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WAGES AND HUMAN CAPITAL IN THE U.S. FINANCE INDUSTRY: 1909–2006*

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We study the allocation and compensation of human capital in the U.S. finance industry over the past century. Across time, space, and subsectors, we find that financial deregulation is associated with skill intensity, job complexity, and high wages for finance employees. All three measures are high before 1940 and after 1985, but not in the interim period. Workers in finance earn the same education-adjusted wages as other workers until 1990, but by 2006 the premium is 50% on average. Top executive compensation in finance follows the same pattern and timing, where the premium reaches 250%. Similar results hold for other top earners in finance. Changes in earnings risk can explain about one half of the increase in the average premium; changes in the size distribution of firms can explain about one fifth of the premium for executives. *JEL* Codes: G2, J2, J3, N2.

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I. INTRODUCTION

Controversies regarding the complexity of financial products and the compensation of bankers seem to follow most major financial crises. In the years leading up to the crisis of 2007–2009, the finance industry hired highly educated workers and paid them high wages to design, originate, and trade complex products. However, we show that high wages, skill intensity, and complexity are not permanent features of the finance industry, and we seek to explain why they appear in some periods but not in others.

We compare the finance industry to the rest of the private sector over the long run, using macro and micro data, and we uncover a new set of stylized facts, reported in Section II. From 1909 to 1933 finance is a high-skill and high-wage industry. A dramatic shift occurs in the second half of the 1930s, when finance loses its relatively high human capital position. Between 1950 and 1980, compensation and skill intensity are similar in finance and the rest of the economy. From 1980 onward, finance once again becomes a high-skill and high-wage industry. In 2000 relative wages and education are back almost exactly to their 1930 levels. We construct an index of the relative complexity of jobs in the finance industry and show that it displays a similar U-shape pattern. Finally, finance accounts for 15% to 25% of the overall increase in wage inequality since 1980. We proceed to analyze these facts in two steps. We first study skill demand in a frictionless labor market in Section III. We later focus on residual wages in Section IV.

Section III emphasizes three factors that predict relative skill intensity: financial regulation, corporate finance activities, and information technology (IT). We find a tight link between deregulation and the flow of human capital in and out of the finance industry. In the wake of Depression-era regulations, highly skilled labor leaves the finance industry and it flows back precisely when these regulations are removed in the 1980s and 1990s. This link holds for finance as a whole, as well as for sub-sectors within finance. Our interpretation is that tight regulation inhibits the creativity of skilled workers. Demands from the non-financial corporate sector, in particular the entry of new firms and the management of credit risk, also predict an increase in the demand for skills in finance. IT plays a role, albeit a more limited one. The advent of computers, for instance, cannot

provide a complete explanation because the finance industry of the 1920s is similar to that of the 1990s. We conclude this section with a discussion of omitted variables and endogeneity issues.

In Section IV we focus on wages, controlling for education and other characteristics. We first construct a benchmark wage series based on observed changes in relative education and time-varying returns to education. The benchmark wage series accounts well for the observed relative wage between 1910 and 1920 and between 1950 and 1990. However, from the mid-1920s to the mid-1930s and from the mid-1990s to 2006 the compensation of employees is about 50% higher than expected. Using micro data, we show that this result holds even if we control for unemployment risk and unobserved individual heterogeneity. During this period chief executive officers (CEOs) in finance earn a 250% premium relative to CEOs elsewhere. A benchmark compensation series that is based on the model of Gabaix and Landier (2008) can account for about 50 percentage points, leaving an unexplained premium of about 200%.

This leads us to study these excess wages from the perspective of dynamic labor contracts. We find that changes in earnings profiles can account for some of the recent excess wages. Until 1980 earnings profiles in finance are similar to profiles in the rest of the economy. In 2000, by contrast, starting wages are 9% higher and, most importantly, profiles are 2% steeper and 8% more dispersed. In other words, pay in the finance industry has become significantly higher, but also riskier and more backloaded. The difference in certainty equivalent wages is therefore lower than the average wage difference. For instance, if we assume that consumption equals income and that workers have a relative risk aversion of 2, the certainty equivalent difference is somewhere between 20% and 30%, instead of the 50% discussed above.

Our work contributes to several strands of literature. A large body of research shows that finance plays an important role in economic development. Economic historians have studied the development of banking systems and securities markets and their impact on economic development within countries, and there is a large literature on financial development and economic growth across countries (e.g., Rousseau and Sylla 2003; and Levine 2005). However, the literature does not explain how the finance industry is organized and how it adapts to serve the needs of the economy. It is also difficult to define a consistent and economically relevant measure of financial innovation because financial

firms typically do not report research and development spending and, until recently, could not protect their new ideas through patents (Lerner 2006). By focusing on human capital, our approach provides a consistent and economically relevant measure of financial organization for almost 100 years. Among other things, it allows us to show that the finance industry of 2000 is surprisingly similar to that of 1930.

Our focus on the skills of finance employees is new in the literature. In contrast, Philippon (2012) studies the overall size of financial markets and of the finance industry, but does not consider skill bias and wage premia. It is important to emphasize that these are not the same facts. From 1945 to 1980 financial markets grow a lot, but that growth is not skill biased: The industry simply hires more workers proportionately. From 1980 to the mid-1990s financial markets keep on growing, the finance industry hires highly skilled workers, but these workers are paid competitive wages. After 1995 we observe growth, skill bias, and excess wages together.

Baumol (1990) argues that economic growth requires the allocation of talent to socially productive activities, and that policies and institutions that can readily influence the allocation of talent across occupations are more important than the overall supply of talent. Baumol (1990) also argues that finance may lure talent away from other industries, and Murphy, Shleifer, and Vishny (1991) emphasize the impact of increasing returns on the career choices of talented individuals. Baumol's concerns are relevant if three conditions are met: (1) The finance industry attracts highly talented individuals, (2) regulations can affect skill demand, and (3) finance jobs are less socially productive than non-finance jobs. Our results support (1) and (2).¹ With regard to (1), Goldin and Katz (2008b) also document a large increase in the fraction of Harvard undergraduates who have worked in the financial sector since 1970, and the increase in their wage premium, whereas Kaplan and Rauh (2010) and Bakija, Cole, and Heim

1. We cannot provide evidence on whether financial jobs are socially productive. This requires a structural model far beyond the scope of this paper. For this issue, our work is best seen as motivation for future research. Philippon (2010) analyzes the case of endogenous growth with financial intermediation and innovation in the nonfinancial sector. Michalopoulos, Laeven, and Levine (2009) model real and financial innovation in a symmetric way. In light of the recent financial crisis, an important and challenging task for future research is to model the social value and cost of new financial products.

(2012) study the evolution of earnings of individuals with very high incomes, with a particular emphasis on the financial sector. Regarding (2), we document significant effects of financial regulation on the demand for human capital.

Our work also contributes to the understanding of demand for skill and income inequality. Katz and Murphy (1992) study the secular growth in the demand for educated workers from 1963 to 1987; Acemoglu (1998) and Autor, Katz, and Krueger (1998), among others, discuss the role of skill-biased technological change.² We show that finance contributes to the increase in income inequality and, by taking a long-term perspective, we can discuss the relative importance of IT and other factors. Finally, our evidence on significant changes in earnings profiles contributes to the study of dynamic labor contracts theory.

The rest of the article is organized as follows. Section II describes the new stylized facts. Section III provides evidence on the effects of financial regulation, corporate finance, and IT. Section IV documents the existence of a time varying wage premium and discusses labor market theories that can explain this premium. Section V studies earnings profiles. We offer concluding remarks and discuss implications for financial regulation in Section VI. Detailed descriptions of data sources and methodologies can be found in the Online Appendix.

II. NEW STYLIZED FACTS: THE U-SHAPE

In this section we describe the evolution of wages, education, human capital, and occupations in the U.S. financial sector from 1909 to 2006. Finance is comprised of three subsectors: credit intermediation (by banks, savings institutions, and companies that provide credit services), insurance, and other finance industries (securities, commodities, venture capital, private equity, hedge funds, trusts, and other investment activities, including investment banks). We analyze the evolution of time series in finance relative to the nonfarm private sector excluding finance (henceforth the nonfarm private sector). Our examination of the historical data from 1909 to 2006 reveals a U-shape pattern for

2. Acemoglu (2002) reviews the literature on skill-biased technological change. See also Acemoglu and Autor (2011) for an up-to-date report on empirical findings and theoretical considerations. For other explanations for the increase in demand for skilled workers see Card (1992), Card and Lemieux (2001), and Acemoglu, Aghion, and Violante (2001).

education, wages, and the complexity of tasks performed in the finance industry—all relative to the nonfarm private sector. These facts have not been previously documented.

We use several data sources to construct the series below. So as not to burden the reader we provide comprehensive documentation about the sources and methodologies in the Online Appendix, and the main text provides only minimal necessary information.

II.A. Education and Wages

1. *Education: 1910–2005.* We construct our education series for the nonfarm private sector and for the financial sector using U.S. Census data and the March Current Population Survey (CPS). The census data cover the period 1910–2000 and the CPS covers the period 1967–2005. Our concept of higher education is the share of employees with strictly more than high school education.³ For the period 1910–1930, for which schooling data are not available, we impute the share of employees with more than high school education by occupation and then aggregate them separately for the nonfarm private sector and for the financial sector.⁴ For the period 1940–1970 we use the census data directly. For the period 1970–2005, we use CPS data.⁵

Let $e_{i,t}$ be a dummy variable equal to 1 if individual i has strictly more than high school education in year t . The share of educated workers in sector j in year t is

$$s_{j,t}^e = \frac{\sum_{i \in j} \lambda_{i,t} h_{i,t} e_{i,t}}{\sum_{i \in j} \lambda_{i,t} h_{i,t}},$$

3. The results are similar when we use the share of college graduates. The share of workers with strictly more than high school education is a more relevant concept of skill for the entire sample; it is comprehensive and includes college graduates. See the Online Appendix and Figure A1.

4. See the Online Appendix for details. In this construction we have assumed that the average educational attainment within occupations has not changed from 1910 to 1940. While this is certainly a strong assumption, we believe that it is made less critical by the fact that we focus on the *relative* education of employees in the finance versus the nonfarm private sector. By construction, our measure is not affected by any general drift in educational attainment in all occupations over time. Figure A1 reports the difference between actual relative education and projections based on this methodology for three levels of education.

5. For the overlapping period 1970–2000 the differences between the census and CPS data are negligible.

where λ and h are, respectively, sampling weights and hours worked, and $i \in j$ indicates that individual i works in sector j .⁶ The relative education of the financial sector is defined as the difference between this share in finance ($j = \text{fin}$) and the corresponding share in the nonfarm private sector, excluding finance ($j = \text{nonfarm}$):

$$(1) \quad \rho_{\text{fin},t} \equiv s_{\text{fin},t}^e - s_{\text{nonfarm},t}^e.$$

2. *Relative Wages: 1909–2006.* We construct a full-time equivalent wage series for the period 1909–2006. The full-time equivalent concept implies that variation in hours worked is taken into account. For the period 1929–2006 we construct full-time equivalent wages from the Annual Industry Accounts of the United States, published by the Bureau of Economic Analysis (BEA). We extend the series using data from Martin (1939) and Kuznets (1941) for the period 1909–1929. The data are described in detail in the Online Appendix. We define the ratio of the average wage in finance to the average wage in the nonfarm private sector excluding finance as

$$(2) \quad \omega_{\text{fin},t} \equiv \frac{w_{\text{fin},t}}{w_{\text{nonfarm},t}}.$$

3. *The U-Shape over the Twentieth Century.* Figure I reports the evolution of the relative wage $\omega_{\text{fin},t}$ and relative education $\rho_{\text{fin},t}$ over the twentieth century and Table I contains summary statistics. The pattern that emerges is U-shaped and suggests three distinct periods. From 1909 to 1933 the financial sector is a high-education, high-wage industry. The share of skilled workers is 17 percentage points higher than in the private sector; these workers are paid more than 50% more than in the rest of the private sector, on average. A dramatic shift occurs after the mid-1930s: The financial sector starts losing its high-human capital and high-wage status. Most of the decline occurs by 1950, but continues slowly until 1980. By that time the relative wage in the financial sector is approximately the same as in the rest of the economy. From 1980 onward another dramatic shift occurs: The financial sector becomes a high-skill/high-wage industry

6. In the 1910–1930 and 1960–1970 censuses the underlying data used to calculate h are missing. We assign $h = 1$ for all individuals in those years.

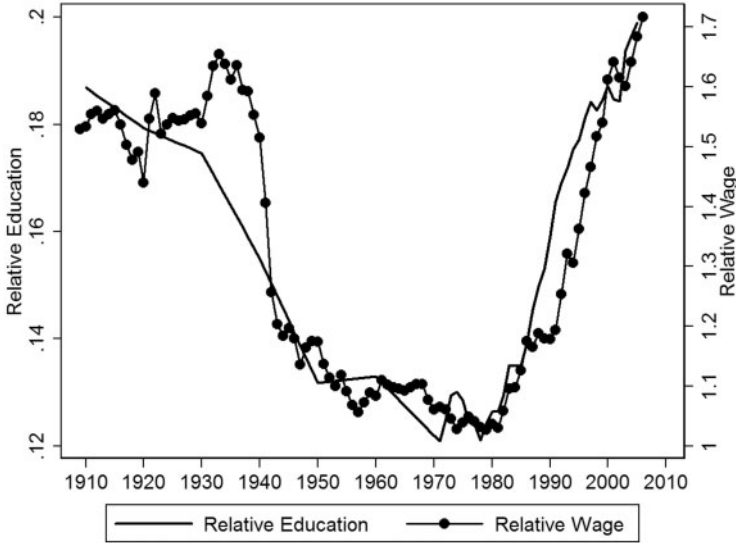


FIGURE I

Finance Relative Wage and Relative Education

Education is the share of workers with strictly more than high school education. Education (1910–2005) is computed from U.S. Census data, and from the Current Population Survey. In 1910–1930 education is imputed by using educational shares within occupations. Relative education is the difference in educated shares between finance and the nonfarm private sector. Wages (1909–2006) are computed from the Industry Accounts of the United States, Kuznets (1941) and Martin (1939). The relative wage is the ratio of the average wage in finance to nonfarm private sector average wage.

again. In a striking reversal, its relative wage and skill intensity return almost exactly to their 1930s levels.⁷

II.B. Top Earners in Finance

1. Relative Employment Share of Top Decile Earners: 1939–2009. Although education is a good indicator of human capital, it is far from perfect. There is significant variation in human capital within educational groups and the meaning of any particular level of education may not be stable over time. For example,

7. We find the tight relation between the relative education series and the relative wage series an indication that the data sources are consistent, particularly at the beginning of the sample. If skilled workers command higher wages, then this is exactly what one would expect to find.

TABLE I
SUMMARY STATISTICS

| | Obs. | Mean | Std. Dev. | Min | Max |
|--|------|--------|-----------|--------|-------|
| A. Time series | | | | | |
| Relative education | 96 | 0.155 | 0.024 | 0.120 | 0.199 |
| Relative wage | 98 | 1.320 | 0.230 | 1.027 | 1.716 |
| Deregulation index | 108 | -1.058 | 1.300 | -2.833 | 1.000 |
| Patents used in finance over total patents | 103 | 0.016 | 0.003 | 0.013 | 0.022 |
| IPO share of market capitalization (normalized) | 103 | 0.000 | 1.000 | -0.948 | 4.557 |
| Default rate on all American corporates (normalized) | 89 | 0.000 | 1.000 | -0.869 | 4.001 |
| Top marginal income tax rate | 99 | 0.590 | 0.248 | 0.070 | 0.940 |
| Foreign assets over GDP | 107 | 0.214 | 0.198 | 0.030 | 1.040 |
| Relative share of IT in capital stock | 60 | 0.032 | 0.038 | 0.000 | 0.141 |
| B. Panel of three subsectors | | | | | |
| Relative education | 171 | 0.176 | 0.073 | 0.082 | 0.303 |
| Relative wage | 171 | 1.299 | 0.600 | 0.739 | 3.942 |
| Deregulation index | 171 | -1.574 | 1.078 | -3.000 | 1.000 |
| Relative share of IT in capital stock | 171 | 0.062 | 0.064 | 0.000 | 0.229 |

Notes. Education is the share of employees with (strictly) more than high school education. Education in 1940–2005 is computed from U.S. Census data and from the Current Population Survey. In 1910–1930 education is imputed by using educational shares within occupations. Relative education is the difference in educated shares between finance and the nonfarm private sector. Wages (1909–2006) are computed from the Industry Accounts of the United States, Kuznets (1941) and Martin (1939). The relative wage is the ratio of wages in finance to the nonfarm private sector. The deregulation index incorporates bank branching restrictions (mostly phased out during the 1980s); the Glass-Steagall Act (enacted in 1933 and repealed in 1999), interest rate ceilings (introduced in 1933 and removed by 1984); and legislation to separate banks from insurance companies (introduced in 1956 and repealed in 1999). Data on the number of patents used in finance and elsewhere are from the Historical Statistics of the United States in 1909–1996; we extend this series using data from Lerner (2006). The IPO share and default rate data are from Jovanovic and Rousseau (2005); the series are normalized to have a zero mean and standard deviation of 1. The top marginal income tax rate data are from the Tax Foundation, based on information from the U.S. Internal Revenue Service. The data on foreign assets as share of GDP are from Obstfeld and Taylor (2004) (1900–1960) and the International Monetary Fund (1980–2005). The share of IT capital in the capital stock uses data from the Bureau of Economic Analysis's fixed assets tables by industry. The relative share is the IT share of capital in finance minus that in the rest of the nonfarm private sector. The three subsectors are credit intermediation, insurance, and rest of finance. In the panel, relative education and relative wage of finance are computed in the same way as above. The deregulation index is adjusted to reflect how each piece of legislation affects each subsector (see text for complete details).

high school graduation indicated relatively more human capital before the expansion of college education than after.

We therefore consider an alternative indicator based on the share of top earners in the industry. Denote the top decile wage in the nonfarm private sector *including finance* as w_t^{top} . Let $k_{i,t}$ be a dummy variable equal to 1 if individual i earns strictly more than w_t^{top} in year t . The share of workers within each sector that earn more than w_t^{top} is

$$s_{j,t}^{top} = \frac{\sum_{i \in j} \lambda_{i,t} k_{i,t}}{\sum_{i \in j} \lambda_{i,t}},$$

where λ are sampling weights and $i \in j$ indicates that individual i works in sector j . We use the 1940–2000 U.S. decennial censuses and the 2010 American Community Survey (ACS). Comprehensive individual-level wage data are not available before the 1940 census. The relative share of top decile workers in finance is defined as the difference between this share in finance ($j = \text{fin}$) and the corresponding share in the nonfarm private sector, excluding finance ($j = \text{nonfarm}$):

$$(3) \quad \kappa_{\text{fin},t}^{top} \equiv s_{\text{fin},t}^{top} - s_{\text{nonfarm},t}^{top}.$$

Figure II reports the evolution of $\kappa_{\text{fin},t}^{top}$ from 1939 to 2009. The pattern corroborates the U-shape and the timing in Figure I. Starting with 15 percentage points in 1939, finance loses its relative top human capital position and drops to 1.3% in 1979, after which it rapidly regains most of it; in 2009 the share of workers from the top decile is 10 percentage points higher than in the nonfarm private sector. Using the top quartile and top 50% wage cutoffs results in very similar patterns.⁸

2. Top Decile Relative Wages: 1939–2009. The BEA aggregate industry wage and employment data are comprehensive (all labor compensation and bodies are counted), but do not allow one to distinguish between different types of workers. Micro data allow this distinction, but high wages are typically top-coded. We compute top average wages by exploiting these differences.⁹

8. See Figure A2 in the Online Appendix.

9. We refer the reader to Kaplan and Rauh (2010) for a detailed analysis of the highest incomes inside and outside finance.

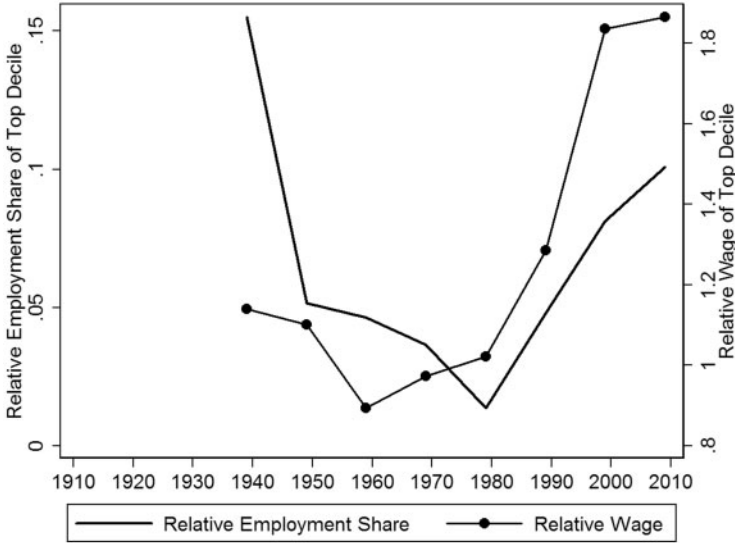


FIGURE II
Top Earners in Finance

The employment share of the top decile in each sector is the share of workers in the sector that earn more than the economy-wide (nonfarm private sector, including finance) top decile wage. The relative employment share is the difference in these shares between finance and the nonfarm private sector excluding finance. The wage of the top decile is the average wage of workers in the top decile within each sector. It is computed by using the average wage below the top decile from the U.S. censuses and the overall average wage using BEA data. The relative wage is the ratio of the average top decile wage in finance to that of the nonfarm private sector. See text for complete details on calculations.

The average wage in any industry (using the BEA data) can be written as a weighted average of the bottom 90% average wage and the top 10% average wage. We use U.S. decennial censuses and the ACS to estimate the average wage of the bottom 90%, which, critically, does not suffer from top-coding. In doing so, we take into account hours worked and sampling weights. This allows us to estimate the average wage of the top decile, denoted $w_{s,t}^{top}$. Thus, the relative top wage in finance is

$$(4) \quad \omega_{fin,t}^{top} \equiv \frac{w_{fin,t}^{top} \cdot \theta_{fin,t}}{w_{nonfarm,t}^{top} \cdot \theta_{nonfarm,t}},$$

where $\theta_{s,t}$ takes into account full-time equivalents. See the Online Appendix for complete details.

Figure II reports the evolution of $\omega_{fin,t}^{top}$ from 1939 to 2009. Once again, the pattern corroborates the U-shape and the timing in Figure I. The average wage in the top decile in finance increases from par with the nonfarm private sector in 1980 to more than 80% in 2000—somewhat more than the increase in the relative average wage.¹⁰ Using the top quartile and top 50% results in very similar patterns.¹¹

3. Comparison to Other Sectors: Top Decile Earners and Top Decile Wages. We study whether the patterns in Figure II hold when we compare finance to specific industries instead of the entire nonfarm private sector. That is, we examine $\kappa_{fin,i,t}^{top} = s_{fin,t}^{top} - s_{i,t}^{top}$ and $\omega_{fin,i,t}^{top} = \frac{(w_{fin,t}^{top})^{\theta_{fin,t}}}{(w_{i,t}^{top})^{\theta_{i,t}}}$, where i is some industry. We focus on three industries: manufacturing, a declining sector in terms of employment; health services, a large and growing services sector; and legal services, a highly paid sector with strong linkages to finance.

Figure IIIA compares finance to manufacturing; the patterns are very similar to those in Figure II. When we compare finance to health services and legal services in Figures IIIB and IIIC, respectively, we find a different pattern for top decile employment shares. But the relative wage of top earners in finance follows a very similar pattern to Figure II, albeit with different magnitudes. While the share of top earners in health and legal services is growing faster than in finance, the wages at the top are, in fact, following the same pattern as in Figures I and II. The upshot is that the U-shape pattern of relative wages is robust. In particular, although there are other growing service industries that attract highly skilled workers, they do not display the same dynamics of wages at the top of the distribution as in finance.

4. Top Executive Relative Compensation: 1938–2005. While the relative wage series capture broad trends, here we focus on

10. Although $\omega_{fin,t}^{top}$ as defined in (4) is correct, we verify that variation in the $\theta_{s,t}$ terms does not explain its evolution.

11. See Figure A2.

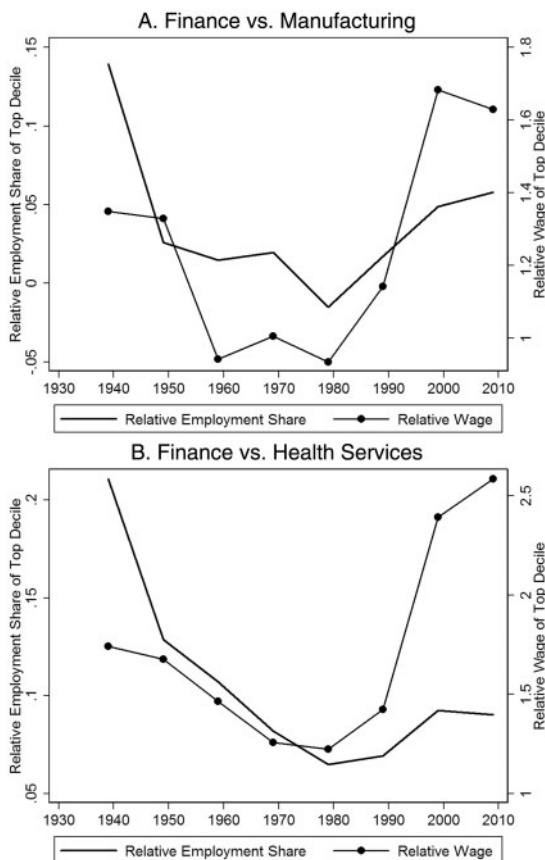


FIGURE III

Top Earners in Finance Relative to Selected Industries

The employment share of the top decile in each sector is the share of workers in the sector that earn more than the economy-wide (nonfarm private sector, including finance) top decile wage. The relative employment share is the difference in these shares between finance and the other sector. The wage of the top decile is the average wage of workers in the top decile within each sector. It is computed by using the average wage below the top decile from the U.S. censuses and the overall average wage using BEA data. The relative wage is the ratio of the average top decile wage in finance to that of the other sector. In Panels A, B, and C we compare the top decile human capital share and top decile wage in finance to those in manufacturing, health services and legal services, respectively. The methodologies are the same as in Figure II. See text for complete details on the calculations.

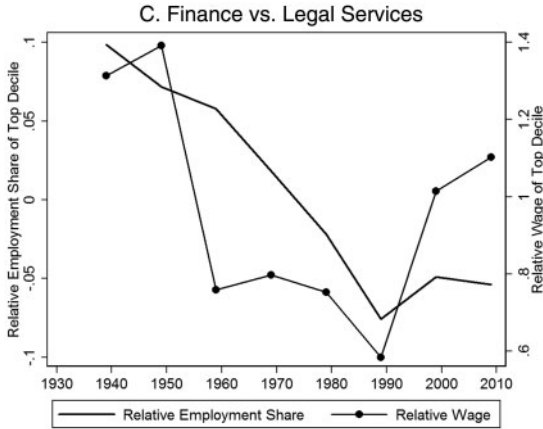


FIGURE III
Continued

some of the most highly paid individuals in finance and juxtapose their earnings with comparable individuals in the nonfarm private sector. We compare executive compensation in finance to executive compensation in the nonfarm private sector. This is informative for two main reasons. First, executives, especially in top firms, are arguably of similar ability; indeed, Gabaix and Landier (2008) calculate that the CEO ability–firm size gradient is nearly zero at the top. Second, the earnings of the most skilled and highly remunerated employees in finance are likely to comove closely with executive compensation.

We obtain data on executive compensation in 1936–2005 for 50 of the largest publicly traded firms in the U.S. from Frydman and Saks (2010).¹² Seven of these firms are in finance, but none span the entire period. The coverage is as follows: CIT Group 1938–1976, Citicorp (Citigroup) 1971–1997, American Express 1977–2005, Chase (JPMorgan Chase) 1972–2005, Aetna 1964–2005, Cigna 1982–2005, and AIG 1970–2005. Note that we observe only one financial firm in 1938–1963 and only two

12. We thank Carola Frydman and Raven Saks for making these data available to us. The trends in the Frydman and Saks (2010) data are similar to those in other sources, such as *Forbes Magazine* (1970–1991) and *Execucomp* (1992–2010), when the data are available: see Figure A3. We thank Kevin J. Murphy for sharing his data from *Forbes Magazine*. See the appendix of Frydman and Saks (2010) and our Online appendix for complete details.

in 1964–1970. On the positive side, we have representation of all three subsectors within finance.¹³ Denote the median compensation for the top three executives outside of finance by $w_{nonfarm,t}^{exec}$ and in finance by $w_{fin,t}^{exec}$. We find no jumps or discontinuities in the $w_{fin,t}^{exec}$ series around the years in which financial firm joins or leave the sample. We define the excess executive compensation in finance as

$$(5) \quad \omega_{fin,t}^{exec} \equiv \frac{w_{fin,t}^{exec}}{w_{nonfarm,t}^{exec}}.$$

Figure IV reports two series for $\omega_{fin,t}^{exec}$, one of which excludes the value of options at the time they are granted. In 1938–1941 executive compensation in finance is 21% higher than in the rest of the private sector, but in 1966–1975 it is actually 24% less. In 1975, relative executive compensation in finance starts to increase, gaining momentum in the 1990s, until in 1995–2005 it is 2.7 times greater than in the private sector, on average. The pattern of relative executive compensation is the same whether or not we include option values. It follows that this form of incentive pay does not drive the changes in relative executive compensation in finance.

Figures II to IV confirm the basic finding of Figure I. Relative wages in finance follow a U-shape over the past 100 years, and this pattern is specific to finance. The next section studies changes in complexity of finance jobs.

II.C. Complexity

Is the pattern of changes in the degree of relative complexity of finance in line with the patterns in Figures I to IV? Designing, originating, and trading complex products requires highly skilled workers. Therefore changes in the intensity of these activities should be reflected in changes in the composition of workers. This, in turn, should be reflected in the pattern of relative wages.

To assess this, we decompose changes in ω_{fin} into within- and between-group changes using the formula

$$(6) \quad \Delta\omega_{fin} = \sum_i \Delta\omega_i \bar{n}_i + \sum_i \Delta n_i \bar{\omega}_i,$$

13. We also use a shorter sample in 1970–2005 with wider coverage, which yields qualitatively similar patterns. See the Online Appendix for details.

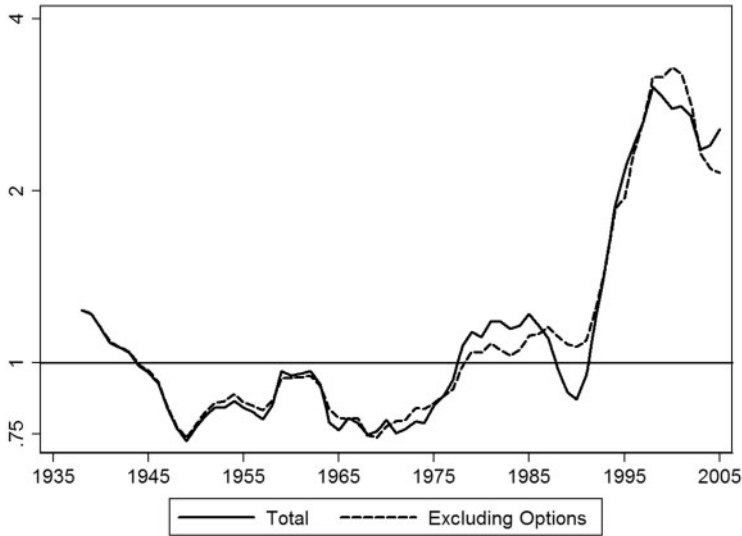


FIGURE IV

Finance Relative Executive Compensation: Top 50 Firms

The figure reports median executive compensation in finance relative to median executive compensation in the rest of the nonfarm private sector. Data are smoothed using a 5-year moving average. The vertical axis is log scale. The sample is the top three executives in each of 50 of the largest publicly traded firms that operated in the U.S. in 1936–2005 and reported executive compensation for at least 20 years, obtained from Frydman and Saks (2007). See their data appendix for complete documentation. None of these 50 firms are in agriculture, and 7 are in finance: CIT Group 1938–1976, Aetna 1964–2005, AIG 1970–2005, Citicorp (Citigroup) 1971–1997, Chase (J.P. Morgan Chase) 1972–2005, American Express 1977–2005, Cigna 1982–2005. The solid line takes into account total executive compensation, including the value of options at the time they were granted estimated by the Black-Scholes formula. The dashed line excludes the value of options.

where i is an index for some subcategory. Here $\Delta\omega_i$ is the change of the relative wage of finance within category i , \bar{n}_i is the average employment share of category i within finance, Δn_i is the change in the employment share of i within finance, and $\bar{\omega}_i$ is the average relative wage of i in the sample. The first sum captures the contribution of changes within categories, and the second sum captures the contribution of compositional changes between categories (see the Online Appendix for complete details).

Table II reports the results of this decomposition along several dimensions. Panels A and B deliver a clear message: changes

TABLE II
DECOMPOSITION OF CHANGES IN RELATIVE WAGE OF FINANCE

| | Within | Between | Total (=Within + Between) |
|---|--------|---------|------------------------------|
| A. Occupations within finance (CPS) | | | |
| 1969–1980 | –0.026 | 0.029 | 0.003 |
| 1980–2005 | 0.097 | 0.304 | 0.401 |
| B. Educational attainment within finance (CPS) | | | |
| 1969–1980 | –0.107 | 0.110 | 0.003 |
| 1980–2005 | 0.103 | 0.298 | 0.401 |
| C. Subsectors within finance (CPS) | | | |
| 1969–1980 | 0.024 | –0.022 | 0.003 |
| 1980–2005 | 0.287 | 0.114 | 0.401 |
| D. Subsectors within finance (Industry Accounts) | | | |
| 1933–1960 | –0.574 | 0.002 | –0.571 |
| 1960–1980 | –0.044 | –0.003 | –0.047 |
| 1980–2005 | 0.592 | 0.056 | 0.648 |
| E. Industries within nonfarm private sector (Industry Accounts) | | | |
| 1933–1960 | 0.353 | –0.004 | 0.349 |
| 1960–1980 | 0.046 | –0.039 | 0.007 |
| 1980–2005 | –0.361 | –0.051 | –0.411 |
| F. Geography, across states (SPI) | | | |
| 1969–1980 | 0.003 | –0.008 | –0.005 |
| 1980–2005 | 0.790 | –0.035 | 0.755 |

Notes. All decompositions are based on equation (6) in the text. The decompositions in A are across seven occupational categories; in B they are across five educational attainment categories; in C and D they are across three subsectors within finance; in E they are across 11 industries within the nonfarm private sector (excluding finance); in F they are across 51 states. See text for complete description of classifications. Panels A–C are based on the Current Population Survey (CPS), using total annual hours worked and total income from wage and salary. Panels E and D are based on the Annual Industry Accounts, using full-time equivalent employment and compensation of employees. The signs in Panel D are reversed because here we decompose the inverse of the finance relative wage (the wage of the nonfarm private sector relative to that of finance). Panel F is based on State Personal Income (SPI), using full- and part-time employment by industry and earnings by industry. Differences in methodologies across data sources explain differences in the total change column. In particular, top-coding in the CPS causes the total change to be much smaller. Availability of SPI employment data starts in 1969; we start the CPS sample from the same year for comparability.

in the composition of education and, in particular, occupations are more important than changes in wages within these categories.¹⁴ In contrast, changes in industrial

14. We use five educational categories: “less than 12 years of schooling,” “high school graduate,” “13–15 years of schooling,” “college graduate” (four-year college), and “more than college” (graduate degrees such as a JD, MBA, or PhD). We use

compositional—across 3 subsectors within finance (Panels C and D) or 11 subsectors within the nonfarm private sector (Panel E)—or changes in the location of financial activity (Panel F) are irrelevant.¹⁵ Figure V reports the evolution of employment shares within finance and the wage of each subsector relative to the nonfarm private sector. Other finance displays a large increase in relative wage, but it also employs a small fraction of employees.

The analysis in Table II underscores the importance of changes in the set of occupations within finance. The next step is to link occupations to the nature of the tasks performed by the industry. The challenge is to construct a consistent and informative measure of tasks over the whole sample.

We rely on the Dictionary of Occupational Titles (DOT) to study the nature of occupations.¹⁶ Each occupation is characterized by a vector of five DOT task intensities: finger dexterity (routine manual tasks); set limits, tolerances, and standards (routine cognitive tasks); math aptitude (analytical thinking); direction, control, and planning (communication and decision making); and eye–hand–foot coordination (nonroutine manual tasks). Each task intensity is a number between 0 and 10; thus it is an ordinal, not cardinal, ranking.¹⁷ The DOT task intensities were calculated by a panel of experts from the National Academy of Sciences in 1977.

seven occupational groups: “managers and professionals,” “mathematics and computers,” “insurance specialists,” “brokers and traders,” “bank tellers,” “administration, including clerks,” and “all the rest” (janitors, security, and miscellaneous). Our classification of occupations attempts to group employees according to the tasks they perform. It is hard to find consistent definitions of occupations that exhibit stable shares over time. The Online Appendix explains in detail how we categorized the data, the constraints we faced, and the reasons for our choices.

15. While sectoral analysis is common in economics, this is mostly because sectoral data are readily available. It is not clear, however, whether distinctions based on Standard Industrial Classification (SIC) or North American Industry Classification System (NAICS) codes are relevant here. For example, does it really matter whether a trader works for an insurance company, a commercial bank, or a hedge fund? Table II suggests that the answer to this question is: no. Table A1 reports the geographical decomposition in much more detail.

16. We thank David Autor for sharing with us data on occupational task intensities.

17. Each one of the five indices is detected by Autor, Levy, and Murnane (2003) as a principal component for indices that are similar in nature. The DOT indices that we use are based on the 1990 census occupational classification, and are further differentiated by gender. See the Online Appendix for a complete description.

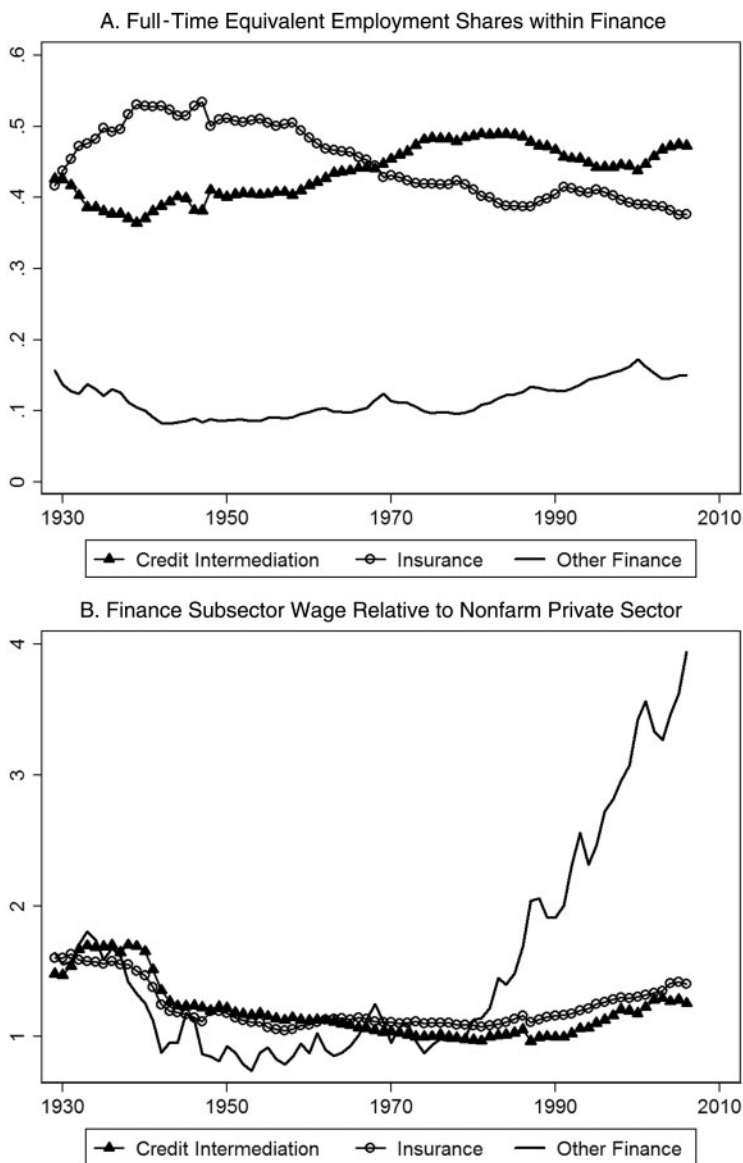


FIGURE V

Employment Shares and Relative Wages of Financial Subsectors.

Panel A reports full-time equivalent employment shares of three subsectors within finance. Panel B reports the ratio of average wage in each subsector of finance to the average wage in the non farm private sector excluding finance. Both wages are per full-time equivalent worker. Calculations based on data from the BEA, Annual Industry Accounts.

Although every occupation combines all five tasks with some degree of intensity, the following examples can help fix ideas and facilitate the interpretation. Production line workers have high finger dexterity intensity; clerks and administrative workers have high set limits, tolerances, and standards intensity; economists exhibit high math aptitude; managers and sales persons have high direction, control, and planning intensity; and truck drivers and janitors have high eye–hand–foot coordination intensity.

We match the DOT task intensities to individuals in the U.S. censuses from 1910 to 2000 and in the 2008 March CPS by occupation. To match the DOT task intensities to individuals we created a consistent occupational classification throughout the sample.¹⁸ In doing so we assume that occupations' characteristics are stable over our sample. While this is certainly a strong assumption, we believe that it is made less critical by the fact that we focus on the *relative* DOT scores of finance versus the nonfarm private sector and by the fact that the DOT task intensities are ordinal in nature. By construction, our measure is not affected by a general drift in DOT scores over time. As long as the actual ranking of occupations does not change much over time, our measure of relative task intensity is informative.

We restrict our attention to workers of aged 15 to 65 who are employed in the nonfarm private sector.¹⁹ Each individual in this sample is characterized by the five task indices. For each task and year we create an average intensity by sector,

$$task_{j,t} = \frac{\sum_{i \in j} task_{i,t} \lambda_{i,t} h_{i,t}}{\sum_{i \in j} \lambda_{i,t} h_{i,t}}.$$

The generic *task* varies over all five tasks described above. Relative task intensity for finance in a given year is given by

$$rel_task_{fin,t} \equiv task_{fin,t} - task_{nonfarm,t}.$$

Figure VI reports the evolution of four relative task intensities (the fifth, relative eye–hand–foot coordination, does not

18. See the Online Appendix for complete details.

19. Due to data limitations, in 1920 we could only restrict to individuals who are in the labor force, whether employed or not. In the 1910–1930 and 1960–1970 censuses the underlying data used to calculate hours are missing. Therefore in those years we assign $h = 1$ for all individuals.

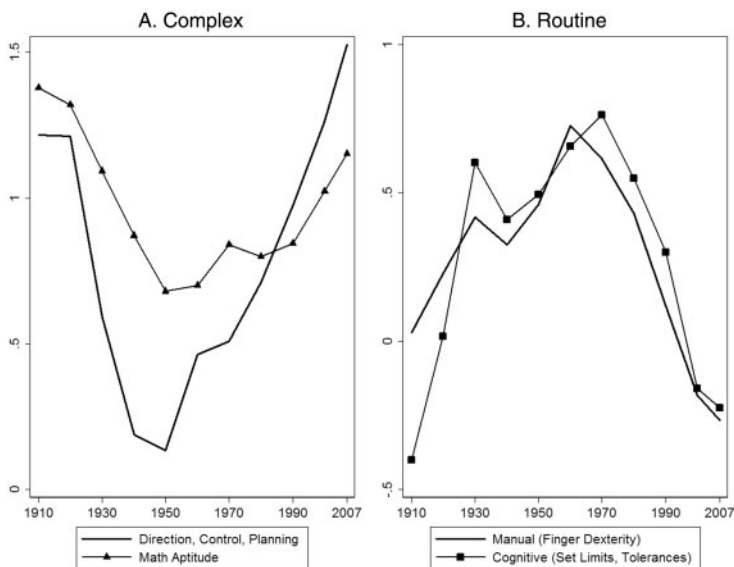


FIGURE VI
Relative Complexity

The figure reports relative task complexity (Panel A) and relative routine task intensity (Panel B) for finance versus the nonfarm private sector. The indices are constructed by merging task data from the Dictionary of Occupational Titles by occupation and gender from Autor Levy, and Murnane (2003) with individual data from the U.S. Censuses 1910–2000 and 2008 March CPS. Relative task intensities are computed by subtracting the index for finance by that of the nonfarm private sector.

change much throughout the sample). The figure conveys a clear message: Finance is relatively more complex and non-routine in the beginning and end of the sample, but not in the middle.

Figure VIA focuses on relative complexity. Finance loses much of its relative analytical complexity (math aptitude) from 1910 to 1950. At that point a slow recovery starts that accelerates in 1990. Decision making (direction, control, and planning) suffers even more in relative terms but the recovery is much stronger. Figure VIB conveys the same message. Routine task intensity rises in finance from 1910 to 1930 and starts to decline from 1980 on. In results that we do not report here, we observe virtually the same patterns within all three subsectors of finance.²⁰

20. The relative decrease and increase in complexity is strongest within other finance. Data are noisy for routine tasks in other finance due to few observations of

II.D. *Contribution to Income Inequality*

We now study the contribution of finance to changes in income inequality.²¹ We consider overall wage inequality, residual wage inequality, and the college premium. We restrict our CPS sample to full-time full-year employees, aged 15 to 65, who have no more than 40 years of potential experience and who earn at least 80% of the federal minimum hourly wage.²² We compare actual measures of inequality to those that are computed from a “simulated sample” in which we simulate wages in finance and take as given wages elsewhere. We assume that the employment share of finance does not change since 1970 and that all wages in finance since 1970 grow at the rate of the median wage in the rest of the nonfarm private sector.²³ In all cases the timing fits the period of financial deregulation that we document later: Contributions to inequality become important after 1980.

1. *Overall wage inequality.* Figure VIIA depicts actual percentile ratios relative to those calculated from the simulated sample. The percentile ratios are not equal to 1 in 1970 (the base year) because we display five-year moving averages of the original ratios to reduce noise. Finance contributes more to inequality at the top of the distribution. The actual 90–10 ratio increases from 3.5 in 1970 to 5.15 in 2005; finance contributes

workers who perform those tasks most intensively in that subsector. The pattern for direction, control, and planning in insurance slightly differs from the aggregate pattern for finance. These results are available on request.

21. We focus on the direct labor market effect since it is manifested in a few widely used measures of inequality. We do not attempt to address indirect effects of finance on inequality, for example, by changing outside options for workers outside of finance, or the effects of new financial products on inequality. For a review of the literature on this channel, see Demirguc-Kunt and Levine (2009).

22. We multiply top-coded wages by a factor that makes the wage bill share of finance relative to that of the rest of the nonfarm private sector in the CPS equal to that in the National Income and Product Accounts (NIPA) each year. The factor varies by year and is, on average, 3.5. Not surprisingly, this is higher than the standard factors that are used in the literature, which are on the order of 1.5 to 2.

23. Median wage growth is a natural choice when we discuss percentile ratios. The results are virtually the same if we use the growth rate of average wages. See the Online Appendix for complete details on this simulation.

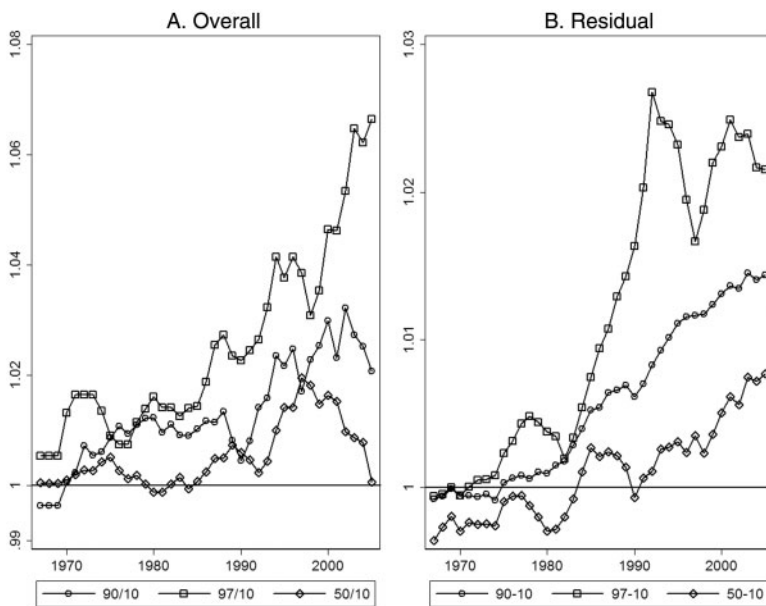


FIGURE VII

Contribution of Finance to Inequality

Both panels present inequality measures as they were computed from the data, relative to the same measures that were computed from a sample in which wages in finance were simulated. Numbers above 1 indicate that inequality would have been lower in the simulated sample. The underlying data for both is the March CPS 1968–2006, full-time full-year employees, age 16 to 60 who have potential experience between 0 and 40 years, who earned at least 80% of the federal minimum hourly wage. Top coded wages are multiplied by 3.5. In the simulated sample we assume that the employment share of finance did not change since 1970 and that all wages in finance since 1970 grow at the rate of the median wage in the rest of the nonfarm private sector. See text for complete documentation of sample and simulation. Panel A presents relative annual wage percentile ratios, taking into account CPS sampling weights. Panel B presents relative percentile differences of residual wages. Residuals are obtained from regressions of the log hourly wage on a full set of experience dummies, dummies for five schooling categories, a full set of interactions among the schooling dummies and a quadratic in age, and indicators for gender, race, urban dwelling, and marriage. Observations were weighted by their CPS sampling weight. The series in the figure are 5-year moving averages of the original series.

6.2% of the increase. The actual 97–10 ratio increases from 5 in 1970 to 9 in 2005; finance contributes 15% of the increase.²⁴

24. Bell and Van Reenen (2010) document similar patterns for the United Kingdom. See also Kaplan and Rauh (2010).

Other measures convey a similar message. We find that finance contributes 14% to the increase in the Gini index, 14% to the increase in the mean log difference index, and 26% to the increase in the Theil index. The Theil index emphasizes inequality driven by the top of the distribution. Therefore it is not surprising that the effect of finance is so large.²⁵

2. *Residual Inequality.* We compute residuals from fitting the log of hourly wages to indicators of race, gender, urban dwellings, marital status, a full set of experience dummies, and a full set of five education dummies and the interactions of all these dummies with a quadratic in experience. We use CPS sampling weights to weigh observations in the regression.

Figure VII B depicts actual percentile *differences*, as they are calculated in the data, relative to those calculated from the simulated sample. The results for residual inequality convey a similar message as overall inequality. The actual 90–10 difference increases from 0.94 in 1970 to 1.23 in 2005; finance contributes 6.6% of the increase over this period. The actual 97–10 difference increases from 1.2 in 1970 to 1.58 in 2005; finance contributes 8.5% of the increase over this period.²⁶ We also find that finance contributes 7.4% to the increase in the standard deviation of residuals (and 8.2% to the increase in the variance of residuals).²⁷

3. *The College Premium.* In supplementary regressions (not reported here), we regress the log of hourly wages on indicators of race, gender, urban dwellings, marital status, a full set of experience dummies, and an indicator for a college degree (16 years of education). We use CPS sampling weights to weigh observations in the regression. We run separate regressions for each year and compare the coefficients on the college indicator in the real data to those in the simulated sample. The results are in line with overall inequality and residual inequality. The college premium in the simulated sample increases from 0.382 in 1970 to 0.568 in 2005,

25. Using a more conventional top-coding factor of 1.75 lowers the contribution of finance to inequality measured by the Theil index to 15% but hardly changes the contribution of the other two indices.

26. These numbers are not affected by our method of top-coding correction because less than 3% of workers in our sample are top-coded in any given year.

27. Since the residuals are centered around zero in any year, the standard deviation is not affected by changes in the level of wages. Gini, Theil, and mean log difference indices are not amenable to residuals, which can be negative.

whereas the actual college premium, as we calculate it, increases to 0.584 in 2005. Finance contributes 8% to the increase.

II.E. Taking Stock of the New Facts

Uncovering the historical evolution of average wages, education, wages at the top, human capital, and job complexity in the finance industry is the first contribution of this study. The remainder of the article seeks to explain these new stylized facts. In particular, it tries to identify the forces responsible for the evolution of human capital in the finance industry. The fact that relative wages and education in finance were just as high in the 1920s as in the 1990s suggests that the IT revolutions of the early and late twentieth century may be an important driving force. But data on IT investment *by sector* do not exist before 1947, so we cannot investigate this hypothesis in the early part of the sample.²⁸ We do find evidence that is consistent with IT having a role—although not the most important role—in explaining variation in demand for skill and in wages across finance subsectors in the latter part of the sample. The historical evidence shows that the evolution of the financial industry is not simply driven by the ratio of stock market value to gross domestic product (GDP) or by globalization, as discussed at the end of Section III.

III. DEMAND FOR SKILL IN THE FINANCIAL SECTOR

III.A. A Simple Framework

We use a simple model of demand for skill to organize the discussion. Suppose that there are two skill levels—high and low—and that the production function of sector j in time t is of constant elasticity of substitution (CES) form

$$Y_{j,t} = \left[\alpha_j (B_{j,t} H_{j,t})^{\frac{\sigma-1}{\sigma}} + (1 - \alpha_j) (A_{j,t} L_{j,t})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

28. Yates (2000) documents the industrial use of IT—telephones, typewriters, improved filing techniques, tabulation techniques, and sorting cards—during the previous information revolution, starting at the end of the nineteenth century. Most of the evidence, which is descriptive, is for management in manufacturing, although some examples exist for insurance. Michaels (2007) argues that this increased the demand for office workers in manufacturing in the early twentieth century and that this phenomenon was more pronounced in more complex industries within manufacturing. We could not obtain data on the relative stock of telephones and such in the finance industry in the early part of the sample.

where L and H are hours worked by low-skill and high-skill workers, respectively; A and B are factor augmenting parameters for low-skill and high-skill workers, respectively; $\alpha_j \in (0, 1)$ and σ is the elasticity of substitution, which we assume to be greater than 1 and the same in all sectors.²⁹ In this section, we view the labor market as a competitive spot market without adjustment costs and without compensating differentials (we address these issues later). Therefore wages are equalized across sectors. Let w_h and w_l be the hourly wages for high- and low-skill workers, respectively. Cost minimization implies that log relative demand for skill is given by

$$h_{j,t} = c_j + (\sigma - 1)\mu_{j,t} - \sigma\pi_t,$$

where $h_{j,t} = \ln\left(\frac{H_{j,t}}{L_{j,t}}\right)$, c_j is a constant, $\mu_{j,t} = \ln\left(\frac{B_{j,t}}{A_{j,t}}\right)$, $\pi_t = \ln\left(\frac{w_{h,t}}{w_{l,t}}\right)$. Goldin and Katz (2008a) provide strong evidence of a secular trend in μ for the aggregate economy throughout our sample. But we are interested in demand for skill of the financial sector *relative* to the rest of the economy. The relative demand for skill in finance versus the nonfarm private sector is given by

$$(7) \quad h_{fin,t} - h_{nonfarm,t} = c + (\sigma - 1)(\mu_{fin,t} - \mu_{nonfarm,t}),$$

where c is a constant. The relative wage π does not affect the *relative* skill intensity in finance because we assume $\sigma_{fin} = \sigma_{nonfarm}$.³⁰ We now turn to potential determinants of relative demand shifters, that is, of $\mu_{fin,t} - \mu_{nonfarm,t}$.

29. Estimates of the aggregate elasticity of substitution are typically greater than 1, and on the order of 1.5; for example, see Katz and Murphy (1992) and Krusell et al. (2000) and others cited in Autor and Katz (1999). However, these aggregate elasticities can mask heterogeneity of elasticities at the sector level, possibly below 1 (Reshef 2011).

30. If we do not restrict elasticities to be equal, then $h_{fin,t} - h_{nonfarm,t} = c + (\sigma_{fin} - 1)\mu_{fin,t} - (\sigma_{nonfarm} - 1)\mu_{nonfarm,t} - (\sigma_{fin} - \sigma_{nonfarm})\pi_t$. In this case it is more likely that $\sigma_{fin} > \sigma_{nonfarm}$ than otherwise: We expect scale effects to be stronger in finance, so it is more likely that similar skill-biased technological improvement will lead to stronger substitution towards skilled workers in finance versus the rest of the economy. But in this case changes in the aggregate skill premium π affect relative skill intensity in finance in the *opposite* direction of what we observe. Goldin and Katz (2008a) show that the skill premium declined from 1914 to 1949 and then increased through today, with a brief, small decline in the 1970s. We observe a higher relative demand for skill in finance exactly when the aggregate skill premium is highest. The finance industry hires relatively more educated people exactly when they are most expensive. Moreover, if the μ factors do not play a major role, then a simple calculation shows that σ_{fin} must be negative. To

III.B. Explanatory Variables

As Equation (7) implies, explaining relative demand for skill requires understanding the sources of comparative advantage of skilled labor in finance versus the rest of the economy. Broadly speaking, this can be affected by technological innovations and organizational choices. We discuss plausible determinants, some of which are displayed in Figure VIII. Summary statistics are reported in Table I.

1. *Information Technology.* Computers are complementary to complex tasks (nonroutine cognitive) and substitutes for routine tasks (Autor, Levy, and Murnane 2003). Employees in complex or analytical jobs become more productive, while the demand for routine jobs decreases; manual jobs are less affected. The financial sector has been an early adopter of IT. We therefore consider the share of IT and software in the capital stock of the financial sector minus that share in the aggregate economy. The capital stock data are from the BEA's fixed assets tables by industry. Our measure of relative IT intensity is displayed in Figure VIIIA. This series does not capture investments in IT in the early part of the sample. We cannot use the IT share in our time series regression, but we will provide evidence of the role of IT in our panel regressions.

2. *Use of Patents in Finance.* New financial products are likely to increase skill demand. Futures and option contracts are more complex than spot contracts and financial innovations can expand the span of control of talented individuals, as emphasized by Murphy, Shleifer, and Vishny (1991). Patenting is, of course, endogenous, but historical evidence suggests that a significant fraction of financial innovations precede the rise in skill

see this, ignore the μ factors and note that from 1980 to 2005 the change in $(h_{fin} - h_{nonfarm})$ is 0.58 and the change in π is 0.32 (our calculations based on the CPS sample described below). This implies that $-(\sigma_{fin} - \sigma_{nonfarm}) = \frac{0.58}{0.32}$, or $\sigma_{fin} = \sigma_{nonfarm} - 1.8125$. Here $\sigma_{nonfarm}$ (excluding finance) is likely to be close to the aggregate elasticity, which is typically estimated below 1.8125 (see again Katz and Murphy 1992; Krusell et al. 2000; Autor and Katz 1999); this renders σ_{fin} to be negative. We conclude that changes in π cannot be the only driving force behind changes in relative skill intensity. The correct explanations must therefore rely on relative demand shifters, not on the aggregate skill premium.

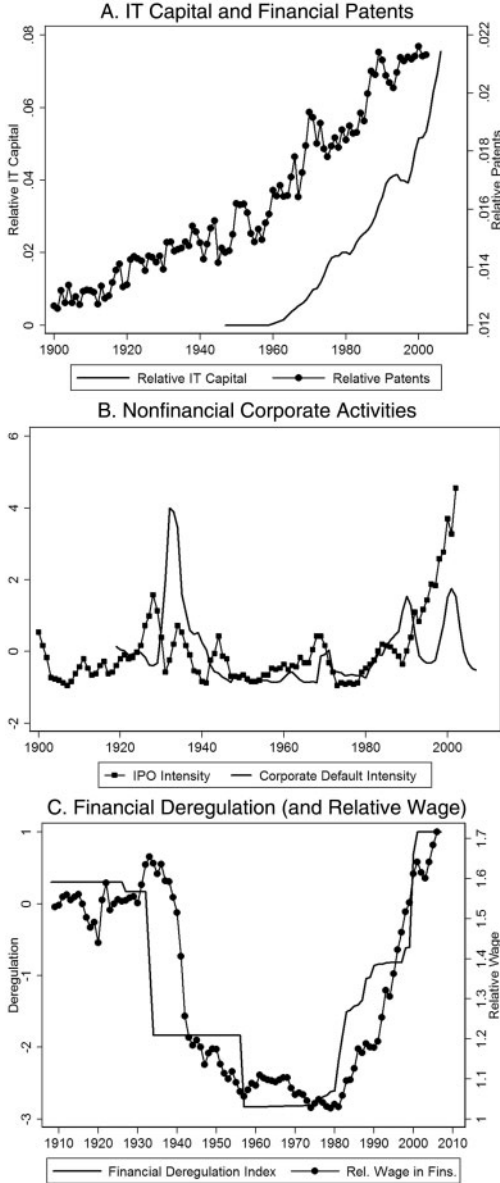


FIGURE VIII
Explanatory Variables

In Panel A, relative IT intensity is the IT share of capital in finance minus the IT share of capital in the economy. Relative patents is the ratio of financial patents to all patents. In Panel B, IPO is IPO value over Market Capitalization. Defaults is the 3-year moving average default rate on all corporations. Both series are normalized (mean = 0, standard deviation = 1) over the sample. Data from Jovanovic and Rousseau (2005). In Panel C, the relative wage is from Figure I. See the text for the definition of the deregulation index.

intensity.³¹ Unfortunately, financial patenting is a relatively recent phenomenon. Instead, we use data on new patents used in finance in 1909–1996.³² We extend the series to 2002 using data from Lerner (2006). We then normalize by the total number of patents used. The series is displayed in Figure VIIIA.

3. *Corporate Finance Activity: Initial Public Offerings and Credit Risk.* New firms are difficult to value because they are often associated with new technologies or new business models, as well as for the simple reason that they do not have a track record. We therefore expect the intensity of initial public offerings (IPOs) to increase demand for skill, as well as returns to skill in the financial sector. We measure IPO activity from 1900 to 2002, using data from Jovanovic and Rousseau (2005). Specifically, we use the market value of IPOs divided by the market value of existing equities. As Jovanovic and Rousseau (2005) show, IPO activity was strong during the Electricity Revolution (1900–1930) and during the current IT Revolution.

Credit risk is another area of corporate finance that experiences dramatic changes over long periods. Corporate defaults were common until the 1930s and the market for high-yield debt was large and liquid. This market all but disappeared for 30 years, until “junk” bonds reappeared in the 1970s. Pricing and hedging risky debt is significantly harder than pricing and hedging safe debt. Risky debt affects all sides of the financial sector. It is used to finance risky firms with high growth potential. Rating risky debt requires skilled analysts. Indeed, Sylla (2002) shows that rating agencies were important players in the interwar period, small and largely irrelevant in the 1950s and 1960s, and growing fast from the late 1970s until today. To measure credit risk, we use a three-year moving average of the U.S. corporate default rate published by Moody’s. For ease of comparison, we normalize the IPO and credit risk series to have a mean of 0 and unit standard deviation over the sample period. Our measures of nonfinancial corporate activity are displayed in Figure VIIIB.

31. Silber (1983) reviews new financial products and practices between 1970 and 1982. Miller (1986), reflecting on financial innovations from the mid-1960s to the mid-1980s, argues that the development of financial futures is the most significant. Tufano (2004) argues that other periods have witnessed equally important innovations.

32. Carter et al. (2006)

4. *Deregulation.* The optimal organization of firms, and therefore their demand for various skills, depends on the competitive and regulatory environment. A regulated financial sector may not be able to take advantage of highly skilled individuals because of rules and restrictions on the ways firms organize their activities. Deregulation may increase the scope for skilled workers to operate freely and to use their creativity to produce new complex products. Deregulation can also intensify innovation and competition for talent. Indeed, there is evidence that competition increases the demand for skill (see Guadalupe 2007 and the references therein). There is also evidence that organizational change can be skill-biased (Bresnahan and Trajtenberg 1995; Bresnahan, Brynjolfsson, and Hitt 2002; Caroli and Van Reenen 2001). We construct a measure of financial deregulation that takes into account the following regulatory legislation:

- (1) Bank branching restrictions. We use the share of the U.S. population living in states that have removed intrastate branching restrictions. It is a continuous variable that ranges from 0 to 1.
- (2) Separation of commercial and investment banks. The Glass-Steagall Act was legislated in 1933. It was gradually weakened starting in 1987 until its final repeal in 1999. This variable ranges from 0 to 1.
- (3) Interest rate ceilings. Legislation was introduced in 1933 and was gradually removed between 1980 and 1984. This variable ranges from 0 to 1.
- (4) Separation of banks and insurance companies. Legislation was introduced in 1956 and was repealed in 1999. This variable ranges from 0 to 1.

The deregulation index is given by $(1) - (2) - (3) - (4)$ and is displayed in Figure VIIC. See the Online Appendix for complete details.

5. *Financial Globalization.* We proxy for external demand forces such as financial globalization by using the ratio of U.S. foreign assets to GDP. The data on foreign assets are from Obstfeld and Taylor (2004) (1900–1960) and the International Monetary Fund (1980–2005). We interpolate linearly between data points when data are missing.

6. *Top Marginal Tax Rate.* The top marginal tax rate controls for either the supply of talented individuals or for the cost of paying high net wages. Tax rate data are from the Tax Foundation, based on information from the U.S. Internal Revenue Service.

III.C. Regression Analysis

1. *Time Series.* We fit simple predictive regressions of relative wages and education on the explanatory variables described above. The regressions ask the following question: If financial regulation tightens for five years, what should one predict about future relative wages? We discuss endogeneity and causality in Section III.D. The regressions are of the generic type

$$(8) \quad y_{fin,t+5} - y_{fin,t} = \alpha + (X_t - X_{t-5})\beta + \varepsilon_t,$$

where $y_{fin,t} = \rho_{fin,t}$ or $\omega_{fin,t}$, and X includes explanatory variables that are listed in Section III.B. Standard errors take into account five years of autocorrelation (Newey–West).³³ We note that our deregulation series is legislation *passed*, not *implemented*. For instance, the Dodd–Frank Wall Street Reform and Consumer Protection Act was passed on July 21, 2010, but will not be fully implemented for years to come. This justifies our lag–lead structure. The timing of the shifts suggests a distinct role for deregulation. The results for regressions in changes are reported in Table III, Panel A.

The most robust determinant of both relative education and wages appears to be deregulation. Deregulation alone accounts for 40% of changes in education and 23% of changes in wages. Patents used in finance do not seem to matter. Corporate IPO intensity matters for relative wages and, to a lesser extent, for relative education. Adding the foreign assets and the top marginal tax rate variables hardly affects the results for changes in education. Changes in globalization matter for relative wages; adding this variable lowers the explanatory power of deregulation in the relative wage regression.

The regressions in changes reported above are relatively conservative. Regressions in levels give more weight to regulation, as

33. Diagnosis of the correlation functions of the residuals indicates gradual decay. After five lags the correlation is close to nil and usually statistically insignificant.

TABLE III
HISTORICAL DETERMINANTS OF EDUCATION AND WAGES IN FINANCE INDUSTRY

| A. Change regressions Dependent variable | Change in Relative Education, t to t+5 | | Change in Relative Wage, t to t+5 | | | | | |
|--|---|-----------------------|--------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | | | | | | | | |
| Change in Deregulation Index, t-5 to t | 0.0099*** (0.0028) | 0.0095*** (0.0026) | 0.0089*** (0.0024) | 0.0072*** (0.0030) | 0.0889*** (0.0231) | 0.0889*** (0.0233) | 0.0587*** (0.0253) | 0.0310 (0.0247) |
| Change in Financial Patents over Total Patents, t-5 to t | | 2.2058 (1.5244) | | | | -0.1079 (12.9115) | | |
| Change IPO share of market capitalization, t-5 to t | | | 0.0031*** (0.0012) | 0.0016 (0.0015) | | | 0.0725*** (0.0260) | 0.0580*** (0.0243) |
| Change in Corporate Default Rate, t-5 to t | | | 0.0015 (0.0010) | 0.0011 (0.0009) | | | 0.0301 (0.0182) | 0.0281 (0.0185) |
| Change in Foreign Assets/GDP, t-5 to t | | | | 0.0548 (0.0365) | | | | 0.4817*** (0.2361) |
| Change in Top Marginal Tax Rate, t-5 to t | | | | -0.0031 (0.0093) | | | | -0.1256 (0.1104) |
| Observations | 91 | 91 | 77 | 77 | 93 | 93 | 78 | 78 |
| R-squared | 0.390 | 0.426 | 0.485 | 0.529 | 0.226 | 0.226 | 0.506 | 0.551 |
| Sample | 1910-2005 | 1910-2003 | 1920-2003 | 1920-2003 | 1909-2006 | 1909-2003 | 1920-2003 | 1920-2003 |

(continued)

TABLE III
CONTINUED

| B. Level regressions Dependent variable | Relative Education | | Relative Wage | | | | |
|--|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | | | | | | | |
| Deregulation Index, t-5 | 0.0178*** (0.0014) | 0.0148*** (0.0015) | 0.0148*** (0.0020) | 0.1700*** (0.0096) | 0.1336*** (0.0140) | 0.1310*** (0.0144) | 0.1110*** (0.0221) |
| IPO share of market capitalization, t-5 | 0.0092*** (0.0020) | 0.0014 (0.0021) | 0.0014 (0.0021) | | 0.0695*** (0.0209) | 0.0818*** (0.0250) | 0.0877*** (0.0238) |
| Corporate Default Rate, t-5 | 0.0023 (0.0021) | 0.0016 (0.0012) | 0.0016 (0.0012) | | 0.0415*** (0.0166) | 0.0425*** (0.0157) | 0.0409*** (0.0154) |
| Foreign Assets/GDP, t-5 | | 0.0641*** (0.0111) | 0.0641*** (0.0126) | | | -0.0980 (0.1553) | -0.2416 (0.1668) |
| Top Marginal Tax Rate, t-5 | | | 0.0000 (0.0085) | | | | -0.1688* (0.0865) |
| Observations | 96 | 82 | 82 | 98 | 83 | 83 | 83 |
| R-squared | 0.804 | 0.856 | 0.931 | 0.819 | 0.897 | 0.898 | 0.908 |
| Sample | 1910-2005 | 1910-2003 | 1920-2003 | 1909-2006 | 1909-2003 | 1920-2003 | 1920-2003 |

(continued).

TABLE III
CONTINUED

| C. Panel of subsectors: credit intermediation, insurance, and other Finance. | | Relative Education | | Relative Wage | |
|--|------------------------|------------------------|---------------------|---------------------|-----------|
| Dependent variable | | | | | |
| Subsector Deregulation Index (t-1) | 0.0194*** (0.00298) | 0.0192*** (0.00267) | 0.260** (0.0999) | 0.259** (0.0997) | |
| Share of IT in Capital Stock of Subsector (t-1) | 0.197*** (0.0449) | 0.195*** (0.0369) | 1.679 (1.415) | 1.649 (1.379) | |
| Subsector fixed effects | Yes | Yes | Yes | Yes | |
| Year fixed effects | Yes | Yes | Yes | Yes | |
| Observations | 165 | 165 | 165 | 165 | |
| R-squared | 0.749 | 0.704 | 0.470 | 0.443 | |
| Sample | 1951-2005 | 1951-2005 | 1951-2006 | 1951-2006 | 1951-2006 |

Notes: Standard errors in parentheses; in Panels A and B Newey-West standard errors with 5 lags of autocorrelation. ***p < .01, **p < .05.

one can expect from examining Figure VIII C. We fit regressions of the type

$$(9) \quad y_{fin,t} = \alpha + X_{t-5}\beta + \varepsilon_t.$$

We do not add the patent series because it is trending upward, whereas the other series are stationary. Standard errors take into account five years of autocorrelation (Newey–West). The results for regressions in levels are reported in Table III, Panel B. In these regressions the effect of deregulation is relatively stable across specifications and plays a significant role. Deregulation alone accounts for 80% of variation in education and in wages.

In the Online Appendix Table A2 we experiment with using each piece of financial regulation separately and in Table A3 we entertain contemporaneous specifications of the level regressions. These regressions convey a similar message to those using the deregulation index. Overall, the time-series regressions confirm the strong link between deregulation, skill upgrading, and wages in finance.

2. Panel of Subsectors. The IT and software capital data are available by subsector (Credit Intermediation, Insurance, and Other Finance) from the BEA. We construct a subsector-specific deregulation index from the four components of the aggregate index, as follows:

- For Credit Intermediation the index is equal to (1) – (2) – (3).
- For Insurance the index is equal to – (2) – (4).
- For Other Finance the index is equal to $-2 \times (2) - (3)$.

Bank branching affects only Credit Intermediation because it is the subsector that includes banks. Glass–Steagall affects all subsectors, but we allow the effect to be twice as large for Other Finance because it changed both the organization of investment banking and competition within the sector and therefore should have a bigger impact there. Interest rate ceilings should not affect Insurance, whereas the separation of banks and insurance companies affects insurance companies more strongly than it affects Credit Intermediation and Other Finance.

For each subsector we have a measure of relative wage, relative education, deregulation, and IT intensity. We use these data to

fit panel regressions with subsector fixed effects and year dummies over the postwar period. The coefficients here tell us how much deviations in the explanatory variables affect relative skill and wages over and above their aggregate trend. We report the results in Table III, Panel C. We find that IT and software intensity is linked to skill upgrading but the effect on wages is not significant. Once again, we find that deregulation has a large effect on both relative education and relative wages. In fact, the effect of deregulation is economically 1.66 times larger than that of the IT share (in Table I, Panel B, the deregulation variable has a standard deviation of 1.078 while the IT share variable has a standard deviation of 0.064). Results using each piece of financial regulation separately are similar (see Online Appendix Table A2, Panel C).

We would have liked to have run the same panel regressions with measures of financial innovation (e.g., patents), but these data do not exist at the subsector level. There is, however, one interesting piece of evidence: The relative stability of the insurance sector is consistent with the role of financial—as opposed to technological—innovations. Among the 38 new financial products and practices introduced between 1970 and 1982 listed by Silber (1983), only two or three are related to Insurance. This is also consistent with the argument by Miller (1986) on the ultimate importance of financial futures markets relative to other financial innovations. These innovations had a larger impact on other financial subsectors, in which we observe stronger relative wage growth, faster skill upgrading, and faster occupational changes.

3. Glass-Steagall Effect on “Wall Street”. Are the regression results driven by the effect of regulation on “Wall Street”, particularly the Glass-Steagall (GS) Act? The GS deregulation dummy has particularly strong predictive power for relative wages and for relative education. In panel regressions the GS dummy predicts well the relative wages and education in other finance.³⁴

Together with the large increase in the relative wage in other finance (documented in Figure VA), these results suggest that the Glass-Steagall Act is the most important part of regulation. If this view is correct, the effects should be concentrated on people

34. In all these cases the coefficient of the GS deregulation dummy is large a statistically significant. Online Appendix Table A2 reports the regression outputs.

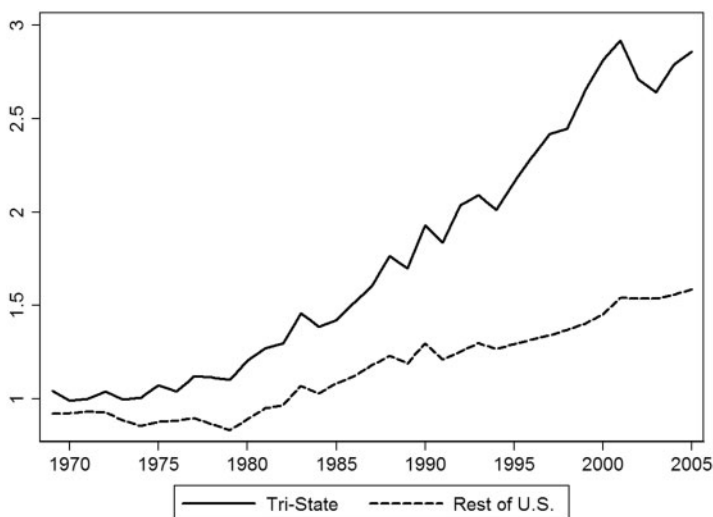


FIGURE IX

Relative Wage in Finance in Tri-State Area

The relative wage is the ratio of wages in finance to wages in the nonfarm private sector excluding finance, within each geographic area. The Tri-State Area includes New York, New Jersey, and Connecticut. The Rest of U.S. includes all other states. Data are from the Annual State Personal Income tables (SPI), using full- and part-time employment by industry and earnings by industry. The data are corrected for changes in industrial classification after 1990.

working in a handful of affected institutions close to “Wall Street”. Figure IX shows evidence in support of this view. It displays the relative wage in finance in the Tri-State Area (New York, New Jersey, and Connecticut), where “Wall Street” employees are likely to generate income, together with the relative wage of finance in the rest of the United States. The relative wage series are based on the State Personal Income (SPI) tables. The relative finance wage in the Tri-State Area increases from roughly 1.2 in 1980 to 3.1 in 2005—much more than in the rest of the U.S., where it increases from roughly 0.9 in 1980 to 1.6 in 2005. Panel F of Table II shows that changes within states—and not across states—explain the increase in the relative wage of finance. Specifically, relative wage changes within the Tri-State Area explains 32.5% of the total increase in the relative wage of finance from 1980 to 2005.³⁵

35. See Online Appendix Table A1 for detailed geographical decomposition.

III.D. Causality

We have considered other potential determinants for the evolution of relative education and relative wages over this long horizon, in particular international trade (ratio of trade to GDP) and equity valuation (ratio of stock market value to GDP). None of these variables has a significant effect on the skill composition of the financial sector once the deregulation index is included. For instance, for the market-to-GDP ratio, the overall correlation is small because there is a stock market boom in the 1960s and a collapse after 2001. We have also looked at the allocation of value added between labor and capital within the finance industry and find the labor share to be stable over time. From a statistical perspective, we believe that we have tried the most plausible explanatory variables and that regulation, IPOs, credit risks, and IT are the best predictors of skill demand in the financial sector.

But can we give a causal interpretation to our regressions? In many cases, we argue that we can. For instance, IPOs are not exogenous but Jovanovic and Rousseau (2005) show that IPO waves follow the introduction of general purpose technologies, such as electricity (1900–1930) or IT (1970 to today). The *timing* of these technological revolutions is exogenous and explains much of the historical fluctuations in IPOs. Credit risk also increases during and after IPO waves because young firms are volatile and because they challenge established firms. The important point is that these changes were not triggered by changes in the finance industry.

Our main point is that regulations matter, that is, that they have a causal impact on finance, even if regulations are also endogenous. First, the idea that regulations (especially in finance) do not matter is inconsistent with the sheer volume of lobbying effort spent to influence regulators (see Igan and Mishra 2011)

Second, although regulations are indeed endogenous, regulators do not react to shocks in a mechanical way. Following the crisis of 1929–1933, regulations were tightened and human capital left the finance industry but, following the crises of the late 1970s and early 1980s, regulations were loosened and wages in finance rose. Therefore the occurrence of a crisis, high unemployment, bank failures, or a long bear market have no direct predictive power for relative wages and skills employed in finance, while regulation does.

Regulations also interact with other forces. For instance, the IT share in the capital stock of the financial sector starts to increase in the 1960s but until 1980 relative wages and education do not change. It is only after deregulation that the relative wages start to increase. At the very least, it appears that large changes in organization required changes in regulation.³⁶

IV. THE FINANCE WAGE PREMIUM

In the previous section we focused on the skills of finance employees. We now study how these skills are compensated, that is, we study wages conditional on human capital. We calculate a wage premium by comparing actual wages to competitive benchmarks.

IV.A. *Historical Wage Premium*

To evaluate the role of education composition on the finance relative wage we construct the following benchmark relative wage series. The benchmark relative wage in finance versus the nonfarm private sector is given by

$$\hat{\omega}_{fin,t} = 1 + \rho_{fin,t}\pi_t,$$

where ρ_{fin} is relative education in finance defined in Equation (1) and π is the college premium. To compute π we use the CPS in

36. Previous studies examine organizational change in response to deregulation across U.S. states but the results are somewhat inconclusive. Black and Strahan (2001) find no effect of branching deregulation across states on the share of managers in banking, whereas Wozniak (2007) does, although her set of control variables is not as elaborate as that of Black and Strahan (2001). We replicated these cross-sectional results (not reported here) and find that the cross-sectional effects are small relative to the time-series effects. For instance, cross-sectional changes in the share of managers are small relative to time-series changes. In addition, cross-sectional changes in regulation only reflect branching restrictions. While undoubtedly relevant, these restrictions may not be as important as the repeal of Glass–Steagall. In addition, we do not claim that all types of deregulation lead to higher wages. That can only be true for changes that increase the demand for skills. We would therefore not necessarily expect an increase in competition across states to have the same consequences as a deregulation that allows the production of new financial instruments. Increased competition presumably lowers rents, but these effects are small relative to the aggregate changes documented above. Finally, our results are consistent with the evidence in Kostovetsky (2007) of a brain drain of top managers from mutual funds to less regulated hedge funds starting in the early 1990s.

1967–2005 and values from Goldin and Katz (2008a) for earlier years.³⁷ Figure XA reports the actual and benchmark relative wage series. The benchmark tracks the actual wage quite closely in the middle of the sample. In addition, the large returns to education in 1910–1920 documented by Goldin and Katz (2008a) account for a significant proportion the relative wage.

Figure XB reports the difference between the actual and benchmark relative wage, that is, the excess relative wage: $\omega_{fin} - \hat{\omega}_{fin}$. The pattern is striking. The late 1920s to early 1930s and the post-1990 periods stand out as times where wages in the financial sector are high relative to the benchmark. In those periods relative levels of education cannot explain the finance relative wage. The most deregulated periods exhibit the highest excess wages. In the relatively unregulated pre-1933 era finance commands a premium as well. The excess wage is 42% in 1933, -3% in 1980, and 51% in 2005. In Panel D of Table II we see that ω_{fin} decreases by 62% in 1933–1980 and then increases by 65% in 1980–2005. We conclude that changes in education composition and returns to education can explain 10–15 percentage points of these swings.

IV.B. Scale Effects and Executive Compensation

Let us now discuss models that emphasize scale effects or star effects, as those of Rosen (1981), Murphy, Shleifer, and Vishny (1991), and Gabaix and Landier (2008). Gabaix and Landier (2008) argue that executive compensation is linked to firm size, using a competitive assignment framework. The 1990s was a period of mergers in finance and, indeed, some of the financial firms in sample of Figure IV participated in mergers in this period (e.g., JPMorgan Chase and Citigroup). Gabaix and Landier (2008) predict the following relation:

$$(10) \quad \log w_{it} = c_i + \frac{\beta}{\alpha} \log s_{Nt} + \left(\gamma - \frac{\beta}{\alpha} \right) \log s_{it},$$

where w_{it} is the wage of the CEO in firm i at time t , $s_{N,t}$ is the size of the N th firm by size (the largest firm is number one), and s_{it} is the size of firm i at time t . Gabaix and Landier (2008) estimate

37. In 1967–2005 we use the average relative hourly wage of college graduates to non-college graduates in the nonfarm private sector, calculated from the CPS sample used in Section IV.C. This is the correct concept for the benchmark wage exercise. We interpolate linearly between observations in earlier years.

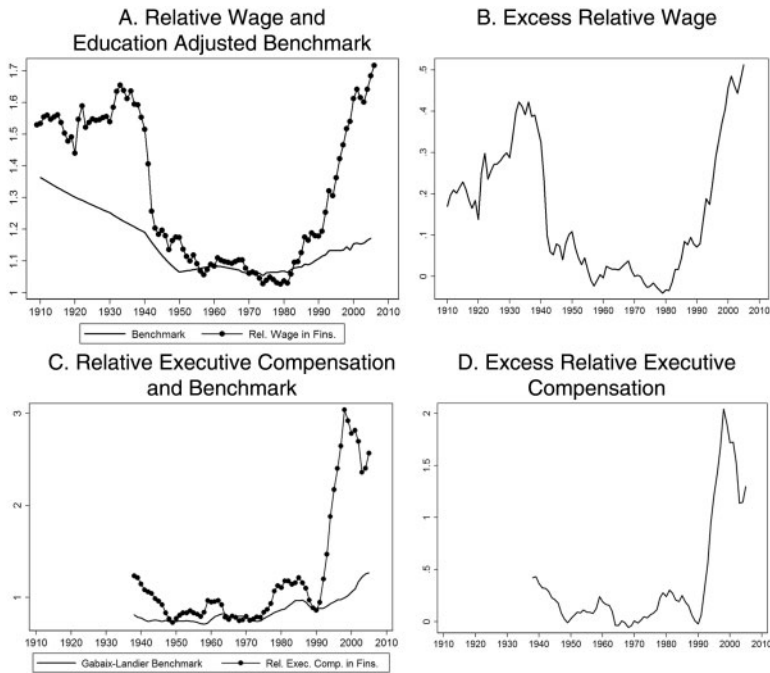


FIGURE X

Financial Sector Wage Premium: Historical Evidence

Panel A reports the relative wage in the financial industry (fins.) from Figure I. The benchmark relative wage series is constructed using the relative skill series from Figure I times and the skill premium series from Goldin and Katz (2008). Panel B reports the difference between the last two series: the excess relative wage. Panel C reports the ratio of executive (total) compensation in finance relative to the nonfarm private sector: the relative executive compensation. This is based on data from Frydman and Saks (2007), used also in Figure IV. The benchmark relative executive compensation series is constructed by applying the Gabaix and Landier (2008) methodology to firm market value data from the Center for Research in Securities Prices, displayed in Online Appendix Figure A3. Both series share the same sampling methodology. See text for full details. Data are smoothed using a 5-year moving average. Panel D reports the difference between the two series in Panel C: the excess relative executive compensation.

$\gamma \approx 1$ and $\frac{\beta}{\alpha} \approx \frac{2}{3}$. We use these estimates to construct a benchmark relative executive compensation series.³⁸ An increase in the

38. If the market for executives is integrated, then the reference firm is the same and only s_{it} matters for relative compensation, assuming equal constants for all firms. In any case, allowing for industry or firm fixed effects does not alter the $\frac{1}{3}$

relative (median) size of financial firms therefore affects relative (median) compensation with an elasticity of $\frac{1}{3}$.

We use market capitalization data from the Center for Research in Securities Prices (CRSP). To allow for comparison with our earlier historical estimates (see Equation (5) and Figure IV), we follow the sampling methodology of Frydman and Saks (2010). We restrict attention to 50 firms that have reported for at least 20 years.³⁹ The relative median market size in this sample is described in the Online Appendix and reported in Figure A4.

Figure XC plots $\omega_{fin,t}^{exec}$ (including options) together with the benchmark implied by (10) and Figure XD plots the difference between the two series—that is, the excess compensation. As in Panel A, the benchmark tracks the actual relative compensation quite closely from the mid-1940s to 1990. After 1990, however, wages in finance appear abnormally high. The patterns in Figures XC and XD are surprisingly similar to those in Figures XA and XB, respectively. The most deregulated periods exhibit both excess wages and excess executive compensation. For top earners, the main effect of deregulation is probably the relaxing of the Glass–Steagall Act from 1987 on until its eventual repeal in 1999. The timing indeed lines up with that of excess wages.⁴⁰

elasticity much (see estimates in Table II of Gabaix and Landier (2008) and our estimates in Table A4, columns 1–3).

39. The number of financial firms in each year follows the sample above (one firm in 1938–1963, two in 1964–1969, three in 1970, four in 1971, five in 1972–1981 and 1998–2005, and six in 1982–1997) and all firms are the largest in their sub-sector (finance or nonfarm private sector).

40. This interpretation is supported by the evidence in Falato and Kadyrzhanova (2010), who show that the performance impact of CEO replacements in finance is stronger since the repeal of Glass–Steagall. If this interpretation is correct, finance CEOs should also have been relatively better compensated in the 1920s. Unfortunately, we do not have data on executive compensation in finance before 1938, and so cannot corroborate a high historical excess relative wage in that period. It is also important to keep in mind that some large financial firms are not publicly traded at the beginning of the sample. For example, Goldman Sachs became public only in 1999. Hedge funds and private equity firms are not publicly traded and therefore are not in the data. This makes it difficult to compare to the NIPA data, which do not distinguish between public and private firms. Nevertheless, the exercise comparing the actual relative compensation series to the benchmark is informative because both compensation and market capitalization data suffer from the same sampling bias toward public firms.

We conclude that the Gabaix and Landier (2008) model can account for some of the increase in relative executive compensation but still leaves much of the excess wage unexplained.⁴¹ This is consistent with Frydman and Saks (2010), who find relatively weak correlations between firm size and executive compensation prior to the mid-1970s. In any case, even if the model accounted for the increase in relative wages, this would not be evidence against the role of regulation. One needs to keep in mind that firm size is an endogenous variable, which is affected by regulation. The Glass–Steagall Act prevented financial firms from merging across banking, insurance, and non-depository activities, and one might argue that the major mergers in finance were enabled by deregulation.

IV.C. Evidence from the CPS: 1967–2005

The main limitation in using the CPS for analysis is that wages are top-coded. However the CPS includes data that allows to control for many demographic dimensions. We use this feature to assess how much of the finance excess wage can be accounted by demographics, education and experience, and other unobserved factors. Note that the higher incidence of top-coding in finance leads to underestimating the finance wage premium.

1. Cross-section Regressions. We fit a series of cross-section regressions in our CPS sample in 1967–2005. We estimate the following regression separately for each year:

$$(11) \quad \log(w_{i,t}) = \alpha_t + \phi_t \mathbf{1}_{i,t}^\phi + \beta_t X_{i,t} + \gamma_t \theta_{j,t} + \varepsilon_{i,t},$$

where w is the hourly wage; $\mathbf{1}^\phi$ is a dummy variable for employment in finance; X includes education, race, sex, marital status, urban residence, (potential) experience and its square; and θ is

41. This is true even if we do not assume the same slopes and intercept in finance and in the rest of the economy. In simple regressions such as those that Gabaix and Landier (2008) and Frydman and Saks (2010) run in 1992–2010, we actually find smaller correlations of executive compensation with market value in finance relative to the nonfarm private sector (see Online Appendix Table A4). Finally, we also entertain constructing the benchmark under the assumption of segregated markets for executives. This results in a similar pattern (see details in the Online Appendix).

industry-specific unemployment risk.⁴² Figure XIA displays the estimated ϕ_t . All estimates are statistically different from 0. Individuals working in finance earn more than observationally equivalent workers. The premium is quite small until the mid-1980s, around 5%. It then increases to more than 20% in 2000. The magnitude of the increase in Figure XIA is less than in Figure XB (50%). However the timing is similar and matches the timing of deregulation.⁴³ Using CPS data in Table II, Panels A and B, we see that ω_{fin} increases by 40% in 1980–2005. Changes in the composition of education, experience, and other demographics can explain 20 percentage points of the increase.

2. Individual Fixed Effects. The pattern in Figures XB and XIA could be explained by sorting based on unobserved individual ability. To address this concern we estimate a model with individual fixed effects and year dummies using the Matched CPS for eight subsamples: 1967–1970, 1971–1975, ... 2001–2005.⁴⁴ In this sample each individual is observed exactly twice. Specifically, we estimate

$$(12) \quad \log(w_{it}) = \alpha_i + \phi_{fe} 1_{it}^{\phi} + X'_{it}\beta + \delta_t + u_{it},$$

where α_i is an individual fixed effect. We restrict attention to individuals who have completed their formal education and therefore their years of education are fixed; therefore their individual return to education is absorbed in α_i .⁴⁵

42. We use hourly wages for w_{it} to prevent ϕ_{fe} from capturing potentially longer working days in finance relative to the rest of the private sector. Using annual wage earnings delivers similar results. We estimate industry-specific unemployment risk across 2-digit industries using the Matched CPS (see details on the construction of the Matched CPS in the Online Appendix). In the regressions we restrict attention to full-time full-year workers in the private sector, aged 15 to 65, who reported wages greater than 80% of the federal minimum wage. We multiply top-coded wages by a factor of 1.75. We report only our findings for finance as whole but we find similar patterns for subsectors within finance.

43. Wurgler (2009) fits similar regressions to ours (without the unemployment component) for the United Kingdom, France, and Germany, post-1970. He finds similar patterns in the United Kingdom, which experienced a similar deregulation process, but not in France and Germany, which did not.

44. The Matched CPS allows observing each individual in the CPS in two consecutive years. See the Online Appendix for a complete description of the methodology involved in matching observations on individuals from consecutive surveys.

45. Trends in changes in returns to, inter alia, education and experience are absorbed in α_i because each individual is observed in only two years. We excluded a

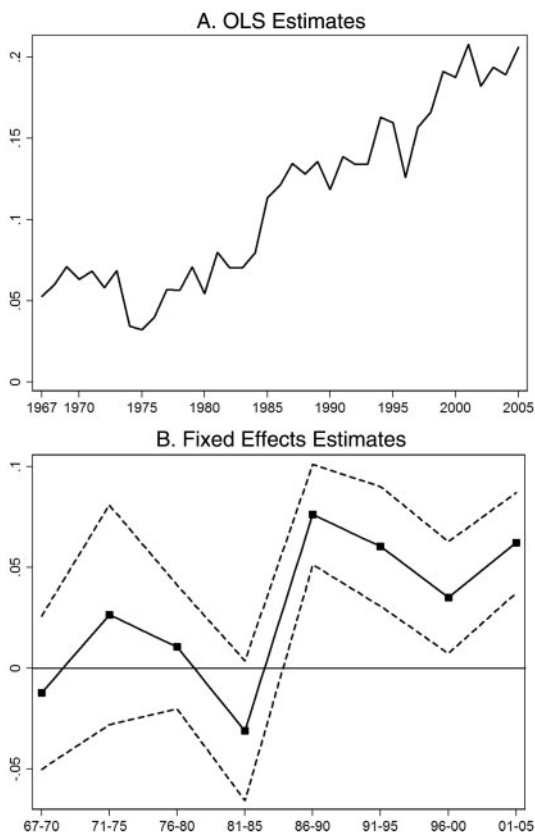


FIGURE XI

Financial Sector Wage Premium: Evidence from the CPS

Panel A plots the coefficient of the finance dummy from ordinary least squares (OLS) regressions of log hourly wages on race, sex, marital status, urban residence, potential experience and its square, as well as education controls and industry-specific probabilities for an unemployment event (see appendix for details on the construction of this last variable). Panel B plots the coefficient of finance dummy from fixed effects regressions of log hourly wages on marital status, urban residence, potential experience and its square; dashed lines are 95% confidence intervals. Panel C presents average annual wage of financiers versus the average wage of engineers, all of which have 18 years of schooling or more, or a postgraduate degree. Data: March CPS and Matched CPS. Top-wages are multiplied by 1.75. All workers are full time full year employees, age 15 to 65 who have potential experience between 0 and 40 years, who earned at least 80% of the federal minimum hourly wage. Averages take into account CPS sampling weights.

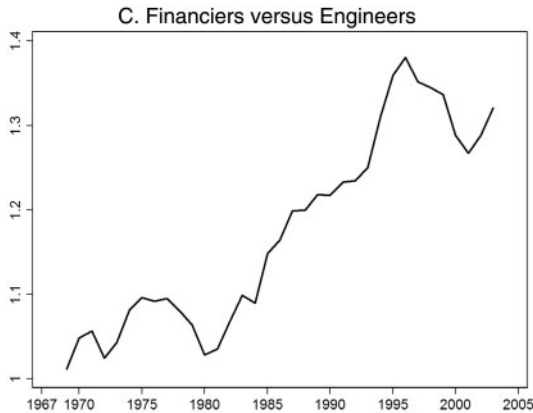


FIGURE XI
Continued.

The results are reported in Panel A of Table IV and plotted in Figure XIB. Once again, we find that the finance premium increases significantly in the mid-1980s. Compared to our previous estimates, the increase is about a third as large but it is well known that measurement error (due to the misclassification of individuals to industries) causes downward bias in fixed effects regressions of industry wage differentials. We correct the estimates as suggested by Freeman (1984).⁴⁶ The corrected coefficients are reported in the last row in Panel A of Table IV. The increase is now almost as large as in Figure XIA.⁴⁷ It appears that the finance excess wage in the cross-section does not suffer from a strong upward bias due to unobserved heterogeneity.

small number of individuals who increased their educational attainment while still working full-time in both years that they were observed. The results are robust to including all these observations, whether we control for education or not.

46. See Freeman (1984) and Krueger and Summers (1988) for a complete discussion of the measurement error attenuation bias in fixed effects regressions. Murphy and Topel (1987) find smaller industry wage differentials but Gibbons and Katz (1992) argue that this last result is likely driven by the use of annual wages. The correction is calculated separately for each period. It assumes that the proportions of individuals switching into and out of finance is equal, which is the roughly the case in our data set. We assume that 2% of individuals in the sample are misclassified. Using a 1% misclassification rate yields slightly smaller coefficients than 2%, and using a 3% misclassification rate yields larger coefficients. Krueger and Summers (1988) use 3.4% and 1.7% for 1-digit industry classifications.

47. Focusing only on college graduates yields slightly larger premia.

TABLE IV
THE FINANCE PREMIUM OVER TIME WITH INDIVIDUAL FIXED EFFECTS

| | | Dependent variable: log of hourly wages | | | | | | | | | |
|---|--|---|-------------------|-------------------|--------------------|---------------------|---------------------|--------------------|---------------------|---------------------|--|
| | | 1967-1970 | 1971-75 | 1976-80 | 1981-85 | 1986-90 | 1991-95 | 1996-2000 | 2001-2005 | | |
| A. Complete sample | | | | | | | | | | | |
| Finance Indicator | | -0.017 (0.019) | 0.022 (0.028) | 0.010 (0.016) | -0.030* (0.018) | 0.076*** (0.013) | 0.060*** (0.015) | 0.036** (0.014) | 0.062*** (0.013) | 0.062*** (0.013) | |
| Observations | | 44740 | 32950 | 97944 | 78172 | 98686 | 71986 | 85268 | 116812 | 116812 | |
| R-squared | | 0.887 | 0.878 | 0.891 | 0.890 | 0.883 | 0.865 | 0.843 | 0.838 | 0.838 | |
| Finance indicator corrected for measurement error | | -0.097 | 0.119 | 0.047 | -0.061* | 0.236*** | 0.173*** | 0.095** | 0.161*** | 0.161*** | |
| B. Drop switchers out of finance | | | | | | | | | | | |
| Finance Indicator | | -0.045* (0.027) | 0.076* (0.040) | 0.029 (0.023) | -0.029 (0.024) | 0.075*** (0.017) | 0.053** (0.021) | 0.034* (0.020) | 0.055*** (0.018) | 0.055*** (0.018) | |
| Observations | | 44498 | 32794 | 97456 | 77806 | 97850 | 71230 | 84214 | 115296 | 115296 | |
| R-squared | | 0.887 | 0.880 | 0.891 | 0.891 | 0.884 | 0.867 | 0.844 | 0.839 | 0.839 | |
| C. Drop switchers into finance | | | | | | | | | | | |
| Finance Indicator | | 0.004 (0.028) | -0.026 (0.038) | -0.008 (0.021) | -0.037 (0.026) | 0.078*** (0.018) | 0.072*** (0.021) | 0.042** (0.020) | 0.073*** (0.018) | 0.073*** (0.018) | |
| Observations | | 44482 | 32804 | 97532 | 77764 | 97752 | 71232 | 84200 | 115366 | 115366 | |
| R-squared | | 0.887 | 0.879 | 0.891 | 0.891 | 0.884 | 0.866 | 0.843 | 0.839 | 0.839 | |

Notes: Standard errors in parentheses, ***p < .01, **p < .05, *p < .1. All regressions include individual fixed effects and within-sample year effects, a constant, indicators for urban dwellings and marital status, experience and its square, and probability of unemployment by 2-digit industry. We do not include indicators for other demographics—for example, education, sex, and race—because they do not vary over time for individuals in this sample. Correction for measurement error follows Freeman (1984) under the assumption that 2% of observed transitions are misclassified. The proportions of switchers into and out of finance are roughly equal, as required. The correction is calculated separately for each period. Data: Matched CPS.

A shortcoming of using the Matched CPS is that individuals who change their residential address are dropped from the sample. This affects mostly young people, but also job switchers, who may decide to move on account of changing jobs. This sample selection biases our fixed effects estimator toward zero. We find economically significant finance premia in the latter part of the sample, while job switching is no less prevalent in that period.

To make sure that the results are not driven by job match shocks, we estimate (12) in two subsamples: one that excludes individuals who switch out of finance; and a second that excludes individuals who switch into finance. The results are reported in Panels B and C of Table IV; they are qualitatively and quantitatively similar to those reported in Panel A.⁴⁸

3. *Financiers versus Engineers.* Figure XIC reports the wages of financiers relative to the wages of engineers, both with postgraduate degrees, that is, 18 or more years of education. All are employed full-time full-year. These individuals are relatively similar in terms of their skills and abilities: They all obtained a postgraduate degree, which includes master's degrees, MBAs, and doctorates. We take five-year moving averages of the relative wage series to reduce noise.

The wages of highly educated financiers were roughly on par with those of engineers until 1980. The CPS underestimates the income of individuals who earn very high salaries due to top-coding. We multiply top-coded wages by a factor of 1.75. Because all top-coded individuals are treated the same, it is less likely to find large differences between these two groups of workers in particular. Nevertheless, we find that following 1980 financiers start to earn more and more relative to engineers with arguably similar skills. The timing fits the timing of deregulation after 1980.

4. *Employment Risk and Wage Differentials.* If finance workers are more likely to lose their jobs, they would have to be

48. Omitting switchers into finance (Panel C) yields a slightly larger premium, whereas dropping switchers out of finance (Panel B) yields a slightly smaller premium. This is consistent with selection by financial firms playing a role, since firms prefer to pay less to each worker, holding individual ability constant. See Freeman (1984) for a detailed discussion.

compensated for this. To test this explanation, we proceed as follows. Let emp_{it} indicate being employed at time t . We fit the following logit regressions of the likelihood of becoming unemployed:

$$(13) \quad \Pr(emp_{it+1} = 0 | emp_{it} = 1) = \Lambda(1_{it}^{\phi}, \log(w_{it}), X_{it}),$$

where Λ is the logistic function, X contains the same vector of observables used in Section IV.C, and 1^{ϕ} is an indicator for working in finance. We add $\log(w)$, the log of the hourly wage, in an attempt to capture unobserved heterogeneity. We fit this regression for the eight subsamples used above, and we include year dummies within each subsample. The coefficient of the indicator 1^{ϕ} captures the additional risk of unemployment for workers in finance. The estimation of equation (13) requires a longitudinal dimension. Therefore we use again the Matched CPS in 1967–2005.

We find that unemployment risk in finance increases relative to the nonfarm private sector by 2.5 percentage points from 1971–1980 to 1991–2005.⁴⁹ We use this finding to estimate the compensating differential in wages that is required to keep workers indifferent to this increase in risk. By calibrating a simple income fluctuation model (see details in the Online Appendix), we find that the increase in unemployment risk could account for about 6 percentage points of the increase in relative wages.

V. EARNINGS PROFILES AND INCENTIVES

The existence of a large excess wage poses a challenge for labor supply theories based on perfect mobility across jobs and for labor demand theories based on static profit maximization. Therefore we move away from the spot market approach of

49. Figure A5 in the Online Appendix summarizes the evolution of unemployment risk in the financial sector relative to the private sector, as captured by the marginal effect of 1^{ϕ} from (13) in each of the eight subsamples. The probability of becoming unemployed is evaluated for the average worker, that is, it is evaluated at the means of all other variables. Although finance employees had safer jobs until the early 1980s, the relative stability of finance jobs decreases over time. We also fit (13) for three wage groups to better capture unobserved heterogeneity. The upward trend in unemployment risk is maintained for all wage groups that we entertained (for complete output results see Philippon and Reshef 2007).

Sections III and IV. We estimate that wage profiles in finance have become steeper and riskier than in the rest of the economy. If markets are incomplete, this should affect the way in which risk-averse workers evaluate different jobs.

We assume that agents choose a career once and for all and then consume their wages in every period. The value of entering industry j in some period is then

$$(14) \quad U_j(0) = E \left[\sum_{\tau=0}^T \beta^\tau u(w_j(\tau)) \right],$$

where $w_j(\tau)$ is the wage of a worker with τ years of experience in industry j . We assume a discount factor $\beta = 0.97$ and a constant relative risk-aversion utility function $u(c) = \frac{c^{1-\rho}}{(1-\rho)}$, with $\rho = 2$ or $\rho = 3$. We then predict the starting wage that would make workers indifferent between working inside or outside the financial sector, for different periods. With free career choices, we should expect $U_j(0) = U_{j'}(0)$ for all j, j' . To test this hypothesis, we perform the following calculations.

Let $\mu_j(\tau)$ be the expected log wage increase after τ years relative to the starting wage $w_j(0)$ in industry j :

$$\mu_j(\tau) \equiv E[\log(w_j(\tau)) - \log(w_j(0))].$$

Similarly, let $\sigma_j(\tau)$ be the standard deviation of the expected log wage increase of a worker with τ years of experience in industry j :

$$\sigma_j^2(\tau) \equiv E\left[(\log(w_j(\tau)) - \log(w_j(0)))^2\right] - \mu_j^2(\tau).$$

We use estimates of $\mu_j(\tau)$ and $\sigma_j(\tau)$ to evaluate (14).

We estimate $\mu_j(\tau)$ and $\sigma_j(\tau)$ for finance ($j = \text{fin}$) and the non-farm private sector ($j = \text{nonfarm}$) in three time periods: 1971–1980, 1981–1990, and 1991–2005. To do this we fit regressions of the type (11), allowing for different linear experience slopes for finance:

$$(15) \quad \log(w_{i,t}) = \alpha_t + \phi \mathbf{1}_{i,t}^\phi + \mu_{1,\phi}(\mathbf{1}_{i,t}^\phi \tau_{i,t}) + \mu_1 \tau_{i,t} + \mu_2 \tau_{i,t}^2 + \beta X_{i,t} + \gamma \theta_{j,t} + \epsilon_{i,t},$$

where w is the hourly wage, α_t are year dummies, and τ is years of experience. The control variables in X are described in Section

IV.C and include industry-specific unemployment risk. We restrict the CPS sample to full-time full-year male workers.⁵⁰

We first estimate (15) for men with zero to five years of experience to limit top-coding issues. Panel A in Table V shows that ϕ and $\mu_{1,\phi}$ increase over time: Starting wages increase and earnings profiles become steeper for young men in finance relative to young men in the nonfarm private sector. In 1971–1980, finance wages start 5% higher but the slope is 0.7 percentage points lower. In 1991–2005, finance wages start 8.64% higher and the slope is 2.45 percentage points higher. We then fit (15) for men with up to 29 years of experience and use the residuals from the regression to estimate $\sigma_j(\tau)$ by sector. Line 9 in Table V shows that wages become more dispersed in finance relative to the rest of the economy: $\sigma_{fin} - \sigma_{nonfarm}$ rises from 4% in 1971–1980 to 9.26% in 1991–2005.

From the estimates of (15) from the sample of 0 to 29 years of experience we also obtain the expected wage profile for the nonfarm private sector, $\mu(\tau)_{nonfarm} = \mu_1\tau + \mu_2\tau^2$. To this we must add $\mu_{1,\phi}\tau$ to get the wage profile for finance, $\mu(\tau)_{fin} = (\mu_1 + \mu_{1,\phi})\tau + \mu_2\tau^2$, but we do not use the estimates of $\mu_{1,\phi}$ from this sample. The high incidence of top-coding in finance precludes using CPS data to compute informative wage profiles beyond a few years of experience in finance. We use two alternative estimates of $\mu_{1,\phi}$ to overcome this drawback. The first is from the short-horizon sample (zero to five years of experience, line 2 in Table V). The second is calibrated to make the predicted relative wage equal to the finance excess wage based on NIPA data, $\omega_{fin} - \hat{\omega}_{fin}$, using equal initial wages. Despite very different methodologies used to obtain them—the calibrated one on line 7 and the imputed one on line 2—the two estimates of the finance linear difference follow the same pattern and are very similar in magnitude.

We use the nonfinance linear term (line 4), the calibrated finance linear term (line 6), and the estimated common quadratic term (line 8) to predict for each time period the starting wage that would make workers indifferent between working inside and outside of finance. We consider two levels of risk aversion: $\rho = 2$ and $\rho = 3$. With $\rho = 2$, the model predicts that starting wages should

50. We find that a finance-specific quadratic term in experience is not statistically significant. All regression results used to estimate $\mu_j(\tau)$ are reported in Online Appendix Table A5. The standard deviations of residuals from those regressions are used to estimate $\sigma_j(\tau)$ and are reported in Table A6.

TABLE V
CAREER WAGE PROFILES

| | 1971--80 (%) | 1981--90 (%) | 1991--2005 (%) |
|--|-----------------|----------------------------------|-------------------|
| A. Estimated wage profiles: men up to 5 years of experience | | | |
| (1) Finance starting wage difference (finance dummy) | 5.14% | 10.7% | 8.64 |
| (2) Finance linear difference relative to nonfinance | -0.69% | 0.04% | 2.45 |
| B. Estimated wage profiles: men up to 29 years of experience | | | |
| (3) Finance starting wage difference (finance dummy) | 2.16% | 10.5% | 15.6 |
| (4) Nonfinance wage linear term | 5.16% | 4.91% | 4.60 |
| (5) Implied finance linear term (=2+4) | 4.47% | 4.95% | 7.05 |
| (6) Calibrated finance linear term | 4.82% | 5.12% | 6.69 |
| (7) Calibrated finance linear difference relative to nonfinance | -0.34% | 0.21% | 2.09 |
| (8) Common quadratic term | -0.11% | -0.09% | -0.09 |
| (9) Excess average log wage dispersion | 3.97% | 5.66% | 9.26 |
| C. Iso-utility starting wage differences | | | |
| CRRA | | | |
| Source of finance linear term | | Implied starting wage difference | |
| Calibrated (using line 6) | 4.96 | -0.04 | -15.5 |
| Estimated (using line 5) | 5.34 | 2.04 | -8.71 |
| | 9.21 | 1.75 | -18.3 |
| | 9.42 | 3.67 | -11.1 |

Notes: Panel A reports results from (log) wage regressions with a separate intercept and a separate linear term in experience for finance and the rest of the nonfarm private sector. We control for a common quadratic term in experience, education categories, race, marital status, urban dwellings, industry-specific risk of unemployment, and year dummies. The sample includes full-time, full-year male workers with 5 years of experience or less (short horizon). Panel B lines 3, 4, and 8 report results from the same regression model, using a longer horizon of up to 29 years of experience. Line 5 uses the difference in linear terms from the short horizon sample to calculate the linear term in finance. Lines 6-7 are calculated by setting the average relative wage of finance over the entire wage profile to the historical excess wage in last year of each sample (the relative wage in finance net of the benchmark is 0.97 in 1980, 1.07 in 1990, and 1.5 in 2005). The excess average log wage standard deviation is calculated from the residuals of the regression in the long horizon. Panel C reports the initial finance wage differential (finance dummy) that would make workers indifferent between finance and nonfinance over a 30-year career, given the linear terms in line 5 or 6, and using a per-period CRRA utility function with $\rho=2$ or 3. All regression results are reported in Online Appendix Table A5 and the standard deviations of residuals by industry and experience level are reported in Online Appendix Table A6.

be 5% higher in finance in the 1970s to compensate for the lower slope and higher risk. This estimate is remarkably close to the estimate from the short-horizon sample, 5.14% (line 1). In the later part of the sample, however, starting wages become inconsistent with the hypothesis that initial expected utility levels are equalized. For 1991–2005 this assumption predicts a starting wage 15.5% *lower*, while it is in fact 8.64% or 15.6% *higher* (lines 1 or 3). The unexplained wage premium is therefore somewhere between 24% and 31%, that is about 27.5 percent points of the average 50% premium documented in Section IV.A.⁵¹

Taking into account earnings profiles therefore reduces the excess wage puzzle from 50% in historical data to about 24–31%. One should keep in mind, however, that our calculations assume extreme market incompleteness (no saving) and might overestimate the impact of earnings risk.⁵²

V.A. *Theoretical Interpretation*

Let us start with models of long-term contracts under limited commitment, analyzed in the classic papers of Harris and Holmström (1982) and Holmström (1983).⁵³ A key insight of

51. These estimates depend on the estimated slope of earnings profiles. Using the larger finance linear term from line 5, we find, unsurprisingly, larger gaps between measured initial wages and those that would make workers indifferent between working inside or outside of finance. The largest gap is 15.6 – (–18.3) \approx 34%.

52. The gap may also reflect short-term adjustment costs. This explanation has some plausibility since much of the growth in finance from 1995 to 2005 is driven by new products and new markets (securitization, credit derivatives, etc.). Tett (2009), for instance, discusses how the growth of credit default swaps has taken even their inventors by surprise. In general, however, simple adjustment costs are unlikely to explain large and persistent rents. Shapiro (1986) estimates that adjustment costs are very small. Helwege (1992) fails to find evidence linking industry wage differentials to short-run demand shifts. Lee and Wolpin (2006) estimate significant mobility costs but also find that entry (increase in supply) and capital mobility completely counteract the effect of persistent increases in demand on wages.

53. In these models, risk-neutral firms commit to state-contingent wage and employment policies, while risk-averse workers are free to quit. The following results then follow. First, there is downward wage rigidity: Wages never decline. Wages are not upward rigid because firms have to bid up wages to retain workers. Second, there is partial employment insurance. Firms can end up retaining workers even though the marginal product of labor is below the market wage. Third, workers pay their insurance premium in advance by accepting low initial wages. Note that in this model there are no rents *ex ante* since all workers are indifferent between all contracts offered, but there can be rents *ex post*.

these papers is that the steepness of wage profiles depends on the ability of workers to quit. This can account for the changes in earnings profiles if skills in finance are easily transferable across firms and if deregulation increases competition for skills. These models, however, also imply that expected utility levels are equalized, which is not consistent with our calculations.

Consider next principal agent models of asymmetric information and moral hazard. As limited commitment models, moral hazard models explain changes in the slope of earnings profiles. An increase in the slope could reflect an increase in the severity of moral hazard. Moral hazard models have the additional advantage that, combined with limited liability, they can potentially explain why expected utility levels are not equalized.⁵⁴

Models with limited commitment and incentives are required to explain earnings profiles that otherwise would appear unnecessarily risky. These models are also consistent with our emphasis on regulation and complexity. If moral hazard indeed accounts for some of the changes that we document, this begs the question of why moral hazard has increased in the first place. One possibility is the increase in the complexity of finance jobs that we document. Deregulation and competition may also increase the value of high-powered incentives. Consistent with this idea, Cunat and Guadalupe (2009) find that foreign competition increases incentive provision and the demand for talent. Falato and Kadyrzhanova (2010) study CEO turnover in finance and show that the effect of performance is stronger after deregulation.⁵⁵

54. Although dynamic moral hazard models are complex, the following benchmark is plausible. Without moral hazard, it would be optimal to let the agent enjoy a flat consumption profile. With moral hazard, it is optimal to pay the agent with promised utility early in her career. In continuous time models such as that of DeMarzo and Sannikov (2006), it is possible to show that when moral hazard increases, the point at which the agent starts to consume is delayed further. Myerson (2010) considers contracts that have maximal backloading of rewards to minimize moral hazard rents. Regarding rents, the principal maximizes expected profits subject to participation and incentive constraints. With unlimited liability on the worker side, the participation constraint always binds and the calculations performed in the previous paragraph apply. With limited liability, however, punishment provides only limited incentives and the principal may optimally choose to increase bonus payments and leave the agent with rents over and above her outside option. An increase in moral hazard can then explain an increase in rents.

55. The case of changes in the organization of finance and worker incentives is more complex. On the one hand, the shift away from partnerships toward publicly

VI. CONCLUSION

Wages in finance relative to the nonfarm private sector exhibit a U-shape between 1909 and 2006. By 2006 the average worker in finance earns 70% more than the average worker in the rest of the private sector. Workers in finance earn the same education-adjusted wages as other workers until 1990, but by 2006 the premium is 50% on average. The pattern is the same for top earners but the differences are larger: the wages of top decile earners in finance grow to 80% more than top decile earners elsewhere. By 2005 executives in finance earn 250% more than executives elsewhere, and there is a 300% premium for workers in finance in the Tri-State Area. We find that changes in earnings risk can explain no more than one half of the increase in the average premium (50%). Changes in the size distribution of firms can explain about one fifth of the premium for executives. Over time, across subsectors, and across regions, we find that deregulation is followed by increases in relative education, relative job complexity, and relative wages.

Our main argument is that changes in financial regulation are an important determinant of all these patterns. The ultimate test of this hypothesis may be the evolution of wages in the next 5–10 years. If new regulations (Basel 3, the Dodd–Frank Act, etc.) are *effectively implemented* and if we are correct, then we expect both wages and skill intensity to converge and excess wages to disappear. This is a meaningful test because all other factors that we find to have an effect on wages and human capital in finance are not likely to reverse course in the near future: Banks are as large as ever, globalization is still here, and the importance of IT is only increasing.

We conclude by highlighting three areas that would greatly benefit from further research. First, regarding earnings profiles, we find that the finance wage bill could be significantly reduced if incentives were the same as in the rest of the private sector. One challenge for future research is to understand why today's

traded companies in the investment banking industry may have decreased the incentives of managers to monitor employees (they have no “skin in the game”). On the other hand, a lack of direct monitoring, mentoring, and promised stock on retirement may be compensated with wage incentives. Although not likely captured in our CPS data, hedge funds operate much like partnerships and offer very high wages.

finance industry requires higher powered incentives than other industries and than the finance industry of the 1960s.

Second, regulators are often blamed for lax oversight, but it seems that they did not have the human capital to keep up with the finance industry. The Pecora hearings of 1933 and 1934 documented such lax oversight and made the case for financial regulation; these hearings led to the Glass–Steagall Act, the Securities Act of 1933, and the Securities Exchange Act of 1934. Recent examples of lax oversight also abound, for example, the 2006 Inter Agency Statement on Sound Practices Concerning Elevated Risk Complex Structured Finance Activities.⁵⁶ The 2010 Dodd–Frank Act attempts to remedy some of the more recent regulatory shortcomings. Given the wage premium that we document, it was impossible for regulators to attract and retain highly skilled financial workers because they could not compete with private sector wages. Using data collected by Ferguson and Johnson (2010) and Frydman and Saks (2010), we find that the ratio of executive compensation in finance (the top regulated) to the highest salaries paid to (non–politically appointed) regulators (the top regulators) grew from 10 in 1980 to over 60 in 2005 (or 40, excluding bonuses).⁵⁷ This provides a potential explanation for regulatory failures.

Finally, and perhaps most important, our results suggest that tighter regulation is likely to lead to an outflow of human capital from the finance industry. Whether this is desirable depends on one’s view regarding economic externalities. Baumol (1990), Murphy, Shleifer, and Vishny (1991), and Philippon (2010) argue that the flow of talented individuals into legal and financial services may not be entirely desirable, because social returns may be higher in other occupations, even though private returns are not. Whether financiers are overpaid from a social point of view is a difficult but important question for future research to answer.

56. See <http://www.sec.gov/rules/policy/2006/34-53773.pdf> (accessed 3 May 2012).

57. The highest (non–politically appointed) positions at the Securities and Exchange Commission, the Commodity Futures Trading Commission, and several other agencies are usually filled by members of the Federal Senior Executive Service (SES). The wage of top regulators is the SES wage. We thank Thomas Ferguson for sharing these data with us.

SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at QJE online (qje.oxfordjournals.org).

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