Rise of the “Quants” in Financial Services

Regulation and Crowding Out of Routine Jobs

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Alberto G. Rossi

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Abstract

We document three recent trends in employment in financial services: (a) the share of science, technology, engineering, and math (STEM) workers grew by 30 percent between 2011 and 2017; (b) while the earnings premium of working in finance has grown, the STEM premium in finance has declined since 2011; and (c) regulatory restrictions in financial services have grown faster than in other sectors. We investigate three economic mechanisms underlying these patterns: (a) capital-skill complementarity, (b) relabeling of non-STEM degree programs as STEM degree programs, and (c) regulation. We show that only the rise in regulation can explain our observations.

JEL codes: G21, G23, G38, J23, J31

Keywords: fintech, financial services, STEM workers, regulation, STEM

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1. Introduction

Regulatory restrictions in financial services have grown more than in any other sector over the past two decades (Al-Ubaydli and McLaughlin, 2017). For example, bank and nonbank credit intermediation rank among the 10 most regulated sectors in the US economy.[1] And yet, labor productivity in financial services has also grown faster than in other sectors. Given the general recognition that regulation has adverse effects on productivity (Djankov et al., 2002; Dawson and Seater, 2013; Coffey, McLaughlin, and Peretto, 2020), these twin facts create a puzzle. The contribution of this paper is to explain these joint phenomena. We show that, although regulation has led to an increase in the number of science, technology, engineering, and mathematics (STEM) workers in financial services, which may have productivity-enhancing effects, this increase has come at the expense of low- and middle-skilled workers in the sector.

Financial services are particularly sensitive to regulatory changes in that a nontrivial share of the regulatory burden is borne by labor because it affects banks' noninterest expenses (Elliehausen, 1998). These noninterest expenses include hiring compliance officers or outside consultants (Hogan and Burns, 2019).[2] These factors have created a market for regtech solutions, which aim to reduce compliance costs and to increase operational efficiency by automating

[1] According to QuantGov, the regulatory database introduced by Al-Ubaydli and McLaughlin (2017), nondepository and depository credit intermediation ranked in 2014 as the fourth- and fifth-most regulated sectors. See McLaughlin and Sherouse (2016).
[2] Elliehausen (1998) provides a detailed survey of the costs of regulation in finance, concluding that "this information suggests that labor costs account for a large share of the total cost of implementing a new regulation and an even greater share of the costs of satisfying regulatory requirements on a day-to-day basis." Labor costs are also quite large for nonsupervisory employees who perform many routine duties, including "preparing and distributing disclosure statements, explaining disclosed information to customers, correcting errors, and resolving disputes."

common tasks. This market is expected to grow from $4.3 billion as of 2018 to $12.3 billion by 2023, according to business intelligence companies such as MarketsandMarkets.

The first part of our paper introduces our measurement strategy and documents several patterns in the relationship between STEM workers and regulation. Using the Occupational Employment Statistics, the American Community Survey, and regulatory restrictions from Al-Ubaydli and McLaughlin (2017), we document three recent trends. First, the share of STEM workers increased faster in finance than in any other sector (except professional services that include legal services, industrial engineering and design, management consulting, marketing, and R&D), growing by 2.1 percentage points from 2011 to 2017, which is roughly 28 percent of the average STEM share over these years. This is consistent with Gupta and Hacamo's (2019) discussion on the reallocation of engineers into financial services. Second, while STEM employment has increased, the earnings premium between STEM and non-STEM workers in finance has declined from roughly 8 percent to 5 percent. These patterns also mimic the decline in the skill premium observed among workers in occupations with higher cognitive and nonroutine skill intensities (Beaudry, Green, and Sand, 2016). Third, regulation grew faster in finance than in other sectors over these years. Even within finance, certain subsectors exhibited much greater growth than others (e.g., agencies, brokerages, and other insurance).

Motivated by these patterns, the second part of the paper investigates the source of the increase in STEM employment, distinguishing among three hypotheses: (a) capital-skill complementarity arising from an increase in technological change or decline in the price of capital, (b) relabeling of STEM degrees and entry of new graduates into STEM employment, and (c) regulation and its impact on the returns to automation. Examining the first hypothesis, we find that changes in STEM employment are not correlated with changes in capital costs and technological change. Examining the second, we find that the share of STEM workers in finance with a finance degree is small and time invariant, which is not what we would expect to see if there was a relabeling of programs from business to STEM.

We subsequently turn toward the third hypothesis. We find that changes in regulation are quantitatively important: a 10 percent increase in regulation is associated with a 5.3 percent rise in STEM employment. Our identification strategy exploits variation within STEM versus non-STEM occupations after controlling for all time-invariant characteristics across industries and occupations, as well as for industry-specific trends. To control for potential time-varying shocks to productivity, we also control for wages. Furthermore, our results are robust to a triple-difference estimator where we compare STEM and non-STEM employment in professional versus financial services after the adoption of Dodd-Frank in 2010. Although the time series of regulation for professional and financial services track each other closely, their paths diverge after the passage of Dodd-Frank, providing us with useful identifying variation.

Here, even though increases in regulation are associated with STEM employment in other sectors (e.g., professional services), the effects are concentrated in finance. Following the increase in labor productivity that financial services exhibited over these years, we also show that the increase in STEM employment parallels a strikingly similar increase in patent applications, particularly among the largest banks.

Our results complement an emerging series of empirical contributions on the returns to skill. For example, Célérier and Vallée (2019) use French administrative data to document the returns to talent in financial services, illustrating that the returns are highest when the output elasticity to scale is also high. Moreover, Harrigan, Reshef, and Toubal (2017) use similar administrative French data to study the impact that STEM workers have on polarization in the labor market, and they find that companies with higher shares of STEM workers in 2002 grew more rapidly in the following decade. Gallipoli and Makridis (2018) show that the earnings premium associated with information technology tasks has increased, particularly in high-technology services sectors, such as finance. Similarly, Philippon and Reshef (2012) investigate the evolution of wages in finance between 1909 and 2006, showing that residual wages in finance began to increase significantly after 1990. Importantly, they decompose the earnings premium into several channels, finding that deregulation can account for 23 percent of the changes in wages.

Our paper complements these findings by illustrating how changes in regulation can alter the price associated with different skills within the labor market, raising, for example, the returns to producing technology that counteracts growing compliance costs. Our paper also builds on a broader literature on financial technology ("fintech") firms; see Greenwood and Scharfstein (2013) and Philippon (2018) for a survey of several recent trends. For example, Fuster et al. (2019) show that fintech mortgage lenders increased their market share from 2 percent to 8 percent between 2010 and 2016. Moreover, Buchak et al. (2018) find a similar expansion of fintech services and show that the increase in regulation among traditional banks can account for 70 percent of the expansion of fintech lenders between 2007 and 2015. Although the term "shadow banks" refers to a broader set of companies that are not governed by traditional banking regulations, fintech companies accounted for roughly a quarter of the shadow banking mortgage market by 2015. The results of Buchak et al. (2018) are consistent with ours when they find that the increased regulatory burden faced by traditional banks accounts for roughly 70 percent of the increase in shadow banking.[3] Our results contribute to this fintech literature by switching the unit

[3] Relatedly, Gete and Reher (2020) show how an increase in mortgage-backed security liquidity related to postcrisis regulations has helped increase nonbanks' market share.

of analysis to the occupational level, and by highlighting how financial services firms may have sought to "escape" regulatory exposure by hiring STEM workers who could automate more tasks and pursue activities outside the scope of existing regulation.

Our paper is also closely related to that of Simkovic and Zhang (2018), who introduce a new measure of regulation intensity and evaluate the effects of Sarbanes-Oxley on regulation-related tasks. Although our two measures of regulation are correlated, our focus on a supply-side measure of regulation is critical because we look at the effects on the composition of labor services, which is influenced by the returns to automation. We nonetheless show that increases in regulation are associated with increases in the number of compliance officers.

Finally, our paper relates to a large literature on the effects of financial regulation on the real economy. For example, Guiso, Sapienza, and Zingales (2004) show that financial development is associated with a range of positive economic benefits, such as new firm entry, competition, and entrepreneurship. Similarly, Jayaratne and Strahan (1996) exploit within-state variation in the deregulation of bank branch restrictions, finding increases in per capita income growth and output. These gains were driven not by the increase in the volume of bank lending, but by the quality. However, the institutional mechanisms behind banking expansions play an important moderating role. For example, Dehejia and Lleras-Muney (2007) find that, while expansions in bank branching accelerated the mechanization of agriculture and growth in manufacturing between 1900 and 1940, expansions in state deposit insurance had negative consequences for these outcomes. More recently, Chen, Hanson, and Stein (2017) and D'Acunto and Rossi (2017) identify the unintended consequences of regulation on small business and mortgage lending, respectively.[4] Our paper, besides being consistent with these papers on the

[4] Bord, Ivashina, and Taliaferro (2016) find that large banks exposed to housing price declines contracted their credit to small firms; Makridis and Ohlrogge (2019) find similar effects for foreclosure.

heterogeneous (and often unintended) effects of financial regulation, also contributes to the recent literature on the political economy of banking crises and their real effects (Calomiris and Haber, 2014; Calomiris, 2017; Antoniades and Calomiris, 2018).

The structure of the paper is as follows. Section 2 outlines the data and measurement approach. Section 3 documents several cross-sectional and time series statistics about the rise of STEM workers in finance. Section 4 investigates several hypotheses for explaining the rise in STEM employment. Section 5 focuses on the role of regulation. Section 6 explores the mechanisms. Section 7 concludes.

2. Data and Measurement

2.1. Defining STEM Occupations

We draw on the Bureau of Labor Statistics' (BLS) definition of STEM occupations, a category that includes "computer and mathematical, architecture and engineering, and life and physical science occupations, as well as managerial and postsecondary teaching occupations related to these functional areas and sales occupations requiring scientific or technical knowledge at the postsecondary level" (see appendix A for a tabulation of every STEM occupation). The BLS definition provides a reliable and harmonized way of tracking STEM jobs across the six-digit standard occupational classification (SOC). Although the tasks performed in these jobs might change over time, our assumption is that the classification is time invariant—a reasonable assumption at the occupational (not task) level.[5]

Before we turn to our main datasets, we provide summary statistics for these sets of workers using the American Community Survey (ACS) for 2011 and 2017. We restrict the

[5] See Black, Muller, and Spitz-Oener (2015) and Peri, Shih, and Sparber (2015) for comparable applications of this STEM definition to identify STEM workers.

sample to full-time workers between age 20 and age 65 who earn more than $2 per hour, examining differences between STEM and non-STEM workers across demographic characteristics (age, education, race, and marital status); income and hours worked; and industry.

Table 1 documents these descriptive statistics. Although the differences between STEM and non-STEM workers tend to be small in many regards (e.g., family size, number of children, and age), there are some important differences. For example, among those who are in a STEM occupation and the financial services sector, 68 percent are male, whereas the share is 76 percent in a STEM occupation and outside of finance, as of 2011 (and 70 percent and 76 percent in 2017, respectively).

The findings reflect the fact that STEM occupations are more dominated by men (see, for example, that the share of males in non-STEM and finance jobs is 39 percent in 2011 and 40 percent in 2017). We also see striking differences in educational attainment. For example, not only is the share of college graduates in the financial sector 12 percentage points higher in STEM occupations as of 2011 (47 percent versus 35 percent), but also the share of master's degree holders in finance is twice as large in STEM jobs (and similarly for doctorate holders). Turning toward the allocation of time, although STEM workers work more hours per year, they exhibit less dispersion. STEM hourly wage income follows a similar pattern, but in contrast exhibits more dispersion outside of finance, which likely reflects greater heterogeneity in the set of tasks across nonfinance occupations.

Table 1. Descriptive Statistics on STEM Workers In and Out of Finance

	STEM, FIN		Non-STEM, FIN		STEM, Non-FIN		Non-STEM, Non-FIN	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2011								
Family size	2.86	1.41	2.84	1.41	2.77	1.43	2.95	1.60
Children	0.93	1.09	0.84	1.07	0.84	1.09	0.83	1.12
Age	41.98	10.61	42.24	12.58	42.56	11.88	42.12	13.39
Male	0.68	0.47	0.39	0.49	0.76	0.43	0.52	0.50
Married	0.68	0.47	0.60	0.49	0.65	0.48	0.55	0.50
White	0.71	0.45	0.80	0.40	0.78	0.41	0.76	0.43
Black	0.07	0.26	0.10	0.30	0.06	0.24	0.11	0.32
College	0.47	0.50	0.35	0.48	0.42	0.49	0.19	0.39
Masters	0.22	0.41	0.11	0.32	0.18	0.38	0.10	0.30
Doctorate	0.01	0.11	0.00	0.07	0.03	0.18	0.01	0.12
Hours worked	2,168	412	2,091	500	2,131	508	1,962	617
Hourly wage	$42.40	$27.00	$31.90	$32.70	$35.70	$23.00	$22.70	$21.60
Annual earnings	$93,036	$66,134	$69,389	$79,484	$75,952	$51,826	$45,050	$47,603
In metro area	0.18	0.38	0.16	0.37	0.14	0.35	0.15	0.36
Observations	4,091		54,939		72,135		1,042,931	
2017								
Family size	2.80	1.40	2.84	1.44	2.75	1.44	2.96	1.62
Children	0.85	1.06	0.82	1.07	0.78	1.06	0.80	1.12
Age	42.25	11.40	43.04	12.98	42.48	12.61	42.21	13.94
Male	0.70	0.46	0.40	0.49	0.76	0.43	0.52	0.50
Married	0.66	0.47	0.59	0.49	0.63	0.48	0.52	0.50
White	0.67	0.47	0.77	0.42	0.74	0.44	0.74	0.44
Black	0.07	0.25	0.11	0.31	0.07	0.25	0.12	0.33
College	0.48	0.50	0.38	0.48	0.44	0.50	0.20	0.40
Masters	0.24	0.43	0.14	0.35	0.20	0.40	0.11	0.32
Doctorate	0.01	0.11	0.01	0.08	0.03	0.18	0.01	0.12
Hours worked	2,152	401	2,107	475	2,126	474	1,990	598
Hourly wage	$44.50	$29.00	$36.60	$39.30	$38.30	$26.40	$23.90	$24.60
Annual earnings	$96,675	$70,677	$80,053	$94,050	$81,573	$59,933	$48,250	$54,257
In metro area	0.17	0.38	0.15	0.36	0.14	0.35	0.14	0.35
Observations	6,145		60,306		89,969		1,139,448	

Note: This table reports the means and standard deviations of different demographic and labor-related characteristics for STEM and non-STEM workers, where STEM workers are those defined by the Bureau of Labor Statistics. Income is deflated using the 2012 personal consumption expenditures price index. Observations are weighted using the American Community Survey sample weights.

2.2. Panel of Occupation-by-Industry Employment and Wages

The primary data come from the BLS's Occupation and Employment Statistics (OES), which covers each six-digit occupation at a national, industry, and regional disaggregation. Although the BLS cautions that these occupations are not necessarily comparable over time because the survey is based on a rotating panel, the OES is the most comprehensive and only viable dataset for these purposes. We can observe, for example, employment, hourly wages, annual income, and different parts of the earnings distribution for each six-digit occupation, as well as occupation-by-industry and occupation-by-metropolitan-area statistics.

2.3. Industry Panel of Regulatory Restrictions

Although a wide array of papers examine the effects of specific regulations, comprehensive measurements of regulation across sectors and time have been challenging to produce. Recent data, made available through George Mason University's Mercatus Center (Al-Ubaydli and McLaughlin, 2017), measure such restrictions across industries starting in 1970, using the *Code of Federal Regulations* (CFR). The CFR is published annually and contains all regulations issued at a federal level across 50 different titles (i.e., broad subject areas).

The count of regulatory restrictions is created in two steps. First, Al-Ubaydli and McLaughlin search for the presence of binding constraints, specifically through the following words: "shall," "must," "may not," "required," and "prohibited." Second, they assign these restrictions to different sectors according to the relevance of the text to different economic sectors. In particular, using natural language processing on the *Federal Register*, which contains mappings between industries and texts, they train a logit-based classifier to generate probabilities for each CFR part (because one part can apply to multiple sectors). Together with the regulatory restriction counts, they produce a weighted aggregation for each North American Industry Classification System (NAICS) × year pair.

There are other ways to measure regulation.[6] For example, Simkovic and Zhang (2018), on the basis of data from O*NET, proxy for regulation using the wage bill across occupations that involve tasks related to compliance. Using a matched sample of 119 four-digit industries between 2002 and 2016, we find a correlation of 0.27 between our measure of regulatory exposure. Moreover, when we focus on finance, we find a correlation of 0.37. We view our measures of regulatory exposure as complements: whereas Simkovic and Zhang (2018) take a demand-side measure through the wage bill of occupations with greater compliance-related tasks, we take a supply-side approach to measuring regulations.

2.4. US Patent and Trademark Office Patent Database

We use patent applications from the US Patent and Trademark Office (USPTO) as a proxy for innovation and thus reliance on STEM workers. We obtain the number of patents applied for and issued each year from 2000 to 2016, and whose assignees were among the top 30 largest banks in terms of assets as of 2019.

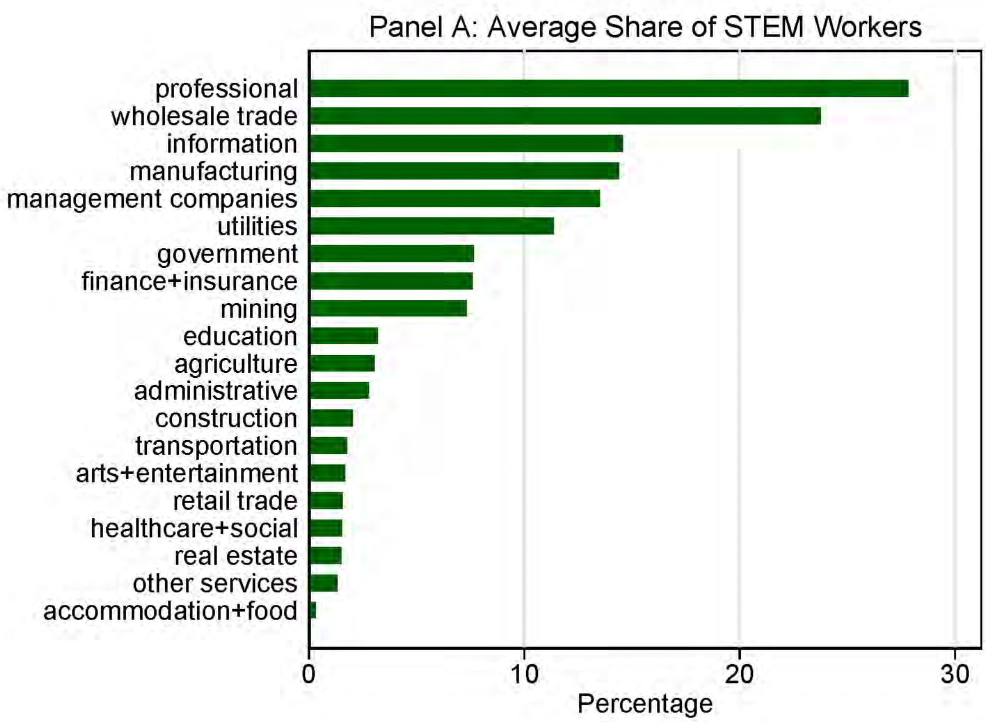
3. Descriptive Evidence

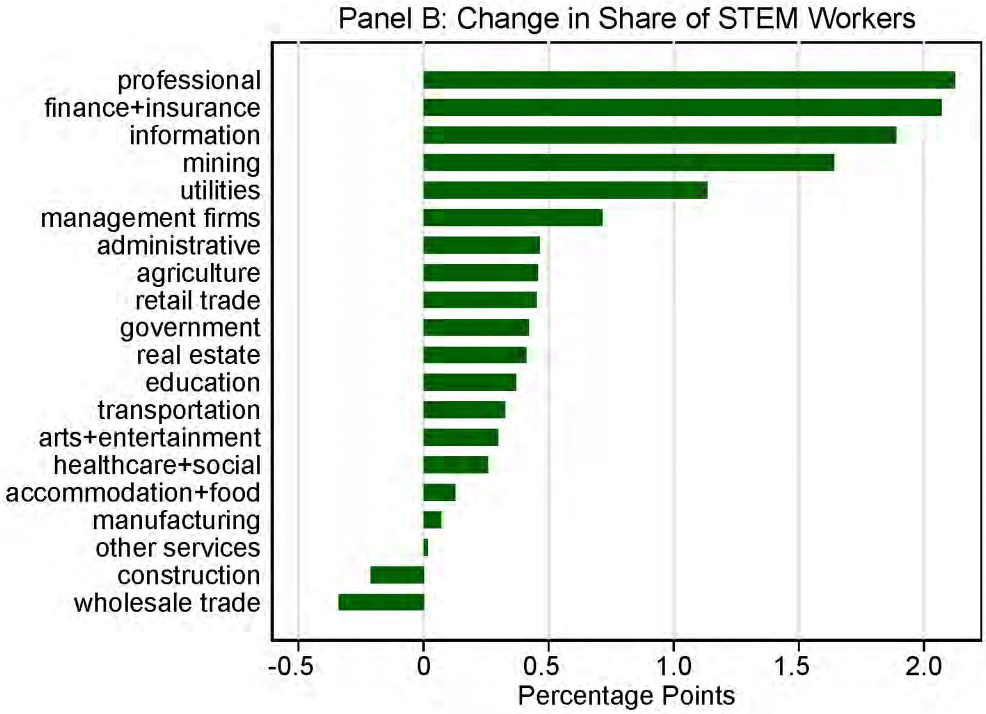
We start by noting some trends in the evolution of STEM workers, their earnings, and the broader changes in the regulatory environment since 2005. First, we examine the dispersion and time series patterns of the STEM share across industries, displayed in figure 1. Panel A shows that financial services ranks in the middle of the distribution of industries, with a STEM share of

[6] Page counts from the CFR are another common alternative measure of regulation; see, for example, Mulligan and Shleifer (2005) and Dawson and Seater (2013).

7.56 percent, whereas the industry ranking the highest is professional services, with a STEM share of 28.2 percent. Panel B shows that the financial services sector exhibited the second-highest growth in the share of STEM workers between 2011 and 2017, with a growth of roughly 2.1 percentage points. The increase in STEM workers in finance and its modernization are related to the rise of shadow banking, which increased significantly between 2007 and 2015, according to Buchak et al. (2018) and Fuster et al. (2019). Moreover, the increase in STEM workers in finance could be a function of a reallocation of engineers into financial services from other sectors (Gupta and Hacamo, 2019).

Figure 1. Cross-Sectional and Time Series Dispersion in the Share of STEM Workers, 2011–2017

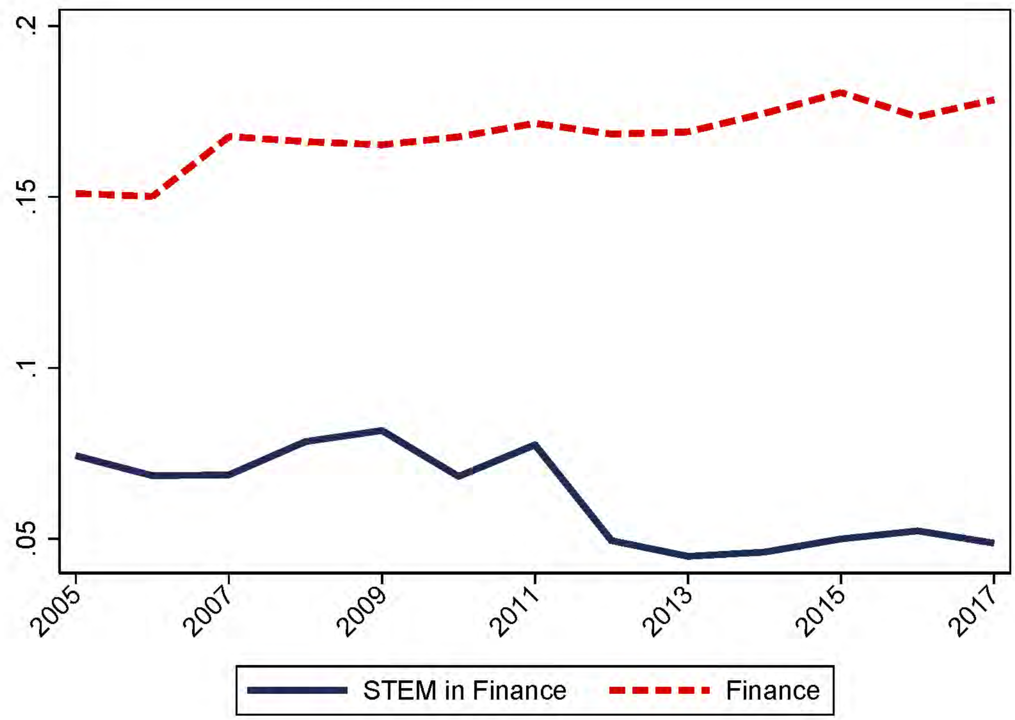




Note: This figure plots the average share (panel A) and the 2011–2017 percentage point change (panel B) of STEM workers across major two-digit industry classifications, using data from the American Community Survey (Integrated Public Use Microdata Series), 2011–2017. STEM workers are those defined by the Bureau of Labor Statistics.

Second, we now investigate earnings differences between STEM and non-STEM workers in finance, relative to the overall finance premium that has been increasing over time, according to Philippon and Reshef (2012). Figure 2 displays these results. Although STEM workers in finance always earn more than non-STEM workers in finance over our sample, we see a rapid decline in the premium from roughly 8 percent in 2011 to 4.5 percent by 2013, subsequently rising to 5.5 percent by 2016. These patterns are consistent with an initial rise in the demand for STEM-related skills to accomplish traditionally lower-paying non-STEM tasks, which leads to an expansion of STEM employment, subsequently moderating the price of such skills.

Figure 2. Earnings Premiums among STEM Finance and Finance, 2005–2017



Note: This figure plots the earnings premium among STEM versus non-STEM workers in finance (left *y* axis) and finance versus nonfinance workers (right *y* axis), using data from the American Community Survey, 2005–2017. STEM workers are those defined by the Bureau of Labor Statistics. Individuals with an hourly wage of at least $2 are included in the sample, and nominal earnings are deflated using 2012 real prices. Observations are weighted by the survey sample weights.

Moreover, the decline in the earnings premium for STEM workers during the Great Recession is consistent with related literature on the skill premium associated with cognitive and nonroutine tasks over these years. For example, Beaudry, Green, and Sand (2016) find that, because the Great Recession led to a significant reduction in lower-skilled and routine jobs, some higher-skilled workers fell down the job ladder to replace those less-skilled workers. Similarly, Hershbein and Kahn (2018) find that firms responded to the Great Recession in part by increasing their requirements for new hires, which led to a higher-quality labor force.

In light of these time series patterns, we also investigate cross-sectional earnings and differences in hours worked between STEM and non-STEM workers in financial services, controlling for occupation, industry, time fixed effects, and individual demographic characteristics. These results are documented in table 2.

Table 2. Earnings and Hours Premiums in Financial Services and STEM Occupations

Dep. var. =	log(annual real earnings)				log(annual hours worked)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Finance × STEM	.062**	.062**	−.262***	.081***	.010*	.010*	−.090***	.021***
	[.025]	[.025]	[.050]	[.021]	[.006]	[.006]	[.030]	[.007]
× Ages 25–29			.201***				.087***	
			[.033]				[.025]	
× Ages 30–34			.272***				.091***	
			[.040]				[.026]	
× Ages 35–39			.329***				.104***	
			[.047]				[.028]	
× Ages 40–44			.364***				.102***	
			[.051]				[.031]	
× Ages 45–49			.375***				.105***	
			[.055]				[.025]	
× Ages 50–54			.382***				.113***	
			[.056]				[.029]	
× Ages 55–59			.382***				.112***	
			[.060]				[.029]	
× Ages 60–65			.411***				.154***	
			[.058]				[.029]	
× College				−.032				−.016***
				[.021]				[.004]
R^2	.46	.46	.47	.46	.11	.11	.12	.11
Sample size	14,910,229	14,910,229	14,910,229	14,910,229	14,893,122	14,893,122	14,893,122	14,893,122
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SOC2 × Year FE	No	Yes	No	No	No	Yes	No	No

Note: This table reports the coefficients associated with regressions of logged annual earnings and logged annual hours worked (usual hours worked per week for weeks worked over the previous year) on an indicator for whether the individual is in the financial services sector and STEM occupation, controlling for demographics. Controls include family size; marital status; race (white, black); education (college, masters, doctorate); and an indicator for whether the individual lives in a metropolitan area. Standard errors are clustered at the five-digit SOC level, and observations are weighted by the American Community Survey sample weights. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Starting with earnings differences, we find that STEM workers in finance earn 6.2 percent more than their counterparts (column 1), which is a robust result even after controlling for two-digit occupation × year fixed effects to capture potential time-varying shocks in the demand for skills (column 2). We subsequently allow for heterogeneity by age bracket and education. Interestingly, we find that STEM workers in finance earn less than their counterparts at the start of their careers (column 3). For example, between ages 25 and 29, they earn 6.1 percent less (–0.262 + 0.201), but by age 30 the premium turns marginally positive and continues to increase over the life cycle. By ages 60 to 65, STEM workers in finance earn 14.9 percent more than their counterparts. However, when we allow for heterogeneity by education, we surprisingly find a slight negative earnings premium of –3.2 percent among those with at least a college degree.[7] Although the negative college premium in STEM jobs may appear counterintuitive, this result is likely driven by a subset of high earners in STEM jobs with nontraditional backgrounds; in contrast, when we do not control for narrow five-digit SOC fixed or industry effects, we find a 30 percent college premium.

Turning toward differences in annual hours worked, we find that STEM workers in finance work roughly 1 percent more than their counterparts (column 5), which is again robust to controlling for occupation × year fixed effects. However, the hours premium rises considerably over the life cycle: by ages 60 to 65, STEM workers in finance work 6.4 percent more than their counterparts (column 7). Nonetheless, this is still less than the earnings premium, suggesting that the hourly wage premium for finance is still positive and increasing over the life cycle. Finally, we see again that STEM workers in finance with a college degree or higher work 1.6 percent fewer hours than their counterparts. The negative earnings and hours premiums among STEM

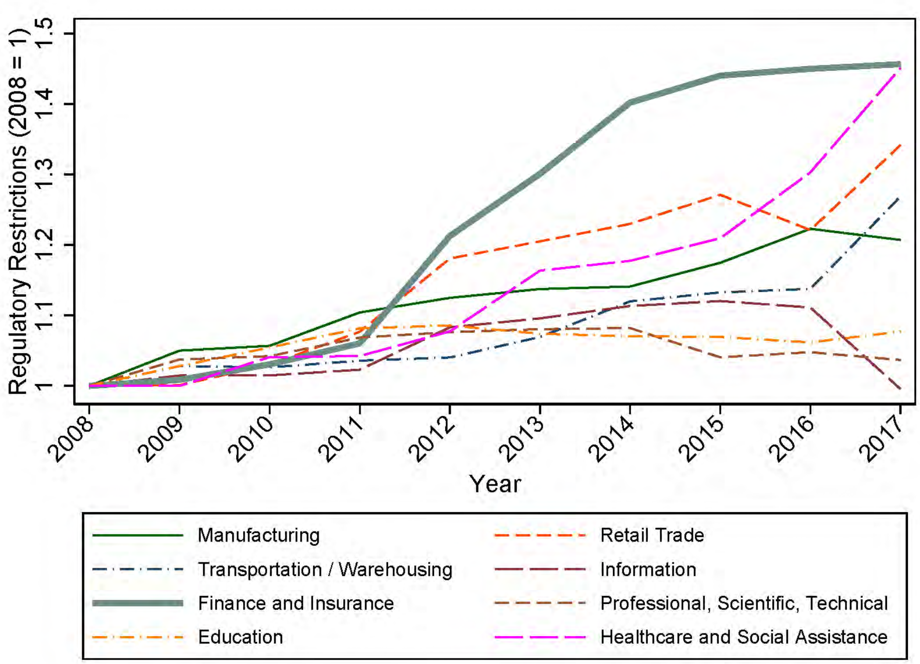
[7] We also investigated the earnings premiums for STEM workers in finance and for workers in finance separately by year. In the former specification, we controlled for four-digit NAICS and five-digit SOC fixed effects, together with demographics. We found a decrease in the premium for STEM workers in finance from 8 percent in 2009 to 5 percent in 2013, whereas we found an increase in the premium for finance workers from 15 percent in 2005 to 18 percent in 2018.

workers in finance with at least a college degree could reflect greater earnings among non-STEM workers, such as investment bankers, relative to software engineers.

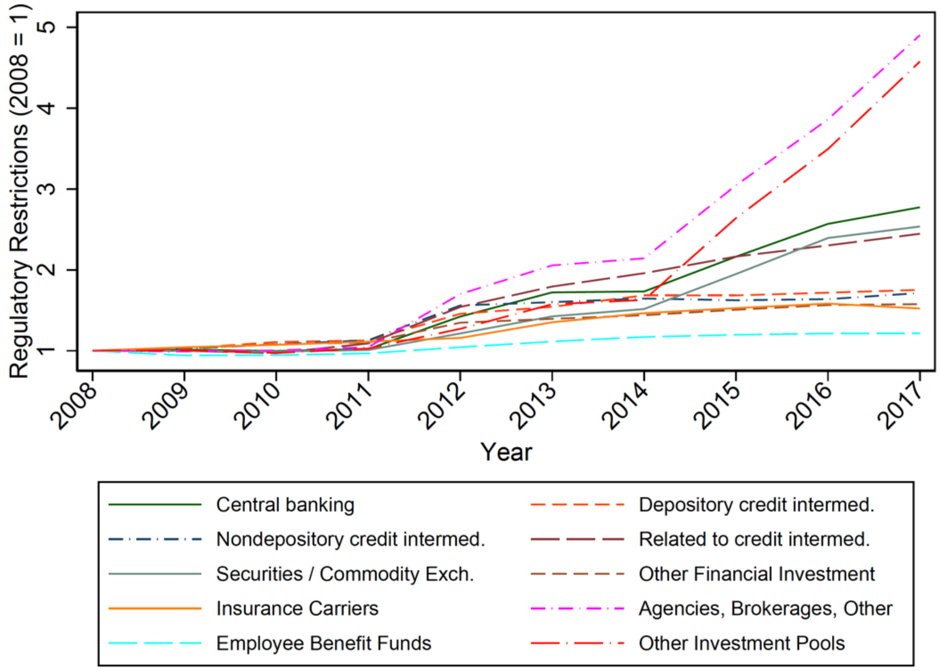
Third, panel A in figure 3 investigates the time series patterns of regulatory restrictions between 2008 and 2017, normalized to 2008 by sector. Although regulation has increased overall, it has increased the most in finance and insurance. However, there is considerable heterogeneity within each subsector. For example, panel B in figure 3 plots the regulatory restrictions, normalized to 2008, within finance. Although the passage of Dodd-Frank was associated with a general regulatory increase across sectors in 2011, some sectors saw a much higher increase than others. Moreover, subsequent financial regulation as of 2014 has affected (a) agencies, brokerages, and other insurance and (b) other insurance pools much more than their counterparts.

Figure 3. Time Series Patterns in Regulatory Restrictions, 2008–2017, Normalized to 2008

Panel A. Time Series Patterns in Regulatory Restrictions for All Sectors



Panel B. Time Series Patterns in Regulatory Restrictions within Finance

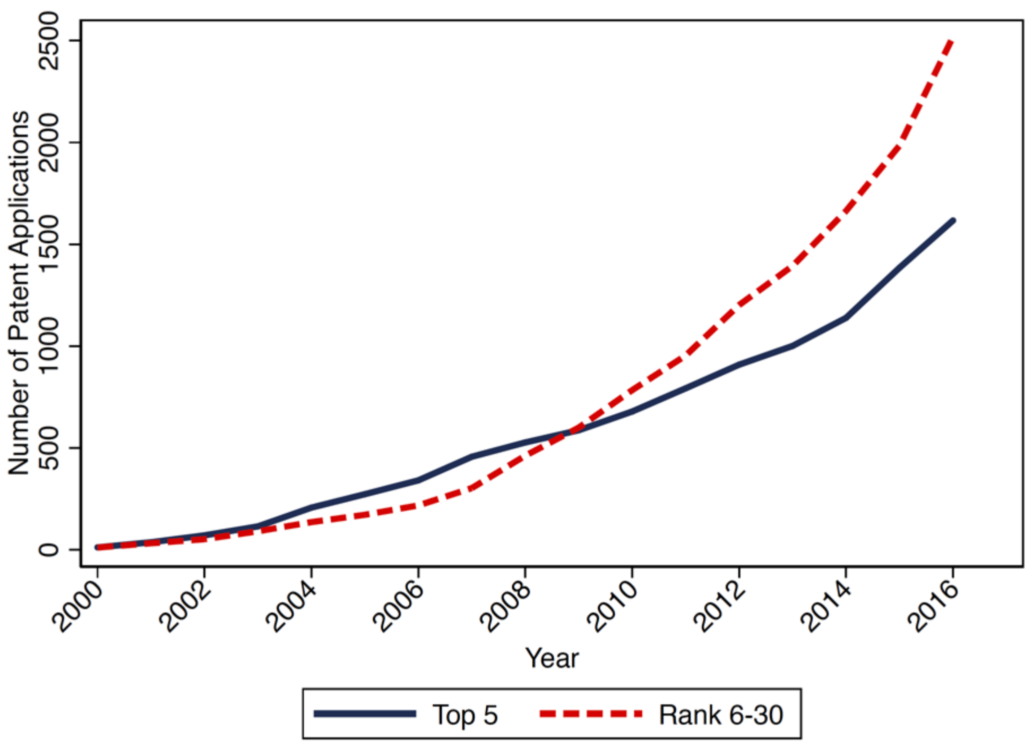


Note: Panel A in the figure plots the normalized number of regulatory restrictions across two-digit subsectors. Panel B plots the normalized number of regulatory restrictions within each of the 10 financial services subsectors.
Source: Al-Ubaydli and McLaughlin (2017).

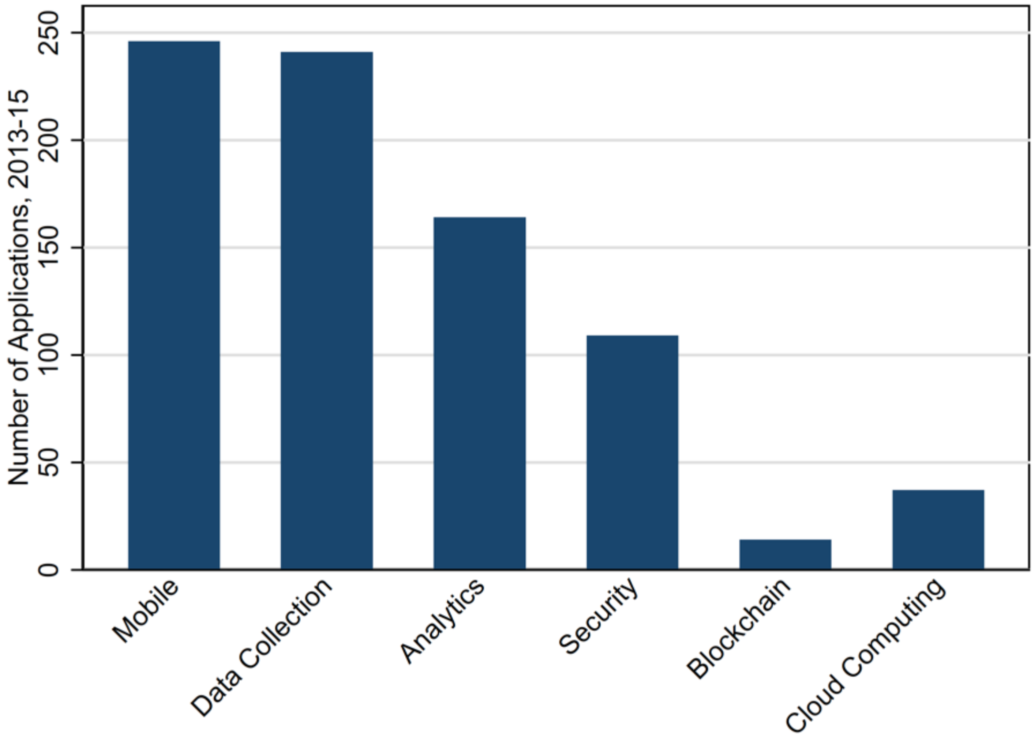
To provide a bridge to our analysis of regulation, we also consider patent issuance by type of institution. Patent issuance provides a measure of innovation and tilt toward technology jobs. We focus on commercial banking, a financial services sector that has seen great regulatory change since 2011. Several recent papers have documented a divergence in the lending behavior and business models of the largest, most heavily regulated banks (Calem, Correa, and Lee, 2016; Chen, Hanson, and Stein, 2017; Gete and Reher, 2020). Building on this literature, we investigate the time series patterns of patent issuance among commercial banking institutions of different sizes. We focus on patents because of their tight link with STEM workers. For example, Autor et al. (2020) show that industries with higher shares of STEM workers also patent more, and Bianchi and Giorcelli (2019) show that earning a STEM degree allows employees to enter jobs that lead to more innovative activities. Panel A in figure 4 plots the cumulative number of patent applications for the top five banks (ranked by asset value) with those between ranks 6 and 30. While there has been a secular increase since 2000, the surge is concentrated among large banks after 2011. Panel B subsequently plots the type of patenting activity across banks, showing a particularly large concentration among mobile, data collection, and analytics.

Figure 4. Patenting Trends and Types among Big and Small Banks

Panel A. Number of Patent Applications Assigned to Commercial Banks



Panel B. Type of Patents among Commercial Banks



Note: Panel A plots the number of patent applications assigned each year to the top five commercial banks (ranked by assets) and to those ranked between 6 and 30. Panel B plots the type of patents among these banks from 2013 to 2015.
Source: Authors' calculations based on data from USPTO (panel A) and Relecura Inc. (panel B).

4. Understanding the Rise in STEM Employment in Finance: Potential Explanations

In this section, we explore the potential economic mechanisms driving our results. We propose three potential explanations for our baseline findings.

The first relates to the work of Griliches (1969). In particular, declines in the cost of capital should lead to increases in the demand for STEM workers if capital and skill are relative complements, which would result in increases in both employment and wages for these workers. Figure 2 casts doubt on this hypothesis because the earnings premium actually has declined since 2008; thus, we investigate the hypothesis more rigorously in two ways.

We first begin by measuring how changes in the cost of capital across finance sectors influence employment in STEM occupations. Although we do not have a direct measure of the cost of capital, we defer to the results from Campbell, Dhaliwal, and Schwartz (2012), who find that financial constraints are an important mediating force on the cost of capital. We also turn to Hoberg and Maksimovic (2015), who measure financing constraints using a text-based classifier applied to about 10,000 files among the sample of publicly traded firms as a proxy for the cost of capital. We subsequently create a four-digit (employment) weighted average of financial constraints for firms in finance and use it as a regressor in the following baseline specification:

$$log(Employment)_{ijt} = \gamma\left(COST_{CAP_{it}} \times STEM_j\right) + \zeta_{it} + \lambda_{ij} + \varepsilon_{ijt}, \qquad (1)$$

where our outcome variable is the logged number of workers in occupation j, industry i, and year t; $COST_{CAP_{it}}$ is a proxy for the cost of capital, *STEM* denotes an indicator for whether the occupation is classified as such by the BLS, and ζ and λ denote industry-year and industry-occupation fixed effects, respectively. Our fixed effects isolate variation within occupations after controlling for all time-invariant heterogeneity across industries and occupations, as well as time-varying industry-specific trends.

The results are reported in columns 1–3 of table 3. We find that, although there is a theoretically consistent negative relationship between STEM employment and the cost of capital, these estimates are not statistically significant across each of our specifications that control for different layers of fixed effects. In particular, using industry × year and industry × occupation fixed effects, we find that a unit increase in financial constraints in STEM occupations is associated with a statistically insignificant 0.25 percent decline in STEM employment.

Table 3. Evaluating the Role of Technological Change and STEM Employment

Dep. var. =	log(occupational employment)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Financial constraints × STEM	−1.700	−1.671	−.248						
	[5.731]	[1.052]	[.408]						
log(IP stock) × STEM				−.547**	1.435***	−.075			
				[.183]	[.325]	[.281]			
log(total factor productivity) × STEM							2.769	2.076***	.198
							[1.858]	[.487]	[.189]
R^2	.00	.94	.95	.00	.94	.96	.00	.94	.96
Sample size	1,552	1,501	1,501	9,609	9,486	9,486	9,093	8,986	8,986
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry × year FE	No	No	Yes	No	No	Yes	No	No	Yes
Industry × occupation FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: The table reports the coefficients associated with regressions of logged six-digit occupational and four-digit industry employment on three right-hand side variables: (a) a four-digit weighted average of financial constraints from Hoberg and Maksimovic (2015) interacted with an indicator for a STEM occupation; (b) the year-to-year growth rate in the net stock of intellectual property (2012 chained prices) interacted with an indicator for STEM; and (c) total factor productivity interacted with an indicator for STEM, conditional on fixed effects. Total factor productivity is obtained by regressing logged output (2012 chained prices) on logged employment and capital, taking the residual as the total factor productivity. STEM workers are those defined by the Bureau of Labor Statistics. Observations are unweighted, and standard errors are clustered at the four-digit NAICS level.
Source: Occupational Employment Statistics, Hoberg and Maksimovic (2015) (2001–2015), and the Bureau of Economic Analysis (2002–2017). *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

One of the concerns associated with our measure of financial constraints is that it proxies for unobserved characteristics across industries in a way that attenuates or biases our estimates. We alternatively use variation in technology to proxy for changes in the cost of capital, although it could bias us in the opposite direction. We measure technological change in two ways. The first is the industry-level year-to-year growth in the net stock of intellectual property stock, available from the BEA. The second is the year-to-year growth in total factor productivity, obtained by regressing logged output (2012 chained prices) on logged employment and capital, taking the residual. We subsequently replace the "financial constraint" variable in equation (1) with these two direct measures of tech intensity.

The results are reported in the remaining columns of table 3. The results in columns 3–6 pertain to the intellectual property stock variable, and the last three columns pertain to total factor productivity. Our preferred specifications are in the sixth and ninth columns, because they control for industry-year fixed effects as well as industry-occupation fixed effects. In both cases, we find the coefficient is insignificant, indicating that the increase in tech intensity does not explain the increase in tech employment over these years. It is possible—and in fact likely—that tech intensity may explain STEM employment over longer horizons.

The second explanation relates to the overall increase in the STEM-designated degrees awarded by business schools over the past decade.[8] The STEM designation is extremely valuable for international students because it allows them to apply for postgraduation work permits—generally known as optional practical training—that last up to 36 months instead of 12 months. Because of the partial enrollment decline in master of business administration programs, business schools have introduced a variety of STEM-designated finance degrees. It is therefore possible that the increase in STEM-designated employment in finance is attributable to the increase in STEM-designated degrees. We can rule out this hypothesis in two ways.

First, we start from the ACS data and restrict the sample to individuals who work in finance (NAICS code 52). We then compute the number of STEM workers who have a finance degree as a fraction of all STEM workers. We find that this fraction is very small overall: only 2.5 to 3.0 percent of STEM workers in finance have a finance degree.[9] More importantly, this fraction has not increased over time: it was 2.88 percent in 2011 and 2.74 percent in 2017.

[8] There is evidence in the popular press about the rise in the attractiveness of offering STEM degrees, even among business schools; see, for example, Cheng (2020).

[9] One concern is that our focus only on finance is too restrictive, because other undergraduate majors also generally enter the finance field (e.g., economics majors). Using the more general business category, we find that the share of business students in STEM is 17 percent. This fraction also has not varied over time: the share moved from 16.4 percent in 2011 to 17.7 percent in 2018.

Second, although the number of STEM workers in finance increased dramatically from 2009 to 2017—from 460,000 to 640,000—the number of new graduates in finance (those younger than age 23) with a STEM degree constitutes a very small fraction of this population. Moreover, this fraction has not increased over time. Using the 2010 ACS sample, we count 881 STEM workers younger than age 23 with a finance degree. The number is 630 and 1,521 for the years 2013 and 2016, respectively.

The third explanation we propose relates to regulation and the returns to automation. In brief, we explore whether increases in regulation increase STEM employment as a way of reducing compliance costs. Our empirical estimation is motivated by many anecdotal examples that point toward increased investments in automation as a result of heightened regulatory burdens, particularly given that regulation in finance has grown more than in any other sector in the past decade. For example, the chief economist for digital regulation at the Spanish bank BBVA remarked in the *Financial Times* that "banks are switching to be really data-driven companies—that will be one of the biggest drivers for the industry in the next few years and regtech will be part of that" (Arnold, 2016). Moreover, Van Liebergen et al. (2016) said that "by making compliance less complex and capacity-demanding, regtech solutions could free capital to put to more productive uses." We investigate this hypothesis and the mechanism more rigorously in sections 5 and 6.

5. Regulation and Automation

We now turn to identifying the impact of regulation on employment and, in particular, on the set of high-skilled jobs. Our hypothesis is that regulation will prompt declines in labor intensity because the bulk of the regulatory incidence falls on labor, rather than capital, in the financial services sector. In appendix B, we present a stylized model consistent with the empirical results that show regulation prompts substitution to STEM tasks.

5.1. Empirical Strategy

To assess the impact of regulation on automation, we replace the "financial constraint" variable in equation (1) with a two-year lag on the logged number of regulatory restrictions. We take the two-year lag of regulatory restrictions for two reasons: (a) to mitigate concerns about reverse causality and (b) to allow for a time delay between the appearance of a new CFR regulation and the response to it by firms.[10] Our baseline specification restricts the sample to the financial services sector, but we also present results that include professional services as a control group. The parameter of interest, γ, is the elasticity of employment with respect to regulation for STEM workers. In both cases, we use variation within, not across, industries (i.e., panel B of figure 3, not panel A).

However, simply correlating employment in STEM occupations with regulation—even with industry, occupation, and time fixed effects—is likely to produce biased estimates for two reasons. First, there has been a secular increase in STEM employment across industries (figure 1). If, for example, demand for STEM employment is correlated with overall growth, and growing industries require greater regulation, this could generate a spurious correlation. Second, declines in economic performance could coincide with increases in regulation, particularly during the Great Recession of 2008–2009. For example, perhaps damaged bank balance sheets would both invite regulation and lead to layoffs of workers with less value-added.

[10] See Al-Ubaydli and McLaughlin (2017) and Coffey, McLaughlin, and Peretto (2020) for additional discussion of appropriate lags. Our results are also robust to using, for example, a one- or three-year regulation lag.

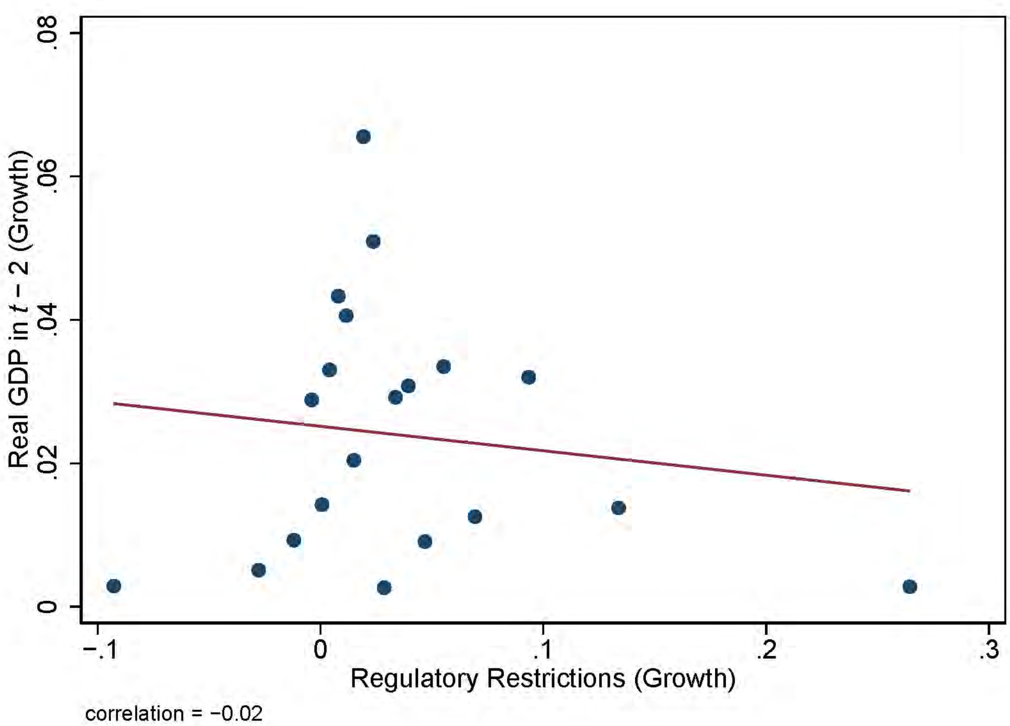
A closely related concern is that high-skilled workers naturally sort into certain areas of finance (Célérier and Vallée, 2019). This concern complicates an identification strategy that relies on variation solely within a given occupation, because the most talented workers within that occupation would gravitate toward industries with the greatest talent premium (e.g., investment banking). To the extent that those industries also invite more intense regulation, one might confound the effect of regulation on the distribution of occupations with the natural sorting of talented workers into particular industries with higher productivity.

To address these identification concerns, we introduce occupation × industry and industry × year fixed effects. By controlling for occupation × industry, we purge variation in employment that is driven by systematic differences in STEM-related skills. For example, investment banking may require different degrees of STEM intensity than insurance. Moreover, by controlling for industry × year, we purge variation in employment that may be driven by industry-specific trends. In this sense, our identification strategy can be interpreted as a triple-difference estimator, whereby we isolate changes in STEM versus non-STEM employment within the same industry × occupation pair after controlling for all shocks that are common within a given industry × year.

As we discussed earlier, one of our primary concerns is that declines in economic performance could lead to increases in regulation. For example, sectors that suffer more during a business cycle could demand greater federal involvement. In particular, the recent rise in financial regulation may have been much lower in a counterfactual world absent the 2008–2009 financial crisis. Although we found a correlation of −0.26 between economic performance and regulation in the national time series, we find no meaningful correlation of such at an industry level: we relate annual growth in regulatory restrictions with a two-year lag of annual real GDP growth at a three-digit NAICS level between 1997 and 2018.

Figure 5 documents our results, weighting by average real GDP (and our results are robust without weights).[11] We find nearly a null association between lagged real GDP growth and regulation growth (*ﬂ* = −0.02). The correlation is also invariant to using a one-year lag of real GDP growth, rather than a two-year lag. This suggests that, although broader sectoral or aggregate declines in economic performance might prompt regulatory responses, the productivity patterns within narrow subsectors may be more plausibly exogenous.

Figure 5. Regulatory Expansions and Historical Economic Performance, 1997–2018



Note: The figure plots the relationship between year-to-year growth in regulatory restrictions and the two-year lag of year-to-year growth in real GDP at the three-digit NAICS level. Observations are weighted by the average real GDP over the sample series. The data sources are Al-Ubaydli and McLaughlin (2017) and the Bureau of Economic Analysis, 1997–2018.

[11] We use the two-year lag because it is our main explanatory variable in the regressions that follow, which relate regulatory restrictions and STEM employment. Table I in appendix C also presents results under alternative specifications. When we use contemporaneous real GDP growth, we find a negative association, which would bias us against finding a result.

5.2. Main Results

Table 4 presents our main results associated with equation (1) under several specifications. Using only cross-sectional variation in column 1, we find a noisy, but positive, association between regulation and employment and a slightly negative relationship for STEM jobs. However, this specification is likely to produce biased estimates. As we discussed earlier, industries and occupations with greater productivity likely have a greater demand for STEM workers to fuel their innovation activities. To the extent that unobserved productivity shocks are negatively correlated with regulation (as we see in the national time series), we will obtain a downward biased estimate on regulation.

Table 4. Baseline Effects of Industry Restrictions on Demand for STEM Workers

Dep. var. =	log(occupational employment)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(regulatory restrictions)$_{t-2}$	.167	.711				
	[.152]	[.410]				
× STEM occupation	−.014***	.566***	.531***	.580***	.540***	.155
	[.004]	[.155]	[.137]	[.135]	[.138]	[.105]
× Compliance occupation					.869***	
					[.141]	
× Finance						.376**
						[.171]
log(annual income)				−.052		
				[.075]		
R^2	.02	.95	.96	.96	.96	.96
Sample size	15,707	15,540	15,540	15,295	15,540	28,374
Year FE	No	Yes	Yes	Yes	Yes	Yes
Industry × year FE	No	No	Yes	Yes	Yes	Yes
Industry × occupation FE	No	Yes	Yes	Yes	Yes	Yes

Note: The table reports the coefficients associated with regressions of logged six-digit occupational and four-digit industry employment on the logged number of industry restrictions and its interaction with an indicator for whether the six-digit occupation is classified as a STEM job, conditional on fixed effects. STEM workers are those defined by the Bureau of Labor Statistics. Observations are unweighted, and standard errors are clustered at the four-digit NAICS level. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.
Source: Occupational Employment Statistics, Al-Ubaydli and McLaughlin (2017) (2005–2017), and the American Community Survey for average five-digit SOC earnings.

Column 2 adds year and industry × occupation fixed effects to isolate the variation within each industry occupation pair over time, while controlling for the overall changes in employment across industries and occupations over time. We now find an insignificant effect of regulation on employment, but a large effect on the interaction with STEM employment: a 10 percent rise in regulatory restrictions is associated with a 5.6 percent rise in STEM employment.

In the third column, we provide an alternative specification where we control for industry × year fixed effects to account for the fact that different industries may have experienced different economic cycles since 2005. This specification compares the response of employment to changes in regulation in the same occupation after controlling for all the shocks that are common across industries over time. The effect uncovered in column 3 is very similar to the one in column 2: a 10 percent rise in regulatory restrictions is associated with a 5.6 percent rise in STEM employment. Note that in this specification, and the ones that follow, the coefficient on the number of regulatory restrictions is absorbed by the industry × year fixed effects.

To address the concern that there are still omitted time-varying characteristics that are correlated with both employment and regulation, we control for income in column 4, which only raises our point estimate. Moreover, if we are capturing an association that is genuinely related to regulation, rather than just a productivity shock correlated with the demand for high-skilled workers, then we should also observe an increase in the demand for compliance workers. Indeed, we find an even larger point estimate for compliance officers: a 10 percent rise in regulatory restrictions is associated with an 8.69 percent rise in employment among compliance officer occupations (even after controlling for STEM workers). We view this estimate, as well as its joint significance, as a comforting robustness exercise, given that the effect of regulation on compliance officers is uncontroversial.

Finally, column 6 presents the results for a specification that includes both professional services and financial industries. This specification uses a triple-difference estimator that treats professional services as a control group. Although the professional services industry is similar to the financial services industry in its demand for high-skilled workers, particularly its demand for STEM workers, it differs in its exposure to regulation. For example, between 2002 and 2017, regulatory restrictions grew by 66.49 percent in finance, but only by 15.37 percent in professional services. We find that a 10 percent rise in regulatory restrictions is associated with a 1.55 percent rise in STEM employment in professional services, but the coefficient is not statistically significant. The coefficient on the interaction between regulation and finance is instead positive and statistically significant. A 10 percent rise in regulatory restrictions is associated with a 3.76 percent rise in STEM employment in financial services. This is consistent with the view that increases in regulation raise the returns to automation, but that the financial services industry is uniquely sensitive to these changes.

Although we do not have a discrete treatment that allows us to precisely test the presence of parallel trends between our treatment and control groups (i.e., STEM and non-STEM), we exploit the fact that regulation surged after the passage of Dodd-Frank in 2010, comparing professional and financial services before and after 2010. Figure I in appendix C documents regulatory restrictions in professional and financial services, normalized to 2002. The series track almost perfectly up until 2011, when regulatory restrictions in financial services begin to surge, whereas they remain flat in professional services.

Treating 2011 as the date of our treatment, figure II in appendix C tests for parallel trends between STEM and non-STEM occupations for our difference-in-difference estimator (panel B), as well as between STEM jobs in finance and STEM jobs in professional services for our triple-difference estimator (panel A). Specifically, we plot interactions between finance × STEM × post-2010 and STEM × post-2010, with logged employment as our outcome variable. We see little evidence of a pre-trend with our difference-in-difference estimator and no evidence of a pre-trend with our triple-difference estimator, which suggests that employment in STEM occupations, particularly in financial services relative to professional services, would have trended similarly in the absence of the growth in regulation that followed Dodd-Frank.

5.3. Robustness Using Dodd-Frank

One potential limitation of our measurement strategy thus far is that our measure of regulatory restrictions is relatively general—that is, we treat each regulatory restriction homogeneously. What specific regulations might be influencing the demand for STEM versus non-STEM workers, and where does the regulatory burden fall? We now present the results associated with our difference-in-difference estimate of the Dodd-Frank legislation in table 5. The specification is analogous to equation (1), except that we replace our measure of regulation, r, with the interaction of an indicator for whether Dodd-Frank has been passed (July 2010) for $t \geq 2011$ and for whether the industry is depository credit intermediation. Many of the regulations surrounding Dodd-Frank disproportionately affect depository institutions (e.g., stress tests), even though the origins of the financial crisis lay in credit intermediation more broadly (e.g., shadow banking), not solely in the already heavily regulated depository institutions. Thus, using more than a decade’s worth of data, we are able to identify the effect of regulation from the difference between depository and nondepository lenders’ hiring of nonbank workers.

Table 5. Supplementary Evidence on the Demand for STEM Workers from Dodd-Frank

Dep. var. =	log(occupational employment)			
	(1)	(2)	(3)	(4)
1[STEM] × 1[t > 2011]	.358***	.378***	.410***	.363***
	[.097]	[.096]	[.129]	[.097]
log(annual earnings)		−.038		
		[.101]		
1[compliance] × 1[t > 2011]				.370***
				[.036]
R^2	.96	.96	.96	.96
Sample size	17,696	17,413	5,515	17,696
Occupation FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes	Yes
Industry × occupation FE	Yes	Yes	Yes	Yes
Sample	All finance	All finance	Credit institutions	All finance

Note: This table reports the coefficients associated with regressions of logged six-digit occupational and four-digit industry employment on an interaction between an indicator for whether the six-digit occupation is classified as a STEM job and for t > 2011 as a proxy for the Dodd-Frank legislation. STEM workers are those defined by the Bureau of Labor Statistics. Compliance officers are those in SOC 13-1040 or 13-1041. Columns 1, 2, and 4 include all financial services jobs, whereas column 3 restricts the sample to the NAICS 522 industry classification (credit intermediation) to create a more homogeneous sample. Observations are unweighted, and standard errors are clustered at the six-digit occupational and four-digit industry level. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level. Source: Occupational Employment Statistics, 2005–2017, and the American Community Survey for average five-digit SOC earnings.

Column 1 presents our baseline results, which suggest that STEM jobs grew by 36 percent, relative to non-STEM jobs in commercial banking, after the passage of Dodd-Frank in 2010. To address the concern that our results pick up a secular increase in demand for STEM workers, we control for several national-level measures of demand for those workers, specifically annual income at the four-digit industry and six-digit occupational level. Doing so produces a slightly higher estimate, but it is not statistically different (column 2).

One concern with these results is the fact that different subsectors within finance are heterogeneously affected by regulation. Column 3 restricts the sample to those industries in NAICS 522, which covers credit institutions—that is, both banks and nonbank entities. Even with this restricted sample, we find a statistically significant (and slightly larger economically) association between occupational employment and STEM jobs after the passage of Dodd-Frank of about 41 percent. To ensure that we are not simply detecting reallocation among government affairs and other compliance-related jobs, column 4 controls specifically for compliance officers. This does not alter the statistical significance of our estimate on STEM.

Table 6 addresses two additional concerns. The first is measurement error induced by the fact that STEM occupations are an imperfect proxy for an ideal measure of STEM jobs. In principle, this measurement error should bias the existing results toward zero through classic attenuation bias, unless the mismeasurement is somehow correlated with the introduction of regulation. The second concern is that regulatory restrictions are anticipated, and thus that the baseline results reflect spurious correlation. We address those concerns by using the Deming (2017) mapping from occupations to skill intensities, which are obtained from O*NET. As described by Deming (2017), the tasks involved in a given occupation vary in the required amount of routine and (nonroutine) mathematical skills.[12]

[12] We follow Deming (2017) exactly in constructing our measures of math and routine skill intensity. Routine skill intensity is defined as the average of the response to the questions, "How automated is the job?" and "How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?" Math skill intensity is defined by the average of the O*NET variables' "extent to which an occupation requires mathematical reasoning," "whether the occupation requires using mathematics to solve problems," and "whether the occupation requires knowledge of mathematics." The variables are on a scale of 0 to 10.

Table 6. Robustness with Occupational Heterogeneity Placebo Analyses

Dep. var. =	log(occupational employment)		
	(1)	(2)	(3)
log(regulatory restrictions)			
× log(math skills)	.483***	.338***	
	[.129]	[.098]	
× log(routine skills)			−.309***
			[.083]
log(regulatory restrictions)$_{t-1}$			
× log(math skills)		.344***	
		[.101]	
log(regulatory restrictions)$_{t+1}$			
× log(math skills)		−.103	
		[.108]	
R^2	.97	.97	.97
Sample size	8,699	6,605	8,699
Occupation FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes
Industry × occupation FE	Yes	Yes	Yes

Note: The table reports the coefficients associated with regressions of logged six-digit occupational and four-digit industry employment on an interaction between whether the occupation has high math skill intensity and regulations. We also explore the relationship with both lagged and forwarded regulations to gauge the potential for omitted variables or reverse causality. Observations are unweighted, and standard errors are clustered at the six-digit occupational level. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.
Source: Occupational Employment Statistics and Al-Ubaydli and McLaughlin (2017) (2005–2017).

Column 1 of table 6 estimates equation (1) after replacing $STEM_j$ with log math skill intensity. We find a similar result as its analogue in the second column of table 2. Next, we consider both forward-looking expectations about regulatory restrictions and sluggish adjustment. We capture expectations by including the interaction between the subsequent year's regulatory restrictions and our measure of STEM workers, $r_{i,t+1} \times STEM_j$. We capture lagged effects by including a similar interaction for the previous year's regulatory restrictions, $r_{i,t\neq 1} \times HITECH_j$. The results are in column 2. Whereas there is a lagged effect, captured by the positive and significant point estimate on the interaction with the previous year's restrictions, there does not appear to be a forward-looking effect. Specifically, the point estimate on the interaction with the subsequent year's restrictions is statistically indistinguishable from zero. This result suggests either that the introduction of regulatory restrictions is unanticipated, or that firms cannot adjust their hiring behavior ex ante.

Finally, column 3 of table 6 tests the hypothesis that occupations requiring routine skills are crowded out by the introduction of regulation. The negative and significant point estimate on the interaction suggests that firms respond to regulation by reducing their employment of routine workers. Viewed through the lens of the framework, these are workers with either low productivity x_j or greater additional costs of regulation μ_j. For example, the ratio of math to routine skills for quantitative financial analysts is 1.7, compared with 1.1 for loan interviewers. These results are consistent with recent evidence from Zhang (2019), who shows that firms have an incentive to adopt labor-saving technology during a recession. Because the opportunity cost of interrupting operations and restructuring is lower during a recession, firms are more likely to make changes—specifically, substitutions from jobs that are heavy in routine-based skills—in those periods. Along these same lines—because regulatory overhauls also reduce the opportunity cost of interrupting normal operations—we show that firms, on average, respond to the rise of regulation by increasing their share of STEM workers.

5.4. Complementary Evidence from Patents

We now use evidence from patenting activity to address the specific concern that regulation might simply proxy for a more general demand for higher-quality workers who can perform multiple tasks, and that these workers tend to be in STEM occupations. For example, there is evidence that firms use recessions as an opportunity to transition low-performing employees away from their workforce (Caballero and Hammour, 1994)—a phenomenon that was heavily present during the most recent financial crisis, particularly for routine jobs (Beaudry, Green, and Sand, 2016; Hershbein and Kahn, 2018; Jaimovich and Siu, 2020).

There is no silver-bullet way to rule out this counterexplanation, because we do not observe a given worker's day-to-day activities. We address it by turning to patenting activity, which we use as a measure of innovative activity within the firm. Our approach here is motivated by two factors. First, figure 4 displays a remarkable surge in patent applications among treated (larger) banking institutions after the implementation of Dodd-Frank, creating extensive variation to study potential drivers of patenting activity. Second, if we are identifying a genuine effect of regulation on automation, we should observe an increase in patenting activity. However, if these skilled workers are simply hired to replace nonproductive workers at traditional tasks, we should not detect differences in patenting.

We focus on banking, exploiting variation in institutional exposure to the post-2010 regulatory overhaul. We define our treatment group as large banks that are part of the "Big 4" (Bank of America, Citigroup, JPMorgan Chase, and Wells Fargo), as in Chen, Hanson, and Stein (2017) and Gete and Reher (2020), but we also conduct further tests according to whether the bank is subject to the Comprehensive Capital Analysis and Review (CCAR) stress tests as a proxy for regulatory burden. In all our analysis, we restrict attention to banks with more than $10 billion in assets to avoid confounding the effect of bank size, and we explicitly control for size effects. The Big 4 are both systemically important financial institutions and major US mortgage lenders that have been subject to heightened scrutiny since the financial crisis, so their burden of regulation is especially large. Although the descriptive evidence from figure 4 suggests that larger banks exhibited substantially different trends in patenting after the passage of Dodd-Frank, we now examine this more formally through difference-in-difference regressions of the form

$$log(Patents)_{it} = \gamma(Post_t \times Treatment_i) + \zeta_i + \lambda_t + \epsilon_{it}, \tag{2}$$

where our outcome variable denotes the logged number of patent applications (or patents issued) for bank i in year t, *Post* denotes our indicator for whether Dodd-Frank has been passed, and *Treatment* denotes an indicator for our different classifications of exposed banks. Table 7 documents our results. We find that Big 4 banks increased their patenting by 31.1 percent after the passage of Dodd-Frank, relative to their counterparts (column 1). Moreover, when we define our treatment indicator on the basis of exposure to the CCAR stress tests, we find a smaller, albeit still positive, gradient of 6.2 percent (column 2). These results are not driven by a spurious correlation between financial regulation and bank assets. Column 3 shows that the point estimates are, in fact, somewhat larger after controlling for the interaction between size (assets) and our *Post* indicator. Because we are working with a small sample with significant autocorrelation in the error, we do not obtain statistically significant estimates when clustering at the bank level. We present heteroskedasticity-robust standard errors.

Table 7. Supplementary Evidence on Patenting Activity Following Financial Regulation

Dep. var. =	log(patent applications)		
	(1)	(2)	(3)
1[t > 2010] × Big 4	.311*		.561**
	[.168]		[.265]
1[t > 2010] × CCAR		.062	.169
		[.058]	[.116]
1[t > 2010] × size			−.026
			−.065
R^2	.84	.84	.85
Sample size	935	935	935
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The table reports the coefficients associated with regressions of patent applications on an interaction between an indicator for whether t > 2010, a proxy for the Dodd-Frank legislation, and whether bank i is a Big 4 bank or subjected to the CCAR stress tests over 2011–2015. Column 3 includes the interaction with log assets as of 2016, denoted as Size. Standard errors are heteroskedasticity robust, and observations are unweighted. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.
Source: Authors' calculations based on USPTO and the Federal Deposit Insurance Corporation, 2005–2015.

Given the relatively large point estimates, we nonetheless view these results as informative and consistent with our primary message: financial regulation raises the returns to automation and crowds out jobs that are traditionally performed by low- and middle-skilled workers exposed to automation. We have also explored logit regressions of an indicator for whether an individual has an advanced degree (e.g., masters or doctorate) on regulatory restrictions and found that the effects are concentrated in jobs where workers have a high degree of training. Although beyond the scope of this paper, an examination would also be interesting of the specific ways that patenting activity—such as the type of patenting—and the competitive landscape among bank and nonbank entities may have changed in response to regulation.

6. Understanding the Mechanisms

Given that we have documented a positive association between increases in STEM workers and regulatory restrictions, we now explore a candidate mechanism behind these results, which we outline in a stylized theoretical model in appendix B. If STEM workers have a higher productivity component, particularly one that allows them to be better at automating tasks that would otherwise be more labor intensive, then organizations subject to greater regulatory burdens can reduce their compliance costs and legal exposure by automating more tasks. We now explore whether such a channel exists: Do financial services firms automate tasks at least in part to mitigate the scope for human error?

To investigate the link between regulation and compliance costs, together with the moderating role that STEM workers may play, we draw on data from Good Jobs First, which is a national resource center that promotes quality and transparent corporate governance practices. One of its products is the Violation Tracker, which provides a comprehensive aggregation of civil and criminal law enforcement action taken by federal regulatory agencies against both public and private corporations.[13] For each company, we see the dollar penalty associated with its violation, which we match with regulatory restrictions at the three-digit level. We subsequently estimate models that relate the logged penalty amount with regulatory restrictions, controlling for both industry and year fixed effects.

Our identifying assumption is that unobserved shocks to the penalty amount are uncorrelated with regulatory restrictions. For example, if regulation reduces firm productivity, and in turn reduces a firm's ability to comply with federal regulations, then our estimates might be biased downward. However, because we would expect a positive association between regulation and penalties, we think that such concerns cause us to underestimate the overall effect. Nonetheless, we also leverage variation in the performance of professional services firms as a suitable control group against our financial services firms because the former were less exposed to the increase in regulation, at least over these years.

Table 8 documents these results. Column 1 shows that a 10 percent rise in regulatory restrictions is associated with an 11.1 percent rise in penalties, which is significant at the 5 percent level. However, one concern with this result is that there are other time-varying shocks that affect both regulatory restrictions at an industry level and regulatory penalties. Column 2 subsequently includes observations from all other sectors, interacting an indicator for the financial services sector and regulatory restrictions. Furthermore, we add two-digit industry-by-year fixed effects to control for common trends across sectors. These results suggest that a 10 percent rise in restrictions is associated with an 11.5 percent rise in penalties in the financial services sector, but no effect in other sectors, on average. This is consistent with our theoretical

[13] We refer readers to Yang (2019) for a more detailed discussion of the data.

mechanism that financial services firms face greater compliance costs, which creates an incentive for them to automate tasks that would otherwise be subject to human error.

Table 8. Regulatory Restrictions and Compliance Costs

Dep. var. =	ln(penalty amount in dollars)	
log(regulatory restrictions)	1.109**	−.042
	[.251]	[.068]
× 1[finance]		1.151***
		[.235]
R^2	.06	.07
Sample size	961	99,493
3-digit NAICS FE	Yes	Yes
Year FE	Yes	Yes
2-digit NAICS × year FE	No	Yes

Note: The table reports the coefficients associated with regressions of logged penalties in real 2012 dollars on the logged number of regulatory restrictions interacted with an indicator for whether the three-digit NAICS code is in financial services, conditional on fixed effects. Standard errors are clustered at the three-digit NAICS level. *** indicates statistical significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.
Source: Good Jobs First's Violation Tracker and Al-Ubaydli and McLaughlin (2017), 2003–2017.

One of the limitations in our analysis is the lack of granularity of the data. Ideally, we would like to observe how the enactment of specific regulatory restrictions manifests in the form of specific penalties for a firm over time. In the absence of firm-level data, these industry regulatory restrictions provide a proxy. Moreover, the fact that we observe a contemporaneous relationship between regulatory restrictions and penalties suggests that firm adjustment is gradual—that is, firms do not, or are not able to, hire STEM workers who automate tasks immediately; these adjustments can take a few years to set in. Our results are consistent with this hypothesis about the gradual adjustment in a firm's labor force: when we use lagged values on regulatory restrictions, we find a null association with penalties.

7. Conclusion

The financial services sector has undergone a profound transformation in the past two decades. We document three new recent trends. First, the share of STEM workers increased faster in finance more than in any other sector (except professional services), growing by 2.1 percentage points from 2011 to 2017. Second, while STEM employment increased over these years, the earnings premium between STEM and non-STEM workers in finance declined from roughly 8 percent to 5 percent. Third, regulation in finance grew faster than in any other sector over these years, particularly in agencies and brokerages and in other investment pools.

Motivated by these patterns, we investigate the source of the increase in STEM employment, distinguishing among three hypotheses: (a) capital-skill complementarity arising from an increase in technological change or decline in the price of capital, (b) relabeling of STEM degrees and entry of new graduates into STEM employment, and (c) regulation's impact on the returns to automation. After finding no evidence that the first two explanations can explain the rise, we focus on the role of regulation, finding that a 10 percent increase in regulatory restrictions is associated with a 5.3 percent rise in STEM employment. We also find that increases in regulation are associated with greater compliance costs, which suggests that regulation raises the returns to automation to reduce the margin of human error and save on labor costs.

Our results raise several questions for further research. For example, although there is emerging empirical evidence about the importance of fintech lenders in the financial services sector (Buchak et al., 2018; Fuster et al., 2019), little is known about hiring practices and employment composition. Nearly all of their services are based on algorithmic decisions, so what role do labor and capital play within these organizations, and how can managers better leverage technology to coordinate tasks in the emerging economy?

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Appendix A: Summary of STEM Occupational Classifications

SOC Code	Occupation Title
11-3021	Computer and Information Systems Managers
11-9041	Architectural and Engineering Managers
11-9121	Natural Sciences Managers
15-1111	Computer and Information Research Scientists
15-1121	Computer Systems Analysts
15-1122	Information Security Analysts
15-1131	Computer Programmers
15-1132	Software Developers, Applications
15-1133	Software Developers, Systems Software
15-1134	Web Developers
15-1141	Database Administrators
15-1142	Network and Computer Systems Administrators
15-1143	Computer Network Architects
15-1151	Computer User Support Specialists
15-1152	Computer Network Support Specialists
15-1199	Computer Occupations, All Other
15-2011	Actuaries
15-2021	Mathematicians
15-2031	Operations Research Analysts
15-2041	Statisticians
15-2090	Miscellaneous Mathematical Science Occupations
17-1011	Architects, Except Landscape and Naval

17-1012	Landscape Architects
17-1021	Cartographers and Photogrammetrists
17-1022	Surveyors
17-2011	Aerospace Engineers
17-2021	Agricultural Engineers
17-2031	Bioengineers and Biomedical Engineers
17-2041	Chemical Engineers
17-2051	Civil Engineers
17-2061	Computer Hardware Engineers
17-2071	Electrical Engineers
17-2072	Electronics Engineers, Except Computer
17-2081	Environmental Engineers
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors
17-2112	Industrial Engineers
17-2121	Marine Engineers and Naval Architects
17-2131	Materials Engineers
17-2141	Mechanical Engineers
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers
17-2161	Nuclear Engineers
17-2171	Petroleum Engineers
17-2199	Engineers, All Other
17-3011	Architectural and Civil Drafters
17-3012	Electrical and Electronics Drafters
17-3013	Mechanical Drafters
17-3019	Drafters, All Other

17-3021	Aerospace Engineering and Operations Technologists and Technicians
17-3022	Civil Engineering Technologists and Technicians
17-3023	Electrical and Electronics Engineering Technologists and Technicians
17-3024	Electro-Mechanical and Mechatronics Technologists and Technicians
17-3025	Environmental Engineering Technologists and Technicians
17-3026	Industrial Engineering Technologists and Technicians
17-3027	Mechanical Engineering Technologists and Technicians
17-3029	Engineering Technologists and Technicians, Except Drafters, All Other
17-3031	Surveying and Mapping Technicians
19-1011	Animal Scientists
19-1012	Food Scientists and Technologists
19-1013	Soil and Plant Scientists
19-1021	Biochemists and Biophysicists
19-1022	Microbiologists
19-1023	Zoologists and Wildlife Biologists
19-1029	Biological Scientists, All Other
19-1031	Conservation Scientists
19-1032	Foresters
19-1041	Epidemiologists
19-1042	Medical Scientists, Except Epidemiologists
19-1099	Life Scientists, All Other
19-2011	Astronomers
19-2012	Physicists
19-2021	Atmospheric and Space Scientists
19-2031	Chemists

19-2032	Materials Scientists
19-2041	Environmental Scientists and Specialists, Including Health
19-2042	Geoscientists, Except Hydrologists and Geographers
19-2043	Hydrologists
19-2099	Physical Scientists, All Other
19-4011	Agricultural and Food Science Technicians
19-4021	Biological Technicians
19-4031	Chemical Technicians
19-4041	Geological and Petroleum Technicians
19-4051	Nuclear Technicians
19-4091	Environmental Science and Protection Technicians, Including Health
19-4092	Forensic Science Technicians
19-4093	Forest and Conservation Technicians
19-4099	Life, Physical, and Social Science Technicians, All Other
25-1021	Computer Science Teachers, Postsecondary
25-1022	Mathematical Science Teachers, Postsecondary
25-1031	Architecture Teachers, Postsecondary
25-1032	Engineering Teachers, Postsecondary
25-1041	Agricultural Sciences Teachers, Postsecondary
25-1042	Biological Science Teachers, Postsecondary
25-1043	Forestry and Conservation Science Teachers, Postsecondary
25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary
25-1052	Chemistry Teachers, Postsecondary
25-1053	Environmental Science Teachers, Postsecondary
25-1054	Physics Teachers, Postsecondary

41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
41-9031	Sales Engineers

Appendix B: Stylized Theoretical Framework

We introduce a simple theoretical model that is consistent with our baseline result that increases in regulation lead to an increase in STEM employment. Suppose that output in financial services is governed by a constant-returns-to-scale production technology. The technology combines labor L_j across occupations j according to the following:

$$Y = A\Pi_j {L_j}^{\theta_j}.$$

Let w_j denote the wage for occupation j, and suppose, for simplicity, that workers in each occupation are paid according to their marginal product: $w_j = x_j\overline{w}$, where $\overline{w}$ is a constant. Next, suppose that each unit of labor entails a regulatory cost $\mu_j r$, where $\sum_j \mu_j = 1$ and r is an average cost of regulation. For example, compliance workers may reduce the firm's overall regulatory costs so that μ_j is small.

Next, consider a firm's problem of hiring across occupations j to maximize profit. It is straightforward to show that the ratio of employment between occupations i and j is as follows:

$$\frac{L_i}{L_j} = \frac{\overline{w} + \mu_j r/\theta_j}{\overline{w} + \mu_i r/\theta_i}.$$

To interpret, the effect of an increase in the cost of regulation r is governed by the occupation's loading on regulation μ_j. When this loading is high, the firm reduces hiring for such jobs. However, there is an attenuating effect through worker productivity x_j. In particular, holding regulatory loading fixed, firms reduce hiring in low-productivity jobs first. Our argument is that STEM workers have a high x_j and, because they enable automation that reduces the scope for human error, a lower μ_j.[14] Therefore, an increase in regulation should lead to relatively greater hiring intensity of STEM workers.

[14] Automation has typically lain outside the purview of conventional regulation. Recently, however, some firms have begun to specialize in algorithmic audits (e.g., ORCAA).

Appendix C: Supplementary Evidence of Identifying Assumptions

One of the concerns we discuss in the main results associated with our regressions of employment on regulatory restrictions is the presence of reverse causality. For example, if industries that are more adversely affected by the financial crisis demand more regulation, or are forced to receive greater regulation, then increases in employment could be a result of changes in output or unobserved productivity. Table I investigates the concern directly by relating the year-to-year growth in real GDP and regulatory restrictions. Because we take the two-year lag of regulation in our main results, we focus on the two-year lag of real GDP growth. However, we also present results with contemporaneous GDP growth.

Table I. Evaluating the Correlation of Real GDP and Regulatory Restrictions Growth

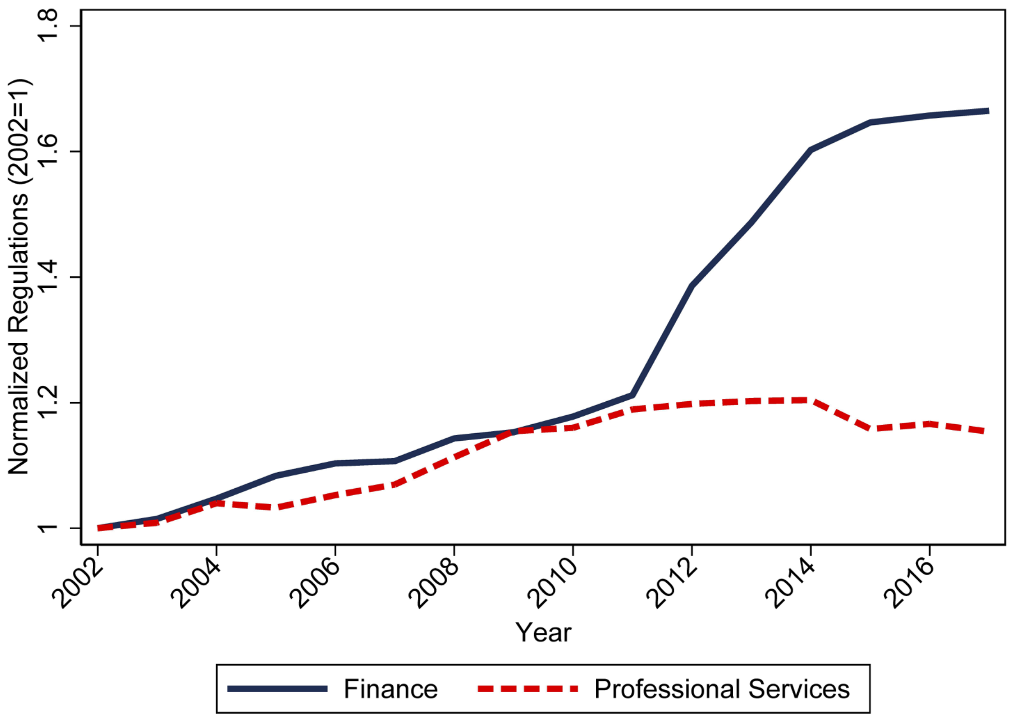
Dep. var. =	Regulatory restrictions (growth)			
	(1)	(2)	(3)	(4)
Real GDP growth (*t*)	−.062*		−.095**	
	[.032]		[.037]	
Real GDP growth (*t* – 2)		−.034		−.027
		[.047]		[.050]
R^2	.00	.00	.01	.00
Sample size	660	594	660	594
GDP weight	No	No	Yes	Yes

Note: The table reports the coefficients associated with regressions of the year-to-year growth in regulatory restrictions on year-to-year growth in real GDP (normalized to 2012 prices). Standard errors are clustered at the three-digit NAICS level. * indicates statistical significance at the 10 percent level, ** indicates significance at the 5 percent level, and *** indicates significance at the 1 percent level.
Source: Bureau of Economic Analysis and Al-Ubaydli and McLaughlin (2017), 1997–2017.

We find that a 1 percentage point rise in real GDP growth is associated with a 0.62 percentage point and 0.95 percentage point decline in regulatory restrictions when we estimate the regression without weights and with weights, respectively. However, when we use the two-year lagged value of real GDP growth, we find an association with regulatory restrictions growth that is lower in economic magnitude and statistically insignificant. In this sense, there is little evidence of a correlation between economic activity and regulation for our main specification, but even when we focus on the contemporaneous association, the negative correlation would bias against our finding any effects because reverse causality requires positive co-movement.

Another exercise that we present in the main text is a triple-difference estimator that compares the financial and professional services sectors. These two sectors are similar in many dimensions, particularly with respect to their labor composition. Figure I presents regulatory restrictions from 2002 to 2017, normalized to 2002 levels. Remarkably, the two series track each other very closely until 2011, a year after the passage of the Dodd-Frank legislation. Whereas regulatory restrictions in professional services plateau, they surge in finance. Motivated by the result that we see earlier, with the surge in regulatory restrictions in finance but not in professional services, we now test for parallel trends in figure II. Although we do not have a perfect triple-difference because the treatment is continuous, we focus on 2011 to 2017 as the posttreatment period for financial services. Panel A plots the coefficients associated with regressions of logged employment on finance × STEM × year interactions, controlling for the direct effects. Panel B plots similar regression coefficients but omits professional services as the control group. We see statistically insignificant negative estimates in the pre-period—particularly when we use professional services as the control group—but statistically significant positive estimates in the postperiod. These results suggest there is little evidence of a pre-trend leading up to the passage of Dodd-Frank.

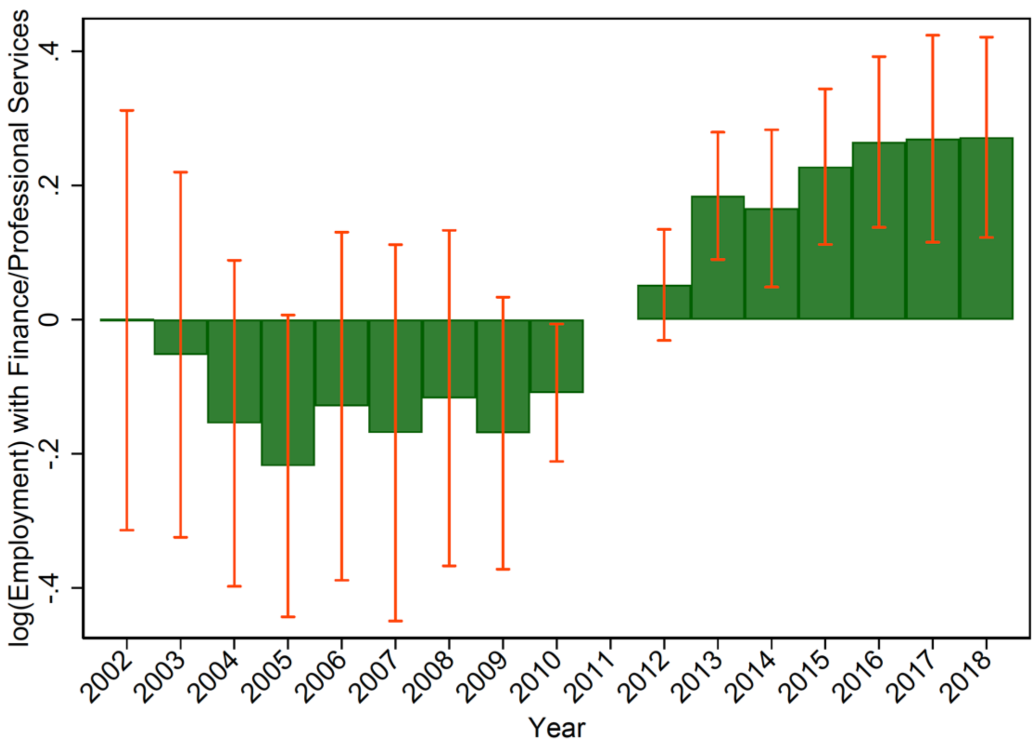
Figure I. Regulatory Restrictions in Financial and Professional Services



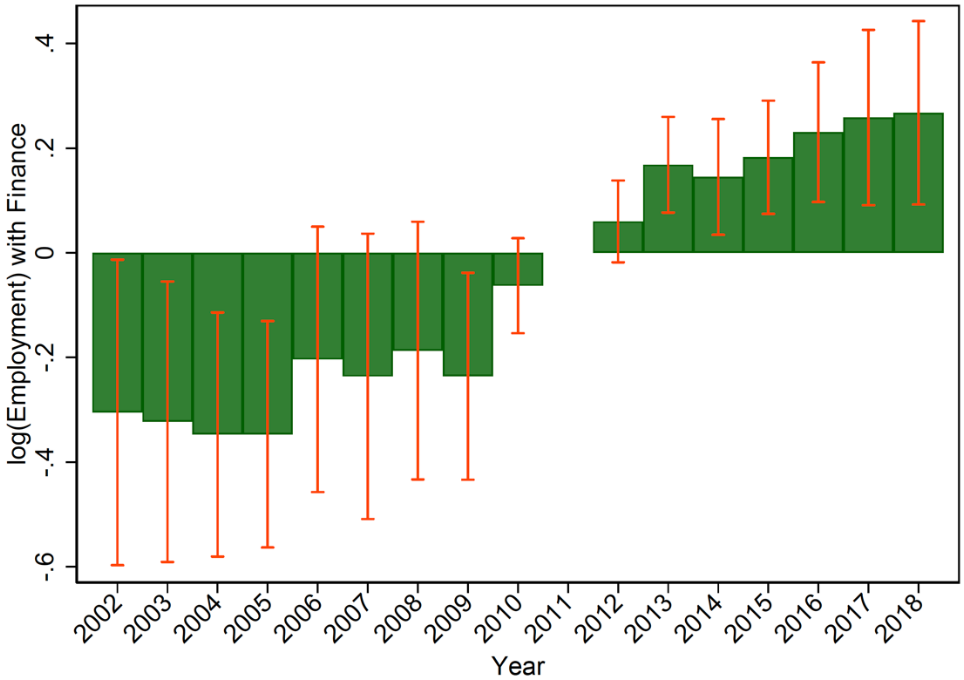
Note: This figure plots the number of regulations in financial and professional services normalized to their 2002 levels.
Source: Al-Ubaydli and McLaughlin (2017), 2002–2017.

Figure II. Testing for Parallel Trends in STEM and Finance Employment

A. Finance and Professional Services



B. Finance



Note: Panel A plots the coefficients associated with regressions of logged employment at a two-digit industry by six-digit occupational level (with finance and professional services as the two sectors) on interactions between year fixed effects (normalized to 2011) and STEM finance indicators, controlling for industry year, STEM year, and industry occupation fixed effects. Panel B plots a similar set of coefficients but omits financial services from the sample such that the coefficients are identified from variation between year fixed effects and STEM occupations. Standard errors are clustered at the occupation level.
Source: Occupational Employment Statistics, 2002–2018.