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

Thomas Philippon†
New York University

Ariell Reshef
University of Virginia

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Abstract

We analyze the evolution of wages, education and occupations in the U.S. financial industry over the past century. Financial jobs were relatively skill intensive, complex, and highly paid before 1933 and after 1980, but not in the interim period. We investigate the determinants of these evolutions. Changes in financial regulations appear to be the main factor behind the changes in skill demand, followed by corporate activities linked to IPOs and credit risk. Computers and information technology play a more limited role. High wages in the financial industry contributed significantly to the rise in inequality since 1980, and are not explained by education or unobserved ability. They are partly explained by changes in unemployment risk and by changes in the profile of earnings over careers in the financial industry. The latter is consistent with an increase in moral hazard in finance.

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We study the evolution of human capital in the U.S. financial industry over the past century. We document historical changes in skill intensity, wages, organization, and occupational complexity in the financial industry and we identify some of the economic forces that influence these evolutions.

There are two broad reasons to study the financial industry. A large body of existing research shows that finance plays a critical role in economic development. Economic historians have studied the developments of banking systems and securities markets and their impact on economic development within countries (Rousseau and Sylla 2003), and there is a large literature on financial development and economic growth across countries (Levine 2005). One of our goals is to shed light on how the financial industry evolves to serve the needs of the economy.

The financial industry also appears to play an important role in major economic crises, such as the Crash of 1929 leading to The Great Depression, or the subprime meltdown of 2007 and the ensuing Great Recession. Controversies regarding the complexity of financial products or the behavior and compensation of bankers invariably follow these crises. In the years leading up to the financial crisis of 2007-2009, the financial industry hired highly educated workers and paid them high wages to design, originate and trade complex products. But what about the 1960s? Or the 1920s? It is important to know whether high wage, high skill intensity, and a high degree of complexity have always been present and, if not, to identify the economic forces that drive the evolution of these characteristics.

Our first task is, therefore, to compare wages, education, and job characteristics in the financial industry and in the rest of the private sector. Using both macro and micro data, we uncover a set of new, interrelated stylized facts. The relative skill intensity and relative wages of the financial sector exhibit a U-shaped pattern from 1909 to 2006. From 1909 to 1933 the financial sector is a relatively high skill and high wage industry. A dramatic shift occurs during the 1930s: the financial sector rapidly looses its relative high human capital position and its wage premium relative to the rest of the private sector. The decline continues at a more moderate pace from 1950 to 1980. In 1980 compensation in the financial sector is similar to compensation in the rest of the economy. From 1980 onward, another dramatic shift occurs. The financial sector becomes once again a relatively high skill and high wage industry. Strikingly, relative wages and relative education levels go back almost exactly to their pre-1930s levels. This U-shape pattern exists also in the complexity of tasks performed in the financial industry: financial jobs were relatively more complex than non-financial jobs before the 1930s and after 1980, but not in between. High wages in the financial industry account for 15% to 25% of the overall increase in inequality since 1980.

Our second task is to explain these new stylized facts. We do so in two steps. We first study the demand for skills from the perspective of a frictionless labor market where wages for similar workers are equalized across industries. We later quantify the extent to which workers in the financial industry earn wages in excess of the frictionless benchmark. In the first step, we document a tight link between deregulation and human capital in the financial sector. Highly skilled labor left the financial sector in the wake of the Depression era regulations, and started flowing back precisely when these regulations were removed. This link holds both for finance as a whole, as well as for sub-sectors within finance. Along with our relative complexity indices, this suggests that regulation inhibits the ability to exploit the creativity and innovative ability of educated and skilled; de-regulation increases the demand for skilled workers and unleashes their creative abilities.

The second set of forces that appear to have a significant influence on the demand for skills in finance are non-financial corporate activities, in particular, 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 obvious reason that they do not have a track record. Similarly, pricing and hedging risky debt is more difficult than pricing and hedging government debt. Indeed, we find that increases in aggregate IPO activity and higher credit risk predict increases in human capital intensity in the financial industry. Computers and information technology also play a role, albeit a more limited one. Contrary to common wisdom, computers cannot completely account for the evolution of the financial industry. The financial industry of the 1920s appears remarkably similar to the financial industry of the 1990s despite the lack of computers in the early part of the sample.

Our last contribution is to study the determinants of the high wages observed in the financial industry. We construct a wage series based on observed changes in relative education as well as time varying market returns to education. Our first departure from the frictionless benchmark is to take into account employment risk using a simple life cycle model. Our adjusted 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 unobserved individual heterogeneity. We then study these excess wages from the perspective of optimal contracts with incomplete markets or asymmetric information.[1] According to this perspective, wages are not determined in spot markets, where ability and effort are costlessly observable and known; instead, they reflect various degrees of insurance and incentives.

The interpretation of the excess wage depends on saving behavior. If workers can borrow and save freely – as in the simple life-cycle model mentioned above – then excess wages are 40%, i.e., relative wages could drop by as much as 40% and workers would still accept jobs in the financial industry. However, if we assume that savings are restricted and that consumption is equal to current wages (as in the benchmark principal agent model), then the excess wage is only 16% on average.

The reason for this discrepancy is that the earnings profile in finance has become steeper and the wage process has become riskier than in the rest of the economy. Risk averse agents who make career choices demand to be compensated for this ex ante. However, the ex post realizations of these earnings profiles include many individuals who earn high wages. Changes in the earnings profile of finance careers can therefore account for the high wage bill paid by financial firms (16% left unexplained) without implying a large disequilibrium in the labor market. If this view is correct, then the challenge is to understand why employers in finance find it profitable to use such high powered incentives. At this point, we can only note that job complexity and excess wages are positively correlated, which is consistent with the idea that moral hazard is more of a concern when jobs become more complex.

[1] Excess wages – defined as the difference between actual wages and wages that reflect only compensating differentials – could also arise from the interaction of adjustment costs in labor supply and demand shocks for financial skills. This explanation is plausible to the extent that much of the growth in finance from 1995 to 2007 was driven by new products and new markets (securitization, credit derivatives, etc.) whose development appears not to have been anticipated even by the very people who invented the new products. For instance, Tett (2009) discusses the credit default swap market. However, it is unlikely that adjustment costs can explain large and persistent rents given that empirical estimates suggest that either these costs are not very large or that their effect is negligible. 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 sizable mobility costs, but find that entry (increase in supply) and capital mobility completely counteract the effect of persistent increases in demand on wages.

Our work contributes to several strands of literature. The literature on financial development argues that financial development is important for economic growth. But this literature does not explain how the financial industry is organized and how it adapts to serve the needs of the non-financial sector, nor does it address the opportunity cost of financial development. We provide evidence on both issues. Since it is difficult to measure productivity and innovation in the financial industry, looking at the choice of skill intensity and complexity is informative.[2] This approach allows us to provide a consistent description of "financial organization" for almost one hundred years. According to this metric we find that the financial industry of 2006 is surprisingly similar to the financial industry of 1929.

Economic growth requires the allocation of talent to socially productive activities, and the financial industry may lure talent away from other industries. Baumol (1990) argues that the allocation of talent across occupations is more readily influenced by institutions and private incentives than the overall supply of talent.[3] Baumol's concerns are material under three conditions: (i) the financial industry can attract highly talented individuals; (ii) regulation can affect the demand for skills; and (iii) some financial jobs are not as socially productive as non-financial jobs. Our results support points (i) and (ii).[4] Regarding (i), we find large and growing wage differences when we compare post-graduate financiers to post-graduate engineers, and when we compare top executives inside and outside finance.

[2] For manufacturing industries, as well as other services industries (e.g. health care), researchers can obtain reasonably accurate data on both inputs and outputs (number of cars produced, health of various individuals). For the financial services industry, however, the output side is difficult to measure. Most of the literature relies on simple ratios such as credit relative to GDP, loans per employee, but hese ratios do not tell us much about the internal organization of the sector. In addition, while the importance of financial innovations has been emphasized by several authors (Silber 1983, Miller 1986, Tufano 1989, Merton 1992, Lerner 2006), new products are more difficult to study in finance than in other sectors. There are thousands of studies for manufacturing industries, but Frame and White (2004) find only 39 empirical articles on financial innovation. This dearth of empirical research is certainly due to the fact that two major sources of data on manufacturing innovation, namely R&D spending and patents, are mostly useless for studying financial innovation. Financial firms typically do not report any R&D spending, and, until recently, could not protect their new ideas through patents Lerner (2006).

[3] Murphy, Shleifer, and Vishny (1991) make a similar point, and also discuss the role of increasing returns to ability in determining the careers of talented individuals. Kaplan and Rauh (2007) study the evolution of earnings of individuals with very high incomes with a particular emphasis on the financial sector.

[4] We cannot provide evidence that financial jobs are not socially productive. Such a claim can only be based on a structural model which is far beyond the scope of this paper. Rather, we show that finance has attracted more talent by paying higher wages. Our work is therefore 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.

These results are consistent with Goldin and Katz (2008b) who 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. Regarding (ii), we document the large effects of financial regulation on the demand for human capital.[5]

Our work also contributes to the understanding of relative demand for skilled labor and income inequality (Goldin and Katz 2008a). Katz and Murphy (1992) study the secular growth in the demand for educated workers from 1963 to 1987, while Autor, Katz, and Krueger (1998) and Acemoglu (1998), among others, discuss the role of technological improvements that are biased in favor of skilled workers.[6] We show that the financial industry alone accounts for 15% to 25% of the increase in inequality from 1970 to 2005. By taking a longer perspective than most previous studies and focusing on a particular sector, we show that computers and information technology are not the only source of increased demand for (and returns to) skilled workers. Frydman and Saks (2007) share our long run perspective in their study of executive compensation and challenge common explanations for the increase in executive compensation. Our analysis highlights the role of regulation and corporate finance in determining the relative demand for skilled labor in finance.

The rest of the paper is organized as follows. Section 1 describes the new stylized facts that we have discovered. Section 2 provides historical evidence on the effect of regulation, technology and financial innovation on wages and skill composition. Identification and causality are also discussed there. Section 3 documents the existence of a time varying wage premium in the financial sector, that is a positive residual after controlling for observed characteristics, and even individual fixed effects. In section 4 we show that some of the wage premium can be explained by unemployment risk and incentives. Section 5 concludes. In the text we restrict descriptions of data sources and series construction to the minimum; detailed descriptions of data sources and methodologies can be found in the appendix.

[5] This finding is consistent with Kostovetsky (2007), who presents evidence about brain drain of top managers from mutual funds to less-regulated hedge funds, starting in the early 1990s.

[6] 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), Acemoglu, Aghion, and Violante (2001) and Buera and Kaboski (2006).

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 industries, including investment banks).[7] 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 financial 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 using the March Current Population Survey (henceforth 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.[8] 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.[9] For the period 1940-1970 we use the Census data directly. For the period 1970-2005, we use CPS data.[10]

Let *high* denote high skill workers and let $high_{i,t}$ be a dummy variable for having strictly

[7] We do not include the real estate sector because it is conceptually different from credit intermediation or investment banking. Our results on wages and education would not change if we included real estate, however, because it is a small fraction of the wage bill and of employment.

[8] The results are virtually unchanged if 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.

[9] 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.

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

more than high school education for employee i at time t. Then the share of high skilled employees, those with strictly more than high school education, in sector s is given by

$$high_{s,t} = \frac{\sum_{i \in s} \lambda_{i,t}\ hrs_{i,t}\ high_{i,t}}{\sum_{i \in s} \lambda_{i,t}\ hrs_{i,t}} \ , \tag{1}$$

where λ and hrs are, respectively, sampling weights and hours worked (when this information exists), and $i \in s$ means that individual i works in sector s.[11] The relative education of the financial sector is defined as the difference between this share in finance ($s = fin$) and the corresponding share in the nonfarm private sector ($s = nonfarm$):

$$\rho_{fin,t} \equiv high_{fin,t} - high_{nonfarm,t} \ . \tag{2}$$

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 details in the appendix. The average wage in the financial industry relative to the average wage in the non-farm private sector is

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

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. 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 started to lose its human

[11] In the 1910-1930 and 1960-1970 Censuses the underlying data used to calculate hrs is missing. Therefore, in those years we assign $hrs = 1$ for all individuals.

capital and its high wage status. Most of the decline occurred by 1950, but continued slowly until 1980. By that time, the relative wage in the financial sector was approximately the same as in the rest of the economy. From 1980 onwards another dramatic shift occurred. The financial sector became a high-skill high-wage industry again. In a striking reversal, its relative wage and skill intensity went back almost exactly to their levels of the 1930s.[12]

1.2 Subsectors

In this section we investigate the role of the subsector composition of finance on the patterns of Figure 1. The source for full time equivalent employment and wages for each subsector is the Annual Industry Accounts of the United States.

Panel A of Figure 2 depicts the evolution of employment shares within the financial industry. The shares of Credit Intermediation and Other Finance decline relative to Insurance during the Great Depression. In the post-War period the share of Insurance declines almost linearly. Credit Intermediation gains in importance until 1980 and declines afterwards. Other Finance grows more rapidly after 1980.

Panel B of Figure 2 depicts the evolution of relative wages by subsector, calculated as in (3). Once again, we see a common downward trend in relative wages starting in the late 1930s. The decline continues more moderately for Credit Intermediation and Insurance until 1985, where a steady recovery commences. The pattern is slightly different for Other Finance, where the initial decline is deeper, but stops completely by 1940. In 1980 the relative wage in Other Finance starts a steep increase, until it completely dwarfs those of the other two subsectors.

We wish to evaluate the relative role of changes in subsector composition on the relative wage of finance. To do so, 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

$$\Delta\omega_{fin} = \sum_i \Delta\omega_i \overline{n}_i + \sum_i \Delta n_i \overline{\omega}_i \ , \tag{4}$$

where i is an index for subsectors. $\Delta\omega_i$ is the change of the relative wage of subsector i, $\overline{n}_i$ is the average employment share of i within finance, Δn_i is the change in the employment

[12] We find the tight relationship between the relative education series and the relative wage series an indication that the data sources are consistent, in particualr in the begining of the sample. If skilled workers command higher wages, then this is exactly what one would expect to find.

share of i within finance, and $\overline{\omega}_i$ is the average relative wage of i 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.[13]

We report the results of the decomposition in Table 1. The message is clear: almost all of the changes in relative wages come from the 'within' component. Thus, changes in sectorial composition do not account for changes in the relative wage of the financial industry. Another way to interpret these results is that all three subsectors exhibit similar patterns.

1.3 Education and occupations

Economic theory calls for decompositions based on tasks and occupations.[14] Indeed, we will show that tasks and occupations paint a much more relevant picture of the evolution of the financial industry than the more usual sectorial decompositions.

We first revisit the within-between decomposition of equation (4) using CPS data over 1980-2005. The CPS allows us to break down the financial industry not only by sub-sectors, but also by education and occupations groups. 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).[15] 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 financial industry using equation

[13] We choose 1933 as the starting point because it marks the begining 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.

[14] While sectorial analysis is common in economics, this is mostly because sectorial 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?

[15] 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.

(4), except that now the index i varies either across subsectors, education categories or occupations. The subsector, education and occupation categories are described above.

We report the results of the decomposition in Table 2. Panel A confirms our previous finding regarding changes in the relative wage: the effect of composition changes across subsectors are dominated by within-sector wage increases. By contrast, in Panels B and C we see that most of the increase in the relative wage in finance is due to reallocation of labor across education and occupation categories: the "between" component is much higher in Panel B than in Panel A, and even more so in Panel C. Therefore, organizational changes within each subsector are more important than changes in sectorial composition. This provides strong support for our focus on occupations in the following section.

But before continuing, 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.[16] 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.[17] Therefore, the wages that we report may not be accurate for certain occupations, in particular Brokers and Traders.[18] 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.

1.4 Complexity

The analysis in Table 2 underscores the importance of changes in the set of occupations within the financial industry. The next step is to link occupations to the tasks performed by the industry. The challenge is to construct a consistent and informative measure over the whole sample.

We rely on the Dictionary of Occupational Titles (DOT) to study the nature of occupations.[19] Each occupation is characterized by a vector of five DOT task intensities: Finger

[16] For technical reasons, the problem is more acute after 1996. See the appendix for complete details.

[17] 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.

[18] We refer the reader to Kaplan and Rauh (2007) for a detailed analysis of the highest incomes inside and outside finance.

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

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.[20] 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.[21] 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.[22] Each individual in this sample is characterized by the five task indices. For each task and year we create an average intensity by sector

$$task_{s,t} = \frac{\sum_{i \in s} task_i \ \lambda_{i,t} \ hrs_{i,t}}{\sum_{i \in s} \lambda_{i,t} \ hrs_{i,t}} \ ,$$

[20] 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.

[21] See appendix for complete details.

[22] Due to data limitations, in 1920 we could only restrict to individuals who were in the labor force, whether employed or not.

where i denotes a particular individual, t denotes the year, λ are sampling weights and hrs are annual hours worked. The notation $i \in s$ means that individual i works in sector s, where $s = fin$ corresponds to the financial sector and $s = nonfarm$ corresponds to the nonfarm private sector.[23] 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 and is dropped from the analysis). 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.[24]

1.5 Inequality

In this section we account for the contribution of finance to overall inequality.[25] We consider overall wage inequality, residual wage inequality and the college premium. Our sample is restricted to full time full year employees, age 16 to 66 who have no more than 40 years of potential experience, and who earned at least 80% of the federal minimum hourly wage.[26]

[23] In the 1910-1930 and 1960-1970 Censuses the underlying data used to calculate hrs is missing. Therefore, in those years we assign $hrs = 1$ for all individuals.

[24] 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.

[25] 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).

[26] 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

In order to account for the contribution of finance to overall inequality we compare actual measures of inequality as computed in the CPS to those that were computed from a sample in which we simulate wages in the financial sector according to the following scenario. We call the sample in which wages in finance were replaced by simulated wages the "simulated sample". 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.[27]

1.5.1 Overall wage inequality

We first turn to wage inequality. Panel A of Figure 4 depicts actual percentile ratios, as they are calculated in the data, relative to those calculated from the simulated sample. Percentiles are calculated according to the weighted position in the distribution. 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. The actual 90/10 ratio in 2005 is 2% higher and the 97/10 ratio is 6.6% higher relative to those ratios based on the simulated sample. The actual 90/10 ratio increased from 3.5 in 1970 to 5.15 in 2005; therefore, finance contributed 6.2% of the increase in this ratio over this period. The actual 97/10 ratio increased from 5 in 1970 to 9 in 2005; therefore, finance contributed 15% of the increase in this ratio over this period.[28]

Finance contributed more to inequality at the top of the distribution. First, it is evident that the relative 97/10 ratio increases much more than the relative 90/10 ratio. In addition, the relative 50/10 ratio increases and then falls, while the 90/10 and 97/10 ratios keep increasing.

Other measures of inequality convey a similar message. Using the same simulated sample we find that finance contributed 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

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.

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

[28] These numbers are not affected by our method of top coding correction becasue less than 3% of workers in our sample are top coded in any given year. Bell and Van Reenen (2010) document similar patterns for the U.K. See (Kaplan and Rauh 2007) for top earners.

that the effect of finance is so large. 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.

1.5.2 Residual inequality

We now turn to residual inequality. We use the same simulated sample to compare actual to simulated residual inequality. In each year 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. We compare inequality across these residuals in the real data versus the simulated sample.

The results for residual inequality convey a similar message as overall inequality, but they are even clearer and more striking. Panel B of Figure 4 depicts actual percentile *differences*, as they are calculated in the data, relative to those calculated from the simulated sample. These series are not equal to one in 1970 (the base year) because we display 5-year moving averages, to reduce noise. The actual 90-10 difference in 2005 is 1.3%% higher and the 97-10 difference is 2% higher relative to those differences based on the simulated sample. The the actual 90-10 difference increased from 0.94 in 1970 to 1.23 in 2005; therefore, finance contributed 6.6% of the increase over this period. The the actual 97/10 difference increased from 1.2 in 1970 to 1.58 in 2005; therefore, finance contributed 8.5% of the increase over this period.[29]

Again, we see that finance contributed more to inequality at the top of the distribution. The relative 97-10 difference clearly increases much more than the relative 90-10 difference. In addition, the relative 50-10 difference is essentially flat until the late 1990s, where it increases slightly and then stabilizes.

As with overall inequality, the timing fits the period of financial deregulation, post 1980. Both the relative 97-10 and relative 90-10 differences increase in earnest after 1980.

We also use the standard deviation of residuals as an alternative measure of inequality.[30]

[29] These numbers are not affected by our method of top coding correction becasue less than 3% of workers in our sample are top coded in any given year.

[30] Since the residuals are centered around zero in any year, the standard deviation is not affected by

Using the same simulated sample we find that finance contributed 7.4% to the increase in the standard deviation of residuals (8.2% to the increase in the variance of residuals). We find it comforting that this measure gives a similar magnitude to the percentile differences.

1.5.3 College premium

Another way to consider the contribution of finance to inequality is the college premium. To evaluate this contribution we fit in each year log hourly wages to 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 compare the coefficients on the college indicator in the real data versus the simulated sample. We call the coefficient on this indicator the college premium.

The results are in line with overall inequality and residual inequality. The actual college premium, as we calculate it, increased from 0.382 in 1970 to 0.584 in 2005, whereas the simulated college premium increased to 0.568 in 2005. This means that finance contributed 8% to the increase in the college premium. This may be due to either unobserved ability sorting or because equally able college graduates earn more in finance. We address these issues below.

1.6 Taking stock of the new facts

Uncovering the historical evolution of wages, education and job complexity in the financial industry is the first contribution of our paper.[31] 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 financial industry.

It is worth mentioning at the outset that the historical evidence places strong restrictions on the set of plausible explanations for the evolution of skill and wages in the financial sector. In particular, 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 main 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

changes in the level of wages. Gini, Theil and Mean Log Difference indices are not amenable to residuals, which can be negative.

[31] This pattern is similar to the one for CEO compensation documented by (Frydman and Saks 2007).

the historical evidence.

The historical stylized facts also rule out some simple macroeconomic explanations. For instance, the average price/earnings ratio and the ratio of stock market to GDP are not very correlated with the relative wage series.[32] The same is true for the ratio of trade to GDP and the ratios of global assets or liabilities to GDP.

We proceed as follows. We first provide a simple economic framework to think about the demand for skill in financial services. Then we try to identify the forces that determine wages and education in the financial industry. Finally, we ask whether the high wages observed in the early 2000s reflect returns to education, compensation for employment or income risk, or rents.

2 Demand for skill in the financial sector

In this section we provide a simple economic framework to think about the demand for skill in the financial services industry. We then present evidence on the determinants of relative education and wages in the historical perspective.

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, *high* and *low*, and that the production function of sector s is

$$y_{s,t} = A_{s,t}\ f\left(\mu_{s,t} \cdot h_{s,t}\ ,\ l_{s,t}\right)\ , \tag{5}$$

where $A_{s,t}$ measures the productivity of sector s at time t, and h and l are hours worked by high education and low education workers, respectively. The parameter $\mu_{s,t}$ captures the relative productivity of highly educated workers in sector s at time t.

In this section of the paper we view the labor market as a competitive spot market without adjustment costs, and without compensating differentials (we address these issues in Sections 3 and 4). Wages must therefore be equalized across sectors. Let $w_{h,t}$ and $w_{l,t}$ be the hourly wages for high and low education workers. Assuming that the function f is homogenous of degree one, cost minimization implies that the relative demand for skilled

[32] There is a stock market boom in the 1960s, and a collapse after 2001. Overall, the correlation with the relative wage series is small.

labor is of the form

$$high_{s,t} = \frac{h_{s,t}}{h_{s,t} + l_{s,t}} = \phi\left(\mu_{s,t}\ ,\ w_{h,t}/w_{l,t}\right)\ . \tag{6}$$

The demanded share of educated workers depends negatively on the education wage premium, and positively on the relative efficiency of skilled labor $\mu_{s,t}$.

The parameter μ can be affected by technological innovations and organizational choices. There is strong evidence of a secular trend in μ for the aggregate economy Goldin and Katz (2008a). However, we are 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.[33] Note that changes in the aggregate skill premium *cannot* be the driving force behind $\rho_{fin,t}$. If this were the case, then we would expect a hump shape, not a U-shape in relative education over the sample. Historically, the aggregate skill premium declined from 1915 to 1950 and then increased until today, with a brief, small decline in 1970-1980 (see Goldin and Katz (2008a), page 300). We observe an increase in relative education in finance exactly when the aggregate skill premium increases most rapidly, staring in 1980: finance 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 $\mu_{fin,t} - \mu_{nonfarm,t}$. We now turn to the potential determinants of $\mu_{fin,t} - \mu_{nonfarm,t}$.

2.2 Explanatory variables

Equation (7) makes it clear that in order to understand the determinants of the skill composition in the financial sector we need to think about what determines the comparative advantage of skilled labor in finance relative to the rest of the economy. We discuss endogeneity issues in sub-section 2.6.

Information technology *(IT)*

It is widely acknowledged that computers can affect the demand for skills. As we mention above in section 1.6, computers are complementary to complex tasks (non-routine cognitive)

[33] 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.

and substitutes for routine tasks (Autor, Levy, and Murnane 2003). As a result, employees in complex or analytical jobs become relatively more productive, the relative demand for routine jobs decreases, while manual jobs are less affected. The financial sector has been an early adopter of information technologies. We therefore consider the share of IT and software in the capital stock of financial sector minus that share in the aggregate economy.[34]

Our measure of relative IT intensity is displayed in Figure 5. This series does not capture investments in telephones and telegraphs in the early part of the sample.[35] We could not obtain data on the relative stock of telephones in the financial industry, but it is difficult to imagine this stock shrinking from the 1920s to the 1970s, even relative to the private sector. For lack of data on the pre-War period, we do not use the relative IT and software share in our time series regression. We will provide evidence on the role of IT at the sub-sector level in Section 2.4 below.

Use of patents in finance *(pat)*

New financial products are likely to increase the required skills of finance employees in the financial industry. Futures and option contracts are more complex than spot contracts. In addition, financial innovations often expand the span over which individuals can apply their skills, making the financial sector more attractive to highly 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.[36]

Unfortunately, we do not have much data on financial patents. Instead, we use patents *used* in finance. We obtain data on new patents used in finance for the period 1909-1996 from the Historical Statistics of the United States.[37] We extend the series to 2002 using data from Lerner (2006). We then normalize by the total number of patents. The series is displayed in Figure 5.

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

[35] Michaels (2007) argues that the advent of early information technology – telephones, typewriters, and improved filing techniques – in the early 20th century increased the demand for office workers in manufacturing. Unfortunately, his data on telephones and typewriters is on production, not use by sector.

[36] (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.

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

Corporate finance activity: IPOs and credit risk *(ipo, def)*

The entry of new firms increases the informational requirements from financial analysts. New firms are difficult to value because they are often associated with new technologies or new business models, and also for the obvious 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.

Another area where financial activity has changed dramatically over long periods is credit risk. Corporate defaults were common until the 1930s, and the market for high yield debt was large. This market all but disappeared for 30 years, until "junk" bonds appeared in the 1970s. Pricing and hedging risky debt is significantly harder than pricing and hedging government 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: this explains the dynamics of rating agencies, which were important players in the interwar period, small and largely irrelevant in the 1950s and 1960s, and growing fast from the 1970s until today (Sylla 2002). 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 6.

Deregulation *(dereg)*

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, use their creativity to produce new complex products, and therefore makes them relatively more productive.

Deregulation can also intensify competition, innovation, and the 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). For the financial industry, Falato and Kadyrzhanova (2010) study CEO turnover and show that the performance impact is stronger after deregulation.

We construct a measure of financial deregulation that takes into account the following regulatory legislation:

1. Bank branching restrictions. We use the share of the U.S. population living in states that have removed intrastate branching restrictions. It is a continuous variable 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 7.

2.3 Time series regressions

We regress the relative wage and relative education on the variables described above. To mitigate endogeneity we use a five year lag for the dependent variables. The relative education equation is

$$\rho_{fin,t} = \alpha + \beta^{d} \times dereg_{t-5} + \beta^{p} \times pat_{t-5} + \beta^{ipo} \times ipo_{t-5} + \beta^{def} \times def_{t-5} + \beta^{time} \times t + \varepsilon_t$$

and the relative wage equation is

$$\omega_{fin,t} = \alpha + \beta^{d} \times dereg_{t-5} + \beta^{p} \times pat_{t-5} + \beta^{ipo} \times ipo_{t-5} + \beta^{def} \times def_{t-5} + \beta^{time} \times t + \varepsilon_t \ .$$

We do not include the IT variable here because it is not available before 1960. We will present IT evidence at the subsector level in the next section. Standard errors are corrected for up to 10 years of autocorrelation.

Table 3 reports the results of the regression. The most robust determinant of both relative education and relative wages appears to be deregulation. In all specifications in Table 3 its effect is relatively stable and always statistically significant, and the economic magnitude is large. In columns (1) and (4), deregulation alone accounts for 90% of changes in education and 83% of changes in wages.

When adding to our specification financial innovation in columns (2) and (5) we detect a significant effect on relative education but not on relative wages. In columns (3) and (6), we find a positive effect of corporate finance activity on the demand for skill and on relative wages, but the effects are only significant for wages. It seems that demand for financial skills that are harder to learn (IPO valuation and pricing risk) result in higher wages to those who have obtained these skills, whereas working with new technologies *per se* only increases demand for skilled workers in general. The effect of deregulation is robust to adding these control variables.

The financial deregulation index varies over a span of 4 units over the sample. Using the estimates from column (3), this translates into 7 percentage points of relative education. Recall that in Figure 1 relative education varies by slightly less than 10 percentage points. Similarly for wages, we find that deregulation appears to be the most important factor.

The time series regressions confirm the strong link between deregulation and skill upgrading in finance visible in Figure 7. The timing of the shift suggests a distinct role for deregulation, because the IT share in the capital stock of the financial sector actually starts increasing in the 1960s. The large organizational changes seem to have waited for deregulation to take place in 1980.

Previous studies have attempted to address organizational change due to bank deregulation across states in the U.S. The results of these studies are inconclusive. Black and Strahan (2001) show no effect of branching deregulation across states on the share of managers in banking, whereas Wozniak (2007) does find such an effect, although her set of control variables is not as elaborate as Black and Strahan (2001). In untabulated results, we replicate both studies. In addition, we find that following branching deregulation the share of managers in banking employment decreases only in states that had strict unit banking laws relative to banking in other states. This is what one should expect if branching restrictions prevented reaping economies of scale in management.

However, this result should be interpreted with caution, since it does not capture the effect of deregulation on the long run trend for more managers in banking. If we do not include time dummies in those regressions reported above, then deregulation actually has significant positive effects on demand for skills. It follows that the state specific effect of bank deregulation is dwarfed by the common trend in banking. It is this common trend that we pick up with our deregulation index.

2.4 Panel regressions: deregulation and information technology

Our main finding so far is the importance of deregulation in the determination of the evolution of relative education and relative wages in finance as a whole. In this section we investigate whether this result holds for the three subsectors that comprise the financial sector, namely Credit Intermediation, Insurance and Other Finance.

Unfortunately, we could not obtain time series data on innovations specific to these subsectors. We discuss the role of financial innovation below, but do not carry out statistical tests. In contrast, IT and software capital data is available by subsector from the BEA. In addition, we construct a deregulation index by sector. We exploit these two series in a panel of three subsectors within finance, which we currently turn to.

In order to construct a deregulation index that varies by sector, as well as by time, we use the components of the deregulation index from section 2.2. These components were (1) Branching restrictions; (2) Separation of commercial and investment banks (Glass-Steagall); (3) Interest rate ceilings; and (4) Separation of banks and insurance companies. Our sector-varying financial deregulation index is constructed 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.[38]

For each subsector we now have a measure of relative wage, relative education, deregulation and the IT and software share in capital by subsector. We use this data to fit panel regressions with subsector fixed effects and year dummies over the post war period.

We report the results in Table 4. 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 1.5 times larger than that of the IT share.[39]

2.5 Financial innovation

Ideally, we would like to perform the same type of cross-sectional tests that we have just performed for IT in Section 2.4 for financial innovation as well. Unfortunately, we do not have data on financial innovation at the subsector level, and we can only offer anecdotal evidence by looking at the insurance sector. In terms of wages and education, the insurance sector has been relatively stable (relative to the rest of the economy). Moreover, one might think that improvements in computers by themselves affected the insurance sector as much as the other financial sectors, and indeed the IT share in insurance is significantly higher than in the rest of the economy and, if anything, its growth has been faster than in Credit Intermediation. Nevertheless, the evolution of wages in Insurance does not suggest strong skill bias. This is inconsistent with IT being the main driving force behind the evolution of skills and wages.

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

[38] We have performed robustness checks on the construction of these indices. The results in Table 3 below are robust to these checks.

[39] The deregulation variable ranges from -3 to 1 (with a standard deviation of 1.05), while the IT share variable ranges from 0 to 0.21 (with a standard deviation of 0.06). Combining these with the coefficient estimates gives a 1.5 larger effect to IT (also, the beta coefficient to deregulation is 1.33 larger than the coefficient to IT).

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.[40]

2.6 Causality and interpretation

We have entertained other possible determinants for the evolution of relative education and relative wages over this long horizon. In particular, we have considered international trade, financial globalization, stock market capitalization (as percent of GDP), stock returns and unionization. None of these variables has a significant effect on the skill composition of the financial sector once the deregulation index is included. We also looked at the allocation of value added between labor and capital within the financial industry. The labor share is stable over time. The evolution of relative wages is therefore not driven by variations in the bargaining power of financial workers.

On the other hand, we do not argue that regulation is exogenous to economic shocks. Depression era regulations are called so for a reason. We would nonetheless argue that the evidence points clearly towards a causal role for regulation, for at least two reasons. First, while legislators and regulators react to economic shocks, they do not do so in a mechanical way. Following the crisis of 1929-1933, regulations were tightened and wages in finance went down, but following the crisis of 1973-1981, regulations were loosened, and wages in finance went up. Therefore, the occurrence of a crisis, high unemployment, bank failures, or a long bear market have no predictive power for relative wages and skills employed in finance, while regulation does.

Second, the timing of changes also suggests a causal role for regulation. The relative wage did not drop in 1929, or in 1930 following the stock market crash. The relative wage dropped only after 1934, when new regulations were enacted. Similarly, there was no sudden change in IT use around 1980, and it is only after deregulation took place that the relative wage started to increase. The pattern across subsectors is consistent with our

[40] Tufano (2004) argues that the more recent decades have also witnessed important financial innovations, but does not provide a breakdown by subsector.

previous historical evidence. First, the subsector most responsible for the increase in the relative education and the relative wage, Other Finance, is most affected by deregulation. This is consistent with evidence from (Kostovetsky 2007), who presents evidence for a brain drain of top managers from mutual funds to less-regulated hedge funds starting in the early 1990s.[41] Second, we find that the role of IT and software is limited. The IT share in the capital stock of Insurance and in Credit Intermediation has increased just as much as Other Finance, but the wage gains are much more modest.

Apart from regulation, we find an important role for corporate finance activities linked to IPOs and credit risk. Once again, we would not argue that IPOs are exogenous, but historical research suggest that they are exogenous enough for our purpose. Jovanovic and Rousseau (2005) have shown 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 it explains the bulk of historical fluctuations in IPOs. Credit risk also increases during and after IPO waves, because young firms are volatile, and because they challenge established firms.

That the quality of human capital employed in the financial industry is determined by the needs of the corporate sector is also important in the current context, because it suggests that at least some of the observed high wages represent an efficient market response to a change in the economic environment. In the last section of this paper, we ask whether employees in the financial industry earn excess wages.

3 The excess wage in finance

In the previous sections we have shown that regulation, the complexity of corporate finance activities and financial innovations drive skill demand in the financial sector. We also show that the relative wage in finance evolves in a U-shape. We now ask whether compositional changes account for this pattern. We find that they do not: even controlling for education and other individual characteristics there remain large differences in relative wages between finance and the rest of the private sector.

We define the excess wage in finance as the wage differential between two identical

[41] Kostovetsky (2007) argues that this lowered returns in mutual funds.

workers, one working in finance and the other working elsewhere in the private sector. In a perfectly competitive world without information asymmetries or incentive problems, excess wages are either zero or equal to the difference in the disutility of work across jobs (i.e., compensating differentials). We document large and time varying excess wages in finance, first using the entire CPS sample and then focusing on two particular sets of highly skilled individuals. In section 4 we entertain potential explanations for the evolution of the excess wage in finance.

3.1 Wage regressions

In this section we ask how much of the increase of relative wages in finance can be attributed solely to working in the financial sector, over and above education, occupation and individual ability. We deal first with observable characteristics, and then address unobserved individual ability.

3.1.1 Observable characteristics

For observable characteristics, we fit a series of cross sectional regressions, one for each year in our sample. For each year we estimate

$$\log(w_i) = \alpha + \phi_{ols} 1_i^{\phi} + X_i' \beta + u_i \ , \tag{8}$$

where X is a vector of individual characteristics that includes controls for educational categories as in section 1.3, as well as indicators for race, sex, marital status, urban residence, and (potential) experience and its square. 1^{ϕ} is an indicator for working in finance. w is the hourly wage. Notice that since these regressions are fit year by year, they take into account, *inter alia*, the changing average returns to education. We restrict attention to full time 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.

Panel A of Figure 8 displays estimates of the coefficients of interest, ϕ_{ols}, plotted against the year in which they were estimated. All estimates were statistically different from zero.[42] The figure confirms that individuals working in finance indeed earn more than observationally equivalent workers. However, the premium was quite small until 1980, around 5%, at

[42] Complete results are available upon request.

which point it started to increase dramatically until it reached 20% at the turn of the century. In untabulated results we find a similar patterns for subsectors within finance. The beginning of the increase in ϕ_{ols} matches the timing of the reduction of regulation. Since we are controlling for education, this increase cannot be interpreted as an increase in the average returns to education.[43]

3.1.2 Individual fixed effects

The pattern in Panel A of Figure 8 could be explained by unobserved individual ability. It might be the case that more able individuals reallocated into finance after 1980. To address this concern we estimate the following equation

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

where w are hourly wages, α_i is an individual fixed effect, 1^{ϕ} is an indicator for working in finance, X is a vector of individual characteristics, and δ_t are year dummies.[44] The coefficient ϕ_{fe} measures the extent to which the average finance employee receives a higher wage, controlling for individual ability. The vector X includes indicators for marital status, urban residence, and continuous variables (potential) experience and its square. We do not include in X educational categories because we restrict attention to individuals who have completed their formal education and therefore their years of education are fixed; therefore, their individual return to education is absorbed in α_i.[45] For the same reason, we do not include in X indicators for race and sex.

Equation (9) can be estimated with longitudinal data. We therefore use the 1967-2005 Matched CPS, which allows us to observe each individual in the March CPS twice, in two consecutive years.[46] As before, we restrict attention to full time workers in the private

[43] Wurgler (2009) fits similar regressions to ours for the U.K., France and Germany. He finds similar patterns in the U.K., which experienced similar deregulation processes, but not in France and Germany, which did not.

[44] 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. In fact, the magnitudes of the results using hourly wages stronger.

[45] 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.

[46] See the data appendix for a complete description of the methodology involved in matching observations on individuals from consecutive surveys.

sector, age 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.

Since each individual is observed only in two consecutive years, α_i captures the trends in the returns to education and experience, as well as all other factors that are individual specific and time invariant within the two years in which the individual is observed. This is an advantage to us, because it allows us to abstract from changes in the returns to such traits. Admittedly, observing α_i in only two periods makes the estimator of α_i very noisy, but this is not a concern for our purposes.

We estimate (9) for eight subsamples: [1967,1970], [1971,1975], ... [2001,2005].[47] The results are reported in Panel A of Table 5 and plotted in Panel B of Figure 8. There was no finance premium before 1986, but from that point in time it is positive and large. One must keep in mind that the magnitude of the increase is affected by top coding in the CPS data. Therefore, it is meaningful to consider the estimates of ϕ_{ols} the total premium, due both to the true industry wage differential and to sorting on individual ability. Comparing the increase in the estimates of ϕ_{fe} after 1986 to the estimates of ϕ_{ols}, we see that 30% to 50% of the excess wage cannot be explained by individual ability.

A well known result is that measurement error may create a strong downward bias in fixed effects regressions that estimate industry wage differentials, due to misclassification of individuals to industries. In order to address this, we correct the estimates as suggested by Freeman (1984).[48] 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 dataset. We assume that 2% of individuals in the sample are misclassified. The corrected coefficients are reported in the bottom row in Panel A of Table 5.[49] Comparing the increase in the corrected estimates of ϕ_{fe} from 1991 and on to

[47] 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 begining of the following subsample are excluded. The results are robust to including these observations.

[48] For a complete discussion of the measurement error attenuation bias in fixed effects regresisons see Freeman (1984) and Krueger and Summers (1988), both of which find wage differentials in such regressions. Murphy and Topel (1987) find very small industry wage differentials after controling for job turnover. However, Gibbons and Katz (1992) argue that this last result is likely driven by use of annual wages; if job switching happens in the middle of the year, the fixed effects estimates for industry switchers will be downward biased.

[49] Using 1% misclassification rate yields slightly smaller coefficients than 2%, and using 3% misclassification rate yields larger coefficients.

the finance dummy ϕ_{ols} in Panel A of Figure 8, we see that 60% to 100% of the excess wage must be explained by factors other than individual ability.

In order to make sure that the results are not driven by positive shocks to individuals who switch into finance, we performed the following robustness check. First we estimated (9) in a sample that excluded individuals who switched out of finance. Then we estimated (9) in a sample that excluded individuals who switched into finance. The results are qualitatively and quantitatively similar. We see that omitting switchers into finance (Panel B) actually yields a slightly smaller premium, whereas switchers out of finance (Panel C) received a slightly larger premium.[50]

To conclude this section, we conservatively estimate that at least 50% to 60% of the excess wage in finance (after controlling for education, experience and demographics) is a true industry wage differential, which is not due to sorting on unobserved individual ability. Since wages in the CPS are top coded, and since top coding is more prevalent in finance, we consider this a lower bound.

3.2 Highly skilled individuals

We now focus on two groups of highly skilled individuals, which are, arguably, similar in ability. We first compare post graduate financiers to post graduate engineers. Our motivation is the ongoing debate on the decline of engineering in the U.S. (National Academy of Sciences 2007). We then compare executives in and out of finance, motivated by the debate on CEO compensation.

3.2.1 Post graduate financiers versus engineers

We use the CPS to compare average wages of financiers to average wages of 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

[50] 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.

are treated the same, it is less likely to find large differences between these two groups of workers in particular. Nevertheless, the picture that emerges is telling.

Panel A of Figure 9 reports wages of financiers relative to wages of engineers, both with post-graduate degrees. We take 5-year moving averages of the relative wage series to reduce noise. Wages of highly educated financiers were 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 exactly the timing of deregulation, post 1980.

A similar picture emerges when we regress log hourly wages on an indicator for finance and the usual set of controls used above, and then plot the estimate of the coefficient to the finance indicator over time. Although the magnitude of the financiers wage differential is slightly smaller, the timing is exactly the same as above.

3.2.2 Executives

We obtain data on executive compensation in 1936-2005 in 50 of the publicly traded largest firms that operated in the U.S. from Frydman and Saks (2007). [51] These firms reported 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.[52] Each firm reports compensation for the top three officers, in 10-K reports (1936-1941), proxy statements (1942-1991) or Compustat (1992-2005). 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. For full documentation we refer the reader to Frydman and Saks (2007).

Denote the median compensation for the top three executives outside of finance by $wage^{exec}_{nonfarm,t}$ and in finance by $wage^{exec}_{fin,t}$. 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 (J.P. Morgan Chase) 1972-2005, Aetna 1964-2005, Cigna 1982-2005, AIG 1970-2005. Thus, until 1964 only CIT Group is used. We did not find jumps or discontinuities in the $wage^{exec}_{fin,t}$ series around the years in which a financial

[51] We are grateful to Raven Saks and Carola Frydman for sharing the data with us.

[52] Frydman and Saks (2007) demonstrate that this is a represenatative sample of the top 300 firms in the U.S. during 1936-2005.

firm joins or leave the sample. Note that before 1964 we have only one financial firm in the sample, and only two before 1971. On the positive side, we have representation of all three subsectors within finance: Credit Intermediation, Insurance and Other Finance.

Define the excess executive compensation in finance as

$$\omega_{fin,t}^{exec} \equiv \frac{wage_{fin,t}^{exec}}{wage_{nonfarm,t}^{exec}} \ .$$

Panel B of Figure 9 reports two series for $\omega_{fin,t}^{exec}$, one of which excludes option value due to the approximation involved in its calculation. Bar one spike in 1961, executive compensation in finance was lower than in the rest of the private sector from 1945 to the late 1970s, 25% less on average. During the 1980s executive compensation in finance was essentially on par with the rest of the private sector. But starting in 1990 executive compensation in finance increases until it outstrips the private sector by 100%-200%.[53] Gabaix and Landier (2008) find very little dispersion in executive talent, which supports our approach of comparing compensation of executives in finance to compensation of executives in other sectors.

It is worthwhile noting that the pattern for relative executive compensation is the same whether or not we include option values or not. Options are usually viewed as incentive pay. It seems that relative executive compensation in finance is not driven by this form of incentives.

The timing fits the period of deregulation. Although bank deregulation started in the 1980s, the main effect of deregulation for the very top earners in finance is more likely the relaxing of Glass-Steagall Act from 1987 and its eventual repeal in 1999. The timing of the increase is in line with the timing in the increase the historical excess wage in finance. This interpretation is supported by the evidence in Falato and Kadyrzhanova (2010) who show that the performance impact of CEO replacements in the financial industry is stronger after the repeal of Glass-Steagall. Clearly, if we are correct, finance CEOs should also have been excessively compensated in the 1920s. Unfortunately, we do not have data on executive compensation in finance before 1938, so we cannot corroborate high historical excess wage in that period.

The 1990s was a period of mergers in finance, and some of the firms in our data indeed merged in this period (J.P. Morgan Chase, Citigroup). Gabaix and Landier (2008) argue

[53] The same pattern is evident for each financial firm in our dataset, with similar magnitudes.

that executive compensation is linked to aggregate firm size (and less so to own firm). However, Frydman and Saks (2007) do not find a correlation between firm size and executive compensation prior to the mid 1970s; they argue that the post 1980s correlation might be spurious.[54] Furthermore, we find very similar patterns in finance firms that merged and those that did not. While testing the Gabaix and Landier (2008) hypothesis is beyond the scope of this paper, we note that the major mergers in finance were enabled by deregulation.

4 Explaining excess wages

In the previous section we found that wages in finance are higher than in other sectors, even after controlling for education levels and unobserved ability via individual fixed effects and by comparing workers with similar ability. In this section we attempt to explain these differences.

We first estimate the importance of the increase in unemployment risk for explaining higher wages in finance, assuming a simple life cycle/permanent income framework. We use this estimate, together with changes in skill intensity and returns to education to calibrate a benchmark relative wage for finance. We find that taking these three components into account still yields an excess wage of 40%. This approach delivers an upper bound on rents in the financial sector.

We then consider the implications of insurance and incentives in long term contracts. We find that earning profiles have steepened in finance, relative to the rest of the private sector. This evidence is consistent with an increase in the importance of moral hazard. Taking this into account yields a lower bound on rents of 16%.

4.1 Employment risk and wage differentials

If finance workers are more likely to loose their jobs they would have to be compensated for this. To test this explanation, we proceed as follows. Let emp_{it} be an indicator for being employed at time t. We fit the following logit regressions of the likelihood of becoming unemployed

$$\Pr\left(emp_{it+1} = 0 \mid emp_{it} = 1\right) = f\left(1^{\phi}_{it},\ \log\left(w_{it}\right),\ X_{it}\right) \tag{10}$$

[54] Frydman and Saks (2007) show that other theories of managerial compensation also do not stand simple empirical tests.

where f is the logistic function, X contains the same vector of observables we used in the previous sections and 1^{ϕ} is an indicator for working in finance. We add $\log(w)$, the log of the hourly wage, in an attempt to capture unobserved heterogeneity. We fit this regression for eight subsamples of equal size in 1967-2005, $\{[1967, 1970], [1971, 1975], ... [2001, 2005]\}$, and we include year dummies within each subsample. The coefficient to the indicator 1^{ϕ} captures the additional risk of unemployment for workers in finance. The estimation of equation (10) requires a longitudinal dimension. Therefore we use the Matched CPS in 1967-2005, which allows us to observe each individual in the CPS twice, in two consecutive years.[55]

Figure 10 summarizes the evolution of unemployment risk in the financial sector relative to the private sector, as captured by the marginal effect of 1^{ϕ} from (10) in each of the eight subsamples.[56] Although finance employees had safer jobs until the early 1980s, the relative stability of finance jobs has decreased over time.[57] The timing of the decrease in unemployment risk coincides with the timing of financial deregulation.

We use these results in order to gauge the effect of the rise of unemployment risk on wages. By calibrating a simple income fluctuations model (see details in the appendix), we find that the increase in unemployment risk could account for 6 percentage points of the increase in relative wages. We compare this to our estimates of the finance dummy depicted in Figure 8.[58]

4.2 A first benchmark for the relative wage

Using historical data on the returns to education, our estimates of the relative education in the financial sector, and assuming that relative unemployment risk was the similar in the 1930s and 1990s, we can construct a benchmark relative wage series for the financial sector. Deviations from this benchmark can be driven by unobserved heterogeneity, or by true excess wages in the financial sector.

[55] See the appendix for a complete description of the methodology involved in matching observations on individuals from consecutive surveys. For a complete documentation of the variables and output results, see Philippon and Reshef (2007).

[56] The probability of becoming unemployed is evaluated for the average worker, i.e., it is evaluated at the means of all other variables.

[57] We also fit (10) for three wage groups in order to better capture unobserved heterogeneity. The upward trend in unemployment risk is maintained for all wage groups that we entertained (Philippon and Reshef 2007).

[58] See Philippon and Reshef (2007) for complete documentation.

The benchmark relative wage in finance versus the nonfarm private sector is given by

$$\widehat{\omega}_{fin} = \rho_{fin} \cdot (1 + \pi) + \theta \ ,$$

where ρ_{fin} is the relative education level in finance defined in equation (2), π is the skill premium, and θ captures the effect of differential unemployment risk. We use our estimates of ρ_{fin}, the estimates of π from Goldin and Katz (2008a) and our own calculations to estimate θ over time.[59]

Panel A of Figure 11 shows the actual and benchmark relative wage series. The benchmark relative wage tracks the actual relative wage well in the middle of the sample. It is important to remember that in the late 1970s the relative wage is one, but finance workers are more educated than in the rest of the economy (see Figure 1). The negative differential appears to be well explained by the lower employment risk that finance workers enjoy in that period. This differential disappears during the 1990s. In 1910-1920 the large returns to education documented by Goldin and Katz (2008a) account well for the relative wage.

Panel B of Figure 11 exhibits the excess relative wage, defined as the difference between the actual and benchmark relative wages in Panel A. 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. It follows that something other than returns to education, skill intensity and employment risk have caused the actual wage to deviate from the benchmark. Compensating differentials are unlikely to explain the evolution of the excess wage, because financial innovations over the past 30 years have made jobs in the financial sector more interesting, not less.

The magnitude of the increase in the excess wage in Figure 11 is larger than in Figure 8 because of top coding in the CPS data. However the timing of the increase in both Figures is remarkably similar. In both cases, excess wages in the financial sector appear only from the mid 1980s onward. Overall, this validates our strategy of using different data sources. The Industry Accounts data is more comprehensive, but does not allow us to rule out unobserved heterogeneity. The CPS data suffers from top coding, but it gives us better

[59] We use the calibration which is described in the appendix to gauge θ under the following assumptions about the relative risk unemployment. We rely on our estimates for the 1968-2005 period directly. We assume that from 1950 to 1970 the risk factor was the same as in 1970. We assume that in 1920-1935 there was no additional risk to work in the financial sector, as in the 1990s. Between 1935 and 1950 we interpolate linearly.

identification.

4.3 Contracts, incentives and insurance

The historical excess wage in finance in Figure 11 is roughly 40% in 2005. This excess wage cannot be explained by education or employment risk. We now ask whether the excess wage can be explained by incentive problems. We cast the problem in terms of the classical principal-agent model, with incentive and participation constraints. We provide evidence on whether the ex-ante participation constraints bind, or in other words, whether lifetime utilities are equalized across careers.

To explore this possibility we focus on lifetime utility and dynamic incentives. We therefore introduce one last stylized fact about compensation in the financial industry: earnings profiles have become steeper in finance relative to the rest of the economy. Panel A of Table 6 reports changes in the difference between the experience gradient for workers in finance versus workers elsewhere. For male workers with less than 5 years of experience in 1971-1980, finance wages start 3% higher with a slope 0.57% flatter. In 1991-2005, finance wages start 8.8% higher with a slope 2.5% steeper. We estimate these from a sample of men in the CPS, using the same controls as in the regressions above.[60]

In order to interpret these estimates we use the following model. Assume that the wage of individual i with experience t in sector s in time period τ follows the process

$$\log\left(w_{i,s,t,\tau}\right) = \log\left(w_{s,0,\tau}\right) + \mu_{s,\tau}\left(t\right) + \sigma_{s,\tau}\left(t\right)\epsilon_{i,t} \ , \tag{11}$$

where μ and σ are positive and we normalize $\mu_{s,\tau}\left(0\right) = 0$ and $\epsilon_{i,t}$ is an i.i.d. shock. So $w_{s,0,\tau}$ is the average starting wage in sector s in time period τ. In practice we will consider three time periods: 1971-1980, 1981-1990, and 1991-2005. In each time period, we estimate sector specific earnings profiles. The function $\mu_{s,\tau}\left(t\right)$ measures the average log wage as a function of experience (in practice we use a quadratic function). The function $\sigma_{s,\tau}\left(t\right)$ measures the dispersion of log wages at a given level of experience. Finally the shock $\epsilon_{i,t}$ is simply the realization of the random wage for the particular individual at a particular time. Note that individuals are identical ex ante.

[60] The estimates, as well as their differences over time, are all statistically significant. These results are available upon request.

We define three concepts to facilitate the discussion. The first concept is the net present value of wages:

$$V_{0,s,\tau} = E\left[\sum_{t=0}^{T} \frac{w_{i,s,t,\tau}}{(1+r)^t}\right] \ . \tag{12}$$

This is how a risk neutral principal would value a stream of payments to an agent who is starting a new job. Therefore, it is the objective that a principal seeks to minimize in a principal-agent model.

The second concept is the lifetime utility of the agent, assuming the agent consumes her wage in all periods:

$$U_{0,s,\tau} = E\left[\sum_{t=0}^{T} \frac{u\left(w_{i,s,t,\tau}\right)}{(1+r)^t}\right] \ . \tag{13}$$

This pins down the participation constraint of the agent, who's wage is controlled by the principal in the optimal contract. Assuming that the agent consumes her wage in all periods makes this a lower bound on lifetime utility. With labor mobility, we should expect in any time period that

$$U_{0,s,\tau} = U_{0,s',\tau} \ \text{ for all } s, s'$$

Short term deviations from this condition can be due to adjustment costs in labor supply or rents.

The third concept is the average wage paid to employees in sector s during period τ. We have already considered the consequences of employment risk in the previous section. Here for simplicity we consider the polar opposite and we assume that there is no attrition (i.e., workers expect to stay in the same industry until they retire). In this case, experience cohorts within an industry have the same size and we can define

$$\bar{W}_{s,\tau} = \frac{1}{T}\sum_{t=0}^{T} w_{s,t} \ . \tag{14}$$

This should be equal to the average wage that we measure using NIPA data.[61] Equation (14) assumes equal weights for each level of experience. In the CPS data the distribution of experience is relatively flat after 10 years of experience. More importantly, the distribution of experience in finance is indistinguishable from the rest of the private sector. Therefore,

[61] This is also what we would measure in the CPS if high wages were not top coded, which is more prevalent for more senior employees.

small deviations from the equal weights assumption in (14) are unlikely to change our conclusions.[62]

We assume a real risk free rate of $r = 3\%$ in all our calculations. We use CPS and NIPA data to calibrate equation (11). We assume that $\mu_{s,\tau}(t) = \mu^l_{s,\tau} t - \mu^q_\tau t^2$. Note that we estimate a common quadratic term μ^q_τ because we find that a separate squared term for finance is not significantly different from that in the rest of the private sector.[63] Finally, we measure sector specific dispersions $\sigma_{s,\tau}(t)$.

Average excess volatility in finance is defined as the average difference with the non farm private sector:

$$\Delta_{fin,\tau} \equiv \frac{1}{T}\sum_{t=0}^{T} \sigma_{fin,\tau}(t) - \frac{1}{T}\sum_{t=0}^{T} \sigma_{nonfarm,\tau}(t) \ .$$

This is reported in Panel C of Table 6. The excess slope of the finance wage profile $\mu^l_{fin,\tau} - \mu^l_{nonfarm,\tau}$ is estimated for relatively young workers. These are reported in Panel A of Table 6. For older workers in finance, top coding makes it impossible to use the CPS. Therefore, we calibrate the excess slope so that the predicted relative wage in finance using equation (14) (i.e. $\bar{W}_{fin}/\bar{W}_{nonfarm}$) equals the historical excess wage ratio (row 6 in Table 6), which relies on the NIPA data. For example, if we want to explain an excess wage of 41%, as in 2005, then we need an excess slope of 1.25% (row 12). The initial wage contributes $e^{0.088} = 1.09$ and the wage profile, based on estimated σ's, estimated $\mu_{1,nonfarm}$ and calibrated excess slope contributes 1.29, and the total ratio is $1.09 * 1.29 = 1.41$. As expected, the implied slopes are lower than the ones estimated for younger workers (1.25% in row 12 instead of 2.50% as in the data and row 4). The important point here is the evolutions in lines 4 and 12 – or, equivalently, lines 5 and 6 – are very similar, and that the NIPA calibration is conservative.

We now turn to the main question: Can we interpret the unexplained excess wage as rents? It is useful to organize the discussion of excess wages around three ideas: adjustment costs, long term contracts under symmetric information, and long term contracts under asymmetric information.

[62] We restrict the CPS sample to men and calculate the empirical distribution of experience, taking into account CPS sampling weights, in 1971-1980, 1981-1990 and 1991-2005. These distributions reflect aging of the population. When we include women, we find slightly more younger workers in finance relative to the rest of the private sector, and higher attrition of female employment in finance.

[63] The regressions that substantiate this are available upon request.

If there are adjustment costs for labor, then unexpected changes in labor demand lead to increases in relative wages. These rents are temporary. They dissipate when new workers move into the booming industry and bid down the wage. 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.).[64] However, one might wonder whether adjustment costs can explain such large and persistent rents given that empirical estimates suggest that these costs are not very large.[65] It is therefore useful to consider other explanations; these rely explicitly on the existence of long term contracts.

Consider now the case of long term contracts under symmetric information. This situation has been analyzed in the classic papers of Harris and Holmström (1982) and Holmström (1983). In these models, the firm is risk neutral while the worker is risk averse and has limited commitment. Firms can commit to any state-contingent wage and employment policies, while workers are always 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 also 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.

An important insight of these papers is that the steepness of the wage profile is linked to the ability of workers to quit. To the extent that skills in the financial industry are easily transferrable across firms and that deregulation has increased competition for skills, this theory can explain the increase in the steepness of the wage profile.[66] The papers also predict a trade-off between current and future wages so that agents remain indifferent among different careers. To test this hypothesis, we perform the following calculations, reported in Panel C of Table 6. We assume a utility function with constant relative risk

[64] The growth of these markets took even their inventors by surprise. See Tett (2009) for the case of credit default swaps, for instance.

[65] 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 sizable mobility costs, but find that entry (increase in supply) and capital mobility completely counteract the effect of persistent increases in demand on wages.

[66] Increased competition for skills is evident in Kostovetsky (2007), who documents that hedge funds actively seek to hire successful mutual fund managers.

aversion

$$u(c) = \frac{c^{1-\rho}}{1-\rho} \tag{15}$$

and we use $\rho = 3$. Suppose that lifetime utility in both sectors was equal, i.e. $U_{0,fin} = U_{0,nonfarm}$. Then using (15) and (13), given the observed changes in μ and σ we predict that the relative starting wage ratio should have come down by 10 percentage points, from 1.05 to 0.95 (row 14), over the past 40 years. That would be consistent with no rents and an increase in the quitting threat. However, in the data the starting wage ratio has increased by 6 percentage points from 1.03 to 1.09 (row 7). Therefore, we estimate an excess starting wage of 16%. In other words, if we assume no rents in the 1970s, we estimate rents around 16% in the 2000s.

In a standard principal agent framework, these last results suggest that the participation constraints do not bind.[67] This might be explained by the interaction of moral hazard and limited liability. With unlimited liability on the worker side, the participation constraint always binds and the calculations performed in the previous paragraph apply (i.e., a rent of 16% is left unexplained). 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 these rents.

An increase in moral hazard can also potentially explain the increase in the relative slope of earnings profiles. Although dynamic moral hazard models are complex, the following benchmark is plausible. Without moral hazard, it would be optimal to let the agent enjoy early consumption. With moral hazard, it is optimal to first pay the agent with promised utility and no consumption. In continuous time models (DeMarzo and Sannikov 2006, Philippon and Sannikov 2007), it is possible to show that when moral hazard increases, the point at which the agent start to consume is delayed further (a theoretical appendix is available upon request). Myerson (2010) also argues that bankers must earn moral-hazard rents but that these rents can be spread over the banker's entire career. Indeed, Myerson

[67]The principal seeks to maximize expected profits subject to two constraints. The participation constraint is the only one that matters in the neoclassical model. The second constraint is the incentive constraint. The latter depends on the degree of moral hazard, measured either by the degree of asymmetric information (for instance the amount of noise in the principal's signal about agent's effort) or by the temptation of the agent to cheat (private benefits from cheating, effort costs, etc.). Both make monitoring more difficult.

(2010) considers contracts that have maximal backloading of rewards in order to minimize the moral hazard rents.

We can think of two main reasons why moral hazard may have increased in the financial industry. The first is complexity. We have argued that 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. A second reason moral hazard might have increased is the shift from partnerships towards publicly traded companies in the investment banking industry. Partners have greater incentives to monitor their employees; and employees hoping to become partners have more incentives to exert effort. Partnerships are also smaller companies, which tends to make monitoring easier. Whether complexity alone or the organization of the industry are the main driving forces for an increase in moral hazard and the observed wage patterns in the data is beyond the scope of this paper.

4.4 Summary

In NIPA data in 2006 the relative wage of finance employees is 1.7 times the relative wage of workers in the rest of the private sector. In this section we summarize our account of this ratio.

We find that accounting for changes in skill intensity, returns to education and employment risk reduces the excess wage from 70% to 40%. We view this 40% as an upper bound on rents because it assumes easy borrowing and lending in capital markets.

On the other hand we compute a lower bound on rents by interpreting the data through the lens of a principal agent model, imposing that consumption equals wage income. In this case we estimate rents at 16%. Note that in this model the principal controls the consumption of the agent and the Euler equation does not hold. This strategy leads to a lower bound on rents because we probably impose more consumption risk than there actually is.

Therefore, we conclude that lifetime rents are between 16% and 40%.

5 Conclusion

While previous analyses of the financial sector have focused on financial assets, we focus on the most important input for finance: human capital. In particular, we examine the financial sector in terms of its skill composition, relative wages and complexity from 1909 to 2005, and we propose explanations for their evolution.

We document a set of new, interrelated stylized facts: the skill intensity and the complexity of jobs in the financial sector relative to the nonfarm private sector exhibit a U-shape from 1909 to 2006. Our main conclusion from the analysis of the determinants of the evolution of education and wages in the financial sector is that deregulation and corporate finance played dominant roles. We find a robust and economically significant positive effect of deregulation on skill and wages in the financial sector, both in the aggregate time series and across subsectors. Moreover, we show that the nature and timing of regulatory changes point toward a causal role for deregulation.

We also find that corporate finance activities linked to IPOs and credit risk increase the demand for skilled labor. Historical evidence on general purpose technologies allows us to claim that there is a causal impact of corporate finance on the demand for skills in the financial industry. Linking IPOs and credit risk to technological revolutions is also an interesting way to conclude our discussion of the IT revolution. We show that the direct impact of IT is limited: the use of computers by the financial industry does not explain its use of human capital. However, the *indirect* impact of IT is important: the creative destruction that IT induced in the *non financial* corporate sector, through the effect of the IPOs that follow, does increase demand for skills in finance.

Finally, we address the issue of the level of compensation in the financial industry. We document significant excess wages in finance in the deregulated period, post 1980, but not before. Furthermore, we demonstrate in a number of ways that the excess wage is not due to unobserved ability. We also document significant changes in wage profiles and wage dispersion. Taking into account these changes can change our interpretation of the data. If we assume that agents borrow and save freely, then the we conclude that finance employees receive large rents, up to 40% of lifetime earnings. If we constrain consumption to be equal to the current wage, then the rents are 16%. In this case, there is not so much a labor market puzzle as a puzzle on the incentives side. The finance wage bill could be significantly reduced if incentives were the same as in the rest of the private sector. If this view is correct, the challenge for future research is to understand why the financial 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.[68] In retrospect, it is clear that regulators did not have the human capital to keep up with the financial industry, and to understand it well enough to be able to exert effective regulation. 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).[69] Our findings therefore provide an explanation for regulatory failures.

Our results also suggest that tighter regulation is likely to lead to an outflow of human capital from the financial industry. Whether this is desirable or not depends on one's view regarding economic externalities. Baumol (1990) and Murphy, Shleifer, and Vishny (1991) argue that the flow of talented individuals into law and financial services might not be entirely desirable, because social returns might be higher in other occupations, even though private returns are not. Our results quantify the rents earned by employees in the financial industry in the late 1990s and early 2000s. Whether financiers are overpaid from the social point of view is a very difficult question to answer. Philippon (2007) studies the optimal allocation of talent in a dynamic general equilibrium model with credit constraints, career choices and industrial innovation. In that model, the financial sector can drain resources from entrepreneurial activities with positive externalities, but it can also alleviate the financial constraints facing would-be entrepreneurs. This trade-off is important in practice. Unfortunately, many critical inputs of the model are not directly observable, which makes it impossible to measure the discrepancy between private and social returns to financial jobs. More research is clearly needed in this area.

[68] 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 "Interagency Statement on Sound Practices Concerning Elevated Risk Complex Structured Finance Activities".

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

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 s according to this classification in 1950, $\alpha_{c,s}^{1950}$. 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 $\alpha_{c,s}^{1950}$ as a base to impute the share in each sector in 1910-1930 by using the distribution across occupations in each sector, $\lambda^t_{c,s}$, and then aggregating up,

$$educ_{s,t} = \sum_c \lambda^t_{c,s} \alpha^{1950}_{c,s} \ ,$$

where $t = 1910, 1920, 1930$; $\lambda^t_{c,s} = \sum_{i \in c} \omega_{i,s,t} \,/\, \sum_i \omega_{i,s,t}$ is the share of workers in occupation c in sector s 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.

(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.

The deregulation index is given by

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

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

$$task_{s,t} = \frac{\sum_{i \in s} task_i \; \lambda_{i,t} \; hrs_{i,t}}{\sum_{i \in s} \lambda_{i,t} \; hrs_{i,t}} \, ,$$

where i denotes a particular individual, t denotes the year, λ are sampling weights and hrs are annual hours. $i \in s$ means that individual i works in sector s, where $s = fin$ corresponds to the financial sector and $s = nonfarm$ corresponds to the nonfarm private sector. The generic'$task$' varies over all five tasks described above.

Unfortunately, it is not possible to calculate hrs 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 $hrs = 1$ for all individuals. The underlying data that is used to calculate hrs 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, Census Bureau 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, Census Bureau 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.

Definition of unemployment

Here we give the exact definition of our unemployment indicator. A person would get a positive indication of unemployment if:

1. did not work last year 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 was looking for work.
3. in survey years 1968-1993 did not work last week due to being laid-off.
4. in survey years 1994-2006 reported being on layoff or looking for work.
5. in survey years 1968-1988 reported reason for working part year was looking for work or being unemployed.
6. reported positive number of weeks looking for work last year.
7. reported positive number of weeks being unemployed last year.

Since the sample for our transition regressions includes only people that were not unemployed in the first year they were surveyed, this eventually reduces our sample.

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 $\left(\sum_{i\le j}\lambda_i\right) / \left(\sum_i \lambda_i\right) = 0.5$, 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 Unemployment risk calibration

Based on the evidence presented so far, we can propose a first interpretation of the data. Regarding the level of compensation, a constant compensating differential appears to be required, since even in the more recent years, the unemployment risk in the finance industry is not higher than in the rest of the economy. It has merely converged to the same level. The increase in the relative unemployment risk in the financial sector can however account for some of the increase in relative wages. Ruhm (1991) finds that layoffs lead to temporary unemployment and long lasting decreases in earnings: "Displaced workers were out of work eight weeks more than their observably similar counterparts in the year of the separation, four additional weeks in period $t+1$, and two extra weeks at $t+2$. By year $t+3$ they were jobless only 1.5 weeks more than the peer group, and the $t+4$ increase was just six days." By contrast, "almost none of the $t+1$ wage reduction dissipated with time. The earnings gap remained at 13.8 percent and 13.7 percent, respectively, in years $t+3$ and $t+4$."

A complete study of the effects of unemployment risk on the level of compensation that is needed to keep workers indifferent between different jobs is clearly beyond the scope of this paper. Nonetheless, we think it is useful to provide some simple benchmark calculations. We do so in the simplest framework possible and we assume that labor income is the only source of risk and that the utility function has constant relative risk aversion. We set the personal discount rate and the market rate both equal to 3% per year. We assume that workers live and work for 40 years, and that the labor income process, y_t, is given by

$$y_{t+1} = \left\{ \begin{array}{c} 1.02\ y_t \text{ with probability } 1-p \\ 0.9\ y_t \text{ with probability } p \end{array} \right\}, \text{ and } y_1 \text{ given.}$$

The increase of 2% captures the normal increase in real labor income. The drop by 10% captures the income loss from displacement documented by (Ruhm 1991). This process implies that shocks are permanent, which makes the effect of unemployment risk more important, so we are likely to obtain an upper bound for the impact on the relative wages.

We perform the following experiment. First, we set $p = 4.41\%$ and $y_1 = 1$, we solve and simulate the model with a coefficient of relative risk aversion equals to 2. We then increase the unemployment risk to $p = 6.91\%$. This increase of 2.5 points corresponds to the increase in relative unemployment risk that we have documented earlier. In order to keep workers indifferent, the new starting wage should be $y_1 = 1.063$, an increase of 6%. If we lower the calibrated risk aversion to 1, the required increase in wages is 6%. If we increase risk aversion to 3, the required increase in wages is 6.6%.

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Table 1: Decomposition of Increase in Relative Wage of Finance by Industry: 1933-2005, Industry Accounts

	Wages (within)			Employment (between)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Change in Relative Wage	Average Employment Share	Within (=1*2)	Change in Employment Share	Average Relative Wage	Between (=4*5)
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
			-0.574			0.002
				-0.571		
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
			-0.044			-0.003
				-0.047		
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
			0.592			0.056
				0.648		

Notes: 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, B and 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.

Table 2: Decomposition of Increase in Relative Wage of Finance: 1980-2005, CPS

	Wages (within)			Employment (between)		
	(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. Industries						
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
			0.313			0.117
			0.430			
B. 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
			0.152			0.278
			0.430			
C. Occupations						
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
			0.126			0.304
			0.430			

Notes: 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 A decomposes the increase by occupations, Panel B decomposes the increase by industries and Panel 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: Education and Wages in Historical Perspective

Dependent variable:	Relative Education			Relative Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Deregulation Index (t-5)	0.0215***	0.0194***	0.0177***	0.183***	0.174***	0.113***
	(0.00174)	(0.00228)	(0.00235)	(0.0140)	(0.0152)	(0.0189)
Financial Patents over Total Patents (t-5)		4.713**	4.204*		21.02	19.30
		(2.119)	(2.370)		(17.11)	(17.75)
IPO share of market capitalization (t-5)			0.00235			0.0896***
			(0.00168)			(0.0183)
Default rate (all american corporates) (t-5)			0.00168			0.0327**
			(0.00128)			(0.0154)
Time trend	0.000303***	-0.000177	-0.000180	0.00109	-0.00100	-0.00309
	(0.000073)	(0.000243)	(0.000268)	(0.000879)	(0.00182)	(0.00193)
Sample	1910-2005	1910-2005	1910-2005	1909-2006	1909-2006	1909-2006
Observations	96	96	96	98	98	98
R-squared	0.893	0.906	0.914	0.832	0.835	0.914

Notes. Newey-West Standard errors with 10 lags of autocorrelation in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Education and Wages in a Panel of Financial Sub-sectors

Dependent variable:	Relative Education	Relative Wage
	(1)	(2)
Deregulation Index (t-5)	0.0206***	0.267***
	(0.00280)	(0.0991)
Share of IT in Capital Stock of Subsector (t-5)	0.252***	1.522
	(0.0388)	(1.374)
Subsector fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Sample	1951-2005	1951-2006
Observations	165	168
R-squared	0.792	0.476
Number of sectors	3	3

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Financial subsectors: Credit Intermediation, Insurance and Other Finance.

Table 5: 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	-0.022	0.023	0.009	-0.033*	0.076***	0.062***	0.038***	0.065***
	(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	-0.161*	0.236***	0.173***	0.095***	0.161***
B. Drop swutchers 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

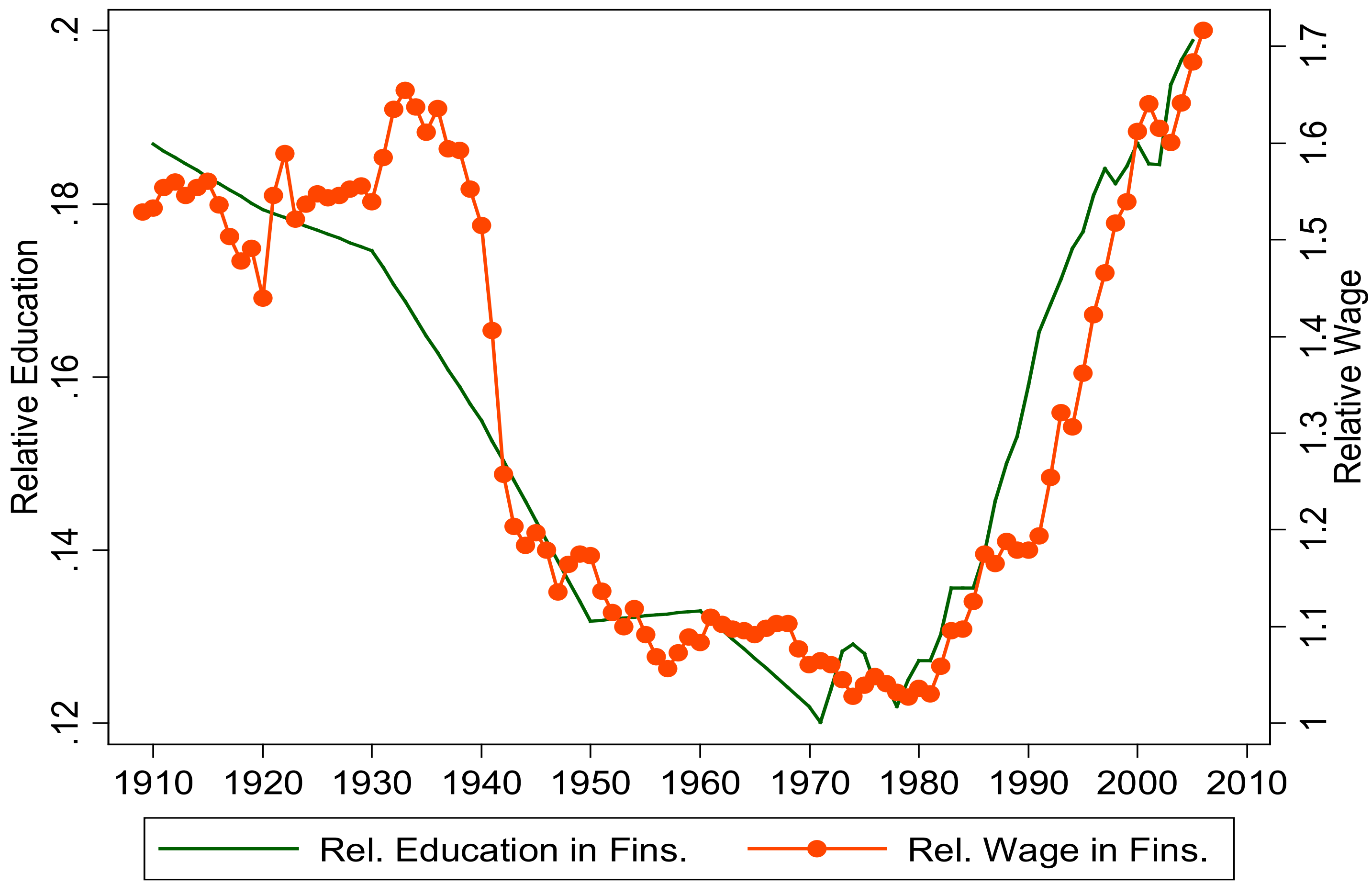
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All regressions include individual fixed effects and within-sample year effects, a constant, indicators for urban dwellings and marital status, experience and its square. We do not include indicators for other demographics - e.g., 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 6: Earnings Profiles

		1971-1980	1981-1990	1991-2005
A. Estimated Wage Profiles				
(1)	Common quadratic trend	-0.16%	-0.13%	-0.12%
(2)	Private sector slope	6.14%	5.59%	5.23%
(3)	Finance dummy	3.04%	8.07%	8.80%
(4)	Excess finance slope for men with experience≤5	-0.57%	0.10%	2.50%
(5)	Finance slope (=2+4)	5.57%	5.69%	7.73%
(6)	Finance slope calibrated to match mean wage ratio	5.89%	5.59%	6.48%
B. Wage Ratios of Finance versus Nonfarm Private Sector				
(7)	Ratio of initial wage (=exp{finance dummy} from 3)	1.03	1.08	1.09
(8)	Ratio of NPV of wage profile	0.98	1.03	1.25
(9)	Ratio of NPV of total wage profile (=6*7)	1.01	1.11	1.37
(10)	Ratio of mean wage profile	0.98	1.03	1.29
(11)	Ratio of total mean wage profile (=6*9)	1.01	1.12	1.41
C. Wage Profiles with No Rents				
(12)	Excess slope	-0.25%	0.00%	1.25%
(13)	Average excess volatility	3.11%	5.19%	8.26%
(14)	Implied initial wage ratio (utility based)	1.05	1.04	0.95
(15)	Implied wage bill ratio (utility based)	1.02	1.07	1.23

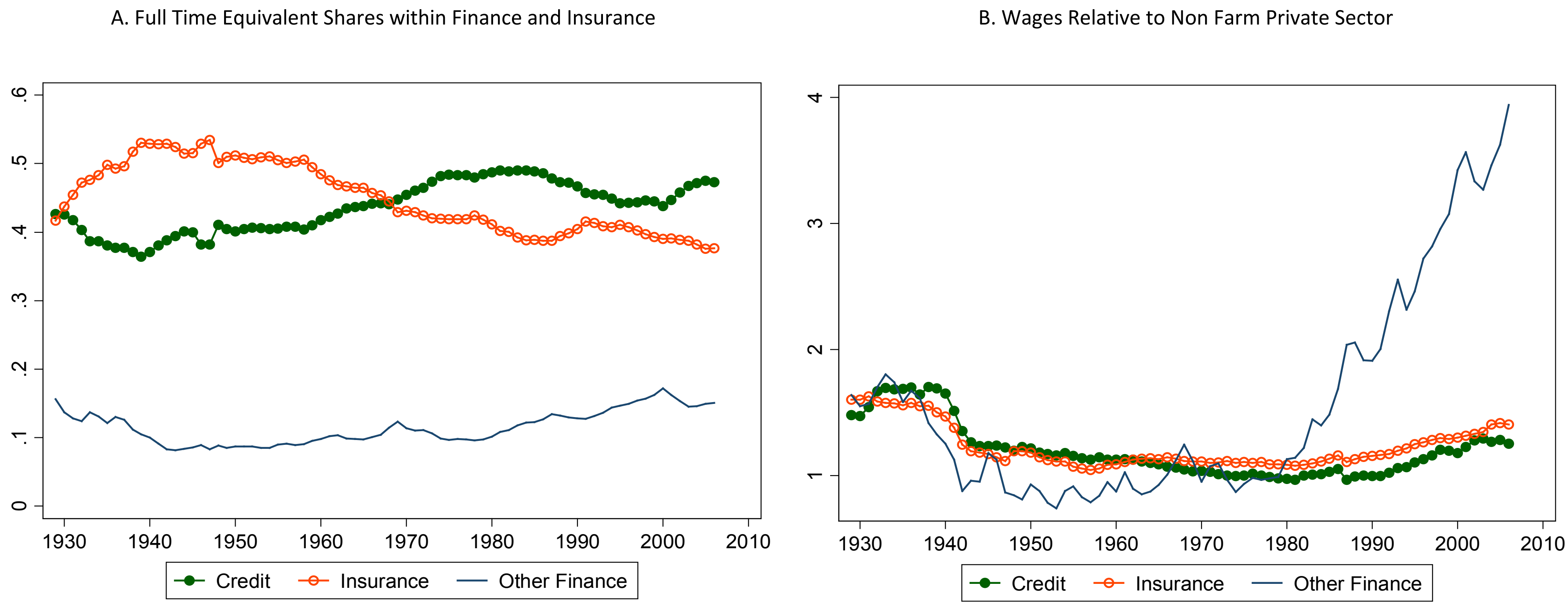
Notes: (1) and (2) are estimated from a regression of log wages on a quadratic in experience, education indicators and indicators for gender, race, urban dwellings and marital status, for all male workers. (3) and (4) are estimated from a regression of log wages on experience with different linear slopes in finance and in the rest of the private sector, as well as the demographic indicators mentioned above, for male works with less than 5 years of experience. (6) The calibrated finance slope 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. (7) The initial wage is the wage at zero years of experience. (8) is the ratio of the NPV of the estimated wage profile in finance to that of the private sector, assuming equal initial wages. (9) is the ratio of the NPV of the estimated wage profile in finance to that of the private sector taking into account different initial wages, and is also the product of the initial wage ratio and the profile wage ratio. To compute the NPV we use 3% annual discounting. (10) is the ratio of the estimated average wage in finance to that of the private sector, assuming equal initial wages. (11) is the ratio of the estimated average wage in finance to that of the private sector taking into account different initial wages, and is also the product of the initial wage ratio and the average ratio. (12) is the excess slope in finance that is implied by (6). (13) is estimated from the standard deviation of residuals from wage regressions as in (1) and (2), separately for finance and for the private sector. (14) is the initial wage that makes workers indifferent between working in finance and in the rest of the private sector, given the excess slope and volatility in (12) and (13) and constant relative risk aversion of 3. (15) is the wage bill ratio that is implied by the excess slope and volatility in (12) and (13).

Figure 1: Relative Wage and Education in the Financial Industry



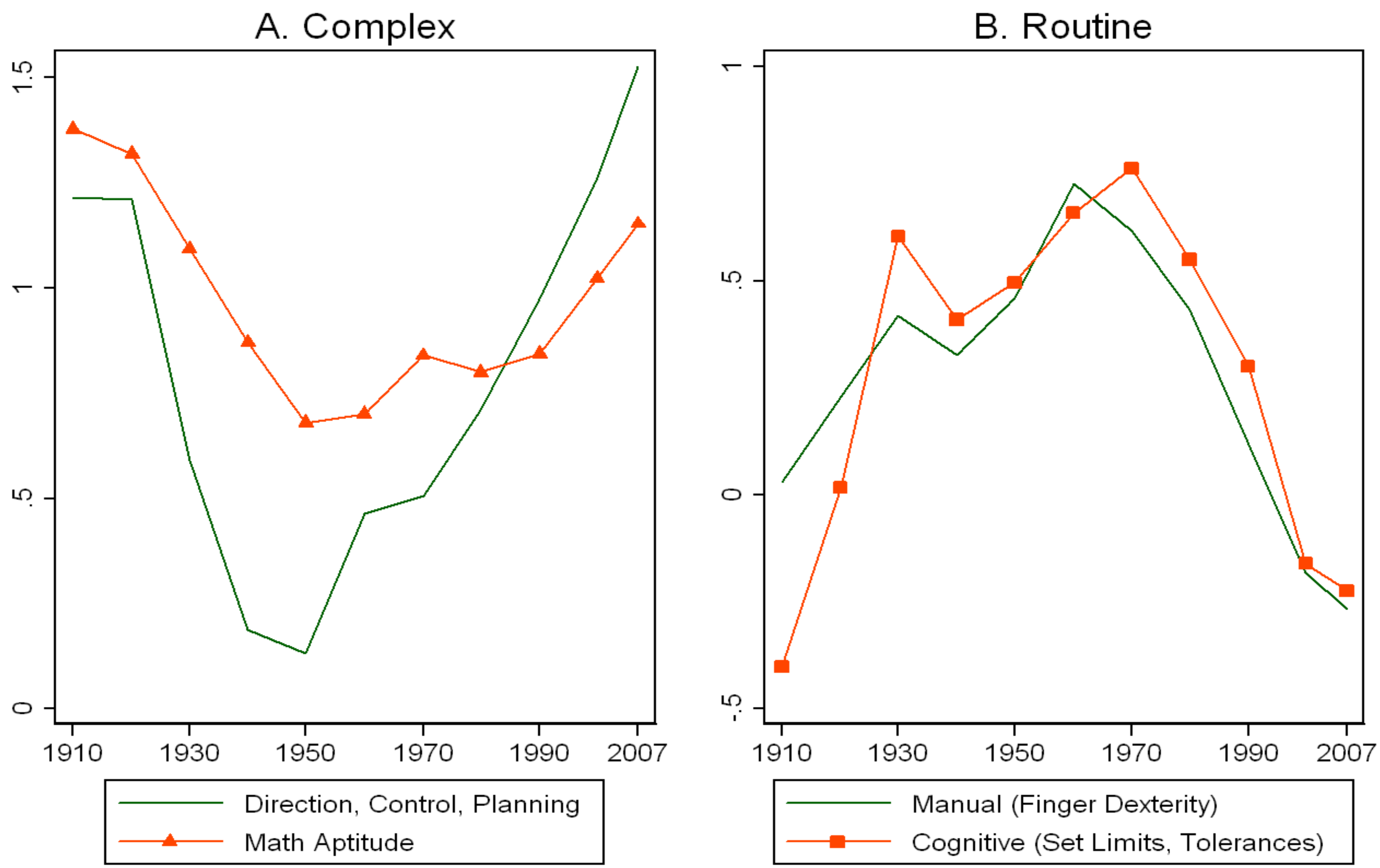
Notes: Fins. includes finance and insurance. Our concept of education is the share of employees with (strictly) more than high school education. Education (1910-2005) is computed from U.S. Census data, and from the Current Population Survey. In 1910-1930 education is imputed by using educational shares 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: Employment Shares and Relative Wages of Financial Subsectors (1929-2006)



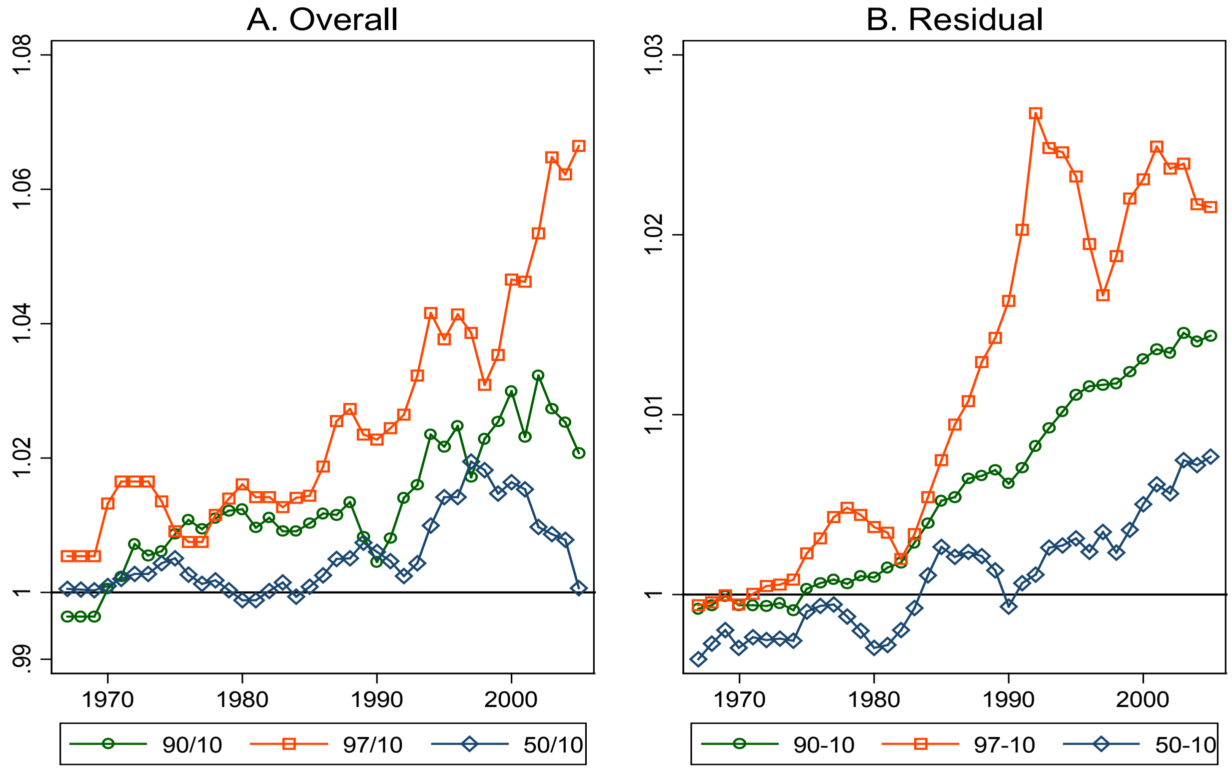
Notes: Ratio of average wage per full time equivalent in the sector to average wage in the non farm private sector. Source: Author's calculations based on the Annual Industry Accounts of the United States.

Figure 3: Relative Job Complexity in the Financial Sector



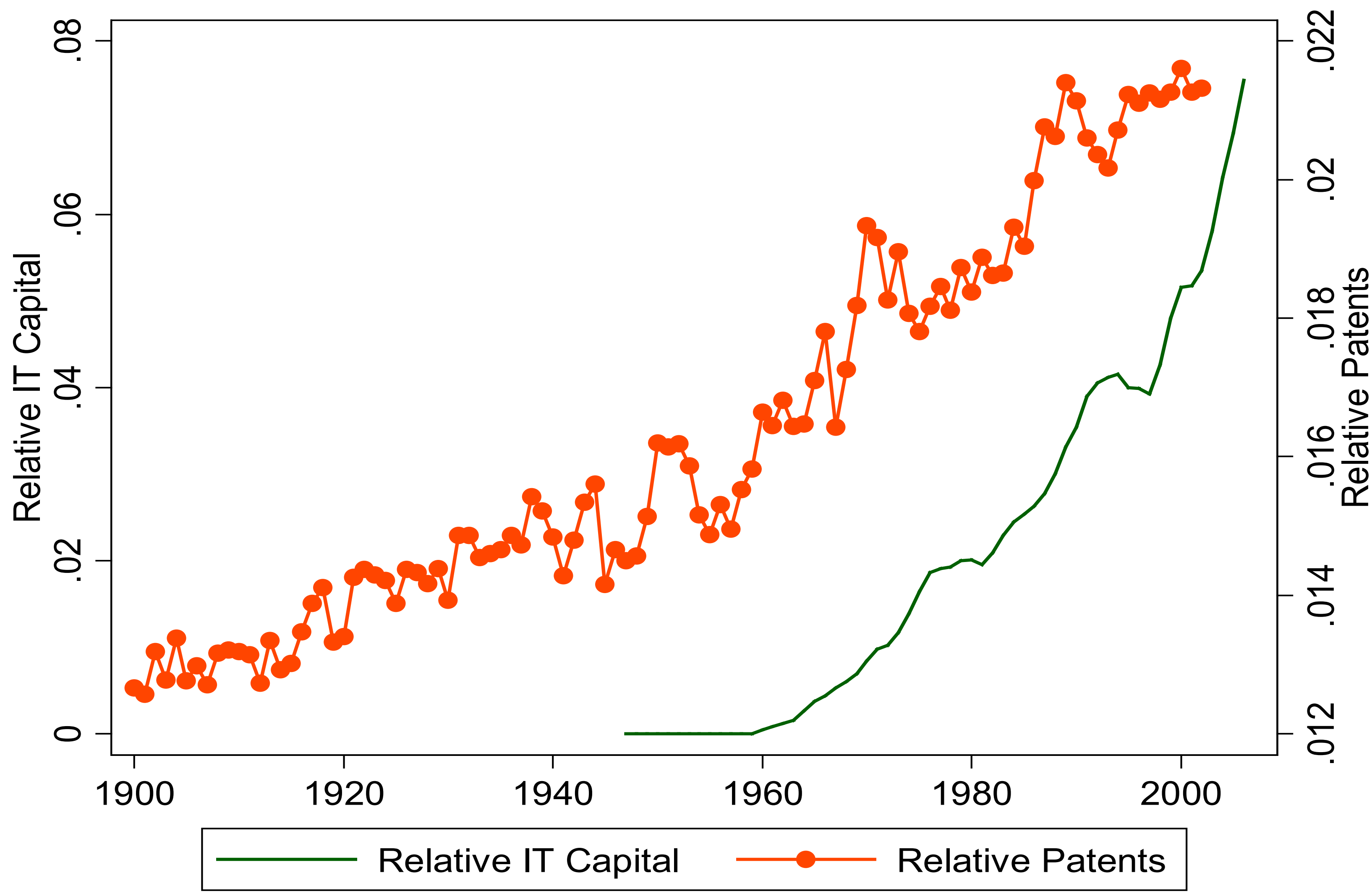
Notes: Relative task indices for finance versus the nonfarm private sector. Data: Dictionary of Occupational Titles, U.S. Censuses 1910-2000 and 2008 March CPS.

Figure 4: Contribution of Finance to Inequality



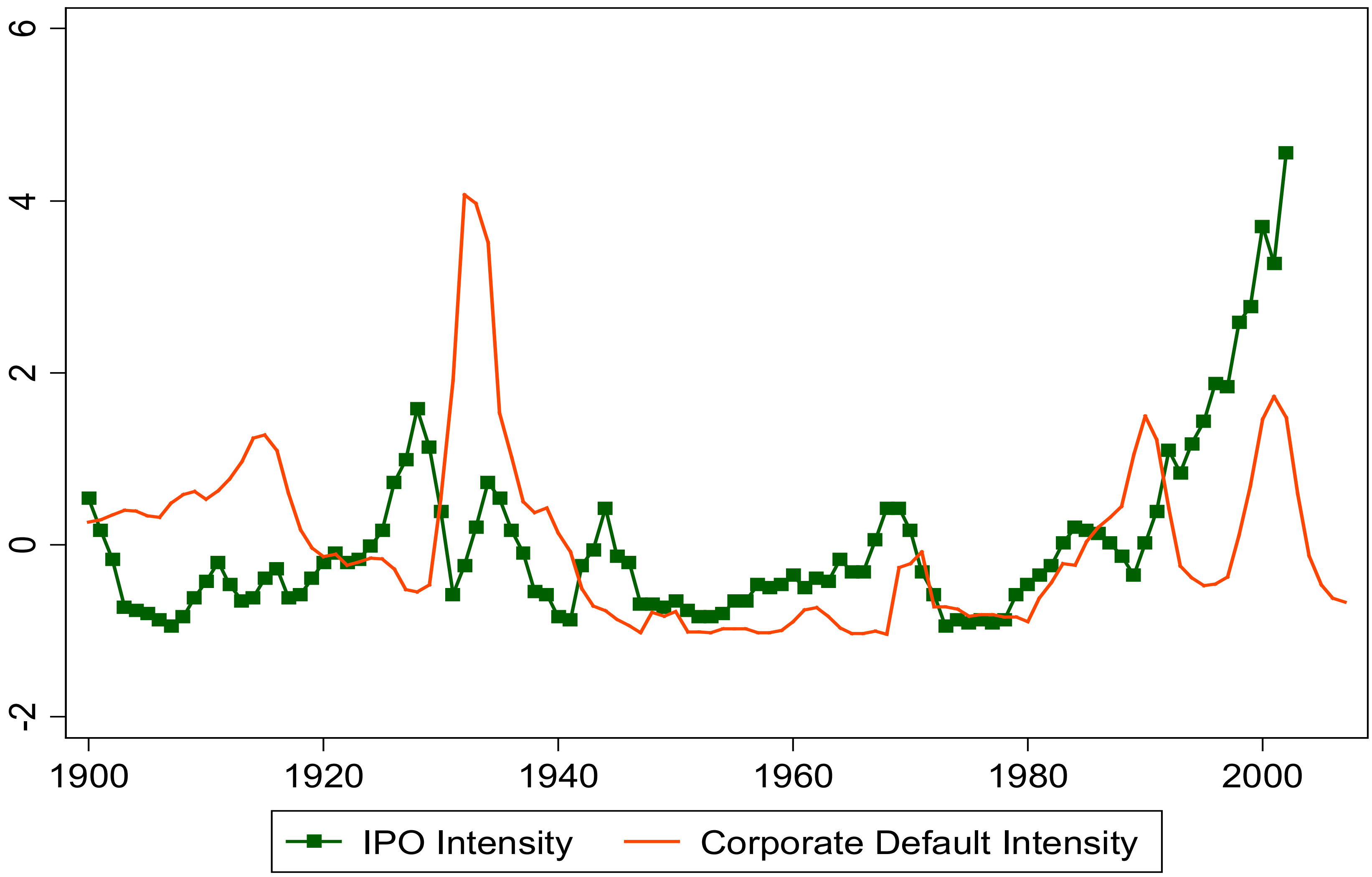
Notes: Both panels present inequality measures as they were computed form the data, relative to the same measures that were computed from a sample in which wages in finance were simulated. Numbers above one indicate that inequality would have been lower in the simulated sample. The underlying data for 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 5: IT Capital and Financial Patents



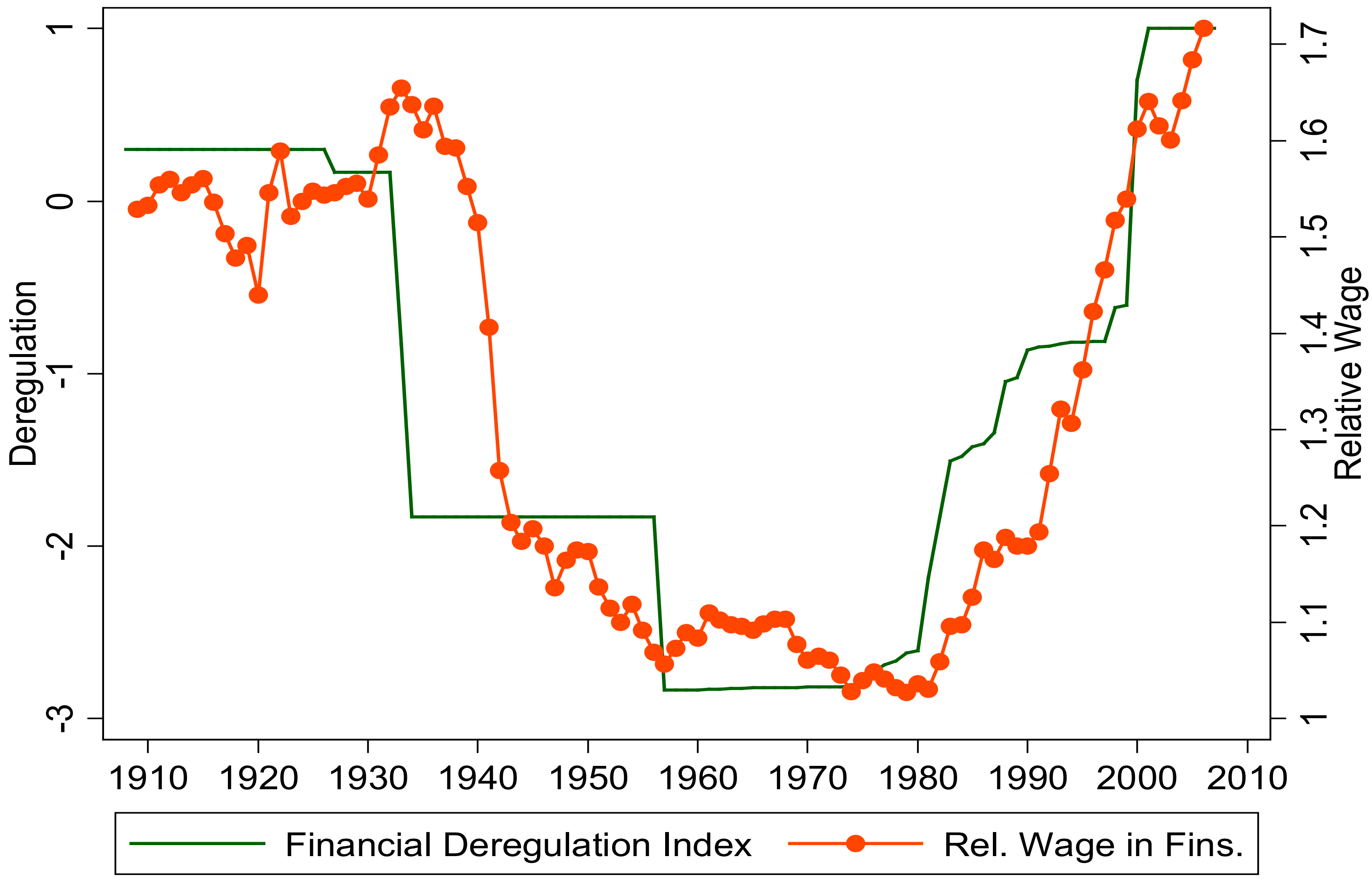
Notes: Relative IT intensity is the IT share of capital in finance minus the IT share of capital in the economy. Relative patents is the ratio of financial patents to all patents.

Figure 6: Non Financial Corporate Activities



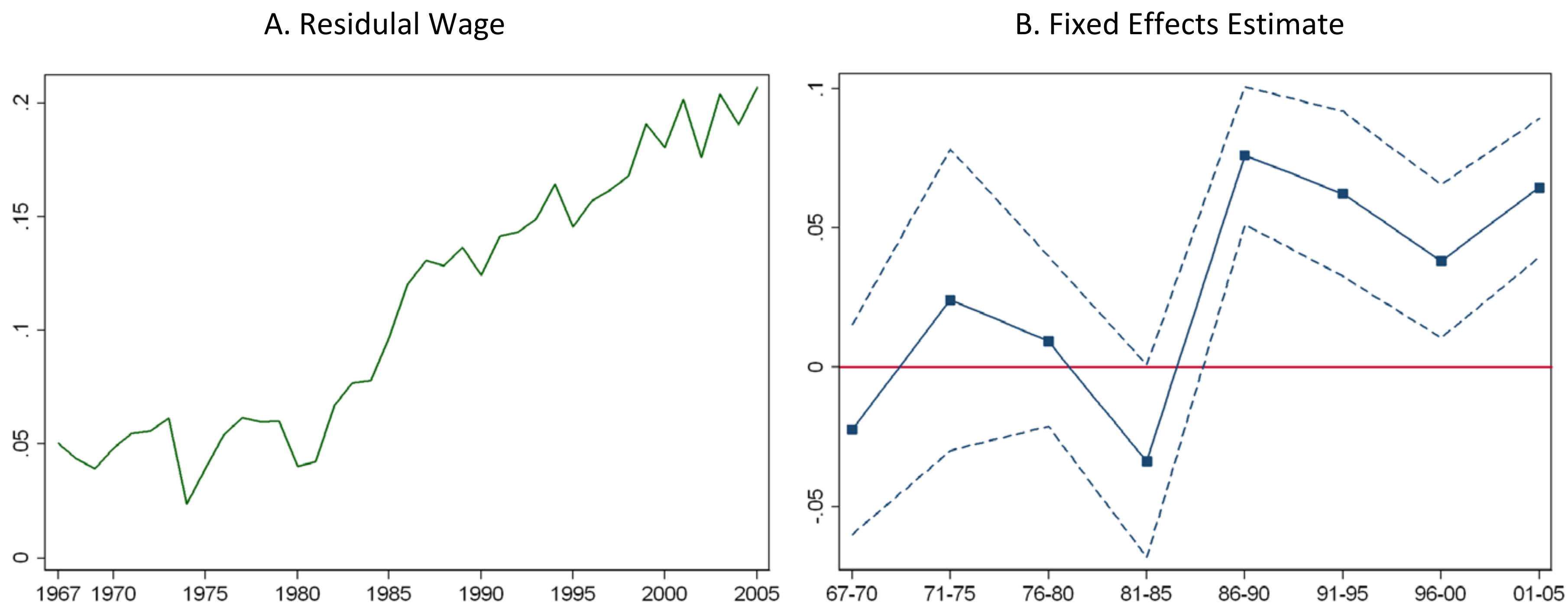
Notes: IPO is IPO value over Market Capitalization. Defaults is the 3-year moving average default rate on all corporations. Both series are normalized (mean 0, std dev 1) over the sample. Data from Jovanovic and Rousseau (2005).

Figure 7: Relative Financial Wage and Financial Deregulation



Notes: Wages are computed from the Industry Accounts of the U.S., from Kuznets (1941), and from Martin (1939). The relative wage is the ratio of Fins to Non Farm Private wages. See the text for the definition of the deregulation index.

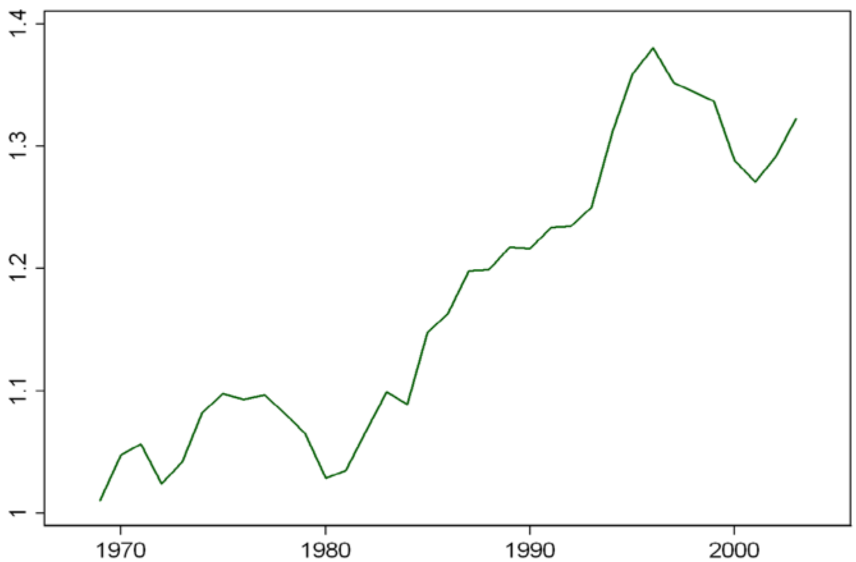
Figure 8: Financial Sector Wage Premium, 1967-2005



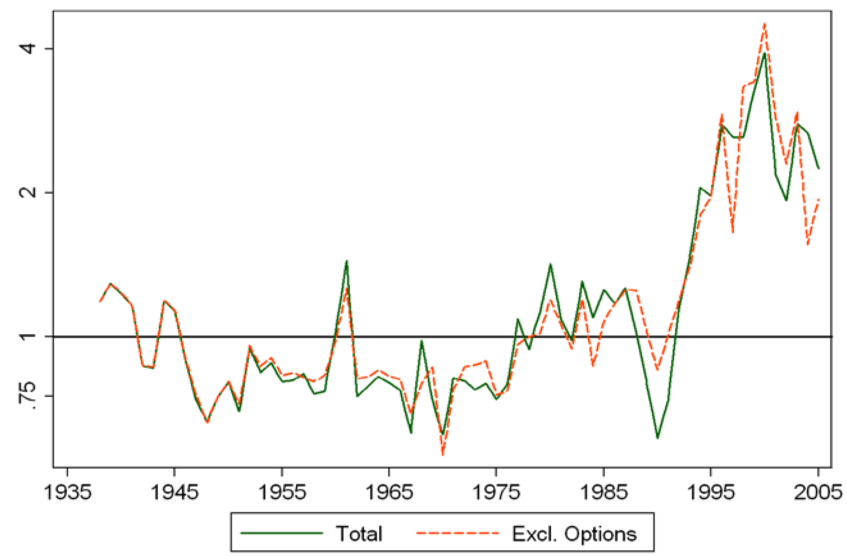
Notes: Panel A plots the coefficient of the finance dummy from OLS regressions of log hourly wages on race, sex, marital status, urban residence, potential experience and its square, as well as education controls. Panel B plots the coefficient of finance dummy from fixed effects regressions of log hourly wages on marital status, urban residence, potential experience and its square; dashed lines are 95% confidence intervals. Data: March CPS and Matched CPS.

Figure 9: Relative Wages of Higly Skilled Individuals

A: Financiers versus Engineers



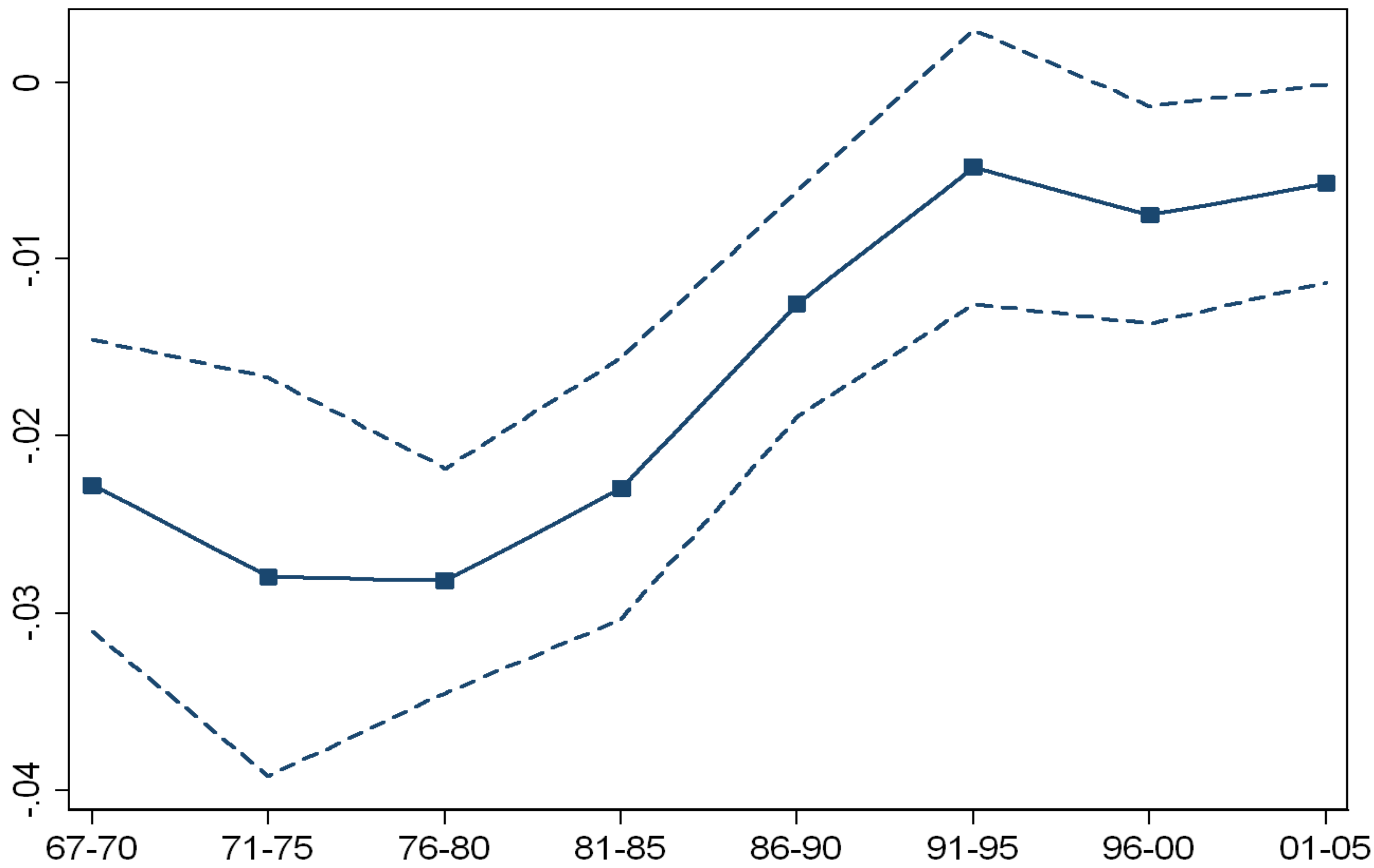
B: Executives in Finance versus the Private Sector



Notes: The figure 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.

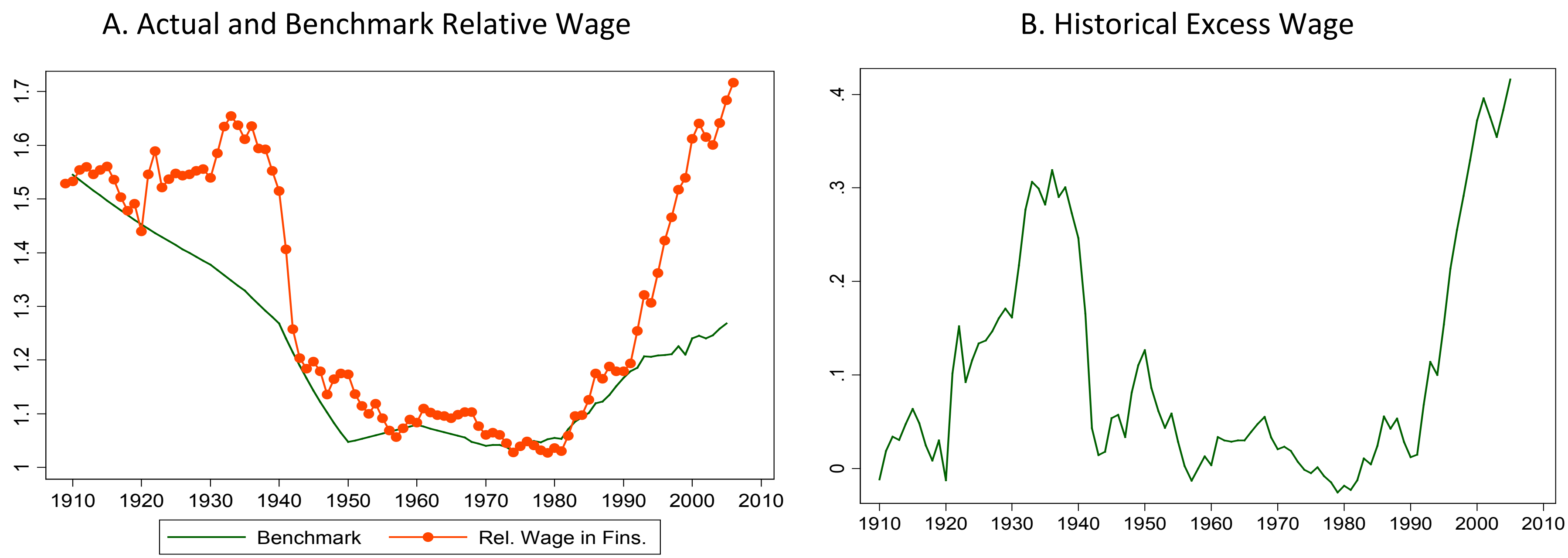
Notes: The figure presents median executive compensation in finance relative to median executive compensation in the rest of the nonfarm private sector. The vertical axis log scale. The sample is the top three executives in each of 50 of the largest publicly traded firms that operated in the U.S. in 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.

Figure 10: Unemployment Risk in Financial Sector Relative to the Private Sector



Notes: Coefficients and 95% confidence intervals of Finance dummy in logit regression of transition from Employment to Unemployment. Controls include current log hourly wage, race, sex, marital status, urban residence, potential experience and its square and education controls. Data: March CPS.

Figure 11: Benchmark Relative Wage Ajusted for Employment Risk and Time Varying Skill Premium



Notes: 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). The benchmark series is then adjusted for changes in employment risk (Figure 10) using a simple permanent income model. See text for the calculation of the adjustment and the assumed parameters of the utility function and the income process. Excess wage is the difference between the actual and benchmark wage series.