Wages and Human Capital in the U.S. Finance Industry: 1909-2006*

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March 2011

Abstract

Jobs in Finance were skill intensive, complex, and highly paid before 1933 and after 1980, but not in the interim period. Financial regulations, corporate finance, and information technology explain the evolution of skill intensity. Changes in skill intensity account for changes in compensation until the mid 1980s, but controlling for education and other characteristics, wages in 2006 are about 40% higher in finance than in the rest of the private sector. Of this, 26% can be attributed to steeper and riskier earnings profiles and 14% is left unexplained. We discuss theoretical models that are consistent with these findings.

*We have benefited from discussions with David Autor, Effi Benmelech, Peter Debare, Douglas Diamond, Carola Frydman, Claudia Goldin, Marty Gruber, Luigi Guiso, Larry Katz, Ross Levine, Marc Lipson, Robert Lucas, Guy Michaels, Holger Mueller, Steve Pischke, Raghu Rajan, Joshua Rauh, Tony Saunders, Sheetal Sekhri, Andrei Shleifer, Bill Silber, Richard Sylla, and Jeff Wurgler, as well as many other seminar participants at NYU, UVA, Harvard, Hebrew University, Tel Aviv University, the NBER Summer Institute, Oxford University, the London School of Economics, IMT Lucca, Bocconi, the European University Institute, EBC/TSE Conference on the Political Economy of the Financial Crisis, the Federal Reserve Bank of Richmond and the Darden School of Business. We thank David Autor for sharing data on occupational task intensities, Raven Saks and Carola Frydman for sharing their executive compensation data with us, and Thomas Ferguson for sharing his data on wages of highest paid regulators. Reshef acknowledges generous support of the Bankard Fund for Political Economy.

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Controversies regarding the complexity of financial products and the compensation of bankers invariably follow 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. It is important to know whether high wages, skill intensity, and complexity are permanent features of this industry, and if not, to explain why they appear in some time 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 set of new stylized facts, reported in Section 1. From 1909 to 1933 finance is a high-skill/high-wage industry. A dramatic shift occurs in the second half of the 1930s, where finance loses its relative high human capital. Compensation and skill intensity are similar in finance and in the rest of the economy between 1950 and 1980. From 1980 onward, finance becomes once again a high-skill/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-shaped 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 2. We later focus on residual wages in Section 3.

In Section 2 we emphasize three factors that predict relative skill intensity: financial regulation, corporate finance activities, and information technology. We find a tight link between deregulation and the flow of human capital. 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 and increased demand for skills in finance. Information technology plays a role, albeit a more limited one. The advent of computers, for instance, cannot provide a complete explanation since the finance industry of the 1920s is similar to the finance industry of the 1990s. We conclude this section with a discussion of omitted variables and endogeneity issues.

In Section 3 we focus on wages, controlling for education and other characteristics. We 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 from 1950 to 1990. However, from the mid-1920s to the mid-1930s and from the mid-1990s to 2006 the compensation of employees is about 40% higher than expected. Using micro data for the more recent period, we show that this result remains even if we control for unemployment risk and unobserved individual heterogeneity. This leads us to study these excess wages from the perspective of dynamic labor contracts.

We find that changes in earnings profiles account for much of the recent excess wages. Until 1980 earnings profiles in finance were 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. If consumption is equal to current income, we estimate that, with a relative risk aversion of 3 and an annual discount rate of 3%, the ex-ante excess wage is only 15%, instead of 40%. If this view is correct, the challenge is to understand why firms in the finance industry find it profitable to use high powered incentives (and more so than in the past and than in the rest of the private sector). We argue that dynamic models with limited commitment and moral hazard are best suited to explain the finance wage puzzle.

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

Baumol (1990) argues that economic growth requires the allocation of talent to socially productive activities, and that policies and institutions can more readily influence the allocation of talent across occupations 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: (i) the finance industry attracts highly talented individuals; (ii) regulations can affect skill demand; and (iii) finance jobs are less socially productive than non-finance jobs. Our results support (i) and (ii).[1] Goldin and Katz (2008b) also document a large increase in the fraction of Harvard undergraduates who work in the financial sector since 1970, and the increase in the wage premium paid to them, and Kaplan and Rauh (2007) study the evolution of earnings of individuals with very high incomes with a particular emphasis on the financial sector. Regarding (ii), 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, while Autor, Katz, and

[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 a motivation for future research. Philippon (2007) analyzes the case of endogenous growth with financial intermediation and innovation in the non financial sector. Michalopoulos, Laeven, and Levine (2009) model real and financial innovation in 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.

Krueger (1998) and Acemoglu (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 information technology and other factors.[3] Finally, our evidence on significant changes in earnings profiles contributes to the study of dynamic labor contracts theories.

The rest of the paper is organized as follows. Section 1 describes the new facts. Section 2 provides evidence on the effects of regulation, corporate finance, and information technology. Section 3 documents the existence of a time varying wage premium and discusses labor market theories that can explain this premium. Section 4 concludes with a discussion of policy implications. Detailed descriptions of data sources and methodologies can be found in the appendix.

1 New stylized facts: wages, education, complexity and inequality

In this section we describe the evolution of wages, education 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 (securities, commodities, venture capital, private equity, hedge funds, trusts, and other investment activities, including investment banks). Our examination of the historical data from 1909 to 2006 reveals a U-shaped pattern for 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.

1.1 Education and wages

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). Census data covers 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.[4] For the period 1910-1930, where schooling data is not available, we impute the share of employees with more than high school education by occupation, and then aggregate separately for the nonfarm private sector and for the financial sector.[5] For the period 1940-1970 we use the Census data directly. For the period 1970-2005, we

[2]Acemoglu (2002) reviews the literature on skill biased technological change. For other explanations for the increase in demand for skilled workers see Card (1992), Card and Lemieux (2001), and Acemoglu, Aghion, and Violante (2001).

[3]Frydman and Saks (2007) share our long run perspective in their study of executive compensation.

[4]The results are similar when we use the share of college graduates. The share of employees 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.

[5]See the appendix for details. In this construction 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 *relative* education of finance versus the nonfarm private sector. By construction, our measure is not affected by a general drift in educational attainment in all occupations over time.

use CPS data.[6]

Let $e_{i,t}$ be a dummy variable equal to one 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

$$s^e_{j,t} = \frac{\sum_{i \in j} \lambda_{i,t} h_{i,t} e_{i,t}}{\sum_{i \in j} \lambda_{i,t} h_{i,t}} , \tag{1}$$

where λ and h are, respectively, sampling weights and hours worked, and $i \in j$ means that individual i works in sector j.[7] The relative education of the financial sector is defined as the difference between this share in finance ($j = fin$) and the corresponding share in the nonfarm private sector ($j = nonfarm$):

$$\rho_{fin,t} \equiv s^e_{fin,t} - s^e_{nonfarm,t}. \tag{2}$$

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 Kuznets (1941) and Martin (1939) for the period 1909-1929. The data are described in detail in the appendix. The average wage in the finance industry relative to the average wage in the non-farm private sector is

$$\omega_{fin,t} \equiv \frac{w_{fin,t}}{w_{nonfarm,t}} . \tag{3}$$

U-shape over the 20th century

Figure 1 shows the evolution of the relative wage, $\omega_{fin,t}$, and relative education, $\rho_{fin,t}$, over the 20th century, and Table 1 contains summary statistics. The pattern that emerges is U-shaped, and suggests three distinct periods. From 1909 to 1933 the financial sector was a high-education, high-wage industry. The share of skilled workers was 17 percent points higher than the private sector; these workers were paid more than 50% more than in the rest of the private sector, on average. A dramatic shift occurred during the 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 onwards another dramatic shift occurs: the financial sector becomes a high-skill high-wage industry again. In a striking reversal, its relative wage and skill intensity goes back almost exactly to their levels of the 1930s.[8]

[6] For the overlapping period 1970-2000 the differences between the Census and CPS data are negligible.

[7] In the 1910-1930 and 1960-1970 Censuses the underlying data used to calculate h is missing. We assign $h = 1$ for all individuals in those years.

[8] We find the tight relationship between the relative education series and the relative wage series an indication that the data sources

1.2 Decomposition: Sectors, Education, Occupations

In Table 2 we decompose the patterns of Figure 1 into within and between group changes, by sectors, education categories, and occupations. We start with subsectors in Panel A. We decompose the change in the relative wage of finance (relative to the private sector, as defined in (3)), $\Delta\omega_{fin}$, using the following formula

$$\Delta\omega_{fin} = \sum_k \Delta\omega_k \overline{n}_k + \sum_k \Delta n_k \overline{\omega}_k \ , \tag{4}$$

where k is an index for subsectors. $\Delta\omega_k$ is the change of the relative wage of subsector k, $\overline{n}_k$ is the average employment share of k within finance, Δn_k is the change in the employment share of k within finance, and $\overline{\omega}_k$ is the average relative wage of k in the sample. The first sum captures the contribution of within-categories changes in the relative wage, while the second sum is the the contribution of employment reallocation between subsectors. We apply this decomposition in three subsamples: 1933-1960, 1960-1980 and 1980-2005.[9] Panel A shows that changes in relative wages come mostly from the 'within' component. Thus, changes in sectoral composition do not account for changes in the relative wage of the finance industry.

Economic theory, however, calls for decompositions based on tasks and occupations rather than industry classification.[10] We revisit the within-between decomposition of equation (4) using CPS data over 1980-2005. The educational categories we chose are "Less than 12 years of schooling", "High School Graduate", "13-15 Years of Schooling", "College Graduate" (4-year college) and "More than College" (graduate degrees, such as JD, MBA, Ph.D.). Our classification of occupations attempts to group employees according to the tasks that they perform. We use seven occupational categories: "Managers and Professionals", "Mathematics and Computers", "Insurance Specialists", "Brokers and Traders", "Bank Tellers", "Administration, Including Clerks", and "All the Rest" (janitors, security and miscellaneous).[11] We focus on the 1980 to 2005 period where the most important changes take place. We decompose the increase in the relative wage of the finance industry using equation (4), except that now the index k varies either across subsectors, education categories or occupations.

We report the results of the decomposition in Panel B of Table 2. We first confirm our previous finding: changes between subsectors are not very important.[12] By contrast, in sections (b) and (c) we see that most of the increase

are consistent, in particular in the beginning of the sample. If skilled workers command higher wages, then this is exactly what one would expect to find.

[9]We choose 1933 as the starting point because it marks the beginning of the regulated period in finance. 1960 marks the beginning of the most regulated period in finance, while 1980 marks the beginning of the least regulated one.

[10]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 SIC codes are relevant or arbitrary. For instance, does it really matter whether a trader works for an insurance company, a commercial bank, or a hedge fund?

[11]Unfortunately, it is hard to find consistent definitions of occupations over time. The appendix explains in detail how we did this, the constraints we faced and the reasons for our choices.

[12]it is worth pointing out a shortcoming of CPS data: wages are top coded. Top coding is, on average, twice as likely in Credit Intermediation and Insurance relative to the private sector; in Other Finance it is 13 times as likely. This leads to under estimation of relative wages in the financial sector. Thus, while in the Industry Accounts the relative wage of finance increases by 0.65 from 1.03 in 1980 to 1.68 in 2005, in the CPS it increases only by 0.43. (The problem is most severe in Other Finance, where the Industry Accounts show an increase in relative wages of 2.5 from 1.1 in 1980 to 3.6 in 2005, but in the CPS it increases by only 0.38.) Therefore, the wages that we report may not be accurate for certain occupations, in particular Brokers and Traders. (We refer the reader to Kaplan and

in the relative wage in finance is due to reallocation of labor across education categories, and even more so across occupation categories. Therefore, organizational changes within each subsector are more important than changes in sectoral composition.

1.3 Complexity

The analysis in Table 2 underscores the importance of changes in the set of occupations within the finance industry. 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.[13] 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 (non-routine manual tasks). Each task intensity is a number between 0 and 10; thus it is an ordinal, not cardinal, ranking.[14] The DOT task intensities were calculated by a panel of experts from the National Academy of Sciences in 1977.

While every occupation may combine 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; mangers and sales persons have a high Direction, Control and Planning intensity; 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 Current Population Survey (which pertains to 2007) by occupation. In order to match the DOT task intensities to individuals we created a consistent occupational classification throughout the sample.[15] 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. And 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 age 15 to 65, who are employed in the nonfarm private sector.[16] Each

Rauh (2007) for a detailed analysis of the highest incomes inside and outside finance.) Top coding also explains the differences between Panel C of Table 1 and Panel A of Table 2, since very high incomes contribute more to the 'within' component.

[13] We thank David Autor for sharing with us data on occupational task intensities.

[14] Each one of the five indices was detected 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 appendix for a complete description.

[15] See appendix for complete details.

[16] Due to data limitations, in 1920 we could only restrict to individuals who were in the labor force, whether employed or not. In the 1910-1930 and 1960-1970 Censuses the underlying data used to calculate hours is missing. Therefore, in those years we assign $h = 1$ for all individuals.

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 3 reports the evolution of four relative task intensities (the fifth, relative Eye-Hand-Foot Coordination, does not change much throughout the sample). The figure conveys a clear message: finance was relatively more complex and non-routine in the beginning and end of the sample, but not so in the middle.

Panel A focuses on relative complexity. Finance lost much of its relative analytical complexity (Math Aptitude) from 1910 to 1950. At that point a slow recovery started, which accelerated in 1990. Decision making (Direction, Control and Planning) suffered even more in relative terms, but the recovery was much stronger. Panel B conveys the same message. Routine task intensity became higher in finance from 1910 to 1930, and started to decline from 1980 onward. In results that we do not report here, we observe virtually the same patterns within all three subsectors of finance.[17]

1.4 Contribution to Income Inequality

We now study the contribution of finance to changes in income inequality.[18] We consider overall wage inequality, residual wage inequality and the college premium. We restrict our sample to full time full year employees, age 15 to 65 who have no more than 40 years of potential experience, and who earned at least 80% of the federal minimum hourly wage.[19] We compare actual measures of inequality to those that are computed from a sample in which we simulate wages in finance as follows. 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.[20] In all cases the timing fits the period of financial deregulation that we document later: contributions to inequality become important post 1980.

Overall wage inequality

[17] The relative decrease and increase in complexity is strongest within Other Finance. However, data is noisy for routine tasks in Other Finance, due to few observations of 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 by request.

[18] We focus on the direct effect as 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).

[19] 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 CPS equal to that in the NIPA in 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.

[20] Median wage growth is a natural choice when we discuss percentile ratios. Results are virtually the same if we use the growth rate of average wages. See appendix for complete details on this simulation.

Panel A of Figure 3 depicts actual percentile ratios relative to those calculated from the simulated sample. The percentile ratios are not equal to one in 1970 (the base year) because we display 5-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 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.[21]

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.[22]

Residual inequality

We compute residuals from fitting log 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 those dummies with a quadratic in experience. We use CPS sampling weights to weigh observations in the regression.

Panel B of Figure 3 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 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.[23] 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).[24]

The college premium

In supplementary regressions (not reported here), we regress log 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, whereas the actual college premium, as we calculate it, increases to 0.584 in 2005. Finance contributes 8% to the increase.

[21] Bell and Van Reenen (2010) document similar patterns for the U.K. See also Kaplan and Rauh (2007).

[22] Using a more conventional top coding factor of 1.75 lowers the contribution of finance to inequality to 15%, but hardly changes the contribution of the other two indices.

[23] 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.

[24] 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.

1.5 Taking stock of the new facts

Uncovering the historical evolution of wages, education and job complexity in the finance industry is the first contribution of our paper. In the remainder of the paper, we seek to explain these new stylized facts. In particular, we try 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 rules out information technology as the sole driving force. There were no computers in private use before 1960. Therefore, the idea that the growth of wages in finance is simply the mechanical consequence of the IT revolution is inconsistent with the historical evidence. The historical evidence also shows that the evolution of the financial industry is not simply driven by the ratio of stock market to GDP or by globalization, as we discuss at the end of Section 2.

2 Demand for skill in the financial sector

2.1 A simple framework

We use a simple model of the demand for skill to organize the discussion. Suppose that there are two education levels, e and o, and that the production function of sector j at time t is

$$y_{j,t} = A_{j,t} f\left(\mu_{j,t} h^e_{j,t}, h^o_{j,t}\right), \tag{5}$$

where $A_{j,t}$ measures the productivity of sector j at time t, h^e and h^o are hours worked by educated and less educated workers, and $\mu_{j,t}$ is the relative productivity of highly educated workers. We view the labor market as a competitive spot market without adjustment costs, and without compensating differentials (we address these issues in later sections). Wages must therefore be equalized across sectors. Let $w_{e,t}$ and $w_{o,t}$ be the hourly wages for high and low education workers. Assuming that the function f is homogeneous of degree one, cost minimization implies that the relative demand for skilled labor is of the form

$$s^e_{j,t} = \frac{h^e_{j,t}}{h^e_{j,t} + h^o_{j,t}} = \phi\left(\mu_{j,t}, \frac{w_{e,t}}{w_{o,t}}\right) . \tag{6}$$

The share of educated workers depends negatively on the skill premium $w_{e,t}/w_{o,t}$, and positively on the relative efficiency of skilled labor $\mu_{j,t}$. Note that changes in the aggregate skill premium *cannot* be the driving force behind $\rho_{fin,t}$. Goldin and Katz (2008a) show that the skill premium declined from 1915 to 1950 and then increased until today, with a brief, small decline in 1970-1980. We observe an increase in relative education in finance exactly when the aggregate skill premium increases most rapidly. The finance industry hires relatively more educated people exactly when they are most expensive. The correct explanations must therefore rely on the relative demand for skills, which is driven by $\mu_{fin,t}$.

Goldin and Katz (2008a) provide strong evidence of a secular trend in μ for the aggregate economy. We are, however, interested in the behavior of the financial sector *relative* to the rest of the economy. A linear approximation of equation (6) leads to

$$\rho_{fin,t} = \alpha + \beta \left(\mu_{fin,t} - \mu_{nonfarm,t} \right) + \varepsilon_t, \tag{7}$$

where $\rho_{fin,t}$ is defined above in (2) and β is positive.[25] We now turn to the potential determinants of $\mu_{fin,t} - \mu_{nonfarm,t}$.

2.2 Explanatory variables

Equation (7) shows that in order to explain relative skill intensity we need to understand the comparative advantage of skilled labor in finance versus the rest of the economy. Broadly speaking, μ can be affected by technological innovations and organizational choices. We discuss plausible determinants, some of which are displayed in Figure 4. Summary statistics are reported in Table 1.

Information technology

Computers are complementary to complex tasks (non-routine 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, and manual jobs are less affected. The financial sector has been an early adopter of information technology. We therefore consider the share of IT and software in the capital stock of financial sector minus that share in the aggregate economy.[26] Our measure of relative IT intensity is displayed in Figure 4A. This series does not capture investments in telephones and telegraphs in the early part of the sample.[27] 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.

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 preceded the rise in skill intensity.[28] Unfortunately, financial patenting

[25] We have assumed here that the aggregation function is similar across sectors. We can relax this assumption and control for the education wage premium to allow for different elasticities. The results are unchanged and available upon request.

[26] The capital stock data are from the BEA's fixed assets tables by industry.

[27] Yates (2000) documents industrial use of information technology – telephones, typewriters, improved filing techniques, tabulation techniques and sorting cards – during the previous information revolution, starting at the end of the 19th 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 20th century and that this 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.

[28] Silber (1983) reviews new financial products and practices between 1970 and 1982. Miller (1986), reflecting upon the financial innovations that occurred from the mid 1960s to the mid 1980s, argues that the development of financial futures was the most significant one. Tufano (2004) argues that other periods have witnessed equally important innovations.

is a relatively recent phenomenon. Instead, we use data on new patents used in finance in 1909-1996.[29] 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 4A.

Corporate finance activity: IPOs and credit risk

New firms are difficult to value because they are often associated with new technologies or new business models, and also for the simple reason that they do not have a track record. We therefore expect the intensity of IPOs to increase the returns to skill in the financial sector and demand for it. 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) have shown, 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 zero and unit standard deviation over the sample period. Our measures of non financial corporate activity are displayed in Figure 4B.

Deregulation

The optimal organization of firms, and therefore their demand for various skills, depends on the competitive and regulatory environment in which they operate. A regulated financial sector might 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

[29] Carter, Gartner, Haines, Olmstead, Sutch, and Wright (2006)

intrastate branching restrictions. It is a continuous variable from 0 to 1.

2. Separation of commercial and investment banks. The Glass-Steagall act was legislated in 1933 and was gradually weakened starting in 1987 until the final repeal in 1999. This variable runs between 0 and 1.

3. Interest rate ceilings. Legislation was introduced in 1933 and was removed gradually between 1980 and 1984. This variable runs between 0 and 1.

4. Separation of banks and insurance companies. Legislation was introduced in 1956 and was repealed in 1999. This variable runs between 0 and 1.

See the appendix for complete details. The deregulation index is given by (1) − (2) − (3) − (4) and is displayed in Figure 4C.

We entertain two other explanatory variables. The ratio of U.S. foreign assets to GDP controls for external demand forces like financial globalization. The data on foreign assets is from Obstfeld and Taylor (2004) (1900-1960) and the IMF (1980-2005). We interpolate linearly between data points for missing data. The top marginal tax rate controls for either supply of talented individuals, or for the cost of paying high wages on net.[30]

2.3 Regressions

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 5 years, what should one predict about future relative wages? We discuss endogeneity and causality in Section 2.4. The regressions are of the generic type

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

where $y_{fin,t} = \rho_{fin,t}$ or $\omega_{fin,t}$. X includes explanatory variables that are listed in Section 2.2 above. Standard errors are corrected for up to 5 years of autocorrelation. The results for regressions in changes are reported in Table 3, 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. Financial patents 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 (the top marginal tax rate is only marginally statistically significant). Changes in the top marginal tax rate lower the explanatory power of deregulation in the relative wage regression. However, we note that both changes in regulation

[30] Tax rate data are from the Tax Foundation, www.taxfoundation.org, based on information from the U.S. Internal Revenue Service.

and in top marginal tax rates are policies that are correlated: large increases in top marginal tax rates were legislated in the wake of the Great Depression; reductions occurred in the period of deregulation, post 1980.

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 regressions in changes reported above are relatively conservative. Regressions in levels give more weight to regulation, as one can see from Figure 4C. We fit regressions of the type

$$y_{fin,t} = \alpha + X_t\beta + \varepsilon_t \ ,$$

where we allow a 5 year moving average structure in the error term. We do not add the patent series because it is trending upwards, whereas the other series are stationary. In these regressions only the deregulation variable plays a significant role. In particular, the top marginal tax rate no longer plays a role. These regressions are estimated using maximum likelihood. In OLS regressions without moving average structure in the error term deregulation alone accounts for 90% of variation in education and 80% of variation in wages.

Overall, the time series regressions confirm the strong link between deregulation, skill upgrading and wages in finance.

Panel of Subsectors

IT and software capital data is available by subsector (Credit Intermediation, Insurance, and Other Finance) from the BEA, and 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, while the separation of banks and insurance companies affects insurance companies more strongly than it affects Credit Intermediation and Other Finance.

For each subsector we now have a measure of relative wage, relative education, deregulation and IT intensity. We use this data to fit panel regressions with subsector fixed effects and year dummies over the post war period. The coefficients here tell us how much deviations in the explanatory variables from aggregate trends affect relative skill and wages over and above their aggregate trend. We report the results in Table 3, 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 both on 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 1, Panel B, the deregulation variable has a standard deviation of 1.078 while the IT share variable has a standard deviation of 0.064).

We would have liked to run the same panel regressions with measures of financial innovation (patents for instance), 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 in Silber (1983), only 2 or 3 are related to Insurance. This is also consistent with the argument in 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.

2.4 Discussion

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 (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 found the labor share to be stable over time. From a statistical perspective, we believe that we have tried most of the 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? Regulations are clearly endogenous: the regulations of the 1930s were a response to the depression; Basel 3 and the Dodd-Frank Act are responses to the 2008 financial crisis. But the idea that regulation (especially in finance) does not matter is inconsistent with the sheer volume of lobbying effort spent to influence regulators.[31] Regulation creates binding constraints, the shadow cost of these constraints changes with the economic environment, and this leads to efforts to alter the regulations. However, regulators do not react to shocks in a mechanical way. Following the crisis of 1929-1933, regulation was tightened and human capital left the finance industry, but following the crises of the late 1970s and early 1980s, regulation was loosened, and wages in finance went up. 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

[31] For example, see Igan and Mishra (2011).

does.[32]

For instance, the IT share in the capital stock of the financial sector actually starts increasing in the 1960s, long before it rises in other sectors. But for 20 years wages and education do not change. There is no sudden change in IT use around or after 1980. It is only after deregulation takes place that the relative wage starts to increase. Even if anticipated changes in IT drove the push towards deregulation, large changes in organization required changes in regulation.[33] Regulation matters, but we readily acknowledge that other factors play a role.[34]

We find an important role for corporate finance activities linked to IPOs and credit risk. Again, we do not argue that IPOs are fully exogenous; Jovanovic and Rousseau (2005) show that IPO waves follow the introduction of General Purpose Technologies (GPT), such as electricity (1900-1930) or IT (1970-today). The timing of these technological revolutions is exogenous, and they explain 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. This suggests that at least some of the observed high wages represent an efficient market response to a change in the economic environment.

3 The finance wage premium

In this section we document the existence of a wage premium in the finance industry. We estimate an excess wage of 30 to 40%, after controlling for education, experience, demographics, unemployment risk and unobserved individual ability. We then discuss some theoretical interpretations. We argue that limited commitment and/or asymmetric information are required to explain the finance wage premium.

3.1 Evidence of wage premium

Historical time series: 1910-2005

We construct a benchmark relative wage series for the financial sector. The benchmark relative wage in finance

[32] Another important point to keep in mind is that crises increase the demand for financial skills needed in debt restructuring. This is evident in the corporate sector in the 1930s, and in the real estate sector in recent years. This is one potential reason for why finance wages keep increasing from 1929 to 1935.

[33] This is consistent with evidence from Kostovetsky (2007) of a brain drain of top managers from mutual funds to less-regulated hedge funds starting in the early 1990s.

[34] Previous studies have looked at 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) finds such an effect, although her set of control variables is not as elaborate as the one in Black and Strahan (2001). We have replicated these cross-sectional results (not reported here) and found 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 in Figures 1 and 4C.

versus the nonfarm private sector is given by

$$\widehat{\omega}_{fin} = 1 + \rho_{fin}\pi \ ,$$

where ρ_{fin} is relative education in finance defined in equation (2) and π is the skill premium from Goldin and Katz (2008a). Panel A of Figure 5 shows the actual and benchmark relative wage series. The benchmark tracks the actual wage quite well in the middle of the sample. Note that in 1910-1920 the large returns to education documented by Goldin and Katz (2008a) account well for the relative wage. The late 1920s-early 1930s and the post 1990 periods stand out as times where wages in the financial sector are high relative to the benchmark.

Cross section regressions: CPS 1967-2005

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

$$\log(w_{i,t}) = \alpha_t + \phi_t 1^{\phi}_{i,t} + \beta_t X_{i,t} + \gamma_t \theta_{j,t} + \epsilon_{i,t} \ , \tag{8}$$

where w is the hourly wage, 1^{ϕ} 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 industry specific unemployment risk.[35] Panel B of Figure 5 displays the estimated ϕ_t. All estimates are statistically different from zero. 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 Panel B is less than in Panel A because of top coding in the CPS data, but the timing is similar and matches the timing of deregulation.[36]

Fixed effects regressions: Matched CPS 1967-2005

The pattern in Panels A and B 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.[37] Specifically, we estimate

$$\log(w_{it}) = \alpha_i + \phi_{fe} 1^{\phi}_{it} + X'_{it}\beta + \delta_t + u_{it} \ , \tag{9}$$

[35] We use hourly wages for w_{it} in order 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 unemployment risk across 2-digit industries with logit 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.

[36] Wurgler (2009) fits similar OLS regressions to ours (without the unemployment component) for the U.K., France and Germany post 1970. He finds similar patterns in the U.K., which experienced a similar deregulation processes, but not in France and Germany, which did not.

[37] We observe each individual in two consecutive years. We make sure that within each subsample each individual is observed exactly twice. Individuals whose incidence is at the end of one subsample and at the beginning of the following subsample are excluded. The results are robust to including these observations. See the data appendix for a complete description of the methodology involved in matching observations on individuals from consecutive surveys

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.[38]

The results are reported in Panel A of Table 4 and plotted in Panel C of Figure 5. 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 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).[39] The corrected coefficients are reported in the bottom row in Panel A of Table 4. The increase is now almost as large as the one in Panel B.[40]

Finally, to make sure that the results are not driven by job-match shocks, we estimate (9) in a sample that excludes individuals who switch out of finance, reported in Panel B. Then we estimate (9) in a sample that excludes individuals who switch into finance, reported in Panel C. The results are qualitatively and quantitatively similar.[41]

Financiers versus engineers: 1967-2005

Panel D of Figure 5 reports wages of financiers relative to wages of engineers, both with post-graduate degrees.[42] Wages of highly educated financiers were roughly on par with engineers until 1980. Following 1980 financiers started to earn more and more relative to engineers with arguably similar skills. The timing fits the timing of deregulation, post 1980.

CEOs in finance versus CEOs elsewhere: 1938-2005

Using data from Frydman and Saks (2007), we examine the long run behavior of CEO compensation in finance relative to other industries.[43] In 1938-1941 executive compensation in finance is 21% higher than in the rest of the private sector; but in 1950-1975 it is actually 20% less; and in the 1980s it was on par. Starting in 1990 executive compensation in finance increases until it outstrips the private sector by 150% on average in 1995-2005. Unfortunately, our relative executive compensation series does not reach back to the pre-Depression era; but the pattern is similar to that of Panel C of Figure 4, and correlates well with deregulation.

[38] We excluded a small number of individuals which 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.

[39] 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 use of annual wages. The correction is calculated separately for each period. It assumes that the proportions of individuals switching into finance 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 1% misclassification rate yields slightly smaller coefficients than 2%, and using 3% misclassification rate yields larger coefficients. Krueger and Summers (1988) use 3.4% and 1.7% for 1-digit industry classifications.

[40] Focusing only on college graduates yields slightly larger premia relative to the results in Panel A.

[41] Omitting switchers into finance (Panel C) yields a slightly larger premium, whereas dropping switchers out of finance (Panel B) receives 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 detailed discussion.

[42] We use financiers and engineers with similar levels of education: 18 years and above. All are employed full time full year. These individuals are relatively similar in terms of their skills and abilities: they all obtained a post-graduate degree, which includes Masters degrees, MBAs and PhDs. As noted above, 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. Since all top coded individuals are treated the same, it is less likely to find large differences between these two groups of workers in particular. We take 5-year moving averages of the relative wage series to reduce noise.

[43] See appendix for details on the construction of this series, which is displayed in Figure A.

3.2 Earnings Profiles and Incentives

In a frictionless labor market excess wages are either zero or they simply reflect compensating differentials for the disutility of work across jobs. A large excess wage poses a challenge for labor supply theories based on perfect mobility across jobs, and for labor demand theories based on profit maximization. Therefore we move away from the spot market approach of Section 2, and take into account earnings profile. Let $w_j(\tau)$ be the wage in industry j of a worker with τ years of experience (from now on, we ignore ex-ante heterogeneity, since it was extensively discussed in the previous section). Let $\mu_j(\tau)$ be the average log wage increase after τ years:

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

where $w_j(0)$ is the starting wage. Similarly, let $\sigma_j(\tau)$ be the standard deviation of log wage increase:

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

We consider three time periods: 1971-1980, 1981-1990, and 1991-2005. In each time period, using CPS data and the same controls as in our previous regressions, we estimate μ and σ for the finance industry and the rest of the private sector.[44]

Table 5 shows that earnings profiles have become steeper but also riskier in finance relative to the rest of the economy. Panel A reports the average returns to experience for male workers with less than 5 years of experience. In 1971-1980, finance wages start 3% higher but the slope is 0.57 percent points lower. In 1991-2005, finance wages start 9.2% higher and grow with a slope 2.5 percent points higher. At the same time, wage dispersion has increased more in finance than in the rest of the economy, from an average excess of 3.11% in 1971-1980 to 8.26% in 1991-2005. For workers with more than 5 years of experience in the finance industry, top coding makes it impossible to use CPS data. As a robustness check, we can calibrate the excess slope to ensure that the predicted relative wage is consistent with NIPA data. The implied slopes, reported in line (5) of Table 5, are somewhat lower than the ones estimated in line (3) but their evolution is similar.

Whether these earnings profiles represent a large labor supply puzzle or not depends on what we assume about the degree of market completeness. Since the cross-sectional regression reported earlier provide an upper bound on potential rents, we focus here on providing a lower bound. To do so 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 at time t is then:

$$U_j(0) = E\left[\sum_{\tau=0}^{T} \beta^{\tau} u\left(w_j(\tau)\right)\right]. \tag{10}$$

[44] We allow for a common quadratic trend in addition to the sector specific linear trends: $\mu_j(\tau) = \hat{\mu}_j \tau + \tilde{\mu}\tau^2$. Separate squared terms for finance and non-finance jobs are not significantly different. All regressions are available upon request.

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. We assume a discount factor of $\beta = 0.97$, 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, for each time period, the starting wage that would make workers indifferent between working inside or outside the financial sector. With relative risk aversion of 3, the model predicts that starting wages should be 3.98% higher in finance in the 1970s to compensate for the lower slope and higher risk. The actual figure, reported on line (1) of Panel A is 3.1%. In the later part of the sample, however, the behavior of starting wages becomes inconsistent with the assumption that initial expected utility are equalized. For the period 1991-2005, this assumption would predict a starting wage 4.6% *lower*, while it is in fact 9.2% *higher*. The gap is almost 14%. Nonetheless, from a labor supply perspective, this is a significantly smaller puzzle than the 40% implied by the pure cross-sectional regressions.[45]

We now interpret our findings. Consider first models of long term contracts under limited commitment, analyzed in the classic papers of Harris and Holmström (1982) and Holmström (1983).[46] An important insight of these papers is that the steepness of the wage profile depends on the ability of workers to quit. To the extent that skills in the finance industry are easily transferable across firms and that deregulation has increased competition for skills, this theory can explain the increase in the steepness of the wage profile. These models, however, also predict a tradeoff between current and future wages so that agents remain indifferent among different careers, and cannot explain the 14% gap described above.

Consider next principal agent models with moral hazard. These models can also explain changes in the slope of earnings profiles. More precisely, the evidence of an increase in the relative slope within finance careers can be explained by an increase in the relative severity of moral hazard.[47] Moral hazard, combined with limited liability, can potentially explain the existence of rents if participation constraints fail to bind.[48] Moral hazard may have increased in the finance industry because of complexity. Job complexity in finance is correlated with excess wages. To the extent that complexity creates scope for moral hazard, this can explain the incidence of excess wages. Deregulation

[45]The gap might partly reflect short term adjustment costs. This explanation has some plausibility since much of the growth in finance from 1995 to 2005 was 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.

[46]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.

[47]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 like 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 back loading of rewards in order to minimize the moral hazard rents.

[48]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 might 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.

and competition might also increase the value of high powered incentives. Cunat and Guadalupe (2009) find that foreign competition increases incentive provision and the demand for talent. Falato and Kadyrzhanova (2010) study CEO turnover in the finance industry and show that the effect of performance is stronger after deregulation.[49]

To conclude this discussion, we emphasize that limited commitment and/or asymmetric information are required to explain earnings profile that otherwise would appear unnecessarily risky. These theories are complementary to theories of changes in the marginal product due to scale effect or star effects (e.g., Rosen (1981), Murphy, Shleifer, and Vishny (1991), Gabaix and Landier (2008)), and both can be caused by deregulation and technological changes. Star and scale effects are especially likely to interact with problems of limited commitment (and moral hazard). This might explain the observed combination of high wages and steep profiles.

4 Conclusion

In 2006 the wage of finance employees is 1.7 higher than the wage of workers in the rest of the private sector. Accounting for changes in skill intensity, returns to education and unemployment risk reduces this cross-sectional excess wage from 70% to 40%. Earnings profiles have also become relatively steeper and riskier in the financial sector. Assuming that consumption equals the current wage, and a risk aversion of 3, the excess starting wage drops from 40% to 14%. If we consider this lower estimate of 14%, there is not so much a labor supply puzzle as a labor demand puzzle. The finance wage bill could be significantly reduced if incentives were the same as in the rest of the private sector. The challenge for future research is to understand why the finance industry requires such high-powered incentives.

Our findings have important implications for financial regulation. Following the crisis of 1930-1933 and 2007-2008, regulators have been blamed for lax oversight.[50] In retrospect, it is clear that regulators did not have the human capital to keep up with the finance industry, and to understand it well enough to be able to exert effective oversight. 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 (2007) 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).[51] This provides a potential explanation for

[49] The issue of firm size is more complex. One the one hand, the shift away from partnerships towards publicly traded companies in the investment banking industry might have decreased incentives to monitor employees. On the other hand, hedge funds operate much like partnerships and offer very high wages. Gabaix and Landier (2008) argue that executive compensation is linked to firm size. However, Frydman and Saks (2007) do not find a correlation between firm size and executive compensation prior to the mid 1970s. While testing the Gabaix and Landier (2008) hypothesis is beyond the scope of this paper, we note that, in any case, the major mergers in finance were enabled by deregulation.

[50] The Pecora Hearings of 1933 and 1934 documented such lax oversight and made the case for financial regulation; this led to the Glass-Steagall Act, Securities Act of 1933 and the Securities Exchange Act of 1934. Recent examples of lax oversight are also abound, for example the 2006 "Inter Agency Statement on Sound Practices Concerning Elevated Risk Complex Structured Finance Activities".

[51] 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

regulatory failures.

Our results also suggest that tighter regulation is likely to lead to an outflow of human capital from the finance industry. Whether this is desirable or not depends on one's view regarding economic externalities. Baumol (1990), Murphy, Shleifer, and Vishny (1991) and Philippon (2007) argue that the flow of talented individuals into legal and financial services might not be entirely desirable, because social returns might 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.

regulators is the SES wage. We thank Thomas Ferguson for sharing his data with us.

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Appendix

A Data

A.1 Wages

The data come from the Industry Accounts, Kuznets (1941), and Martin (1939). The industry accounts are prepared by the Current Industry Analysis Division, Bureau of Economic Analysis (BEA), U.S. Department of Commerce. The only issue here is to obtain a consistent industry classification. From 1987 to 2006, we use the NAICS classification for "Compensation of employees" (wages and salaries, and supplements) and for "Full-time equivalent employees." From 1947 to 1987 we use the SIC classification, which itself changes in 1972. From 1929 to 1946, we use tables 6.2A and 6.5A from the Income and Employment by Industry, also published by BEA. Mapping the data before and after 1946 requires adjusting for changes in the classification of real estate activities.

Kuznets (1941) gives estimates of net income, wages and salaries and number of employees separately for banking, insurance, and real estate, over the period 1919-1938. The banking category, however, covers only commercial banks, savings banks, and federal reserve banks. Brokerage, investment banking, and other financial activities are not included. As a result, the size of the industry is smaller than the one implied by BEA data. Fortunately, there is large overlap of 10 years with the BEA data, over which the correlation between the two series is 96.6%. It seems therefore quite safe to impute values for the period 1919-1928 using Kuznets' data.

Martin (1939) provides data for the finance, insurance and real estate, but not for finance and insurance only. For the period 1909-1929, the estimates are based on data collected from banking, insurance and real estate. For the period 1899-1908, however, the 1909 estimate was "projected to 1899 on the basis of other data indicating a probable trend for this period." We find this procedure questionable, so we truncate our sample in 1909. For the period 1909-1919, we also collected data from Mitchell (1921) for the banking sector. The implied banking wage from Mitchell (1921) is quite similar to the implied wage from Martin (1939) and the Census data to measure the number of employees, except that it grows slightly faster.

As we have mentioned, the data from Martin (1939) includes real estate. This does not appear to raise a problem for the long run trends. Using BEA data for the period 1929-2005, we find a correlation of 0.993 between the relative wage series including real estate the and the wage series excluding real estate .

A.2 Imputing education shares for 1910-1930

For the period 1910-1930, where schooling data is not available we impute the share of employees with more than high school education by occupation, separately for each sector (nonfarm private sector and for the financial sector). Although occupational classifications change across Censuses, IPUMS provides a consistent classification for occupations that is based on the 1950 Census. Essentially, occupational classifications from other years are matched with the classification of 1950. We calculate the share of employees with more than high school education in each occupation c separately for each sector j according to this classification in 1950, $\alpha_{c,j}^{1950}$. We use 1950 as a base year rather than 1940 because 1950 contains all possible occupations according to this classification, whereas 1940 is missing several. We use $\alpha_{c,j}^{1950}$ as a base to impute the share in each sector in 1910-1930 by using the distribution across occupations in each sector, $\lambda_{c,j}^{t}$, and then aggregating up,

$$s_{j,t}^{e} = \sum_{c} \lambda_{c,j,t} \alpha_{c,j}^{1950},$$

where $t = 1910, 1920, 1930$; $\lambda_{c,j,t} = \sum_{i \in c} \omega_{i,j,t} \,/ \sum_{i} \omega_{i,j,t}$ is the share of workers in occupation c in sector j in Census t; and $\omega_{i,t}$ is the sampling weight for that observation.

A.3 Financial deregulation

We construct a measure of financial deregulation that takes into account branching restrictions, the Glass-Steagall act, interest ceilings, the separation of insurance companies from banks, and restrictions on the investment opportunities of insurance companies and banks. The deregulation index is given by

$$deregulation = (i) - (ii) - (iii) - (iv).$$

(i) Branching

We use the share of the U.S. population living in states that have removed branching restrictions via mergers and acquisitions. The data is from Black and Strahan (2001). Our branching deregulation indicator is a continuous variable. It starts at 16.7% in 1960 and increases to 100% by 1999. We set our indicator at 16.7% from 1927 to 1960. The McFadden Act of 1927 prevented branching of nationally chartered banks. Before the McFadden Act branching was less clearly limited. To capture this, we set our indicator to 0.3 in the years 1909-1926.

(ii) Separation of commercial and investment banks

The Glass-Steagall indicator is a continuous variable between 0 and 1. It is 0 until 1932, 0.5 in 1933 and 1 from 1934 to 1986. The Glass-Steagall act is relaxed in 1987, 1989, 1997 and was finally repealed in 1999, by the Gramm-Leach-Bliley Act. In 2000 this indicator is back to zero.

(iii) Interest rates ceilings

Ceilings were introduced in 1933 and removed after 1980. Our indicator variable is 0 until 1932, 0.5 in 1933 and 1 from 1934 to 1980. S&Ls were further deregulated by the Garn-St. Germain Depository Institutions Act of 1982. To capture these features, our index moves gradually to zero between 1980 and 1983.

(iv) Separation of banks and insurance companies

The Bank Holding Company Act of 1956 prohibited a bank holding company from engaging in most non-banking activities and from acquiring voting securities of certain companies. It was repealed in 1999. The Armstrong investigation of 1905 took place before the beginning of our sample and therefore is not directly relevant.

A.4 Relative task intensity indices

In order to construct our relative task intensity indices we matched occupational task intensity indices from the Dictionary of Occupational Titles (DOT) into individual occupations in the US Censuses from 1910 to 2000 and in the 2008 March CPS (which pertains to 2007). Five DOT task intensities by occupation (373) and gender (2) were obtained from David Autor, to which we are grateful for sharing this data. The occupations are classified according to the 1990 Census system. The task intensity measures vary over the [0,10] interval. We call this data DOT1990. Census and CPS data were extracted from IPUMS.

DOT task intensities

The DOT task intensities were originally calculated in 1977 by a panel of experts from the National Academy of Sciences for 3886 DOT occupations. Each occupation was assigned a vector of characteristics. From this vector we use only five elements that sufficiently characterize each occupation: Finger Dexterity (routine manual tasks), Set Limits, Tolerances and Standards (routine cognitive tasks), Math Aptitude (analytical thinking), Direction, Control and Planning (decision making) and Eye-Hand-Foot Coordination (captures non-routine manual tasks).

The 3886 DOT occupations were allocated across 411 occupations of the 1970 Census classification. The task intensity for each 1970 Census occupation is a weighted average over the tasks of the original DOT occupations that were allocated to it, where the weights are CPS sampling weights. This was done using the April 1971 CPS (which pertains to 1970). The averages were different for men and women, hence the separation by gender. Each one of the five indices was detected as a principal component for indices that are similar in nature; see Autor, Levy, and Murnane (2003). The 1970 Census classification was matched into the 1990 Census classification using information based on the OCC1990 variable in IPUMS (this was done by Peter Meyer from the Bureau of Labor Statistics).

Consistent occupational classification

In order to match the DOT1990 data to occupations in 1910-2007 we had to create a consistent classification system for the entire period. For 1960-2007 we could use the 1990 Census classification directly, using the OCC1990 variable in IPUMS. For 1910-1950 we used the 1950 Census classification, using the OCC1950 variable in IPUMS. We created a crosswalk for OCC1950 into OCC1990 using the 1950 Census, the first year for which OCC1990 exists. We used 1950 as a base for the crosswalk because all Census 1950 occupations appear in 1950. Another option we tried was to use the 1990 Census as the base for the crosswalk; this had no effect on our results.

When matching the DOT1990 data we had to make a few modifications. These modifications are due to the fact that not all of the 1990 Census occupations are represented in DOT1990. Therefore, we allocated task intensities to these occupations using data for other occupations that we thought were very similar in nature, *a priori*. The only substantial modification was to allocate task intensities to "Professionals, not elsewhere classified" according to the average task intensity for professionals by year, 2-digit industry and gender. Our results are not affected by dropping all the occupations that were not matched or to modifications of these allocations.

Eventually, we constructed a data set with a consistent classification of occupations. The DOT1990 information was then merged into this data set, using the 1990 Census classification and gender. Thus, every individual in the data set has five task intensity indices that characterize her occupation.

Aggregation
We restrict attention to workers age 15 to 65, who are employed in the nonfarm private sector (in 1920 we could only restrict to individuals who were in the labor force). For each task and year we aggregate up by sector as follows

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

The generic'*task*' varies over all five tasks described above. Unfortunately, it is not possible to calculate h for all years. In the 1910-1930 and 1960-1970 Censuses the underlying data to do so is missing. Therefore, in those years we treat $h = 1$ for all individuals. The underlying data that is used to calculate h is the number of weeks worked times the number of hours worked per week. The 1910-1930 Censuses do not contain such information at all. In 1940-1950 we use data on hours worked in the week before the census. The 1960-1970 Censuses contain only categorical data on weeks and hours worked, according to some ad-hoc intervals; we could not calculate hours worked because we could not adjust for longer hours or more weeks accurately. In the 1980-2000 Censuses, as well as the 2008 March CPS, we use data on usual hours worked per week. Our attempts to gauge hours and weeks worked in 1960-1970 by using data from 1950, 1980 or both resulted in severe jumps in the *task* series in those years.

Relative task intensity for finance for each year is given by

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

A.5 The Current Population Survey

Our data on individuals comes from the March supplement of the Current Population Survey (Annual Social and Economic Study) from survey years 1968-2006, which pertain to 1967-2005 actual years. A CPS year refers to data of the preceding year, i.e. March CPS 2006 documents annual data from calendar year 2005. We therefore adopt the following taxonomy: We call "year" the actual year that the survey pertains to, while a CPS year is denoted as "survey year". The Current Population Survey (CPS) is a monthly survey of about 50,000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. Currently, there are more than 65,000 participating households. The sample is selected to represent the civilian non-institutional U.S. population. The CPS includes data on employment, unemployment, earnings, hours of work, and other demographic characteristics including age, sex, race, marital status, and educational attainment. Also available are data on occupation, industry, and class of worker. We choose to use only one particular month survey, the March supplement, for two reasons. First, this supplement contains more demographic details, in particular on work experience and income sources and amounts. Since 1976, the survey has also been supplemented with a sample of Hispanic households (about 2,500 interviewed). Second, it has been extensively used in the empirical labor and macro-labor literature, which lends to the comparability of our results. Let us now define the groups that we use in our empirical analysis. We restrict attention to individuals who are in the labor force, of at least 15 years of age.

Occupations
Examining the distribution of occupations within finance and its three subsectors lead us to choose seven occupation groups (henceforth, "occupations"), which describe the major occupational groups in our sample. These are: "Managers and Professionals", "Mathematics and Computers", "Insurance Specialists" (insurance sales persons, statisticians and actuaries), "Brokers and Traders", "Bank Tellers", "Administration, Including Clerks", and "All the Rest" (janitors, security and miscellaneous). As with industry classifications, major occupational re-classifications occurred in survey year 1983, from the Census 1970 system to the 1980 system, and in survey year 2003, from the Census 1990 system to the 2000 system. Of these two re-classifications, the latter was more substantial. We examined the occupational crosswalks, which are provided by the Census Bureau to make sure that our occupational groups are consistently defined over time Census Bureau (1989, 2003). Our criteria for grouping occupations under one title was stability in occupational shares and relative wages. In some cases we could not consistently separate "managers" from "professionals" due to re-classifications in survey years 1983 and 2003; some occupations that were defined as "professional" were split and re-classified as "managerial" and vice versa. However, these two groups

together are consistently identified, without any "jumps" or "drops" in their employment shares over time, or in their relative wages. Much effort was devoted to making sure that the other occupation groups are also consistently defined throughout our sample. Note that some of these occupations potentially mean different things in different industries. For instance, in Credit Intermediation the “Managers and Professionals” include “bank officers”, but these officers do not exist in the two other industries. The composition of “Administration, Including Clerks” also varies across subsectors of finance. However, our more narrowly defined occupations, “Mathematics and Computers”, “Insurance Specialists”, “Brokers and Traders” and "Bank Tellers" are consistently defined.

Industry Classification

The financial sector includes three industries: “Credit Intermediation”, “Other Finance Industries”, and “Insurance”. To define the private sector, we exclude all government employees, as well as employees of the United States Postal Services. Banks, thrift and saving institutions are included in “Credit Intermediation”. Securities, commodities, funds, trusts, and other financial investments as well as investment banks are all included in “Other Finance Industries”. These sectors are consistently identified, without any "jumps" or "drops" in their shares of total employment, despite changes in industrial classifications in the CPS in our sample, which occur following each decennial census. The major industrial re-classifications occurred in survey year 1983, from the Census 1970 system to the 1980 system; and in survey year 2003, from the Census 1990 system to the 2000 system. Of these two re-classifications, the latter was more substantial overall, yet it does not affect our sectors. The Census Bureau provides industrial crosswalks for the 1970-1980 systems and for the 1990-2000 systems, from which one can gauge how some industries are split or merged into others Census Bureau (1989, 2003). These crosswalks are basically a transition matrix for all industries from one classification to the other. A close examination of these transition "probabilities" lead us to conclude that our industries are consistently defined throughout our sample. In the transition from the 1970 system to the 1980 system 99.9% remain inside each industry; and for the transition from the 1990 system to the 2000 system over 95% of workers remain inside each industry. This is due to the fact that the functions of our three industries are narrowly and well defined, and due to the fact that they are not too large.

Education and experience

Educational Categories are "Less than 12 years of schooling", "High School Graduate", "13-15 Years of Schooling", "College Graduate" (4-year college), "More than College" (graduate degrees, such as JD, MBA, Ph.D.). Until survey year 1991 years of education are reported in annual steps, starting with 0 years till 18 years (which also absorbs instances of more than 18 years). Also until survey year 1991 we correct years of schooling for individuals who did not complete the last year in school by subtracting one year. This correction is not needed after survey year 1992. From survey year 1992 and on early school attainment is lumped into groups: 0 years, 1-4 years, 5-6 year and 7-8 years. Also starting in survey year 1992 school attainment starting with high school is marked by degrees, not years, therefore it is not possible to distinguish between, e.g., 13, 14 and 15 years of school. To make our education variable consistent throughout our sample, we adopt the coding that starts in survey year 1992, i.e., we group early school attainment into brackets for all the sample and assign maximal values to each bracket. Also, we group 13, 14 and 15 years of school together and assign 14 years for all individuals within that bracket in all years. In addition, we lump 17 years of schooling together with 16 years, for similar reasons. This makes the educational shares smooth throughout the sample, and in particular around the 1991-1992 surveys. Experience is potential labor market experience. It is measured as $min\{age - edu - 6; age - 18\}$, where ‘$edu$’ is years of schooling. The CPS does not contain data on job spells.

Wages and top-coding

We deflate all wages reported in the CPS using the deflator for personal consumption expenditures from the Bureau of Economic Analysis. The reference year is 2000. Hourly wages are calculated by dividing annual wage income by number of hours worked. The CPS underestimates the income of individuals who earn very high salaries, due to top-coding of income. Therefore, the wages that we report may not be accurate for certain occupations, Securities and Financial Asset Sales in particular. In our sample, the percent of top-coded observations in the private sector increases from 0.06% in 1967 to 1.1% in 1980, after which it fluctuates in the range 0.38%-1.6%, due to secular adjustments of the top-coding income limit. However, in the financial sector there are many more incidents of top-coding: in Credit Intermediation there are on average twice as many top-coded observations, in Insurance there are on average 2.4 as many top-coded observations, whereas in Other Finance Industries there are on average 13 times as many top-coded observations. This leads to an under-estimation of relative wages in the financial sector. In an attempt to compensate for this, we multiply top-coded incomes in all survey years until 1995 by a factor of 1.75. From survey years 1996 and on, top-coded incomes are average amounts of actual earnings for 12 socioeconomic cells; therefore we do not adjust them.

A.6 Construction of Matched CPS

We thank Donghoon Lee for providing us with his methodology. The "Matched CPS" takes advantage of the fact that households in the CPS are sampled for more than a year, in the following pattern. Each household that enters the survey at any given month is sampled for four months, leaves for eight months, and then returns for four more months, after which it exits. Therefore, theoretically, every household that is surveyed in March of any given year must have been surveyed in the previous March, or will be surveyed in the next. Of course, in practice not all individuals get surveyed twice due to survey attrition, non-compliance, etc.'.

Unfortunately, the CPS does not hold a definitive person ID, by which one could easily match two observations on the same individual from two consecutive surveys. The following methodology is used to match observations on the same individual from two consecutive surveys. We match individual observations from two consecutive surveys by household ID, their "line" within the household (which is an intra-household identifier), state of residence, race, sex and year of birth. These are supplemented with a few more identifiers generated by the CPS (segment number, serial number and a random cluster code). We make sure that there are only two observations within each cell defined by these identifiers and drop all other cells.

Some survey years cannot be matched. Survey year 1968 cannot be matched backwards, because our sample starts with that survey year. Likewise, survey year 2006 cannot be matched forward, because our sample ends with that survey year. Other survey years that cannot be matched for technical reasons are 1971, 1972, 1976, 1985, 1995 and 2001. Approximately 93% of all observations are actually matched from within survey years that can be matched.

A.7 Unemployment risk

Here we give the exact definition of our unemployment indicator. We use the Matched CPS to do this. A person would get a positive indication of unemployment in survey year t pertaining to survey year $t+1$ if:

1. did not work last year (from survey $t+1$) and reported: could not find work, looking for work or on layoff.
2. in survey years 1968-1993 major activity in the week before the survey (from survey t) was looking for work.
3. in survey years 1968-1993 did not work last week (from survey t) due to being laid-off.
4. in survey years 1994-2006 reported being on layoff or looking for work (from survey $t+1$).
5. in survey years 1968-1988 reported reason for working part year was looking for work or being unemployed (from survey $t+1$).
6. reported positive number of weeks looking for work last year (from survey $t+1$).
7. reported positive number of weeks being unemployed last year (from survey $t+1$).

We fit logit regressions over 8 subsamples to gauge the differential risk of unemployment in finance versus the rest of the nonfarm private sector. The results of these regressions are used to calculate θ, the compensating differential for unemployment risk. To construct unemployment risk series for the wage regressions in this paper we take averages of unemployment indicators by 2-digit industries for each possible year. As always in this paper, we restrict attention to workers that in survey year t were full time full year workers in the private sector, aged 15 to 65, who reported wages greater than 80% of the federal minimum wage. In t+1 there are no such restrictions; for instance, they can be unemployed.

We set the value in survey year 2006 to that of survey year 2005. In survey years that cannot be matched for technical reasons (see Section A.6) we take the average of the year before and the year after the gap, by 2-digit industry. In both cases we are calculating a conditional probability, where we condition on being employed full time full year in survey year t. We tried doing this at the 3-digit level, but too many years had missing values and the risk series that resulted were rather noisy.

B Inequality simulation

We use the sample of workers in finance in 1970, denoted as $FI70$, as a base to simulate wages in finance in all other years. Define this sample as $\{\lambda_i, w_i, X_i\}_{i\in FI70}$, where λ are the CPS sampling weights, w are annual wages and X is a vector of characteristics (to be used for calculating residual inequality). In all other years $t = 1967$ to 2005 observations in finance are simulated as $\{\lambda_i \cdot \kappa_t, w_i \cdot (1+\gamma_t), X_i\}_{i\in FI70}$, where $\kappa_t = \left(\sum_{i\in fi} \lambda_{it}\right) / \left(\sum_{i\in FI70} \lambda_i\right)$ updates sampling weights to keep the same sum of weights as in the original data and γ_t denotes the growth of the median wage relative to 1970. In order to fix employment shares we further multiply sampling weights in finance by a factor of s^{fi}_{1970}/s^{fi}_t and in the rest of the private sector by s^{ps}_{1970}/s^{ps}_t, where $s^{fi}_t = \left(\sum_{i\in fi} \lambda_{it}\right) / \left(\sum_i \lambda_{it}\right)$ is the employment share of finance in year t, and similarly for the private sector (ps). Updating sampling weights is important because the measures of inequality take these weights into account directly. For example, percentiles are calculated according to the weighted position in the distribution. The median wage in some year is given by w_j such that j solves $\left(\sum_{i\leq j} \lambda_i\right) / \left(\sum_i \lambda_i\right) = 0.5$, where the observations are arranged in ascending order of wages. In addition, updating weights is a natural way to update the number of people across years.

The sample in which wages in finance were replaced by simulated wages as described above is called the "simulated sample".

C Executive Compensation

We are grateful to Raven Saks and Carola Frydman for sharing with us data on executive compensation in 1936-2005 in 50 of the largest American publicly traded firms. These firms report executive compensation for at least 20 years within at least one of three windows (1936-1966, 1943-1973 and 1970-2000). Out of these 50 firms seven are included in the financial sector; none are in agriculture. Frydman and Saks (2007) demonstrate that this is a representative sample of the top 300 firms during 1936-2005. Each firm reports compensation for the top three officers. Compensation includes salary, bonus and option value. Most bonuses are paid in cash. Bonuses that are paid in stock are evaluated using the stock price at the time they were granted. The value of options at the time they were granted is calculated using the Black-Scholes formula.

None of the financial firms in the sample spans the entire period. The coverage is: CIT Group 1938-1976, Citicorp (Citigroup) 1971-1997, American Express 1977-2005, Chase (JPMorgan Chase) 1972-2005, Aetna 1964-2005, Cigna 1982-2005, AIG 1970-2005. Note that before 1964 we have only one financial firm in the sample (CIT), and only two in 1964-1969 (CIT and Aetna). On the positive side, we have representation of all three subsectors within finance: Credit Intermediation, Insurance and Other Finance.

Denote the median compensation for the sample of top three executives outside of finance by $wage^{exec}_{nonfarm,t}$ and in finance by $wage^{exec}_{fin,t}$. We do not find jumps or discontinuities in the $wage^{exec}_{fin,t}$ series around the years in which a financial firm joins or leave the sample. The relative executive compensation in finance is

$$\omega^{exec}_{fin,t} \equiv \frac{wage^{exec}_{fin,t}}{wage^{exec}_{nonfarm,t}} \ .$$

This series is virtually unchanged if we exclude bonuses that are paid in stock and is displayed in Figure A.

Table 1: 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
Financial Patents 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 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 (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 (Fins.) and the Non Farm Private sector. Wages (1909-2006) are computed from the Industry Accounts of the U.S., Kuznets (1941) and Martin (1939). The relative wage is the ratio of wages in Finanace (Fins.) to Non Farm Private wages. The three subsectors are credit intermediation, insurance, and rest of finance.

Table 2: Decomposition of Relative Wage of the U.S. Finance Industry

	(1) Change in Relative Wage	(2) Average Employment Share	(3) **Within** (=1*2)	(4) Change in Employment Share	(5) Average Relative Wage	(6) **Between** (=4*5)
A. National Industry Accounts, 1933-2005						
			(a) 1933-1960			
Credit Intermediation	-0.571	0.402	-0.230	0.031	1.411	0.043
Other Finance	-0.933	0.118	-0.110	-0.039	1.339	-0.053
Insurance	-0.488	0.480	-0.234	0.009	1.333	0.011
Total	-0.571		-0.574			0.002
			(b) 1960-1980			
Credit Intermediation	-0.149	0.452	-0.068	0.070	1.050	0.073
Other Finance	0.259	0.100	0.026	0.003	1.002	0.003
Insurance	-0.005	0.448	-0.002	-0.073	1.087	-0.079
Total	-0.047		-0.044			-0.003
			(c) 1980-2005			
Credit Intermediation	0.308	0.481	0.148	-0.012	1.130	-0.014
Other Finance	2.494	0.125	0.313	0.048	2.379	0.114
Insurance	0.333	0.394	0.131	-0.036	1.251	-0.045
Total	0.648		0.592			0.056
B. Current Population Survey, 1980-2005						
			(a) Decomposition by Sub-Sector			
Credit Intermediation	0.412	0.492	0.203	-0.024	1.090	-0.027
Other Finance	0.383	0.130	0.050	0.107	2.271	0.242
Insurance	0.160	0.378	0.060	-0.082	1.195	-0.098
Total	0.430		0.313			0.117
			(b) Decomposition by Education			
<12 Years	0.068	0.021	0.001	-0.019	0.626	-0.012
High School	0.067	0.315	0.021	-0.219	0.787	-0.172
13-15 Years	0.060	0.295	0.018	0.017	0.972	0.016
College Graduate	0.208	0.280	0.058	0.155	1.772	0.274
More than College	0.607	0.088	0.054	0.066	2.593	0.172
Total	0.430		0.152			0.278
			(c) Decomposition by Occupation			
Other	-0.043	0.026	-0.001	0.002	0.919	0.002
Managers and Professionals	0.229	0.371	0.085	0.181	1.687	0.305
Math and Computer	0.402	0.032	0.013	0.039	1.477	0.058
Insurance Specialists	0.067	0.087	0.006	-0.062	1.390	-0.086
Brokers and Traders	-0.167	0.066	-0.011	0.067	2.670	0.180
Bank Tellers	0.002	0.076	0.000	-0.053	0.521	-0.028
Administrative	0.100	0.341	0.034	-0.174	0.725	-0.126
Total	0.430		0.126			0.304

Notes to Panel A. The relative wage in finance versus the private sector decreased by 0.57 from 1.65 in 1933 to 1.08 in 1960, it further decreased by 0.05 to 1.03 in 1980, and then increased by 0.65 to 1.68 in 2005. Panels A.a, A.b and A.c decompose the increase by finance subsectors in 1933-1960, 1960-1980 and 1980-2005, respectively. Columns (1)-(3) report the contribution of changes in relative wages within categories, while holding the composition fixed at the average for the period. Columns (4)-(6) report the contribution of reallocation of employment between categories in finance, while holding relative wages fixed at the average for the period. Together, columns (3) and (6) must sum up to the total change, acording to the decomposition equation in the text. Source: authors calculations based on the Annual Industry Accounts of the United States.

Notes to Panel B. In the CPS data the relative wage in finance versus the private sector increased by 0.43 from 1.07 in 1980 to 1.503 in 2005. Panel B.a decomposes the increase by occupations, Panel B.b decomposes the increase by industries and Panel B.c decomposes by education categories. Columns (1)-(3) report the contribution of changes in relative wages within categories, while holding the composition fixed at the average for the period. Columns (4)-(6) report the contribution of reallocation of employment between categories in finance, while holding relative wages fixed at the average for the period. Together, columns (3) and (6) must sum up to the total change, acording to the decomposition equation in the text. Source: authors calculations based on the CPS.

Table 3: Determinants of Education and Wages in Finance Industry

A. Historical Time Series: Differences (lead-lag 5 years)

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	0.00990***	0.00955***	0.00887***	0.00717**	0.0889***	0.0889***	0.0587**	0.0310
	(0.00282)	(0.00261)	(0.00238)	(0.00296)	(0.0231)	(0.0233)	(0.0253)	(0.0247)
Change in Financial Patents over Total Patents, t-5 to t		2.206				-0.108		
		(1.524)				(12.91)		
Change IPO share of market capitalization, t-5 to t			0.00308**	0.00156			0.0725***	0.0580**
			(0.00124)	(0.00151)			(0.0260)	(0.0243)
Change in Corporate Default Rate, t 5 to t			0.00151	0.00109			0.0301	0.0281
			(0.00104)	(0.0009)			(0.0182)	(0.0185)
Change in Foreign Assets/GDP, t-5 to t				-0.00308				-0.126
				(0.00931)				(0.110)
Change in Top Marginal Tax Rate, t-5 to 5				0.0548				0.482**
				(0.0365)				(0.236)
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

B. Historical Time Series: Levels (no lead or lag)

Dependent variable	Relative Education (t)	Relative Wage (t)
Deregulation Index (t)	0.0653***	0.0047***
	(0.0154)	(0.0008)
IPO share of market capitalization (t)	0.0032	0.0014
	(0.0073)	(0.0009)
Corporate Default Rate (t)	0.0177*	0.0005
	(0.0108)	(0.0013)
Foreign Assets/GDP (t)	0.1652	0.0333**
	(0.1916)	(0.0157)
Top Marginal Tax Rate (t)	-0.0135	-0.0086
	(0.0493)	(0.0061)
Observations	84	84
Chi-squared (9 d.f.)	190	891
p-value	0.0	0.0
Sample	1919-2002	1919-2002

C. Panel of Subsectors: Credit Intermediation, Insurance and Other Finance

Dependent variable	Relative Education			Relative Wage		
Subsector Deregulation Index (t-1)	0.0194***		0.0192***	0.260**		0.259**
	(0.00298)		(0.00267)	(0.0999)		(0.0997)
Share of IT in Capital Stock of Subsector (t-1)		0.197***	0.195***		1.679	1.649
		(0.0449)	(0.0369)		(1.415)	(1.379)
Subsector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165	165	165	165	165	165
R-squared	0.749	0.704	0.801	0.470	0.443	0.477
Sample	1951-2005	1951-2005	1951-2005	1951-2005	1951-2005	1951-2005

Notes: In Panel A we use Newey-West standard errors with 5 lags of autocorrelation. In Panel B all series are in levels and a 5 year moving average in the errors is allowed. Estimation uses maximum likelihood and the chi-squared statistic test the null hypothesis that all coefficients, including error coefficients, are zero. In Panel C all variables are in levels. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The Finance Premium Over Time with Individual Fixed Effects

	Dependent Variable: Log of Hourly Wages							
	1967-1970	71-75	76-80	81-85	86-90	91-95	96-00	2001-2005
A. Complete sample								
Finance Indicator	-0.017	0.022	0.010	-0.030*	0.076***	0.060***	0.036**	0.062***
	(0.019)	(0.028)	(0.016)	(0.018)	(0.013)	(0.015)	(0.014)	(0.013)
Observations	44740	32950	97944	78172	98686	71986	85268	116812
R-squared	0.887	0.878	0.891	0.890	0.883	0.865	0.843	0.838
Finance indicator corrected for measurement error	-0.097	0.119	0.047	-0.061*	0.236***	0.173***	0.095**	0.161***
B. Drop switchers out of finance								
Finance Indicator	-0.045*	0.076*	0.029	-0.029	0.075***	0.053**	0.034*	0.055***
	(0.027)	(0.040)	(0.023)	(0.024)	(0.017)	(0.021)	(0.020)	(0.018)
Observations	44498	32794	97456	77806	97850	71230	84214	115296
R-squared	0.887	0.880	0.891	0.891	0.884	0.867	0.844	0.839
C. Drop switchers into finance								
Finance Indicator	0.004	-0.026	-0.008	-0.037	0.078***	0.072***	0.042**	0.073***
	(0.028)	(0.038)	(0.021)	(0.026)	(0.018)	(0.021)	(0.020)	(0.018)
Observations	44482	32804	97532	77764	97752	71232	84200	115366
R-squared	0.887	0.879	0.891	0.891	0.884	0.866	0.843	0.839

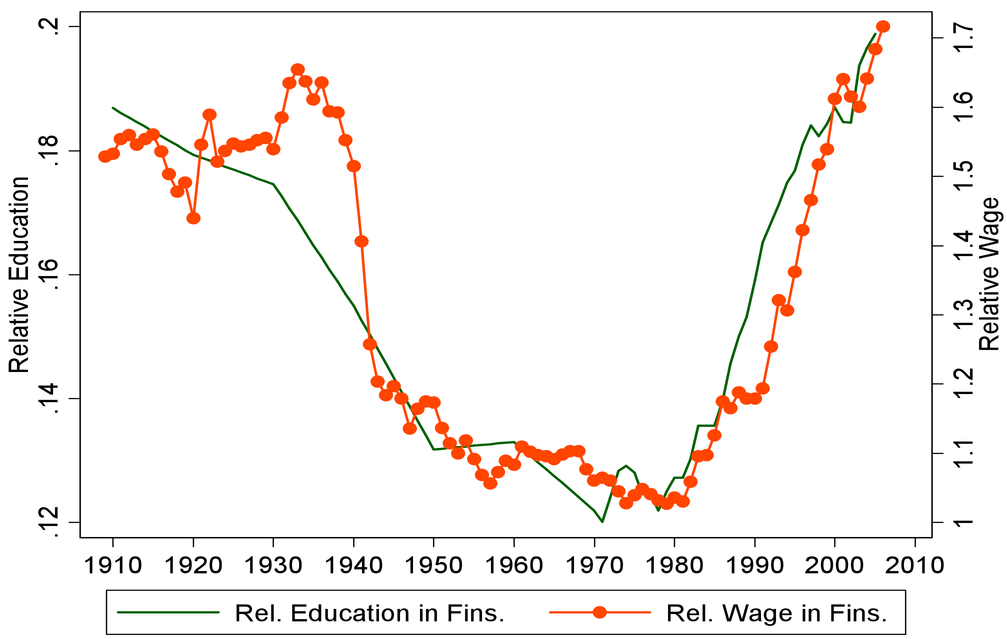
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All regressions include individual fixed effects and within-sample year effects, a constant, indicators for urban dwellings and marital status, experience and its square, and probability of unemployment by 2-digit industry. We do not include indicators for other demographics - e.g., 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.

Table 5: Career Earnings Profiles

		1971-1980	1981-1990	1991-2005
Panel A. Estimated Wage Profiles				
(1)	Starting Wage Difference	3.09%	8.40%	9.20%
(2)	Non Finance log-Earnings Slope	6.14%	5.59%	5.23%
(3)	Finance log-Earnings Slope	5.57%	5.69%	7.73%
(4)	Average Excess log-Earnings Dispersion in Finance	3.11%	5.19%	8.26%
(5)	Finance log-Earnings Slope (alternative measure)	5.89%	5.59%	6.48%
Panel B. Iso-Utility Starting Wage Differences				
(6)	CRRA = 2	3.98%	2.00%	-9.00%
(7)	CRRA = 3	4.70%	3.70%	-4.60%

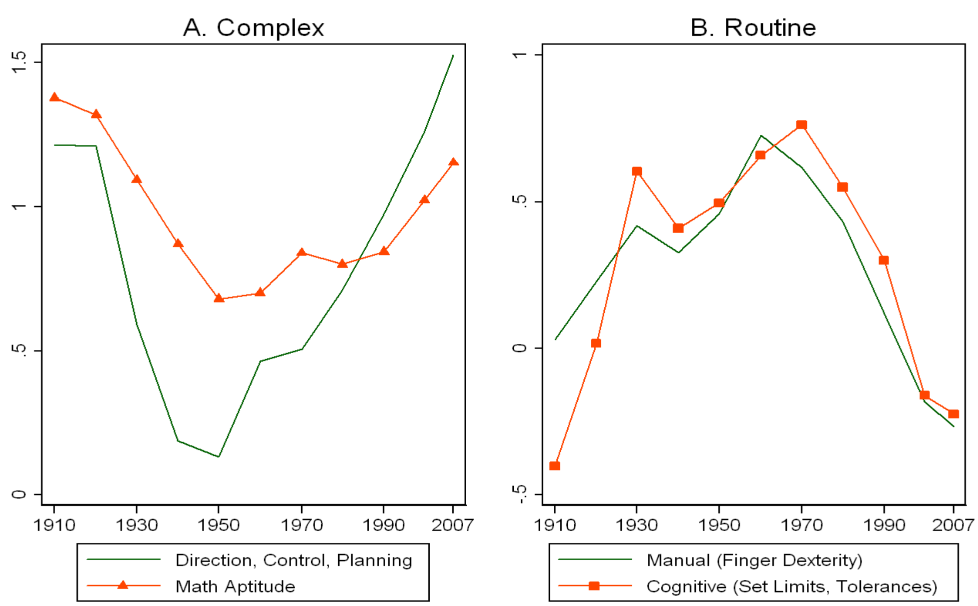
Notes: (1) to (4) are estimated from a regression of log wages on a quadratic in experience, education indicators and indicators for gender, race, urban dwellings and marital status, for male workers with less than 5 years of experience. The starting wage is the wage at zero years of experience. (5) is chosen so that the predicted mean wage ratio according to the wage processes in the text equals the actual wage ratio in NIPA data. (6) and (7) are the initial wage differences that would make workers indifferent between working in finance and in the rest of the private sector, given the excess slope (5) minus (2), and the excess dispersion (4). In (6) and (7) we assume a utility function with constant relative risk aversion and an annual discount rate of 3%.

Figure 1: Relative Wage and Education in the Finance Industry



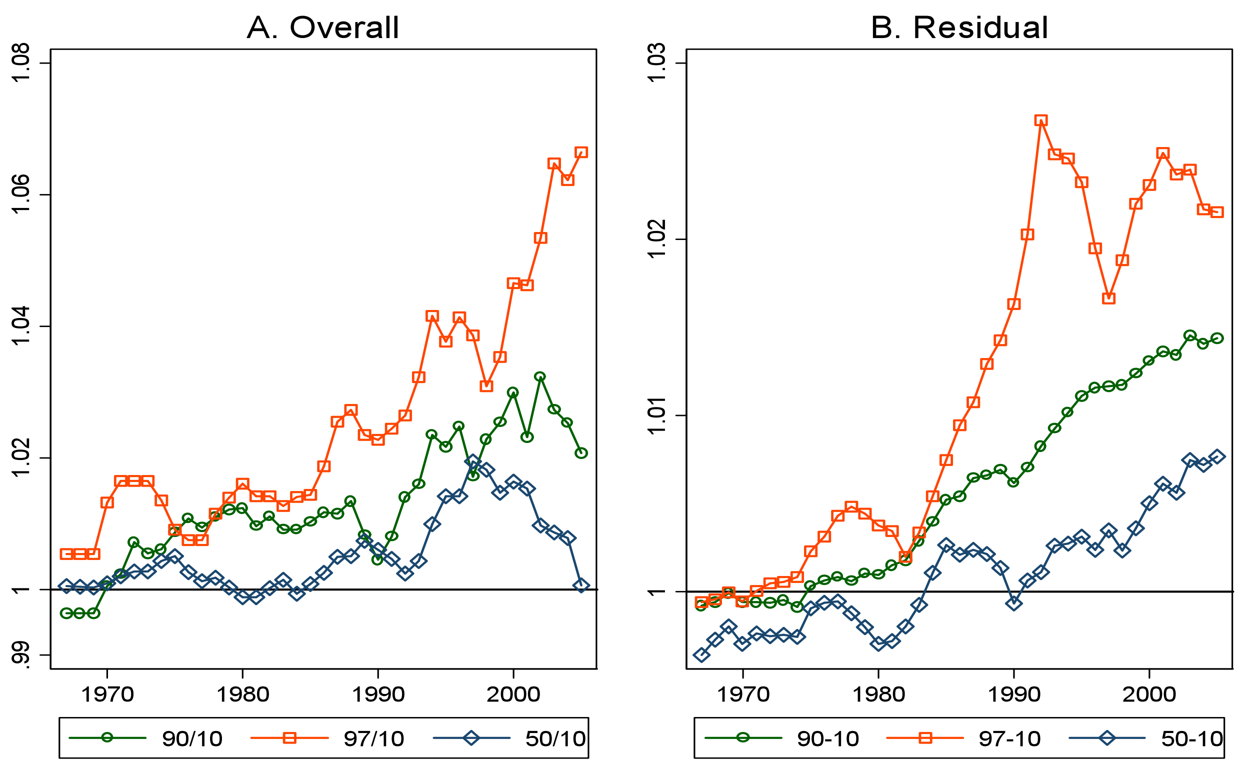
Notes: Fins. includes finance and insurance.Education is the share of employees with (strictly) more than high school education. Education (1910-2005) is computed from U.S. Census data, and from the Current Population Survey. In 1910-1930 education is imputed by using educational shares within occupations. Relative education is the difference in educated shares between Finance (Fins.) and the Non Farm Private sector. Wages (1909-2006) are computed from the Industry Accounts of the U.S., Kuznets (1941) and Martin (1939). The relative wage is the ratio of wages in Finanace (Fins.) to Non Farm Private wages.

Figure 2: Relative Job Complexity



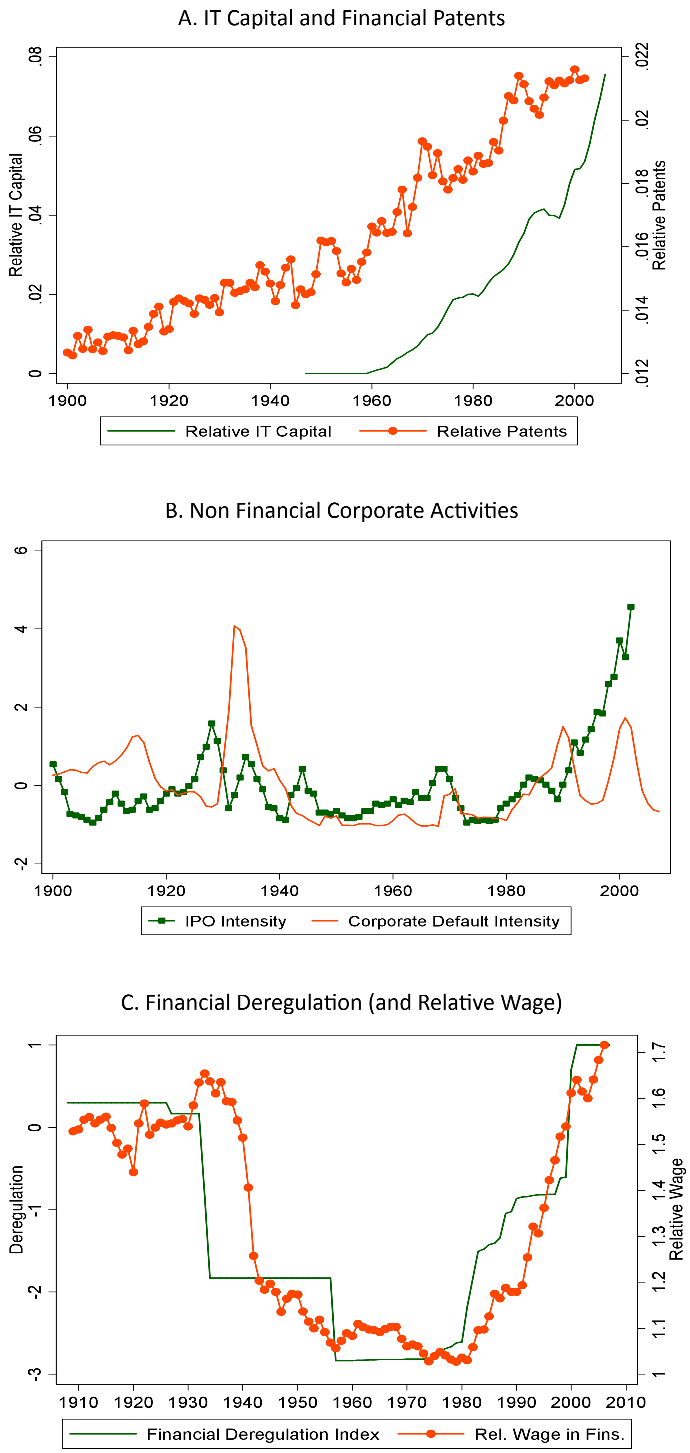
Notes: Relative task indices for finance versus the nonfarm private sector. Data: Dictionary of Occupational Titles, U.S. Censuses 1910-2000 and 2008 March CPS.

Figure 3: Contribution of Finance to Inequality



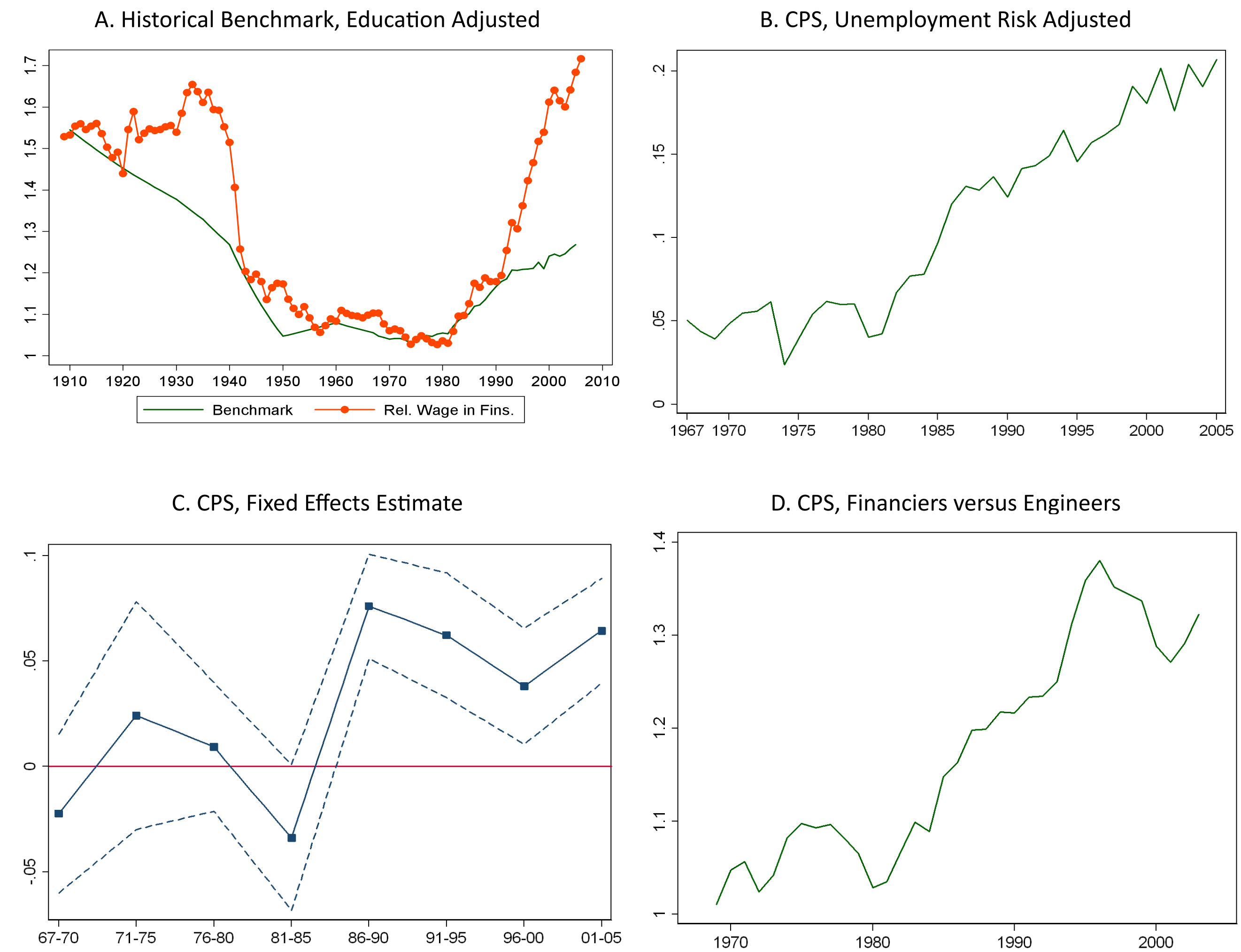
Notes: Both panels present inequality measures as they were computed form the data, relative to the same measures that were computed from a sample in which wages in finance were simulated. Numbers above one indicate that inequality would have been lower in the simulated sample. The underlying data for 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 were multiplied by 1.75. 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 grew 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.

Figure 4: Explanatory Variables



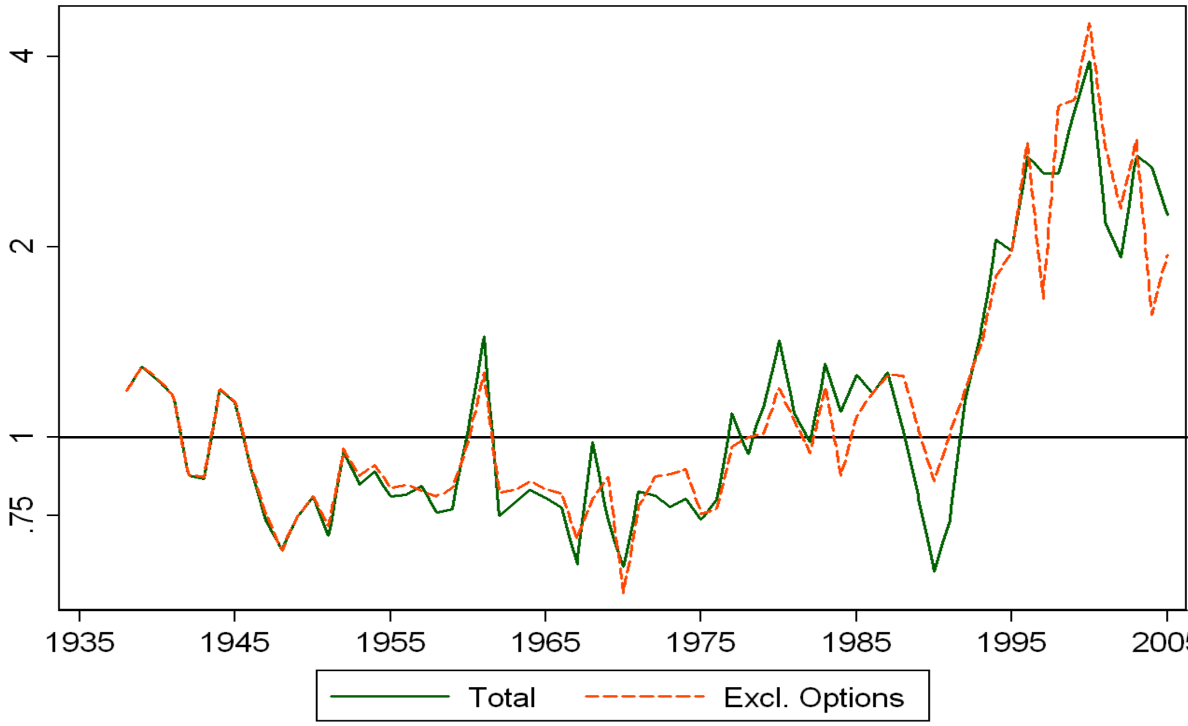
Notes. In Panel A relative IT intensity is the IT share of capital in finance minus the IT share of capital in the economy. Relative patents is the ratio of patents used in finance to all patents. In Panel B IPO intensity is IPO value over Market Capitalization. Corporate Default Intensity is the 3-year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

Figure 5: Financial Sector Wage Premium



Notes. In Panel A, Relative Wage in Financial Industry is the same as in Figure 1. The benchmark wage series is constructed using the skill composition series from Figure 1 and the skill premium series from Goldin and Katz (2008). Panel B plots the coefficient of the finance dummy from OLS regressions of log hourly wages on race, sex, marital status, urban residence, potential experience and its square, as well as education controls. Panel C 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. Data: March CPS and Matched CPS. Panel D presents average annual wage of financiers versus the average wage of engineers, all of which have have 18 years of schooling or more, or a post graduate degree. The underlying data is from the March CPS 1968-2006. Top coded wages were 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 A: Executives in Finance versus the Private Sector



Notes: The figure presents median executive compensation in finance relative to median executive compensation in the rest of the nonfarm private sector. The vertical axis 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, 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, Citicorp (Citigroup) 1971-1997, American Express 1977-2005, Chase (J.P. Morgan Chase) 1972-2005, Aetna 1964-2005, Cigna 1982-2005, AIG 1970-2005. The solid line take 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.