the period 2000-2007, when the second wave of liberalization occurred, the difference becomes imprecisely estimated and is no longer statistically significant. However, the effect is large: compared to the nearly absent growth of STEM input in other key sectors, finance keeps absorbing an increasing fraction of STEMs. Moreover, the imprecisely estimated coefficient for dummy finance in the period 2000-2007 masks a highly heterogeneous effect in different sub-sectors of finance. To illustrate, Table A1 in the Appendix A replicates these estimates by replacing the dummy finance with a dummy for investment banking, showing a large and significant acceleration concomitant with the liberalization waves of the 80s and the early 00s. Between 2000 and 2007, the growth of STEM skills in investment banking was significantly larger than the very small (0.02 pp) growth of STEM inputs in other key sectors. Interestingly, Table A1 also shows, holding everything else constant, that there has been an outflow of STEM from investment banking as would be expected after the collapse of this specific sub-sector in 2007.

Similar results are obtained using different measures of STEM input but with a few important differences. For the share of graduates employed in STEM jobs (Panel B), the relatively larger increase in finance in the 1980s and after the Great Recession period (2007-2014) are separated by the 1990s, when STEM input decreased in finance relative to other key sectors, although the coefficient is only statistically significant at the 10-percent level. This finding is consistent with the fact that the 1990s were a decade of rapid technical change and that productivity growth in capital equipment industries was thus able to ensure bright career opportunities for new graduates in STEM disciplines.

The second notable difference is that the share of postgraduates employed in STEM jobs increased only in finance with respect to other key sectors after the Great Recession (Panel C). This finding suggests that the STEM requirements became increasingly complex in the financial sector, possibly reflecting the diffusion of high-frequency trading. This interpretation is corroborated by the pattern of postgraduate hiring in STEM jobs by investment banks, which increases significantly more than in other key sectors despite the conditional decrease in the share of STEM jobs in this sub-sector after the Great Recession (see Table A1). In turn, using the DOT math attitude score (Panel D), the differential trend in STEM demand from finance is uniquely concentrated between 2000 and 2007 in both finance and investment banking. As math intensity is calculated as an average across all workers, while the share of core STEM considers only a specific subset of professionals, it is plausible that top workers explain the bulk of the documented brain drain effect.

A third difference emerges when estimating equation 2 for postgraduates in any discipline. Panel E shows, conditional on a host of demographic and technological controls, that the share of postgraduates grew at a significant slower pace in finance than in other key sectors between 1990 and 2007.

Overall, these results reinforce and confirm the first main finding of our paper: the skill upgrading in finance has been strongly biased toward STEM skills. Moreover, although not uniform across the finance sub-sectors and STEM measures, the findings after the 2000 are particularly striking given the sharp reversal in the demand of cognitive workers documented by Beaudry et al. (2016) and are contrary to what could be expected given the negative shock that hit the financial sector. Benefiting from new information in the field of study in the ACS data, the next section delves deeper into the post-crisis period.

4 STEM graduates after the Great Recession, 2009-2014

In the previous sections, we documented an acceleration in the process of STEM workers' reallocation toward finance. This section investigates whether these trends persisted after the Great Recession and the subsequent regulatory changes, notably the Dodd-Frank Act (see Krainer, 2012). As mentioned in section 2, the advantage of using the ACS data after 2009 is that they provide detailed information on the field of study of graduate workers. This feature is particularly important for directly observing the extent to which STEM graduates are employed in finance, either in STEM jobs or in non-STEM jobs. In addition, we can measure the wage premium of STEM graduates in finance compared to other sectors. Finally, we can indirectly validate the admittedly imperfect measures of STEM skills used for the longer panel. This validation is important for the last part of the paper, in which we evaluate the association between the STEM brain drain into finance and productivity growth in the real economy.

4.1 Comparison of our STEM measures

Table 8 presents simple descriptive statistics for our degree-based and occupation-based measures of STEM input across key sectors.[15] Notice first that in 2009, there is a small excess of STEM graduates (5.6% of total employment) relative to STEM jobs (5.5% of total employment) in the US economy. The financial sector is rather balanced, with a 6.7% share of workers that are STEM graduates (column 1) and a 7.3% (resp. 7.1%) share of workers employed in STEM (resp. core STEM) jobs (column 4). Among the other key sectors, the excess of STEM graduates relative to core STEM jobs is concentrated only in education and other industries, while KIBS display a large deficit of STEM graduates compared to STEM jobs.

[Table 8 about here]

Although the measure of STEM input based on STEM occupations rather than degrees seems accurate in aggregate, it is also interesting to use ACS data to further examine the distribution of STEM graduates in different occupations in the financial sector. Based on a rich anecdotal body of evidence, we expect that a portion of the STEM graduates employed in finance work as financial

[15] We extend our comparison group to include education and healthcare, which absorb a significant fraction of STEM graduates.

analysts rather than as computer software developers. To illustrate, Table 7 reports detailed information on the distribution of occupations and degree types in the finance sector averaged between 2009 and 2014. Clearly, there is mismatch as the share of STEM graduates working in core STEM occupations is only 39%. This mismatch is offset by the large share of STEM graduates working either in typical financial occupations or in other job positions. More than 2/3 of financial and STEM occupations are taken by graduate workers, and one out of ten financial jobs and one out of two for STEM jobs is held by STEM graduates. When decomposing these figures by degree field, we observe that although nearly all STEM jobs in finance are core STEM jobs, core STEM graduates (i.e., graduates in physics, math and computer science) do not constitute the whole population of STEM graduates working in finance. Specifically, computer and information science is the main STEM field of study for core STEM jobs in finance, while non-STEM jobs (financial or other jobs) have large shares of graduates in engineering, physics and, especially for financial jobs, mathematics and statistics.

[Table 7 about here]

4.2 Trends in the allocation of STEM graduates

Although depicting any trends in the short time frame between 2009 and 2014 may be difficult, Figure 5 reveals the emergence of some clear patterns. The hiring of STEM graduates (top-left and bottom-left) and of STEM postgraduates (top-right panel) are upwardly trended for the financial sector but shrinking for HT and stagnating for KIBS. Particularly striking is that the financial sector's ability to attract STEM talents has barely been damaged by the great financial crisis and the subsequent re-regulation of several financial activities.

[Figure 5 about here]

In the financial sector, the share of STEM graduates grew faster than the share of STEM jobs (also see panel B of Table 8). This finding can reflect either the hiring of STEM graduates in typical financial jobs, such as financial examiners, quantitative analysts or even CEOs (see Table 2 for the definition of typical financial jobs). In Figure 6, we address this issue by contrasting the evolution of STEM graduates in typical financial jobs (a measure of how the STEM input changed in typical financial jobs) with that of college graduates (in general), STEM graduates and graduates in business-related disciplines across the entire financial sector. The figure clearly indicates that the share of STEM graduates in typical financial jobs grew as fast as the share of STEM graduates in the financial sector as a whole. Moreover, the evolution of the two measures, both for the whole financial sector and for a typical financial job, outpaced that of college graduates and of graduates in business-related disciplines.

[Figure 6 about here]

In sum, our descriptive evidence based on information on STEM graduates rather than STEM workers as measure of STEM input is consistent with the picture that emerged from the analysis made over the period 1980-2014. The financial sector employed an increasing share of STEM graduates both in traditional STEM jobs and in typical financial jobs. The natural question is then whether STEM graduates are paid more in the financial sector and in finance jobs than in the rest of the economy and thus if finance is able to attract the most talented STEM graduates.

4.3 Wage differentials across sectors and jobs

Figure 7 gives an impressionistic picture of the unconditional wage differences for STEM graduates (left panel) and postgraduates (right panel) working in five alternative positions ranked from the highest to the lowest hourly wage: 1. financial jobs (highest), 2. STEM jobs in finance, 3. STEM jobs in HT, 4. STEM jobs in KIBS, 5. STEM jobs in the rest of the economy (lowest). In the left panel, we observe that after a modest decline at the beginning of our series, the divergence between the hourly wage of STEM graduates in financial jobs and the hourly wage of STEM graduates in STEM jobs began to widen again. The unconditional hourly wage premium for a STEM graduate working in a financial job is large not only compared to STEM jobs in other sectors (approximately 40% in 2014) but also compared to STEM jobs in high-tech manufacturing (about 24% in 2014). As evident from the right panel, this 'finance' premium becomes even larger for STEM postgraduates: the unconditional wage of a STEM postgraduate choosing a career in a typical financial job is expected to be 30% higher than that of a STEM postgraduate choosing a career in an HT STEM job. Note that the premium documented here is likely to be a lower bound of the actual wage premium of STEM graduates in finance. In fact, equity-based, cash and deferred bonuses, which are not included in our measure of hourly wage, constitute a much larger fraction of total earnings in finance than in other sectors (Lemieux et al., 2009; Bell and van Reenen, 2014).

[Figure 7 about here]

These large wage premiums for STEM graduates working in financial jobs could merely reflect differences in other characteristics of STEM workers employed in finance rather than rents or returns to STEM skills. To account for these differences, we estimate on a yearly basis variants of the following equation for individual j working in one of the key industries as defined above:

$$\begin{aligned} \log(w_j) &= \beta STEM\_D_j + \gamma FIN\_O_j + \\ &+ \eta STEM\_D_j \times FIN\_O_j + X_j'\theta + \varepsilon_j. \end{aligned} \quad (3)$$

X_j is a vector of standard controls in wage equations[16] and ε_j is the idiosyncratic error term. The main variable of interest is the interaction between a dummy variable that is equal to one for those with a STEM degree $STEM\_D_j$ and a dummy variable for those in a typical finance job FIN_O_j. Because we allow $STEM\_D_j$ and FIN_O_j to have an independent effect on wages, our variable of interest should be interpreted as the wage premium of STEM graduates when

[16]We include two-digit NAICS sector dummy variables, two-digit SOC occupation dummy variables, age and its square, a dummy variable for those living in a metropolitan area and dummy variables for male, married, foreign born, black, other ethnic group than white, some college, college graduates and postgraduates.

employed in a typical financial job compared to the average STEM graduate (and conditional on the worker's general educational attainment, broad occupational dummy variables and other characteristics). We also want to evaluate whether STEM graduates earn a higher or lower wage depending on the sector (rather than the occupation) where they work. To this end, we estimate the following equation:

$$\begin{aligned}\log(w_j) &= \beta STEM\_D_j + \gamma FIN\_I_j + \\ &+ \eta STEM\_D_j \times FIN\_I_j + X'\theta + \varepsilon_j,\end{aligned} \tag{4}$$

where FIN_I_j is a dummy variable for individuals working in the finance sector (which is however absorbed by 2-digit NAICS sector dummy variables included in the vector X). Our coefficient of interest is that of the interaction between this dummy variable and the STEM graduate dummy variable. To be consistent with the rest of the analysis, both equations are estimated for the key sectors only and using person weights.

[Table 9 about here]

Table 9 reports the main results, with panel A focusing on the wage premium of STEM graduates in financial jobs (equation 3) and panel B focusing on the wage premium of STEM graduates in the finance sector (equation 4). Across the board, we detect significant and slowly increasing wage premiums of approximately 8 percent for STEM graduates that should be added to the estimated but unreported graduate wage premium. Turning to our variable of interest, we find that the additional wage premium for STEM graduates working in typical financial jobs remains statistically significant when we control for a rich set of worker characteristics. Although this bonus is strongly declining over time, possibly reflecting the effect of the Great Recession, it is still considerable, corresponding to an additional hourly wage of 2.9 percent in 2014; that is, a wage premium that is 30% higher than the basic STEM graduate premium. Note that this premium is also large compared to what a typical financial worker can make holding everything else constant. In 2014, the additional premium for a STEM graduate working in a typical financial job is more than 25% higher than the average wage premium for this kind of job.

When considering the industry-specific dimensions of the STEM wage premium (panel B), we observe that STEM graduates are paid significantly more in the financial sector compared to other sectors. Again, this premium is significantly lower in 2014 than at the end of the Great Recession but remains statistically different from zero. Overall, we observe that the significant and large conditional wage premium for STEM graduates working in the financial sector has both a sectoral and an occupation-specific component.

[Figure 8 about here]

In addition to the average wage premiums, we also investigate whether STEM graduates obtain a differential wage premium at different quantiles of the wage distribution by means of quantile regression. This exercise is useful for discriminating between the wage premium of highly talented versus normally talented STEM graduates as ranked by their position in the wage distribution.

In Figure 8, we plot for each decile of the wage distribution i. the average wage premium of STEM graduates; ii. the wage premium for STEM graduates employed in typical financial occupations; and iii. the wage premium for STEM graduates employed in finance industries. To gauge trends at various points of the distribution, we estimate these premiums separately for years 2009 (panel A) and 2014 (panel B). The main message is that the wage premium of a STEM graduate working in a typical financial job is uniformly increasing along the wage distribution. This finding contrasts with the flat profile of the premium of STEM graduates employed elsewhere.

Looking at the changes over time, the STEM wage premium for those working in the financial sector becomes much flatter than that of those working in a typical financial job and closely resembles that of STEM graduates employed elsewhere. While the steepness of the STEM premium in a typical finance job also decreased considerably in 2014 as compared to 2009[17], in the 9^{th} decile, this premium remains two times larger than that for STEM graduates employed elsewhere. The occupation component of the STEM wage premium in finance appears to be far more important than the sectoral component at the top of the wage distribution. This enriches previous analyses of the finance wage premium that focus on the sectoral dimension only Philippon and Reshef (2012).

The lesson we can draw from this section is that the wages of STEM graduates are significantly higher in the financial sector and in typical financial jobs whether we control for observable individual characteristics or not. Unless STEM graduates do not have strong preferences for working on path-breaking scientific discoveries to solve real problems, our estimated wage premiums suggest that finance is able to attract the best STEM graduates and, as our quantile estimates indicate, that the brightest among them likely work in typical financial jobs. The next step is to make a preliminary effort to investigate the possible consequences of this reallocation of STEM talent for the real economy.

5 Productivity and STEM talents

This section provides empirical evidence on the long-term impact of the reallocation of STEM workers into the financial sector on the performance of the real (non-financial) economy. Following previous studies (e.g. Barth et al., 2016) that documented the key role of STEM graduates as drivers of technological progress and productivity growth, our measure of performance is the long-term change in labor productivity.

We focus on both the whole US economy and the manufacturing sector alone. This focus is consistent with the fact that manufacturing has experienced a decline in the capacity to attract STEM workers that may be partially explained by the poaching of STEMs by finance.

5.1 Data

Data on capital stock, output and labor productivity (output per worker in constant prices) at the industry level for the whole economy were retrieved from the "Multifactor Productivity Measures for Major Sectors and Manufacturing"

[17]To illustrate, while the the difference between the 9^{th} and the first decile was 19.1% in 2009, this difference shrinks to 11.1% in 2014.

of the Bureau of Economic Analysis (BEA). These data cover the private business sector for the period 1987-2014 with a breakdown of 59 NAICS industries (see Table B1 in the Appendix B). For the analysis on the manufacturing sector alone, we employ the NBER-CES 'Manufacturing Industry Database' [18]. The main advantage is that the NBER-CES database has a breakdown of 63 manufacturing sectors (see Table B4), while in the BEA database, the breakdown for manufacturing comprises only 18 sectors. Moreover, the NBER database allows us to compute productivity measures starting from 1980, i.e., the beginning of the financial sector deregulation to which Philippon and Reshef (2012) ascribe the bulk of changes in wages and human capital examined here. As a result, our analysis of the whole real economy covers the timespan 1990-2014 split in three sub-periods (1990-2000, 2000-2007 and 2007-2014), while our analysis on the manufacturing sector covers the timespan 1980-2007 split in three sub-periods (1980-1990, 1990-2000 and 2000-2007).

For each year, proxies of STEM input by industry are calculated as usual: the sectoral average of the STEM measure (e.g., core STEM jobs and math intensity) weighted by sampling weights multiplied by the average hours worked. To match the industrial classification of the harmonized Census and ACS (*ind1990*) with the NAICS classification of the BEA and NBER-CES database, we exploit the fact that from 2000 onward, the industry of each employee in the ACS is double coded in both *ind1990* and NAICS. We instead use a weighted crosswalk to match *ind1990* and NAICS for the decennial censuses (1980, 1990, 2000), inferring weights from ACS data in 2000.[19]

5.2 Estimation framework

Our starting point is a standard production function framework augmented for human capital (e.g. Mankiw et al., 1992). The general estimation equation is:

$$\begin{aligned} log(y_{i,t}) &= \psi log(k^s_{i,t}) + \phi log(k^e_{i,t}) + \\ &+ \eta log(l_{it}) + \theta_t RTI_{i,0} + \beta STEM_{it} + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where $log(y)_{i,t}$ is the log of the output (in constant price) per worker in sector i at time t, $log(k^s_{i,t})$ is the log of the capital stock in structures per worker, $log(k^e_{i,t})$ is the log of the capital stock in equipment per worker, $log(l_{it})$ is the log of employment to allow for the possibility of increasing or decreasing returns to scale, $RTI_{i,0}$ is the initial routine task intensity index measured in the first year

[18] See, http://www.nber.org/nberces/.

[19] The NAICS code of workers in IPUMS data is available only in the ACS (2000-2014) data (283 industries in the private sector) while an harmonized industry classification (*ind1990*, with 163 industries in the private sector) is available both in ACS and in the decennial censuses. To harmonize information about industry-level STEM input for the years in which we use the decennial censuses (1990 and 2000) to match the BEA-NAICS and NBER-NAICS aggregations we build a weighted crosswalk between *ind1990* and the detailed NAICS codes using individual data in ACS that are coded both with *ind1990* and NAICS. The average weights (based on year 2000) for the crosswalk are based on sampling weights multiplied by the average number of hours worked per individual. Out of 196 (70) *ind1990* industries, as many as 177 (62) can be matched one-to-one to the corresponding BEA-NAICS (NBER-NAICS) industry. The exact *ind1990*-NAICS crosswalks for BEA and NBER classifications are reported in Tables B2 and B5 in the Appendix B, while the weighted *ind1990*-NAICS crosswalks are reported in Tables B3 and B6 in the Appendix B, respectively.

and interacted with time dummy variables to flexibly account for the exposure of the labor force to automation, μ_t are time effects and $\varepsilon_{i,t}$ is the idiosyncratic error term.[20]

This production function framework is extended to account for the role played by human capital in productivity growth and to evaluate how the reallocation of STEM talents to finance contributes to productivity growth in other sectors but finance. The key variable here is $STEM_{it}$, which is the share of workers employed in core STEM occupations in sector i and year t. Consistent with the descriptive evidence above, we consider all core STEM workers as well as core STEM workers with a college degree.

We estimate equation 5 in first-difference form for all variables as we are interested in the effect of $STEM_{it}$ input on productivity growth. Because there is no consensus on whether the stock or flow of human capital input affects productivity dynamics (Benhabib and Spiegel, 1994), we estimate an alternative specification where the STEM input is the average value between start and end period. In both specifications, we also include the pre-sample mean of output per capita (in log) to account for different productivity dynamics depending on initial conditions. Finally, sectors are weighted by initial hours worked in the industry. Finance sectors (see Table B1) are excluded from the analysis.

Our simple strategy to account for the effect of STEM reallocation into finance on productivity in the rest of the economy consists of simulating a counterfactual productivity growth in the absence of such reallocation. In practice, we assume that the share of STEM workers in finance remained fixed at the initial level. We then reallocate the exceeding STEM workers from finance to non-finance industries proportional to the ratios of STEM workers relative to the whole economy at the beginning of each period. For instance, if an HT industry employed 3% of all STEM workers in 1990, it will receive 3% of the difference in the number of STEM workers in finance between 1990 and 1980. The counterfactual productivity is computed using the estimated contribution of STEM workers to productivity ($\hat{\beta}$).

A caveat is required at this point. Our counterfactual measure is not obtained through a structural equation model and thus does not provide a precise account of the global welfare losses and gains in the absence of such a reallocation. Moreover, our exercise can be best seen as a preliminary way to isolate a particular channel through which the absorption of STEM into finance can affect the real economy. The next section illustrates the main result of this preliminary exercise and discusses in greater detail the source of bias in our estimates.

5.3 Results and discussion

The results of the estimates of equation 5 reported in Appendix C and in Tables C1 and C2 suggest statistically significant and large contribution of STEM workers to labor productivity in all specifications, as expected. This finding means that the documented shift of STEM talent to the finance sector had the effect of reducing labor productivity in the real economy and thus can be labeled as a "misallocation".

[20]When considering the whole real economy, we also allow for specific time dummy variables in the manufacturing sectors.

[Tables 10 and 11 about here]

To frame our simulated counterfactual, the cumulative labor productivity growth in the whole real economy over the period 1990-2014 was 34.35 percent, while the cumulative labor productivity growth in manufacturing over the period 1980-2007 was 135.42 percent. If we assumed that the share of STEM workers in finance remained fixed at the initial level (1990 for the whole real economy, 1980 for manufacturing) and the excess of STEM workers were reallocated proportionally to non-finance sectors, we would have observed a relative increase in the share of STEM workers of 6.6 percent and 9.84 percent for the whole real economy and the manufacturing sector, respectively (9.46 percent and 12.44 percent if we consider STEM workers with a college degree). This assumption means that we simulate that about 261 thousand STEM workers who were actually employed in finance in 2014 were reallocated back to non-finance sectors.

When considering the whole real economy, we estimate a very modest gap between the actual cumulative productivity growth and the simulated counterfactual growth with no misallocation. Depending on the specification chosen, the cumulative growth of productivity would have been 0.31 to 0.98 percent higher in the absence of the STEM reallocation to finance. The impact is only slightly larger when considering STEM workers with a college degree (between 0.33 percent and 1.14 percent). However, the gap becomes economically meaningful for the manufacturing sectors alone for the period 1980-2007. The cumulative gains in output per capita are now in the range of 6.6 to 7.8 percent, again with no notable differences between STEMs and graduate STEMs. These results are fully consistent with the fact that the decline of STEM input has been mostly concentrated in manufacturing. Note also that these impacts are larger in high-tech sectors that employ a larger share of STEM workers. The cumulative gains in the absence of the reallocation of STEM workers to finance for high-tech manufacturing sectors would have been between 9.71 and 12.39 percent (between 8.21 and 9.62 percent when considering STEM workers with a college degree). Given the substantial technological spillovers of these high-tech sectors on the rest of the economy (Lockwood et al., 2017), these estimated effects are likely to be a lower bound of the true misallocation effect.

Other sources of bias can affect our counterfactual estimate of the misallocation effect. First, there is no doubt that financial development is a key driver of growth and prosperity (Rajan and Zingales, 1998; Levine, 2005). An increase in the efficiency of finance can have positive repercussions on the real economy, and this is what may have occurred thanks to a more intensive use of mathematical and statistical inputs. The limited variation of our data does not allow for the identification of such spillovers that would work against our conclusion that there has been a misallocation of STEM into finance. However, anecdotal evidence suggests that STEM graduates are employed in tasks such as algorithmic trading that have little direct impact on the real economy. Put differently, it seems quite unlikely that STEM inputs have been used to improve the channels through which finance can positively affect the real economy, such as the production of information about investment opportunities, monitoring firms or the provision of credit to innovative firms.

Second, we cannot isolate endogenous supply responses driven by the STEM wage premium in Wall Street jobs. For instance, it may be the case that part of the substantial immigration of STEM talents to the US has been driven by high expected rewards in finance.[21] Likewise, we cannot measure the extent to which the increase in STEM graduates over the past four decades has been driven by high expected earnings in finance. On the one hand, since both these endogenous supply responses increase the mass of STEM in the economy, they should mitigate the misallocation effect. On the other hand, the inflow of foreign STEM in the US decreases the global capacity to innovate and may have negative spillovers for the US economy as well.

Third, we cannot measure talent heterogeneity within the STEM group. If, as is suggested by our analysis of the STEM wage premiums in finance, the most talented STEM workers end up working in finance (e.g., in high-frequency trading) rather than in high-tech industries (e.g., discovering new drugs and cleaner technologies), our estimated effects are definitely a lower bound. To illustrate, it is well-known in the literature that the distribution of research productivity is highly skewed, with few inventors accounting for the bulk of valuable innovations (e.g., Narin and Breitzman, 1995). As a result, the consequence of a few top scientists moving from high-tech manufacturing to finance can be considerable in terms of productivity growth. This issue relates to the recent debate on declining research productivity (Bloom et al., 2017), questioning the extent to which the poaching of the best STEM graduates by finance has contributed to reducing scientific productivity in the US economy.

Overall, the sources of bias tend to offset each other and may even be favorable to our conclusions. We can hence conclude that the reallocation of core STEM talents into finance has been *de facto* a misallocation given its negative consequences for productivity in the real economy, especially so in the manufacturing sector.

6 Concluding remarks

We document the remarkable change in the sectoral allocation of STEM talents in the US economy over the past four decades. The salient feature is an impressive inflow of STEM workers and graduates into finance at the expense of high-tech manufacturing sectors. The general skill upgrading in finance has been strongly biased towards STEM skills. The large wage premium paid to STEM graduates in the financial sector and even more in typical financial jobs is compatible with several anecdotes of top scientists going to work in hedge funds or investment banks. Indeed, not only is this premium large compared to that received in STEM jobs outside finance but it also is magnified at the top of the income distribution.

Our study seeks to provide a preliminary answer to the fundamental question as to the impact of the STEM brain drain into finance on the real economy. We find that this impact has been modestly large in manufacturing and accounts for approximately 6.6% of lost cumulative productivity gains over the sample period. Although our strategy may not be able to identify the size of the effect precisely, we still believe that we are at least depicting a strong correlation between the STEM inflow towards finance and productivity growth in the real

[21] There is a active literature on the increasing importance of STEM immigrants in the US economy. See, e.g, Hanson et al. (2016) and Jaimovich and Siu (2016).

economy. With this caveat in mind, we can draw some policy implications from these results.

First and foremost, our results indicate that focusing on STEM education to reignite sluggish productivity growth may not suffice in the presence of distortions that prevent the first-best allocation of STEM talent to sectors and jobs. Given the extremely high education cost of an engineer compared to other graduates (Altonji and Zimmerman, 2017), the US economy cannot afford to waste the brightest STEM talents on unproductive rent-seeking uses. Regulation can help solve the allocation problem by reducing the negative externality generated by a pure market allocation of talents. The first-best option would be a sort of Pigouvian tax equivalent to the marginal damage (in terms of forgone productivity improvements) created by a STEM graduate employed in finance. However, it may be extremely difficult to precisely estimate the size of this negative externality.

An alternative measure would be to enforce more serious limits on the range of activities that can be performed by the financial sector, up to the point of banning STEM-intensive activities such as high-frequency trading altogether. Clearly, the recent regulation of the financial sector (i.e., the Dodd-Frank Act) has not been sufficient to restore a more efficient allocation of STEM talents toward productive uses. A more ambitious approach is thus required but will hardly be pursued by the new US administration. Either way, a much-needed political priority is to carry out a detailed evaluation of the net social value created by certain financial activities where STEM graduates are intensively employed.

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Tables and figures

Table 1: Definition of STEM degrees (for ACS 2009-2014)

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

Table 2: Definition of STEM and Finance occupations (based on the *occ1990* classification in IPUMS)

Core STEM occupations	**Non-core STEM occupations**	**High-skill financial occupations**
Computer systems analysts and computer scientists	Aerospace engineer	Chief executives and public administrators
Operations and systems researchers and analysts	Metallurgical and materials engineers	Financial managers
Actuaries	Petroleum, mining, and geological engineers	Accountants and auditors
Statisticians	Chemical engineers	Insurance underwriters
Mathematicians and mathematical scientists	Civil engineers	Other financial specialists
Physicists and astronomers	Electrical engineer	Actuaries
Atmospheric and space scientists	Industrial engineers	
Physical scientists, n.e.c.	Mechanical engineers	
Computer software developers	Not-elsewhere-classified engineers	
	Chemists	
	Geologists	
	Agricultural and food scientists	
	Biological scientists	
	Foresters and conservation scientists	

Figure 1: Evolution of STEM jobs and other skill measures: finance vs. selected sectors, 1980-2014

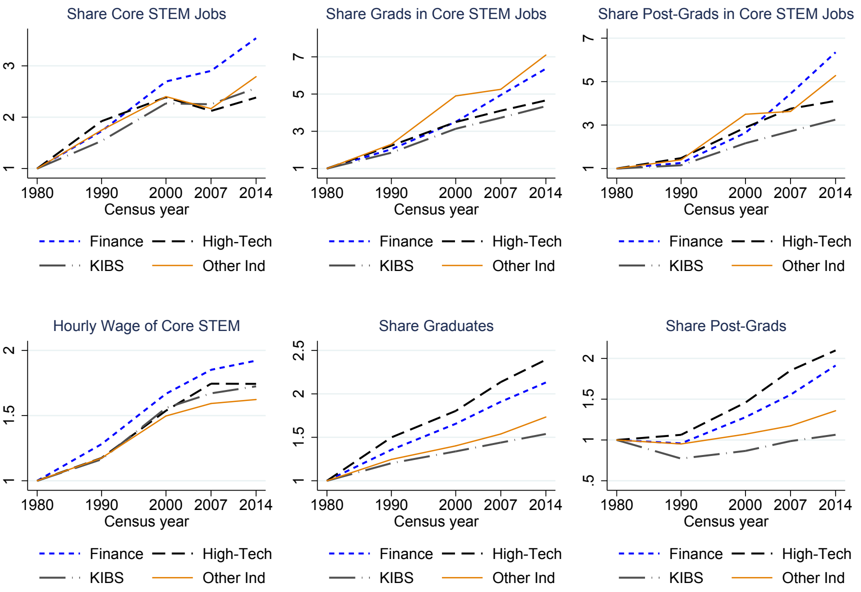


Figure 2: Evolution of DOT task measures: finance vs. selected sectors, 1980-2014

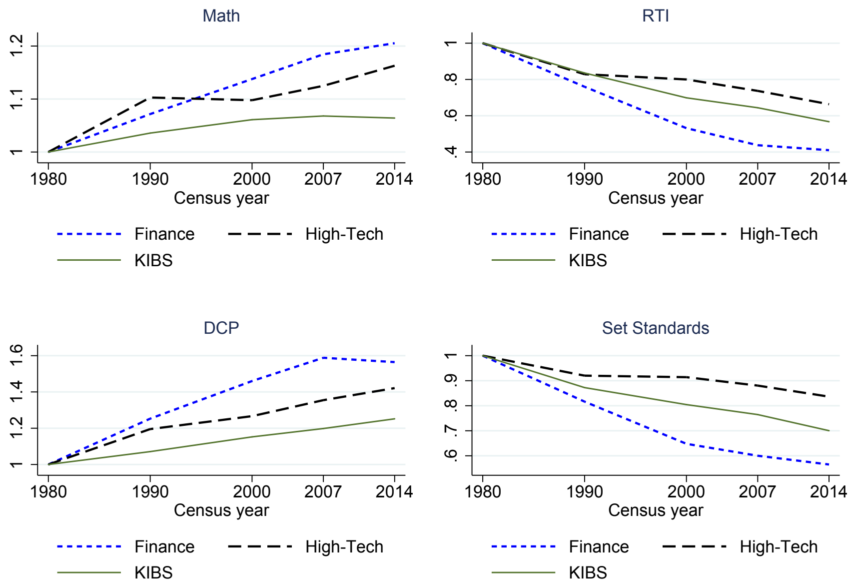


Table 3: Definition of key industries (based on the *ind1990* classification in IPUMS)

Finance:	**Medium-low tech manufacturing:**
Banking	Meat products
Savings institutions, including credit	Dairy products
Credit agencies, n.e.c.	Canned, frozen, and preserved fruits and vegetables
Security, commodity brokerage, and investments companies	Grain mill products
Insurance	Bakery products
	Sugar and confectionery products
KIBS:	Beverage industries
Computer and data processing services	Misc. food preparations and kindred products
Engineering, architectural, and surveying services	Food industries, n.s.
Research, development, and testing services	Tobacco manufactures
	Knitting mills
Health:	Dyeing and finishing textiles, except wool and knit goods
Offices and clinics of physicians	Carpets and rugs
Offices and clinics of dentists	Yarn, thread, and fabric mills
Offices and clinics of chiropractors	Apparel and accessories, except knit
Offices and clinics of optometrists	Miscellaneous fabricated textile products
Hospitals	Pulp, paper, and paperboard mills
Nursing and personal care facilities	Miscellaneous paper and pulp products
Health services, n.e.c.	Paperboard containers and boxes
	Newspaper publishing and printing
Education:	Printing, publishing, and allied indust
Elementary and secondary schools	Plastics, synthetics, and resins
Colleges and universities	Soaps and cosmetics
	Paints, varnishes, and related products
Utilities:	Agricultural chemicals
Gas and steam supply systems	Industrial and miscellaneous chemicals
Electric and gas, and other combination	Petroleum refining
Water supply and irrigation	Miscellaneous petroleum and coal products
	Tires and inner tubes
Mining and quarrying:	Other rubber products, and plastics footwear and belting
Coal mining	Miscellaneous plastics products
Oil and gas extraction	Footwear, except rubber and plastic
	Leather products, except footwear
High-tech manufacturing:	Logging
Drugs	Sawmills, planing mills, and millwork
Computers and related equipment	Wood buildings and mobile homes
Machinery, except electrical, n.e.c.	Furniture and fixtures
Machinery, n.s.	Glass and glass products
Household appliances	Cement, concrete, gypsum, and plaster products
Radio, TV, and communication equipment	Structural clay products
Motor vehicles and motor vehicle equipment	Pottery and related products
Aircraft and parts	Misc. nonmetallic mineral and stone products
Ship and boat building and repairing	Blast furnaces, steelworks, rolling and finishing mills
Railroad locomotives and equipment	Iron and steel foundries
Guided missiles, space vehicles, and parts	Primary aluminum industries
Cycles and miscellaneous transportation	Other primary metal industries
Scientific and controlling instruments	Cutlery, handtools, and general hardware
Medical, dental, and optical instruments and supplies	Fabricated structural metal products
	Metal forgings and stampings
	Ordnance
	Miscellaneous fabricated metal products
	Metal industries, n.s.
	Engines and turbines
	Farm machinery and equipment
	Construction and material handling machines
	Metalworking machinery
	Toys, amusement, and sporting goods
	Miscellaneous manufacturing industries
	Manufacturing industries, n.s.

Table 4: Allocation of STEM workers across industries: 1980-2014

Distribution of STEM jobs across sectors (share of total STEM jobs)	1980	2014
Finance	0.0377	0.0801
KIBS	0.1588	0.3120
High-Tech Manuf.	0.2830	0.1652
Low-Tech Manuf.	0.1775	0.0736
Oil	0.0278	0.0131
Utilities	0.0127	0.0068
Health	0.0199	0.0384
Education	0.0452	0.0478
Other Industries	0.2374	0.2631
Distribution of core STEM jobs across sectors (share of total core STEM jobs)	**1980**	**2014**
Finance	0.0965	0.1150
KIBS	0.1805	0.3396
High-Tech Manuf.	0.1998	0.0847
Low-Tech Manuf.	0.1194	0.0447
Oil	0.0115	0.0042
Utilities	0.0110	0.0042
Health	0.0326	0.0508
Education	0.0949	0.0638
Other Industries	0.2538	0.2930

Table 5: STEM intensity by industry, 1980 and 2014

Share of STEM jobs over total employment in the industry	1980	2014
Finance	0.0211	0.0699
KIBS	0.2998	0.4209
High-Tech Manuf.	0.0923	0.1585
Low-Tech Manuf.	0.0281	0.0450
Oil	0.0755	0.0768
Utilities	0.0572	0.0744
Health	0.0073	0.0160
Education	0.0175	0.0255
Other Industries	0.0134	0.0222
Share of core STEM jobs over total employment in the industry	**1980**	**2014**
Finance	0.0192	0.0680
KIBS	0.1210	0.3104
High-Tech Manuf.	0.0231	0.0551
Low-Tech Manuf.	0.0067	0.0185
Oil	0.0111	0.0165
Utilities	0.0176	0.0313
Health	0.0043	0.0143
Education	0.0130	0.0231
Other Industries	0.0051	0.0167

Figure 3: Relative comparison: finance vs. high-tech manufacturing

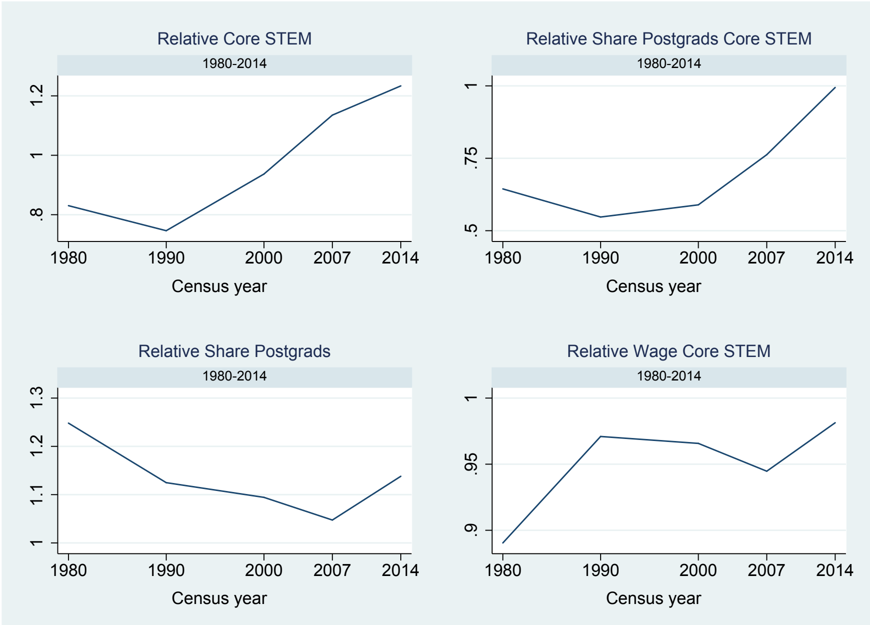


Figure 4: Relative comparison: finance vs. KIBS

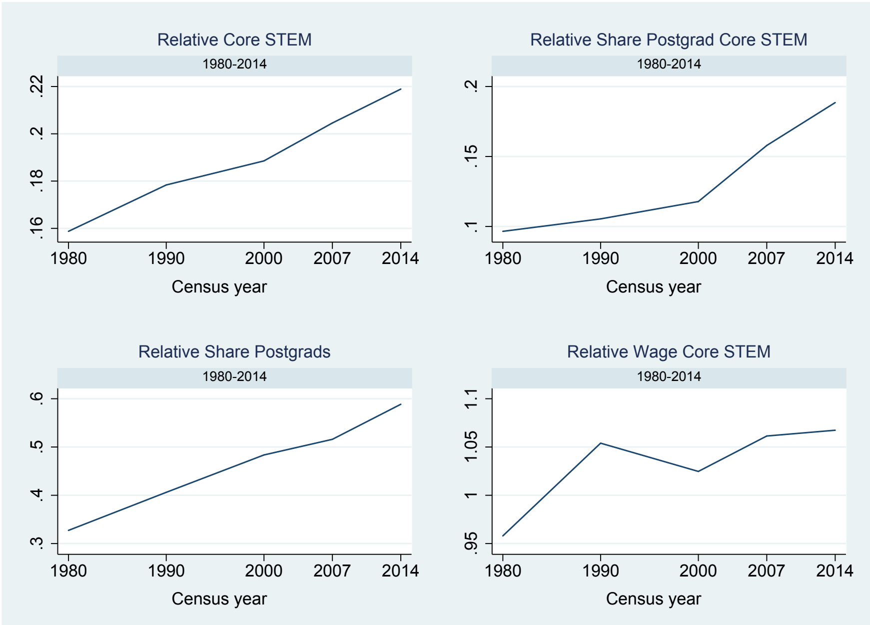


Table 6: Conditional differences in STEM skill growth - key sectors only

	1980-1990	1990-2000	2000-2007	2007-2014
	Panel A - △ share workers in core STEM occupations			
Finance	0.00717**	0.00274*	0.00372	0.00901***
	(0.00318)	(0.00156)	(0.00551)	(0.00317)
R-squared	0.742	0.861	0.0966	0.191
	Panel B - △ share graduate workers in core STEM occupations			
Finance	0.00300*	-0.00809*	0.00620	0.00981***
	(0.00164)	(0.00442)	(0.00586)	(0.00248)
R-squared	0.890	0.832	0.853	0.410
	Panel C - △ share postgraduate workers in core STEM occupations			
Finance	0.000178	-0.00393	0.00350	0.00421***
	(0.000673)	(0.00276)	(0.00311)	(0.00104)
R-squared	0.0618	0.807	0.679	0.631
	Panel D - △ average Math task intensity			
Finance	0.00432	0.00158	0.0132***	0.00667
	(0.00608)	(0.00780)	(0.00307)	(0.00592)
R-squared	0.220	0.195	0.242	0.0518
	Panel E - △ share postgraduate workers			
Finance	-0.00159	-0.0227***	-0.0140***	0.00770
	(0.00645)	(0.00618)	(0.00484)	(0.00779)
R-squared	0.562	0.358	0.456	0.355

N=97. Regressions weighted by average hours worked in industry. Only key industries included: KIBS, manufacturing, education, health, oil, utilities, finance. Controls not shown: log years of school, log age, RTI index, lagged STEM. Robust std errors. * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Overlap of STEM and Finance occupations with STEM degrees in finance (average 2009-2014)

	Core STEM occupations	Financial occupations	Other occupations	Total
Distribution of employment in finance sector	0.0686	0.2700	0.6614	-
Distribution of total STEM degrees in finance	0.3903	0.2761	0.3336	-
Share with a college degree	0.7031	0.6487	0.3894	0.4825
Share of graduates with STEM degrees	0.5514	0.1036	0.0937	0.1413
Composition of STEM degrees:				
Computer and Information Sciences	0.4875	0.1788	0.2410	0.3260
Engineering	0.2693	0.3788	0.3569	0.3388
Mathematics and Statistics	0.1506	0.2564	0.1761	0.1691
Physical Sciences	0.0615	0.1459	0.1647	0.1213
Engineering Technologies	0.0291	0.0346	0.0528	0.0397
Biology and Life Sciences	0.0020	0.0056	0.0085	0.0052

Table 8: STEM intensity by industry, 2009-2014

Panel A - STEM intensity in 2009					
	STEM degree	STEM degree (postgrad)	Core STEM degree	STEM occ	Core STEM occ
Finance	0.0671	0.0260	0.0473	0.0727	0.0711
KIBS	0.3254	0.1327	0.1864	0.4708	0.3286
High-Tech Manuf.	0.1833	0.0752	0.0869	0.2043	0.0672
Low-Tech Manuf.	0.0552	0.0158	0.0161	0.0645	0.0159
Oil	0.0918	0.0330	0.0178	0.0894	0.0195
Utilities	0.0839	0.0221	0.0263	0.0900	0.0334
Health	0.0299	0.0196	0.0112	0.0207	0.0151
Education	0.0606	0.0390	0.0369	0.0307	0.0242
Other Industries	0.0336	0.0107	0.0162	0.0264	0.0165
Total	0.0562	0.0227	0.0286	0.0547	0.0331
Panel B - Change in STEM intensity 2009-2014					
	STEM degree	STEM degree (postgrad)	Core STEM degree	STEM occ	Core STEM occ
Finance	0.0119	0.0061	0.0052	0.0097	0.0091
KIBS	0.0136	0.0039	0.0101	0.0107	0.0286
High-Tech Manuf.	-0.0027	0.0005	-0.0088	-0.0054	-0.0047
Low-Tech Manuf.	0.0044	0.0023	0.0016	0.0047	0.0015
Oil	0.0006	-0.0014	-0.0011	0.0057	-0.0003
Utilities	0.0133	0.0135	0.0021	-0.0010	0.0024
Health	0.0123	0.0071	0.0025	0.0018	0.0016
Education	0.0098	0.0053	0.0017	0.0019	0.0025
Other Industries	0.0061	0.0022	0.0029	0.0028	0.0028
Total	0.0079	0.0036	0.0028	0.0040	0.0041

Figure 5: Evolution of STEM degrees in selected sectors, 2009-2014

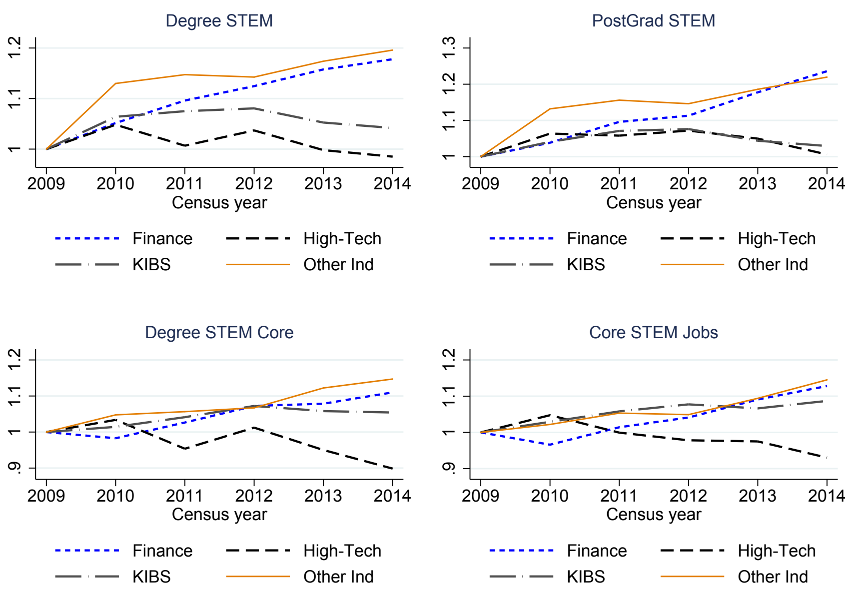


Figure 6: Trend in various skill measures in the financial sector, 2009-2014

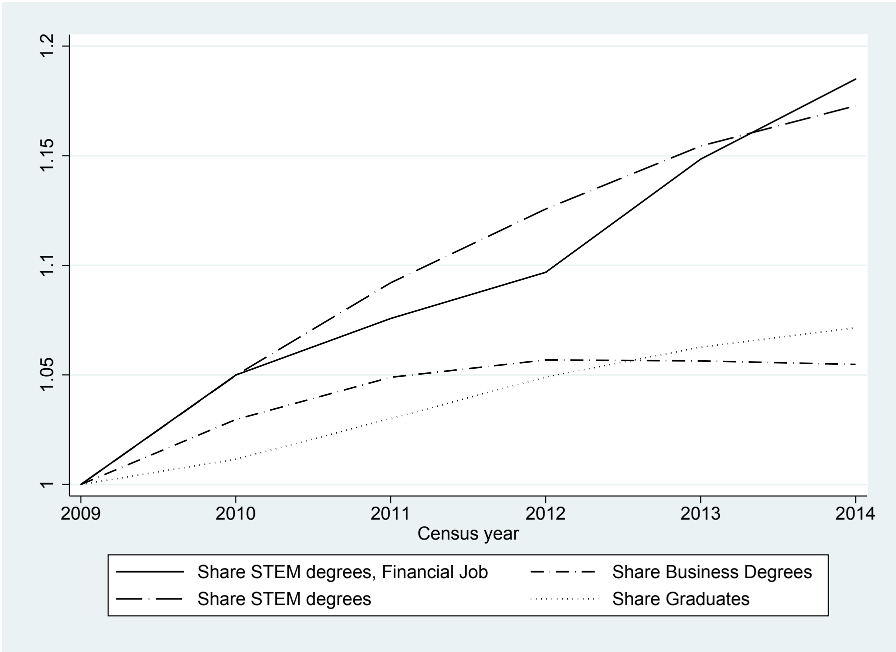


Figure 7: Trend in average hourly wage (current US$) of STEM graduates in selected sectors, 2009-2014

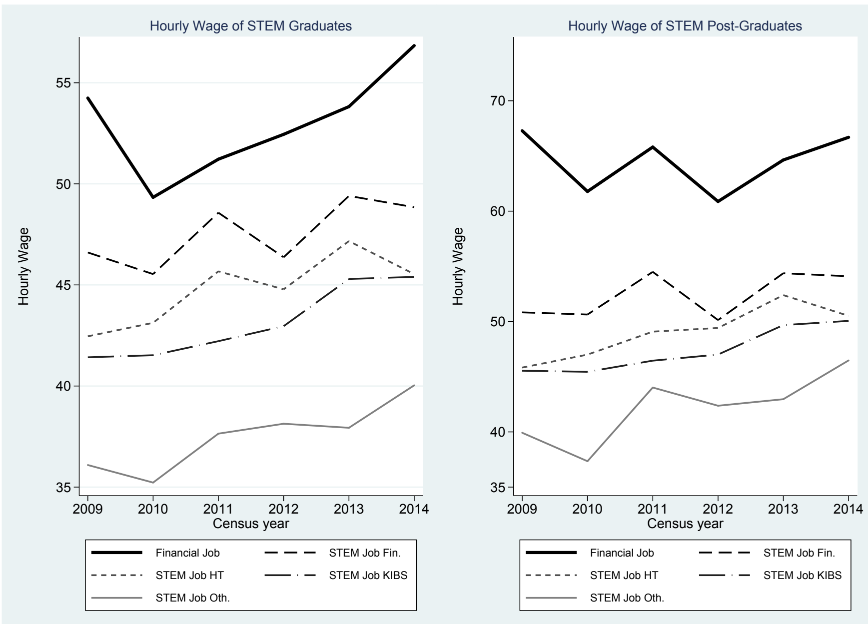
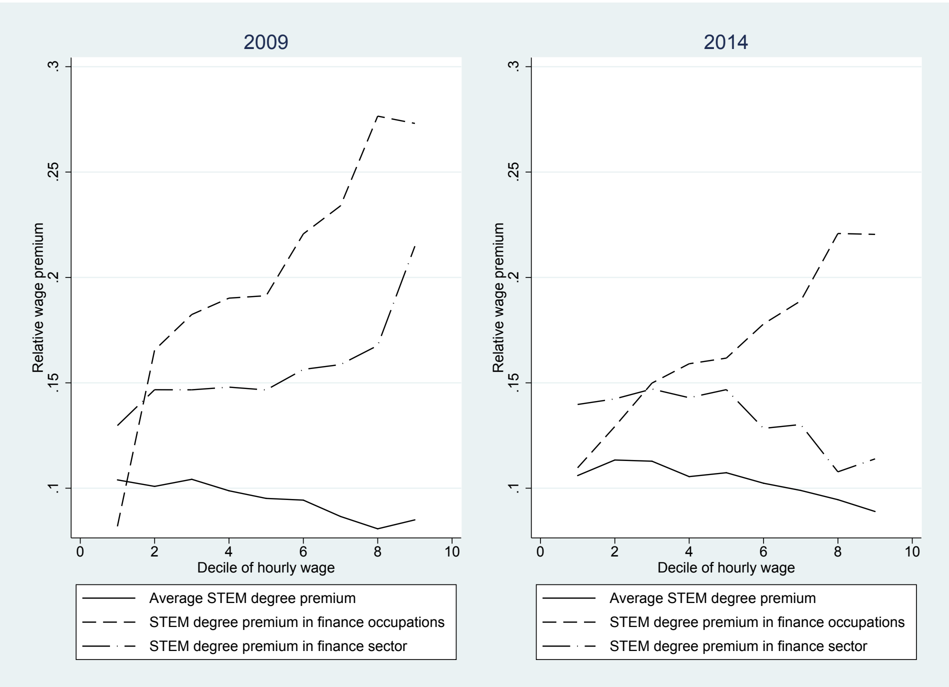


Table 9: Wage premium of STEM degrees

Panel A - Wage premium of STEM graduates in finance jobs						
Dep var: log(hourly wage)	2009	2010	2011	2012	2013	2014
STEM degree	0.0829***	0.0721***	0.0875***	0.0949***	0.102***	0.0987***
	(0.00355)	(0.00363)	(0.00366)	(0.00358)	(0.00354)	(0.00354)
Finance occupation	0.0847***	0.0740***	0.0898***	0.0998***	0.110***	0.111***
	(0.00473)	(0.00473)	(0.00493)	(0.00480)	(0.00483)	(0.00485)
STEM degree x Finance occupation	0.0969***	0.0624***	0.0559***	0.0529***	0.0225	0.0286**
	(0.0146)	(0.0148)	(0.0153)	(0.0144)	(0.0148)	(0.0144)
R-squared	0.416	0.411	0.416	0.421	0.417	0.418
Observations	623585	611660	606538	613418	629787	627617
Panel B - Wage premium of STEM graduates in finance sector						
Dep var: log(hourly wage)	2009	2010	2011	2012	2013	2014
STEM degree	0.0771***	0.0700***	0.0872***	0.0888***	0.0999***	0.0949***
	(0.00418)	(0.00416)	(0.00460)	(0.00439)	(0.00435)	(0.00428)
STEM degree x Finance sector	0.0827***	0.0435***	0.0306**	0.0302**	0.0247*	0.0307**
	(0.0123)	(0.0122)	(0.0140)	(0.0125)	(0.0128)	(0.0122)
R-squared	0.384	0.379	0.384	0.386	0.386	0.388
Observations	623585	611660	606538	613418	629787	627617

OLS estimates on ACS-IPUMS microdata weighted by person weights. Sample: workers employed in key industries. Control variables: SOC 2-digit occupation dummy variables, NAICS 2-digit industry dummy variables, age (linear and squared), metro-area dummy variable, sex dummy variable, married dummmy, black dummy variable, non-white dummy variable, foreign born dummy variable, some college dummy variable, college degree dummy variable, postgraduate dummy. Robust standard in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Figure 8: Wage premium of STEM degrees by decile of wage



Results based on quantile regression estimates on ACS-IPUMS microdata weighted by person weights. Sample: workers employed in key industries. Control variables: SOC 2-digit occupation dummy variables, finance occupation dummy variable, NAICS 2-digit industry dummy variables, age (linear and squared), metro-area dummy variable, sex dummy variable, married dummmy, black dummy variable, non-white dummy variable, foreign born dummy variable, some college dummy variable, college degree dummy variable, postgraduate dummy.

Table 10: Predicted increase in productivity in the real economy assuming fixed (first year) STEM input in the finance industry - All non-finance and non-agricultural private sector (data from BEA)

	Core STEM occ	Graduate core STEM occ
Actual cumulative labor productivity growth 1990-2014	0.3697	
Relative predicted increase in STEM input with constant STEM input in finance (1990-2014)	0.0660	0.0946
First difference estimation		
Simulated labor productivity growth 1990-2014	0.3795	0.3810
Difference with respect to actual growth	0.0098	0.0114
First difference estimation (with average STEM input in t, t-1)		
Simulated labor productivity growth 1990-2014	0.3728	0.3730
Difference with respect to actual growth	0.0031	0.0033

The estimated contribution of STEM workers to labor productivity is derived from Table C1. To compute simulated growth, we assume that the share of STEM workers in finance remained fixed at its initial level and that all exceeding STEM workers were attributed to non-finance industries according to their year-specific number of actual STEM workers.

Table 11: Predicted increase in productivity in the real economy assuming fixed (first year) STEM input in the finance industry - Detailed manufacturing industries (data from NBER)

	Core STEM occ	Graduate core STEM occ
Actual cumulative labor productivity growth 1980-2007	1.6526	
Relative predicted increase in STEM input with constant STEM input in finance (1980-2007)	0.0984	0.1244
First difference estimation		
Simulated labor productivity growth 1980-2007	1.7187	1.7072
Difference with respect to actual growth	0.0661	0.0545
First difference estimation (with average STEM input in t, t-1)		
Simulated labor productivity growth 1980-2007	1.7324	1.7144
Difference with respect to actual growth	0.0797	0.0617

The estimated contribution of STEM workers to labor productivity is derived from Table C2. To computed simulated growth, we assume that the share of STEM workers in finance remained fixed at its initial level and that all exceeding STEM workers were attributed to non-finance industries according to their year-specific number of actual STEM workers.

A Conditional differences in STEM skill growth - additional results

Table A1: Conditional differences in STEM skill growth - Focus on investment banking

	1980-1990	1990-2000	2000-2007	2007-2014
Panel A - △ share workers in core STEM occupations				
Investment banking	0.0215***	0.00695***	0.0158**	0.000367
	(0.00368)	(0.00254)	(0.00639)	(0.00355)
R-squared	0.767	0.861	0.174	0.103
Panel B - △ share graduate workers in core STEM occupations				
Investment banking	0.0141***	-0.0126	0.0198***	0.00445
	(0.000937)	(0.00858)	(0.00665)	(0.00285)
R-squared	0.906	0.836	0.880	0.339
Panel C - △ share postgraduate workers in core STEM occupations				
Investment banking	0.00428***	-0.00812	0.00602	0.00423**
	(0.000326)	(0.00549)	(0.00603)	(0.00187)
R-squared	0.200	0.810	0.681	0.623
Panel D - △ average Math task intensity				
Investment banking	0.0224***	-0.00882	0.0105**	-0.00850
	(0.00574)	(0.0148)	(0.00467)	(0.00664)
R-squared	0.234	0.165	0.127	0.0340
Panel E - △ share postgraduate workers				
Investment banking	0.0116	-0.0154	-0.0110**	-0.00466
	(0.00792)	(0.0115)	(0.00554)	(0.00817)
R-squared	0.563	0.380	0.469	0.312

N=93. Regressions weighted by average hours worked in industry. Only key industries included: KIBS, manufacturing, education, health, oil, utilities, investment banking. Finance industries different from investment banking were excluded. Controls not shown: log years of school, log age, RTI index, lagged STEM. Robust std errors. * p<0.1, ** p<0.05, *** p<0.01.

B Details on sectoral cross-walks

Table B1: Sectoral aggregation of BEA data (based on NAICS)

NAICS	Description
	Real economy
211	Oil and Gas Extraction
212	Mining, except Oil and Gas
213	Support Activities for Mining
22	Utilities
23	Construction
311,312	Food and Beverage and Tobacco Products
313,314	Textile Mills and Textile Product Mills
315,316	Apparel and Leather and Applied Products
321	Wood Products
322	Paper Products
323	Printing and Related Support Activities
324	Petroleum and Coal Products
325	Chemical Products
326	Plastics and Rubber Products
327	Nonmetallic Mineral Products
331	Primary Metals
332	Fabricated Metal Products
333	Machinery
334	Computer and Electronic Products
335	Electrical Equipment, Appliances, and Components
336	Transportation Equipment
337	Furniture and Related Products
339	Miscellaneous Manufacturing
42	Wholesale Trade
44,45	Retail Trade
481	Air Transportation
482	Rail Transportation
483	Water Transportation
484	Truck Transportation
485	Transit and Ground Passenger Transportation
486	Pipeline Transportation
487,488,492	Other Transportation and Support Activities
493	Warehousing and Storage
511	Publishing industries, except Internet [includes software]
512	Motion Picture and Sound Recording Industries
515,517	Broadcasting and Telecommunications
518,519	Data processing, Internet publishing, and Other Information Services
531	Real Estate
532,533	Rental and Leasing Services and Lessors of Intangible Assets
5411	Legal Services
5412-5414,5416-5419	Miscellaneous Professional, Scientific, and Technical Services
5415	Computer Systems Design and Related Services
55	Management of Companies and Enterprises
561	Administrative and Support Services
562	Waste Management and Remediation Services
61	Educational Services
621	Ambulatory Health Care Services
622,623	Hospitals and Nursing and Residential Care Facilities
624	Social Assistance
711,712	Performing Arts, Spectator Sports, Museums, and Related Activities
713	Amusements, Gambling, and Recreation Industries
721	Accommodation
722	Food Services and Drinking Places
81	Other Services, except Government
	Finance
521,522	Federal Reserve Banks, Credit Intermediation, and Related Activities
523	Securities, Commodity Contracts, and Investments
524	Insurance Carriers and Related Activities
525	Funds, Trusts, and Other Financial Vehicles

Table B2: Exact crosswalk between *ind1990* and NAICS (BEA)

ind1990	NAICS	*ind1990*	NAICS	*ind1990*	NAICS
12	5412-5414,5416-5419	320	333	631	44,45
20	561	322	334	633	44,45
40	212	332	333	641	722
41	212	340	335	642	44,45
50	212	341	334	650	44,45
60	23	351	336	652	44,45
100	311,312	352	336	660	44,45
101	311,312	360	336	662	44,45
102	311,312	361	336	663	44,45
110	311,312	362	336	670	44,45
111	311,312	370	336	671	44,45
112	311,312	371	334	672	44,45
120	311,312	372	339	681	44,45
121	311,312	390	339	682	44,45
122	311,312	391	339	701	521,522
130	311,312	400	482	702	521,522
140	313,314	401	485	711	524
141	313,314	402	485	712	531
150	313,314	411	493	721	5412-5414,5416-5419
151	315,316	420	483	722	561
152	313,314	421	481	731	561
160	322	450	22	740	561
161	322	452	22	751	81
162	322	470	22	752	81
171	511	472	22	760	81
180	325	500	42	761	81
181	325	501	42	762	721
182	325	502	42	770	721
190	325	511	42	771	81
191	325	512	42	772	81
192	325	521	42	780	81
200	324	530	42	781	81
201	324	531	42	800	512
210	326	532	42	802	713
211	326	540	42	812	621
212	326	541	42	820	621
221	315,316	542	42	821	621
222	315,316	550	42	822	621
231	321	551	42	831	622,623
241	321	552	42	832	622,623
242	337	560	42	840	621
250	327	561	42	841	5411
251	327	562	42	842	61
252	327	571	42	850	61
261	327	580	44,45	860	61
262	327	581	44,45	861	624
270	331	582	44,45	862	624
271	331	591	44,45	870	622,623
272	331	600	44,45	871	624
280	331	601	44,45	872	711,712
281	332	610	311,312	880	81
282	332	611	44,45	881	81
291	332	612	44,45	882	5412-5414,5416-5419
292	332	620	44,45	890	5412-5414,5416-5419
300	332	621	44,45	891	5412-5414,5416-5419
310	333	622	44,45	892	5412-5414,5416-5419
311	333	623	44,45	893	711,712
312	333	630	44,45		

Table B3: Weighted crosswalk between *ind1990* and NAICS (BEA)

ind1990	NAICS	Weight	*ind1990*	NAICS	Weight
42	213	0.81	651	44,45	0.50
42	211	0.19	710	523	0.87
172	323	0.81	710	525	0.87
172	511	0.19	710	55	0.08
331	333	0.67	732	5415	0.80
331	332	0.33	732	532,533	0.05
342	334	0.67	732	511	0.03
342	335	0.33	741	561	0.54
410	484	0.76	741	5412-5414,5416-5419	0.16
410	487,488,492	0.24	741	532,533	0.06
432	487,488,492	0.72	741	512	0.02
432	561	0.28	741	518,519	0.02
440	515,517	0.45	742	532,533	0.50
440	518,519	0.06	742	81	0.50
441	515,517	0.37	791	81	0.83
441	518,519	0.04	791	5412-5414,5416-5419	0.17
451	22	0.77	810	532,533	0.50
451	486	0.23	810	713	0.50
471	562	0.79	852	518,519	0.49
471	22	0.21			

Table B4: Sectoral aggregation of NBER-CES/IPUMS data (based on NAICS)

NAICS	Description
3111,3112	Animal Food Manufacturing; Grain and Oilseed Milling
3113	Sugar and Confectionery Product Manufacturing
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
3115	Dairy Product Manufacturing
3116	Animal Slaughtering and Processing
3118	Bakeries and Tortilla Manufacturing
3121	Beverage Manufacturing
3122	Tobacco Manufacturing
3131	Fiber, Yarn, and Thread Mills
3132	Fabric Mills
3133	Textile and Fabric Finishing and Fabric Coating Mills
314	Textile Product Mills
3151	Apparel Knitting Mills
3152	Cut and Sew Apparel Manufacturing
3159	Apparel Accessories and Other Apparel Manufacturing
3161,3169	Leather and Hide Tanning and Finishing; Other Leather and Allied Product Manufacturing
3162	Footwear Manufacturing
3211	Sawmills and Wood Preservation
3212	Veneer, Plywood, and Engineered Wood Product Manufacturing
3219	Other Wood Product Manufacturing
3221	Pulp, Paper, and Paperboard Mills
3222	Converted Paper Product Manufacturing
3231	Printing and Related Support Activities
3241	Petroleum and Coal Products Manufacturing
3251,3259	Basic Chemical Manufacturing; Other Chemical Product and Preparation Manufacturing
3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing
3254	Pharmaceutical and Medicine Manufacturing
3255	Paint, Coating, and Adhesive Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing
3261	Plastics Product Manufacturing
3262	Rubber Product Manufacturing
3271	Clay Product and Refractory Manufacturing
3272	Glass and Glass Product Manufacturing
3273,3274	Cement and Concrete Product Manufacturing; Lime and Gypsum Product Manufacturing
3279	Other Nonmetallic Mineral Product Manufacturing
3311,3312	Iron and Steel Mills and Ferroalloy Manufacturing; Steel Product Manufacturing from Purchased Steel
3313	Alumina and Aluminum Production and Processing
3314	Nonferrous Metal (except Aluminum) Production and Processing
3315	Foundries
3321	Forging and Stamping
3322	Cutlery and Handtool Manufacturing
3323,3324	Architectural and Structural Metals Manufacturing; Boiler, Tank, and Shipping Container Manufacturing
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing
3328	Coating, Engraving, Heat Treating, and Allied Activities
3329	Other Fabricated Metal Product Manufacturing
3331	Agriculture, Construction, and Mining Machinery Manufacturing
3332,3334,3339	Industrial Machinery Manufacturing; Ventilation, Heating, Air-Conditioning, and Commercial Refrigeration Equipment Manufacturing; Other General Purpose Machinery Manufacturing
3333	Commercial and Service Industry Machinery Manufacturing
3335	Metalworking Machinery Manufacturing
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342,3343	Communications Equipment Manufacturing; Audio and Video Equipment Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3351,3353,3359	Electric Lighting Equipment Manufacturing; Electrical Equipment Manufacturing; Other Electrical Equipment and Component Manufacturing
3352	Household Appliance Manufacturing
3364	Aerospace Product and Parts Manufacturing
3365	Railroad Rolling Stock Manufacturing
3366	Ship and Boat Building
3369	Other Transportation Equipment Manufacturing
3371,3372,3379	Household and Institutional Furniture and Kitchen Cabinet Manufacturing; Office Furniture (including Fixtures) Manufacturing; Other Furniture Related Product Manufacturing
3391	Medical Equipment and Supplies Manufacturing
3399	Other Miscellaneous Manufacturing

Table B5: Exact crosswalk between *ind1990* and NAICS (NBER-CES)

ind1990	NAICS	*ind1990*	NAICS	*ind1990*	NAICS
100	3116	192	3251,3259	291	3321
101	3115	200	3241	292	3329
102	3114	201	3241	310	3336
110	3111,3112	210	3262	311	3331
111	3118	211	3262	312	3331
112	3113	212	3261	320	3335
120	3121	221	3162	322	3341
121	3111,3112	222	3161,3169	340	3352
130	3122	241	3219	341	3342,3343
132	3151	242	3371,3372,3379	351	3351,3353,3359
140	3133	250	3272	352	3364
141	314	251	3273,3274	360	3366
152	314	252	3271	361	3365
160	3221	261	3271	362	3364
161	3222	262	3279	370	3369
162	3222	270	3311,3312	371	3345
180	3252	271	3315	372	3391
181	3254	272	3313	390	3399
182	3256	280	3314	391	3399
190	3255	281	3322	610	3118
191	3253	282	3323,3324		

Table B6: Weighted crosswalk between *ind1990* and NAICS (NBER-CES)

ind1990	NAICS	Weight
150	3132	0.79
150	3131	0.21
151	3159	0.06
151	3152	0.94
172	3231	0.48
172	3231	0.33
231	3219	0.59
231	3212	0.12
231	3211	0.29
300	3323,3324	0.74
300	3328	0.26
331	3332,3334,3339	0.67
331	3327	0.33
332	3333	0.81
342	3351,3353,3359	0.33
342	3342,3343	0.67

C Productivity effect of STEM reallocation - estimate results

Table C1: Non-agriculture and non-finance private sectors (data: BEA-BLS; years: 1990, 2000, 2007, 2014)

Dependent variable: △log(output per worker)	(1)	(2)	(3)	(4)
log(output per worker, t=1987-1989)	-0.00422	-0.00315	-0.00554	0.000350
	(0.0194)	(0.0211)	(0.0205)	(0.0215)
△ log(stock of structure per worker)	0.0422	0.0188	0.0246	0.0241
	(0.123)	(0.119)	(0.119)	(0.120)
△ log(stock of equipment per worker)	0.202***	0.214***	0.209***	0.221***
	(0.0657)	(0.0717)	(0.0683)	(0.0732)
△ log(employment)	-0.607***	-0.51***	-0.599***	-0.581***
	(0.128)	(0.131)	(0.128)	(0.132)
△ Share of empl in STEM core occ	3.680***			
	(1.062)			
Share of empl in STEM core occ (average t, t-1)		0.665**		
		(0.305)		
△ Share of empl in STEM core occ with degree			3.858***	
			(1.258)	
Share of empl in STEM core occ with degree (average t, t-1)				0.709**
				(0.337)
R sq	0.517	0.549	0.511	0.536
N	159	159	159	159

Estimates weighted by initial hours worked in industry. Robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Additional control variables: year dummy variables, initial RTI index interacted with year dummy variables, year-specific dummy variables for manufacturing sectors.

Table C2: Manufacturing sectors (data: NBER-CES; years: 1980, 1990, 2000, 2007)

Dependent variable: △log(output per worker)	(1)	(2)	(3)	(4)
log(output per worker, t=1977-1979)	-0.256***	-0.154**	-0.236**	-0.183**
	(0.0880)	(0.0599)	(0.0896)	(0.0768)
△ log(stock of structure per worker)	-0.300	-0.472**	-0.360*	-0.452**
	(0.185)	(0.209)	(0.198)	(0.195)
△ log(stock of equipment per worker)	0.137	0.240*	0.235*	0.292**
	(0.104)	(0.122)	(0.120)	(0.127)
△ log(employment)	-0.450***	-0.330***	-0.394***	-0.326***
	(0.146)	(0.0995)	(0.104)	(0.0950)
△ Share of empl in STEM core occ	8.122*			
	(4.510)			
Share of empl in STEM core occ (average t, t-1)		5.783***		
		(1.815)		
△ Share of empl in STEM core occ with degree			7.169**	
			(3.527)	
Share of empl in STEM core occ with degree (average t, t-1)				6.126***
				(1.808)
R sq	0.595	0.631	0.568	0.600
N	189	189	189	189

Estimates weighted by initial hours worked in industry. Robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Additional control variables: year dummy variables, initial RTI index interacted with year dummy variables.

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