Wages and Human Capital in Finance: International Evidence, 1970–2005*

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Abstract

We study the allocation and compensation of human capital in the finance industry in a set of developed economies in 1970–2005. Finance *relative* skill intensity and skilled wages generally increase—but not in all countries, and to varying degrees. These changes explain 36% of the average increase in overall skill premium. Financial deregulation, financial globalization and bank concentration are the most important factors driving these patterns. Differential investment in information and communication technology does not have robust or causal explanatory power. We show that high finance wages attract skilled immigration to finance, raising concerns for "brain drain".

JEL classifications: G2, J2, J3.

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High wages in finance have recieved significant attention following the 2007–2009 financial crisis, both in the United States and Europe. The crisis sparked a growing interest in understanding what explains high wages in finance, due to the perceived centrality of finance as the cause, catalyst or propagator of the current economic downturn. There are three main reasons for this. First, the persistence of high wages in finance even after the crisis begs the question whether social returns are dwarfed by private returns to workers in finance. To the extent that high wages in finance reflect short-term high power incentives, these incentives may not be aligned with long-term social returns. Second, socially inefficient high wages in finance may draw talent from other more productive sectors of the economy. Third, high wages in finance contribute significantly to overall inequality.

We start by documenting a set of facts about wages and skill intensity in the financial sector relative to the rest of the nonfarm private sector in a set of 22 industrialized and transition economies in 1970–2005. We then investigate five potential explanations for the rise in relative wages and relative skill intensity in finance: Technology, financial globalization, expansion of domestic credit, financial deregulation, and industry concentration. Finally, in an attempt to identify allocation effects, we ask whether high wages in finance attract skilled workers across international borders.

The first fact that we document is that there is significant heterogeneity in the trends of relative wages in finance: Half of the countries see increases, while the remainder are split between decreases and mixed trends. Second, we find that these trends are not explained by broad changes in skill composition; within-group relative wage changes in finance explain almost all of the variation in finance relative wages, in particular, relative skilled wages in finance. A benchmark wage series based on observed changes in skill composition and time-varying returns to skill does not track well the finance relative wage, both in levels and changes over time. As a result, the evolution of finance excess wages, defined as the difference between the finance relative wage and the benchmark series, is very similar to the evolution of relative wages in finance.[1] Third, about half of the countries in the sample exhibit increasing relative skill intensity in finance. However, the pattern of increases and their magnitudes are not commensurate with changes in relative wages in finance, which is consistent with the second finding. Fourth, we show that finance can explain a large part of changes in overall skill premium across countries in our sample.

We find that deregulation is the most important driver for wages and relative skill intensity in finance in our sample. In particular, deregulation of international capital flows, i.e. *de jure* financial globalization, has a robust, positive and *causal* effect on relative wages in finance across all regression specifications that we entertain, and its impact is economically large. For example,

[1] Célérier and Vallée (2013) estimate that the finance wage premium in France is driven by higher private returns to talent in finance. This shows up in our data as high skilled finance relative wages.

when restrictions on international capital flows are removed (to the extent that they were in, say, Australia, Belgium and the Netherlands), the relative wage in finance increases by 0.27 and the relative skilled wage in finance increases by 0.3. This is compared to average increases of 0.13 and 0.08 in the sample, respectively. Thus, using panel data for several countries we are better able to identify the forces highlighted in Philippon and Reshef (2012) for the U.S. alone.[2]

The regulatory and competitive environment affects the optimal organization of firms. Tight financial regulation in certain dimensions inhibit the ability of the financial sector to take advantage of highly skilled individuals because of rules and restrictions on the ways firms organize their activities, thus lowering demand for skill in finance (Philippon and Reshef (2012)). Therefore, deregulation may increase relative demand for skill and relative wages in finance. Indeed, Guadalupe (2007) provides evidence that competition in the product space increases demand for skill. And there is evidence that organizational change can be skill-biased.[3] In contrast, we find that lower barriers to entry, another form of deregulation, lowers demand for skill and wages in finance.

We also find that *de facto* financial globalization and demand for domestic credit—in particular non-bank credit—are related to skill intensity and relative wages in finance—in particular skilled wages. Serving investors from abroad and managing investments overseas require specific skills. If supply of such skills is not perfectly elastic, then a more globalized financial system will drive up wages of those who possess these skills. Similarly, when demand for credit is high, it may be necessary to employ more highly skilled workers to screen potential borrowers and then to monitor them. Monitoring may require efficiency wages in order to avoid the threat of moral hazard. We find that both *de jure* and *de facto* measures of financial globalization (the main drivers of wages and skill intensity in finance) have much stronger effects within Anglo-Saxon countries.

Information and communication technology (ICT) may drive demand for skill because, as we document, finance increased its relative intensity of ICT and, as we estimate, ICT is relatively more complementary to skill in finance. Autor, Levy, and Murnane (2002) document how computerization affects demand for labor and job complexity in two large banks.[4] In the presence of unobserved heterogeneity in the ability to exploit ICT, relative ICT intensity can help explain within-group changes in relative wages in finance, as Célérier and Vallée (2013) also conjecture.

[2] Using micro data for the U.S., U.K., Germany and France, and controlling for observables, Wurgler (2009) finds similar trends to our excess wage series for these countries. Wurgler (2009) also argues that financial deregulation may help explain the different experiences of the U.S. and the U.K. on one hand, versus Germany and France on the other hand—but he does not estimate this, nor does he test alternative hypotheses.

[3] See Bresnahan and Trajtenberg (1995), Bresnahan, Brynjolfsson, and Hitt (2002), and Caroli and Van Reenen (2001).

[4] Autor, Levy, and Murnane (2002) focus on digital imaging technology. A more recent technology in banking is internet-based services, that can replace low and medium-skilled employees, and leverage the skills of highly skilled employees who design these services.

We find that the increase in relative ICT intensity in finance is positively correlated with relative demand for skill and with skilled wages in finance, but this relationship is not stable nor is it causal. The relationship vanishes when we estimate regressions that allows for nonlinear effects of deregulation, when we estimate predictive regressions, and when we use IV methodology (although these hardly affect the relationships for *de jure* and *de facto* financial globalization). These results suggest that the *differential* investment in ICT in finance relative to the rest of the private sector is itself driven by deregulation or other forces.

Morrison and Wilhelm (2004) and Morrison and Wilhelm (2008) argue that investment in ICT affected the optimal organization of investment banks in the U.S.: Codification of activities reduced the incentives for accumulation of tacit human capital through mentorship, which led to change from partnerships to joint stock companies. This change would also lead to higher wage compensation versus illiquid partnership stakes that are "cashed in" only upon retirement. While this argument is germane only to American investment banks—while we study 22 countries—our results are not inconsistent with it: Deregulation or other forces are the impetuses for investment in ICT and reorganization in finance.

One shortcoming of the results discussed above is that they are based on a sample that ends in the late 1990s, because variation in the regulation variables all but dies out in the mid 1990s.[5] For the latter part of the sample we fit similar regressions, replacing regulatory variables with another measure of financial market structure. Specifically, we use bank asset concentration data from the World Bank, which is available from 1997 onward. Less competition in banking contributes to abnormal profits and rents, and this can drive up finance wages if profits and rents are shared with workers, for example as in Akerlof and Yellen (1990)—but this should not affect skill intensity. The results support this idea, and the estimates are economically large. We also find that financial globalization is important in explaining relative skill intensity in finance in the later period. Overall, these results are in line with those from the earlier period, in the following sense: market structure (regulation and bank concentration) drive wages, while other demand shifters are more important for explaining relative demand for skill.

One concern about high wages in finance is that they attract skilled workers from other parts of the economy, where they may be more productive socially. Addressing the distinction between social and private returns is beyond the scope of this paper. However, if competition for talent is fierce, the same forces may manifest themselves across international borders. Here, it is plausible that attracting skilled workers from other countries has detrimental effects on the country of origin.

[5] We use data on financial reforms from the Abiad, Detragiache, and Tressel (2008) dataset, which is explained in detail in Section 3.1

We examine whether high wages in finance attract skilled workers across international borders. To examine this hypothesis we use bilateral immigration data in a sample of 15 industrialized countries, where immigrants in each destination are differentiated by level of education and industry. We fit regression models that resemble gravity equations from the international trade literature (e.g., Ortega and Peri (2012)), and find that high wages in finance do attract skilled workers across borders. This effect is not present for unskilled workers or for skilled workers in other sectors of the economy. This raises concerns that high wages in finance cause brain drain.

Our work contributes to several strands of literature. First, it is related to the—mostly theoretical—literature that tries to explain high wages in finance. The equilibrium theory in Axelson and Bond (forthcoming) shows an association between the threat of moral hazard and high wages in finance, whereas Bolton, Santos, and Scheinkman (2011) present a model showing that high wages for traders in the "over the counter" markets is due to informational rents in these markets. Some of our results are in line with the importance of moral hazard, although we are not able to test this directly. Our results are most consistent with Korinek and Kreamer (2013) who present a model in which financial deregulation increases efficiency in the financial sector (due to ability to take on more risk) at the expense of the real economy (due to instability of credit). They show that bank concentration and availability of new types of financial activities lead to greater risk-taking by the financial sector and allocate higher surplus to this sector at the expense of the rest of the economy. Our results support these predictions.

The closest paper to ours is Philippon and Reshef (2012) that documents the fall and rise of relative wages and human capital in the U.S. finance industry and argues that financial regulation and deregulation is the main driving force of this pattern. Our results are consistent with this, to which we add the following contributions. First, we document significant heterogeneity in the evolution of relative wages and skill intensity in finance across these countries. Second, we use IV regressions to identify the causal impact of deregulation and technology in driving wages and skill intensity in finance. Third, we investigate the impact of high wages in finance on absorbing talent from other countries. Our paper has two shortcomings compared to Philippon and Reshef (2012). One is that our sample is shorter. The second is that the consistency of the regulation variables across countries may neglect country-specific features of legislation.

Focusing on human capital sheds light on the organization of the financial sector. Financial development has an important role in explaining economic development in broad cross sections of countries (e.g., Rousseau and Sylla (2003) and Levine (2005)). Therefore, understanding how it functions is important for understanding how finance performs its role and contributes to society, in terms of higher income and faster growth. However, it is important to distinguish between human capital and wages within finance, and its overall size. The growth of finance and its internal organization are not the same phenomena, and follow different—although probably not independent—paths.[6]

We also contribute to the literature on the allocation of talent. Both Baumol (1990) and Murphy, Shleifer, and Vishny (1991) stress the importance of allocating the most talented individuals in society to socially productive activities. Policies and institutions that can readily influence this allocation can be much more important for welfare than the overall supply of talent. Indeed, we find that regulation is the most important determinant of wages in finance. In line with this, Goldin and Katz (2008b) document a large increase the number of Harvard undergraduates who choose a career in finance since 1970, as well as an increasing wage premium that they are paid relative to their piers. Wurgler (2009) and Cahuc and Challe (2012) argue that the existence of financial bubbles can attract skilled workers to finance, and Oyer (2008) shows that during financial booms more Stanford MBAs are indeed attracted to finance. Kneer (2013a) and Kneer (2013b) argue that financial deregulation is detrimental to other skill intensive sectors, while Cecchetti and Kharroubi (2013) argue that credit growth hurts disproportionately R&D-intensive manufacturing industries. Although direct evidence is not provided, these authors interpret their findings as indicating a brain-drain from the real economy into finance. Here we provide direct evidence that internationally, high wages in finance attract highly educated individuals.

Finally, our work contributes to the understanding of demand for skill and income inequality. The overall rise in relative demand for more educated workers in developed countries, as well as the increase in their relative wages, is well documented, e.g. Machin and Van Reenen (1998). Berman, Bound, and Machin (1998) attribute this to skill-biased technological change. Autor, Katz, and Krueger (1998) and Autor, Levy, and Murnane (2003) discuss the role of computers in driving this shift in relative demand. Acemoglu and Autor (2011) highlight these and other forces that may affect relative demand, in particular globalization and offshoring. We argue that financial deregulation affects the bias in technological change through its effect on investment incentives and demand for ICT in finance.[7]

[6] For example, juxtaposing the findings in Philippon and Reshef (2012) with Philippon and Reshef (2013), we see that in the U.S., finance grows continuously from 1945 and on, but that growth is not always skill biased. In 1945–1980 finance hires more workers with the same skill composition as the rest of the economy. In 1980–1995 growth of finance comes with disproportionately highly skilled workers, but these workers are paid competitive wages. Only after 1995 we observe growth, skill bias, and excess wages together. We do not ask whether there is "too much finance", *cf.* Arcand, Berkes, and Panizza (2012), Cecchetti and Kharroubi (2012), and Beck, Degryse, and Kneer (2012). Philippon and Reshef (2013) show that the rise of the size of finance is not correlated with growth in a set of currenlty industrial countries. In addition, the relationship of finance to income is not straightforward. The evolution of wealth in Piketty (2014) may have a direct effect on the total payments to finance—not on the wage rate per worker nor on organization within finance.

[7] See Acemoglu (2002b) for a review of the early literature on skill biased technological change. Acemoglu and

In the next section we document a set of fact about wages and skill intensity in finance. In section 2 we entertain explanations for the rise in demand for skill and wages in finance. In Section 3 we show how high wages in finance attract skilled workers across borders (skilled immigration). In Section 4 we offer concluding remarks.

1 The facts

In this section we describe the evolution of wages and human capital in the financial sector in a set of 22 mostly developed countries in 1970–2005. While many countries experience a rise in wages in finance, in particular for skilled workers—not all do, and there is much heterogeneity in magnitudes. Skill intensity in finance increases in many countries, but this is not a strong driver of the rise in average wages in finance. Before turning to describing our findings, we briefly describe the data underlying the series that we construct. We rely on the EU KLEMS dataset, March 2008 release. See O'Mahony and Timmer (2009) for detailed documentation.

Finance is comprised of three subsectors: Financial intermediation, except insurance and pension funding (by banks, savings institutions, and companies that provide credit services); insurance and pension funding, except compulsory social security; and other activities related to financial intermediation (securities, commodities, venture capital, private equity, hedge funds, trusts, and other investment activities, including investment banks). For notational simplicity we will refer to this sector as "Finance".[8] We analyze the evolution of time series in finance relative to the non-farm, non-finance, private sector, which we denote as NFFP.

All labor concepts pertain to employees. We chose not to use the slightly different concept of "persons engaged", which includes proprietors and non-salaried workers in addition to employees, for the following reason. Total compensation of persons engaged is calculated in the EU KLEMS by total compensation of employees multiplied by the ratio of hours worked by persons engaged to hours worked by employees. This implies the same average wage for salaried and non-salried workers, which is woefully inadequate when comparing finance to other sectors of the economy.

Autor (2011) provide an up-to-date report on empirical findings and theoretical considerations. Acemoglu (2002a) argues that the increase in supply of more educated workers biases innovation towards equipment that is more complementary to their skills. For other explanations for the increase in demand for skilled workers see Card (1992), Card and Lemieux (2001), and Acemoglu, Aghion, and Violante (2001).

[8] Disaggregating finance into its sub-sectors does not yield informative time series for two reasons. First, there are relatively few observations on separate sub-sectors within finance, and they typically start relatively late in the sample. Second, and perhaps more importantly, the separation into subcomponents of finance is not very informative in countries that have universal banking/insurance systems, which are the majority in our sample. The industrial classification of sub-sectors within finance does not clearly represent functional differences in the EU KLEMS dataset (as well as in the OECD STAN database). While this separation is informative in the U.S., it is relatively uninformative elsewhere.

1.1 Trends in finance relative wages

We start with the relative average wage in finance, or simply finance relative wage, defined as

$$\omega_{fin,t} \equiv \frac{\overline{w}_{fin,t}}{\overline{w}_{nffp,t}} \ , \tag{1}$$

where the average wage in each sector $\overline{w}_{i,t}$ is calculated as total compensation of employees divided by the total hours worked by employees. Figure 1 depicts the finance relative wage for four groups of countries. In Panel A and Panel B we group countries who see relative wages in finance increasing. Luxemburg exhibits the largest increase, followed by the U.S., Spain and The Netherlands. In these countries the average wage in finance reaches about twice the average wage in the NFFP sector.

Figure 1 Panel C depicts countries with decreasing finance relative wage, with the largest drop in Italy, mostly in 1975–1985. Panel D depicts countries with mixed trends in ω_{fin}. Notable here are the United Kingdom, where ω_{fin} fluctuates substantially; and Australia, with a sharp decrease until 1985, and then an equal increase until 2005. Overall, there is significant heterogeneity in the trends of ω_{fin} across countries: 11 countries see increases, while the remainder are split between decreases and mixed trends.

We wish to know what is the importance of changes in the skill composition of finance for the relative wage of finance. To assess this, we decompose changes in ω_{fin} into within and between skill group changes using the formula

$$\Delta\omega_{fin} = \sum_i \Delta\omega_i \overline{n}_i + \sum_i \Delta n_i \overline{\omega}_i \ , \tag{2}$$

where $i \in \{\text{skilled,unskilled}\}$ denotes skill groups. Here $\Delta\omega_i$ is the change of the wage of skill group i in finance relative to $\overline{w}_{nffp}$, $\overline{n}_i$ is the average employment share of skill group i in finance, Δn_i is the change in the employment share of i within finance, and $\overline{\omega}_i$ is the average relative wage of skill group i in finance in the sample. The first sum captures the contribution of wage changes within groups, while the second sum captures the contribution of changes of skill composition (the "between" component). We compute this decomposition for each country in the sample. The definition of high skilled workers in the EU KLEMS is consistent across countries, and implies a university-equivalent bachelors degree.

Table 1 Panel A reports $\Delta\omega_{fin}$, the within share $(\sum_i \Delta\omega_i \overline{n}_i / \Delta\omega_{fin})$ and the between share $(\sum_i \Delta n_i \overline{\omega}_i / \Delta\omega_{fin})$ for all countries, sorted by $\Delta\omega_{fin}$. We ignore five countries with particularly small changes in ω_{fin} in absolute value (Germany, U.K., Austria, Belgium, Slovenia) because in these cases the within and between shares become arbitrarily large, often exceeding unity (for example, the U.K.). After ignoring these countries a clear pattern emerges. First, the within share is on average larger than the between share, 0.64 versus 0.36, which implies that within group wage changes matter more than changes in skill composition (this conclusion holds even without ignoring the five lowest $\Delta\omega_{fin}$ countries). Second, the within share is strongly positively correlated with the absolute value of $\Delta\omega_{fin}$; the rank correlation is 0.66 with a p-value of 0.02. This implies that big changes in the finance relative wage are associated with big within-skill group wage changes; composition changes matter less where changes are bigger.

To illustrate this point more clearly we compute a benchmark wage for finance

$$\widehat{\omega}_{fin,t} = \frac{1 + h_{fin,t}\pi_{nffp,t}}{1 + h_{nffp,t}\pi_{nffp,t}} \ , \tag{3}$$

where $h_{i,t}$ is the employment share of skilled workers in sector i, and $\pi_{nffp,t}$ is the skill premium (relative wage of skilled workers minus one) in the NFFP sector. The benchmark wage $\widehat{\omega}_{fin,t}$ is the relative wage that would prevail in finance if skilled and unskilled workers earned the same as in the NFFP sector.[9] Variation in the skill premium will have a strong effect on $\widehat{\omega}_{fin}$ if $h_{fin} - h_{nffp} > 0$ and if this difference is increasing, which is the case, as we show below. The finance excess wage is

$$\phi_{fin,t} = \omega_{fin,t} - \widehat{\omega}_{fin,t} \ . \tag{4}$$

Figure 2 reports $\phi_{fin,t}$ using the same country grouping as Figure 1. Due to the availability of data on skilled employment and wages, we are unable to match the sample of Figure 1. We see that although the level of $\phi_{fin,t}$ is generally lower than the finance premium, defined as $\omega_{fin,t} - 1$, the trends are almost identical, with few exceptions. This reinforces the point made above: most of the variation in the finance relative wage is due to within-skill wage shifts.

A closer inspection of the data shows that most of the excess wage is due to the relative wage of high skilled workers in finance. The relative wage of skilled workers, defined below, tracks ω_{fin} very closely. Therefore, we examine this variable next.

1.2 Finance relative skilled wages

The relative high skill wage in finance is defined as

$$\sigma_{fin,t} \equiv \frac{s_{fin,t}}{s_{nffp,t}} \ , \tag{5}$$

where the average wage of skilled workers in each sector $s_{i,t}$ is calculated as total compensation of skilled employees divided by the total hours worked by skilled employees. Figure 3 depicts the finance skilled relative wage for four groups of countries. The sample reduces relative to Figure 1

[9] See appendix for derivation of (3).

due to availability of data on wages and employment by skill. In Panel A and Panel B of Figure 3 we group countries who see skilled relative wages in finance increasing. Here Australia exhibits the largest increase (but recall the drop in ω_{fin} until 1985), followed by the U.K., the U.S. and Canada. In these countries skilled workers in finance command a wage premium of 50–80%.

Panel C depicts countries with decreasing finance relative wage, with Italy again exhibiting the largest drop. Panel D depicts countries with mixed trends in σ_{fin}. As with relative average wages, there is significant heterogeneity in the trends of σ_{fin} across countries: 12 countries see increases, three see decreases, and seven exhibit mixed trends.

1.3 Finance relative skill intensity

We now consider relative skill intensity in finance, defined as

$$\rho_{fin,t} \equiv h_{fin,t} - h_{nffp,t} \ ,$$

where $h_{i,t}$ is the employment share of high skilled workers in sector i. Figure 4 depicts the finance relative skill intensity for two groups of countries. In Panel A we group countries who see relative skill intensity in finance consistently increasing. By far, Spain and Japan see the largest increases, where their financial sector becomes more than 30 percent points more skill intensive in 2005.

It is interesting to compare the changes in $\rho_{fin,t}$ to changes in finance relative wages. Spain and The Netherlands see significant increases in both. But Luxemburg and the U.S., while exhibiting the largest increases in ω_{fin}, see only very modest increases in relative skill intensity. This is manifested in the poor ability of the benchmark wage to track the finance relative wage, especially in the countries and periods when the increase in the finance relative wage is large.

1.4 Finance wages and overall inequality

Changes in the relative wage of skilled workers are an important dimension of overall changes in wage inequality. Therefore, we wish to assess how much finance contributes to changes in the relative wage of skilled workers in the nonfarm private sector (including finance), denoted here as

$\Delta\pi$.[10] We follow a similar approach as in (2), and decompose

$$\Delta\pi = \sum_j \Delta\pi_j \overline{h}_j + \sum_j \Delta h_j \overline{\pi}_j \ , \tag{6}$$

where $j \in \{\text{fin,nffp}\}$ denotes the two sectors that comprise the nonfarm private sector (finance and NFFP). Here $\Delta\pi_j$ is the change in the relative wage of skilled workers in sector j relative to the overall average wage of unskilled workers in the nonfarm private sector and $\overline{\pi}_j$ is the average relative wage of skilled workers in sector j, thus defined. This definition is useful because, as we note above, most of the variation in the finance relative wage is driven by skilled wages in finance. Here $\overline{h}_j$ is the share of skilled workers employed in sector j out of the entire nonfarm private sector and Δh_j is the change in that share for sector j. The first sum captures the contribution of wage changes within sectors, while the second sum captures the contribution of allocation of skill across sectors (the "between" component). We compute this decomposition for each country in the sample.

Another way to arrange the elements of (6) is

$$\Delta\pi = \left(\Delta\pi_{fin}\overline{h}_{fin} + \Delta h_{fin}\overline{\pi}_{fin}\right) + \left(\Delta\pi_{nffp}\overline{h}_{nffp} + \Delta h_{nffp}\overline{\pi}_{nffp}\right) \ . \tag{7}$$

The first term in parentheses captures the contribution of finance, due to both the effect of changes in finance skilled wages, and the effect of changes in allocation of skilled workers to finance.

Table 1 Panel B reports $\Delta\pi$, the within share ($\sum_j \Delta\pi_j\overline{h}_j/\Delta\pi$), the between share ($\sum_j \Delta h_j\overline{\pi}_j/\Delta\pi$), and the finance share ($\left(\Delta\pi_{fin}\overline{h}_{fin} + \Delta h_{fin}\overline{\pi}_{fin}\right)/\Delta\pi$) for all countries, sorted by $\Delta\pi$ in decreasing order. First, we see that π has increased in several countries in our sample, while in others it has not, and even declined. Second, the within share completely dominates the decomposition, it is on average equal to one: Changes in relative skilled wages overall, not changes in allocation of skilled workers to finance (despite $\pi_{fin} > \pi_{nffp}$), drives $\Delta\pi$.

When we examine the contribution finance in Table 1 Panel B, it is useful to differentiate between cases in which the finance share is positive, and when it is negative. When the finance share is positive, finance contributes to changes in π in the same direction that π changes. The average contribution across these cases is 36% (26% without Australia). When the finance share is negative, this means that finance contributes to $\Delta\pi$ in the opposite direction. With the notable exception of

[10] Using survey data and corrections for top coding, Philippon and Reshef (2012) find that finance accounts for 15% to 25% of the overall increase in wage inequality in 1980–2005. Roine and Waldenström (2014) show how close the finance relative wage in Philippon and Reshef (2012) tracks the share of income of the top percentile in the U.S. over the entire 20$^{\text{th}}$ century. In line with this, Bakija, Cole, and Heim (2012) document that financial professionals increased their representation in the top percentile of earners (including capital gains) from 7.7% in 1979 to 13.2% in 2005, while their representation in the top 0.1 percentile of earners from 11.2% in 1979 to 17.7% in 2005 (see also Kaplan and Rauh (2010)). For similar evidence for the United Kingdom and France, see Bell and Reenen (2013) and Godechot (2012).

Italy (where finance relative wages decline sharply, albeit from a high level), this happens when $\Delta\pi$ is negative. This implies that even as overall trends in the economy are to lower inequality, finance counters this and contributes to increasing inequality. The average contribution across these cases is -21%. Given the size of finance in total skilled employment (6%, or 5.4% without Luxemburg, which employes 20% of its skilled workers in finance) these are large contributions to skill premium. Since the between component within the finance share, $\Delta h_{fin}\overline{\pi}_{fin}$, is very small, almost all of the finance share is explained by increases in relative skilled wages within finance.

2 Explaining finance relative demand for skill and relative wages

We entertain four theories for explaining variation in relative demand for skill and relative wages in finance: One that relies on technology, one that relies on demand for scarce skills, one that relies on regulation, and lastly, one that relies on lack of competition. In this section we test which theory has more explanatory power.

Autor, Katz, and Krueger (1998) and Autor, Levy, and Murnane (2003) highlight the role of ICT in changing demand for skill—in particular, replacing routine tasks and augmenting non-routine cognitive skills. If computers diffuse more rapidly in finance relative to the rest of the economy, then this can help explain relative skill intensity and relative wages in finance. In addition, the strong complementarity of ICT with non-routine cognitive skills can help explain changes in within-education group finance relative wages. If highly educated workers possess such non-routine cognitive skills, then higher ICT intensity in finance can help explain the higher wages that highly educated workers in finance command, relative to similar workers in the rest of the economy.

Demand for scarce skills can come from various sources. Screening and monitoring debtors, especially managing investments overseas, and serving investors from abroad all require specific skills that may be in short supply. We expect an increase in these activities to both increase demand for skill and increase wages, in particular of skilled workers. For example, an increase in the global scope of financial intermediation may increase demand for communication skills with foreign investors, or for the ability to conduct business abroad. Likewise, higher demand for credit may increase demand for debtor monitoring skills. Moreover, these activities are prone to threats of moral hazard (Axelson and Bond (forthcoming)). Our regression analysis tries to distinguish between the effects of different types of credit.

In contrast, Philippon and Reshef (2012) argue that financial deregulation is the main driver of relative demand for skill in finance, and that technology and other demand shifters play a more modest role. Finally, lack of competition may increase wages, if profits are shared with workers.

We stress that we wish to explain the *differential* part of the rise in demand for skill and wages in finance, the part that is net of demand for skill and wages in the NFFP sector. Some of the forces that affect demand for skill operate in analogous ways in finance and in the NFFP sector; for example, the precipitous drop in the price of computing power. However, the differential demand for skill is the more interesting object—we document this part in Section 1 above—and which may be driven by forces that do not operate in the NFFP sector.

We use a simple framework to organize the discussion. Suppose that output in sector j in time t is produced using three factors: High skill labor H, low skill labor L and computer capital C. Let the production function take a nested CES form as follows

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

where $\alpha_j, \gamma_j \in (0,1)$, $\mu_{j,t}$ is a factor augmenting parameter for the skill-capital composite, and $\sigma > 1$. The important feature of this production function is that the elasticity of substitution between skilled and unskilled labor σ is greater than the elasticity of substitution between skilled labor and computers, which is equal to one here: This implies computer-skill complementarity.[11] We assume that σ is the same in all sectors, while α_j and γ_j may vary across sectors.

If factor markets are competitive, without adjustment costs and without compensating differentials, then factor returns are equalized across sectors. Let s and w be the wages for high and low skill workers, respectively, and let r be the rental cost of computers. Cost minimization implies

$$\ln \left(\frac{C}{H} \right)_{j,t} = \ln \frac{\alpha_j}{1-\alpha_j} + \ln \left(\frac{s}{r} \right)_t$$

and

$$\ln h_{j,t} = c_j - \sigma \ln \pi_t + (\sigma - 1) \alpha_j \ln \left(\frac{s}{r} \right)_t + (\sigma - 1) \ln \mu_{j,t} ,$$

where $h_{j,t} = H_{j,t}/L_{j,t}$, c_j is a constant and $\pi_t = s_t/w_t$. All else equal, a drop in the cost of computers r increases their use in production, which, in turn, increases relative demand for skill in any sector. Similarly, an increase in μ drives up relative demand for skilled labor. Evidence in Goldin and Katz (2008a) and Machin and Van Reenen (1998) supports the notion of a secular trend in μ for the aggregate economy in the U.S. and other OECD countries. But we are interested in demand for skill in the financial sector *relative* to the rest of the economy. The relative demand

[11] Estimates of the aggregate elasticity of substitution between skilled and unskilled labor are typically greater than one, and on the order of 1.5; for example, see Katz and Murphy (1992) and Krusell, Ohanian, Rios-Rull, and Violante (2000) and others cited in Autor and Katz (1999). However, these aggregate elasticities can mask heterogeneity of elasticities at the sector level, possibly below one (Reshef (2011)). Adding a second type of capital along the lines of Krusell, Ohanian, Rios-Rull, and Violante (2000), or a different elasticity of substitution between skilled labor and computers (while maintaining the ranking) unnecessarily complicates the analysis.

for skill in finance versus the NFFP sector is given by

$$\ln h_{fin,t} - \ln h_{nffp,t} = c + (\sigma - 1)(\alpha_{fin} - \alpha_{nffp}) \ln \left(\frac{s}{r}\right)_t + (\sigma - 1)\left(\ln \mu_{fin,t} - \ln \mu_{nffp,t}\right) \ , \qquad (8)$$

where $c = c_{fin} - c_{nffp}$ is a constant. The relative wage π does not affect the *relative* skill intensity in finance because we assume $\sigma_{fin} = \sigma_{nffp}$. Philippon and Reshef (2012) show that π, in conjunction with different elasticities, cannot be an important factor in explaining the increase in relative skill intensity in finance. We view $\mu_{fin,t}$ as capturing all non-computer factors that increase relative demand for skill in finance.

Differences in the intensity of computers in production allow for an effect of computer prices r on relative demand. All else equal, if finance is more computer intensive, i.e. $\alpha_{fin} > \alpha_{nffp}$, then a drop in r drives up the relative demand for skill in finance. If $\alpha_{fin} = \alpha_{nffp}$, then changes in r have no effect. However, note that in this case an increase in μ_{fin} will still drive up the relative use of computers in finance, because an increase in μ_{fin} increases the marginal productivity of all factors in finance, including computers.

We now move on to describe our explanatory variables, and then estimate the ICT complementarity to skill in finance and compare it to complementarity in NFFP. We then fit relative wage and relative skill regressions that allow entertaining a horse race between potential explanations.

2.1 Explanatory variables

Information and communication technology

We consider the share of information technology capital, communication technology capital, and software in the capital stock of the financial sector minus that share in the aggregate economy. Reductions in the price of computers, software and information and communication technology (ICT) spur investment in this type of capital equipment. Investment in ICT should have a big return for finance, which is an industry that relies almost entirely on gathering and analyzing data.[12] The return may be greater than in the NFFP sector, leading to relatively more ICT investment and higher stocks in finance than in the rest of the economy.

The EU KLEMS dataset provides data on real capital stocks by industry (in 1995 prices), the share of ICT in the real capital stock, and quantity indices for the total industry capital stock, ICT capital and non-ICT capital. Not all countries in the sample report data on real capital stocks, but all report data on quantity indices. For the purpose of illustrating an increase in ICT intensity we appropriately use the share of ICT in the real capital stock. We define the relative ICT intensity

[12] Indeed, the financial sector has been an early adopter of IT. According to U.S. fixed asset data from the Bureau of Economic Analysis, finance was the first private industry to adopt ICT in a significant way. In the EU KLEMS data, the average ICT share of the capital stock in finance is 2.6% in 1970, double the 1.3% share in the NFFP sector.

in finance as

$$\theta_{fin,t} = ICT\_share_{fin,t} - ICT\_share_{nffp,t} \ ,$$

where $ICT\_share_{i,t}$ is the share of ICT in the real capital stock in sector i.

Table 2 reports θ_{fin} for countries that have the underlying data at four mid-decade years and decade-long changes. For almost all countries θ_{fin} increases over time, in almost all decade intervals. The changes also become bigger over time. Finance becomes more ICT-intensive relative to the NFFP sector practically everywhere, at an increasing rate. Finland exhibits by far the largest increase, followed by Denmark, Australia and the United States. Canada exhibits a low value of θ_{fin}, but this is because ICT intensity is high in the NFFP sector.

Financial regulation

The optimal organization of firms, and therefore their demand for various skills, depends on the competitive and regulatory environment. Tight regulation inhibits the ability of the financial sector to take advantage of highly skilled individuals because of rules and restrictions on the ways firms organize their activities, thus lowering demand for skill in finance (Philippon and Reshef (2012)). Therefore, deregulation will affect relative demand for skill and relative wages in finance.

In order to capture the regulatory environment we rely on data on financial reforms from the Abiad, Detragiache, and Tressel (2008) dataset. The dataset includes measures of financial reform along eight dimensions, of which we use six:[13]

1. *Directed credit/reserve requirements.* This measure combines the restrictiveness of reserve ratios (>20%, 10-20%, <10%); and whether the government directs credit to certain sectors. Overall, this captures restrictiveness on the profitability of existing banks from lending, either by restricting leverage (but also risk), or by preventing optimal decisions on allocation of lending. When the measure is high, there are less restrictions.

2. *Interest rate controls.* This measure captures the degree to which the government regulates deposit and/or lending rates. Overall, these are interventions in the optimal choice of deposit and lending rates. When the measure is high, there are less restrictions.

3. *Entry barriers/pro-competition measures.* This measure captures: (1) The extent to which foreign banks are allowed to enter the domestic market; (2) Whether entry of new domestic

[13] The remaining two dimensions are the existence of aggregate credit ceilings, and policies regarding security markets. We drop the aggregate credit ceilings indicator because data on this dimension is missing for most countries. The security markets policy indicator is omitted because it has almost no variation in the sample of countries we consider, where other data exist. This measure captures two (very different) dimensions securities market policy: (1) Whether a country takes measures to develop securities markets; and (2) Whether a country's equity market open to foreign investors.

banks is allowed; (3) Whether there are restrictions on bank branching; and (4) whether banks are allowed to engage in a wide range of activities. The last component distinguishes between universal banking versus Glass-Steagall-type separation of credit intermediation from investment activities, but it is not available separately. The measure is high when there is less restriction on activities and lower entry barriers.

4. *Banking supervision.* This measure captures: (1) Whether a country adopted a capital adequacy ratio based on the Basle standard; (2) Whether the banking supervisory agency is independent from executive branch influence; (3) Whether a banking supervisory agency conducts effective supervision through on-site and off-site examinations; and (4) Whether the country's banking supervisory agency covers all financial institutions without exception. A higher measure here implies that more of these conditions are met.

5. *Privatization.* This measure captures the degree to which the banking sector is public (>50%, 25-50%, 10-25%, <10%). Higher values mean a lower public share.

6. *International capital flows.* This measure captures three dimensions of interventions in foreign exchange: (1) Whether all types of international activities face the same exchange rate ("unified system"); (2) Whether there are restrictions on capital inflows; and (3) Whether there are restrictions on capital outflows. A higher measure implies fewer restrictions.

All measures take discrete values from 0 to 3. Higher values mean fewer restrictions, except for banking supervision, where some of the sub-components imply larger restrictions. This dimension is not easily comparable to the deregulation measure in Philippon and Reshef (2012), which captures removal of restrictions on organization and financial activities. This is captured, although very partially, in the entry barriers/pro-competition measures.[14] A shortcoming is that none of the measures addresses insurance services, which are an important part of the financial system.

Table 3 summarizes levels of the linear regulation measures in 1973 and 1995, together with their change over this period.[15] Many countries in the sample obtain the highest level in several dimensions by 1995, but there is substantial cross-country variation. In unreported tabulations we show that cross country variation all but ceases after 1995. Therefore, when we use deregulation

[14] We say "partially" because, as an example, entry barriers recorded in Abiad, Detragiache, and Tressel (2008) do not reflect the timing of branching deregulation in the US during 1970s to 1994, which is used in Philippon and Reshef (2012). In fact, the measure of entry barrier for the US is constant from 1970s to 1995 in Abiad, Detragiache, and Tressel (2008). Therefore, the of results of this paper may not be easily comparable with those in Philippon and Reshef (2012). Our measure of banking concentration, explained later, is perhaps more comparable with what is used in Philippon and Reshef (2012).

[15] Data for the Czech Republic and Hungary start in 1990.

in regressions we restrict the sample so that there is variation in deregulation variables.[16]

Financial globalization and domestic credit

When demand for credit is high, it is necessary to employ highly skilled workers to screen potential borrowers and then to monitor them. Monitoring may require efficiency wages in order to avoid the threat of moral hazard (Axelson and Bond (forthcoming)). We capture this using domestic credit provided by the financial sector as a share of GDP. This concept includes gross credit to the private sector, as well as net credit to the government. The data are from the World Bank's World Development Indicators database.

We also use data from Jordà, Taylor, and Schularick (2014) (JST) on domestic bank credit to the private sector for 11 countries that are in our sample, and supplement these data with domestic bank credit data from the World Bank when possible. Overall, the bank credit data from JST and from the World Bank are very close for observations that exist in both sources. We use JST data to split bank credit into household versus corporate credit, and to mortgage versus non-mortgage credit. These two splits are not the same: Although mortgage credit is a large part of household credit, substantial mortgage credit is obtained by the corporate sector, and households have substantial non-mortgage credit. When using World Bank domestic credit we made a few corrections for breaks in the series. See appendix for detailed descriptions of data and the corrections we made.

Foreign investors that are represented by local financial firms demand high quality services, which can be performed only by skilled workers. Likewise, investment overseas is a more complex type of activity, which also requires highly skilled workers. If the skills needed to preform these tasks is in fixed supply, or supply does not keep up with demand, then wages of those who can perform these tasks well will be bid up. We capture this using a measure of *de facto* financial globalization, namely foreign assets plus foreign liabilities as a ratio to GDP. The data are from Lane and Milesi-Ferretti (2007).

Bank Concentration

Less competition in banking may contribute to abnormal profits and rents, and this can drive up finance wages if profits and rents are shared with workers, as in Akerlof and Yellen (1990).

We measure bank concentration by the log of the share of the three largest banks in total commercial banking assets.[17] The data are from the World Bank's November 2013 version of the

[16] For example, when we use right hand side variables in levels and with three lags, our sample ends in 1998; see below.

[17] Total assets include total earning assets, cash and due from banks, foreclosed real estate, fixed assets, goodwill, other intangibles, current tax assets, deferred tax, discontinued operations and other assets.

Global Financial Development Database (originally collected by Bureau van Dijk in the Bankscope dataset). The data are available for many countries, but only from 1997 and on. However, these data allow us to study determinants of finance wages after 1995, when variation in the deregulation indices vanishes. Although banks do not comprise the entire financial sector, changes in bank concentration over time are indicative of overall concentration, even in the U.S. and U.K.

2.2 ICT and complementarity with high skilled workers

In this section we estimate that ICT capital is more complementary with skilled workers in finance than with skilled workers in the NFFP sector. This, together with the increase in relative ICT intensity in finance, can be a mechanical force driving demand for skill and wages in finance.

Our starting point is the short run industry variable cost function in a competitive setting:

$$CV\left(W_h, W_l\ ;\ C, K, Q\right)\ ,$$

where W_h and W_l are wages of high skill and low skill workers, respectively. Here C is ICT capital, K is all other forms of capital, and Q is output. We assume that capital is quasi-fixed and that the cost function can be approximated by a translog function. Standard manipulations yield

$$S = \eta + \alpha \ln\left(\frac{W_h}{W_l}\right) + \beta \ln\left(\frac{C}{Q}\right) + \gamma \ln\left(\frac{K}{Q}\right) + \delta \ln Q\ , \tag{9}$$

where S is the wage bill share of skilled labor.[18] Here β and γ capture the degree of complementarity of skilled labor with ICT and other types of capital. Positive values imply complementarity to skilled labor.[19] If the underlying production function is constant returns to scale, then $\delta = 0$. This is a reasonable assumption at the industry or aggregate level, but we do not impose it.

We estimate empirical versions of (9) separately for finance, for the entire economy, and for the NFFP sector in panel data from the EU KLEMS dataset:

$$S_{ct} = \eta_c + \alpha \ln\left(\frac{W_h}{W_l}\right)_{ct} + \beta \ln\left(\frac{C}{Q}\right)_{ct} + \gamma \ln\left(\frac{K}{Q}\right)_{ct} + \delta \ln Q_{ct} + \varepsilon_{ct}\ , \tag{10}$$

where c denotes countries, t denotes years, η_c are country fixed effects, and ε_{ct} is the the error term that captures technological shocks that are not embodied in capital. Our identifying assumption is that technology is stable over time, and that its curvature is the same across countries within an industry (the coefficients α, β, γ and δ do not vary over time or countries within an industry). The η_c terms allow technology to be different across countries within industries. All variables are

[18] See, e.g., Berman, Bound, and Griliches (1994).

[19] To be precise, positive β or γ imply that either type of capital (ICT or other, respectively) is more complementary with skilled labor relative to unskilled labor.

industry-specific, including relative wages.

We use industry-specific quantity indices for C, K and Q, which are equal to 100 in 1995. This renders the C/Q and K/Q ratios equal to unity in 1995, but does not affect the estimation in the presence of country fixed effects. The proportional adjustment to make the ratios "real" is additive in logs and is absorbed by the country fixed effects η_c. Quantity indices are available for 22 countries in the EU KLEMS, and for different time periods.[20] Quantity indices are available for financial intermediation (finance in our taxonomy) and the aggregate economy. We manipulate indices for the aggregate economy, finance, farm and public sectors, to obtain indices for NFFP; see appendix for details. This reduces the sample to the 16 countries in Table 2.

We follow standard methodology (e.g. Berman, Bound, and Griliches (1994)) and estimate (10) by TSLS, instrumenting for the capital shares using lagged values. We report results using up to three lags; results using other lags are similar. We report robust standard errors.[21]

The results are reported in Table 4. ICT is complementary to skill in all sectors, and in the aggregate—but is more complementary to skill in finance. Owing to the high precision of the estimates, this difference is also highly statistically significant. These results hold whether or not we include $\ln Q$. In untabulated results we find similar results in specifications that constrain the country dummies to be equal in finance, the aggregate and NFFP.[22]

2.3 Econometric specification for wage and skill regressions

We fit two sets of regressions. The first set is in levels

$$y_{c,t} = \beta' x_{c,t-3} + \alpha_c + \delta_t + \varepsilon_{c,t} \ , \tag{11}$$

where y is either the finance relative wage ω_{fin}, the finance skilled relative wage σ_{fin}, the relative skill intensity ρ_{fin}, or the finance excess wage ϕ_{fin}. Here α_c and δ_t are country and year fixed effects, respectively, and ε_{ct} is the error term. The vector x includes explanatory variables. We lag x by three years to guard against simultaneity. Using longer lag lengths yield similar results, but reduces explanatory power. We use deregulation data in 1973–1995, which restricts t to 1976–1998. We estimate (11) using OLS; identification of β relies on within-country variation, relative to the average level in a particular year.

[20] These are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Spain, Finland, France, Germany, Hungary, Irland, Italy, Japan, Korea, Luxemburg, Netherlands, Portugal, Slovenia, Sweden, United Kingdom, United States (NAICS based data).

[21] We do not cluster standard errors at the country level because there are only 13 to 20 countries.

[22] These results are available upon request.

The second set of regressions are predictive regressions in changes

$$\Delta y_{c,t+3} = \beta' \Delta x_{c,t} + \alpha_c + \varepsilon_{c,t} \ , \tag{12}$$

where $\Delta y_{c,t+3} = y_{c,t+3} - y_{c,t}$ and $\Delta x_{c,t} = x_{c,t} - x_{c,t-3}$.[23] We use deregulation data in 1973–1995, which again restricts t to 1976–1998. This specification is more demanding than (11) because it controls for country-specific trends, over an above country-specific levels. Identification of β relies on within-country variation in changes.[24]

Specification (12) allows us to identify plausibly excludable instruments for variables in changes. We use the relative price of ICT investment relative to other types of investment in the economy as an instrument for changes in relative ICT intensity in finance, which is calculated based on capital stocks.[25] A decrease in the relative price will increase relative demand for ICT investment, and hence will have an effect on the change in ICT intensity. As long as the response of finance and NFFP are not the same, this instrument is relevant. It is also excludable, because in the presence of changes in ICT intensity, the relative price has no predictive power (equation (8) is derived by substituting ICT with its relative price). We use financial regulation in levels as an instrument for changes in financial regulation, i.e. deregulation. Abiad and Mody (2005) discuss political economy models that justify this specification.[26] From a mechanical point of view, since the range of financial reform variables is limited between zero and three, a higher level (less regulation) is negatively correlated with increases (deregulation), and hence it's relevance as an instrument. It is difficult to think of mechanisms by which the level of deregulation affects changes in demand for skill and wages in the presence of changes in deregulation, hence it is plausibly excludable.

We estimate four different specifications for each dependent variable. In the first specification we only include relative ICT use in finance, domestic credit as percentage of GDP, and financial globalization. In the second and third columns we include only financial reform indices. The difference between these two columns is the sample: While the second column uses all available

[23] In the appendix we also report estimates where we code the changes in each deregulation measure into indicators for $I\{\Delta v = -1\}$, $I\{\Delta v = 0\}$, $I\{\Delta v = 1\}$, $I\{\Delta v = 2\}$, where Δv is the change in the value of the regulation measure. There are no $\Delta v = -2$ or $\Delta v = 3$ events the sample. When using indicators for changes in regulation, the reference group is no change in all six dimensions of regulation.

[24] Our main results are robust to using no fixed effects or both country and time fixed effects.

[25] We calculate the relative price of ICT investment relative to other types of investment in the economy based on data from the EU KLEMS as follows. We divide real ICT capital expenditures by the quantity index of ICT capital expenditures, further divided by the same ratio for non-ICT expenditures. Since we use this variable only in the presence of country fixed effects, the relative price captures within-country variation in a statistically meaningful way. In other words, country fixed effects prevent us from comparing across countries uncomparable magnitudes.

[26] Abiad and Mody (2005) use a nonlinear ordered logit regression, and include also the square of the level as predictor of change. The nonlinear specification does not lend itself to TSLS. We experimented with adding the square of the level in the first stage, but in our sample the squared level has almost no predictive power for the change and therefore we omit it.

observations, in the third column we restrict the sample to observations for which we have data on the other three explanatory variables. We do this in order to demonstrate that our results on regulation are not affected by potentially dropping influential observations that do not have data on the other variables. Finally, we use all explanatory variables together in the fourth column. Descriptive statistics are reported in Table 5 (we report correlations in the appendix Tables A5 and A6). We test for serial correlation in all regressions using the procedure in Wooldridge (2002), page 310–311.[27] We do not reject the null of no serial correlation at conventional levels of statistical significance. In addition, inspection of the partial autocorrelation functions reveals no evidence of autoregressive or moving averages in the errors.

Overall, we find a positive, significant and robust impact of financial globalization and financial deregulation—in particular, removing restrictions on international capital flows—on relative wages in finance. There is some evidence that relative ICT use is correlated with relative demand for skill and skilled wages in finance, but this does not hold in the predictive regressions, whether we estimate with TSLS or not. In addition, we do not even find a statistically significant correlation between relative ICT use in finance and skilled wages when we correctly control for deregulation measures. This shows that increase in use of ICT in finance over and above the rest of the economy is itself driven by financial deregulation. In unreported regressions, we show that deregulation of international capital flows does strongly predict changes in relative ICT use in finance.

2.4 Level regression, 1973–1998

Table 6 reports the results from level regressions (11). Relative ICT intensity in finance has a positive and statistically significant correlation with relative skilled wages and with relative skill intensity in finance. The estimates in column 8 and 12 imply that a one standard deviation increase in the relative ICT use in finance increases relative skilled wages and relative skill intensity in finance by 0.2 and 0.14 of a standard deviation, respectively. However, when deregulation measures are included, relative ICT use in finance does not have explanatory power for the excess wage in finance, as shown in column 16. This suggest that the positive effect of relative ICT intensity on skilled workers' wages is offset by a negative effect on unskilled wages.[28] This is in line with findings in Autor, Levy, and Murnane (2002) and Autor, Levy, and Murnane (2003).

Moreover, overall domestic credit is positively associated with relative skilled wages in finance, relative skill intensity and the excess wage but not with *average* relative wages in finance. This effect is also economically large. A one standard deviation increase in domestic credit increases relative

[27] Drukker (2003) presents simulation evidence that this test has good size and power properties.

[28] Below we show that when we correctly allow for non-linear effects of deregulation, the correlation of ICT and skilled wages/intensity in finance disappears.

skilled wages, relative skill intensity, and the excess wage in finance all by about 0.3 of a standard deviation. These results are consistent with the hypothesis that higher demand for credit leads to stronger demand for skilled labor by financial institutions to be able to screen potential borrowers, monitor them, and manage the overall risk of their business. Furthermore, as shown in Table 6, *de facto* financial globalization has a positive and significant effect on finance relative wage, relative skill intensity and the excess wage, but no effect on finance relative skilled wage when deregulation measures are included. This is consistent with an increase in demand for specific skills, some of which are in short supply. A one standard deviation increase in *de facto* financial globalization increases average relative wage, relative skill intensity and the excess wage in finance by 0.4, 0.5, and 0.3 of a standard deviation, respectively. Therefore, these effects are not only statistically significant but also economically large.

Our last hypothesis is that financial (de)regulation affects the structure of the market and hence demand for skill and wages in finance. As table 6 shows, financial regulation is important for explaining relative wages in finance, but not much for relative skill intensity in finance. In particular, lower restrictions on international capital flows has a positive and robust impact on all wage concepts, which is statistically significant at the 1% level across all specifications.[29] The magnitude of the effect is economically large. The estimated coefficient to the international capital flow indicator in column 8 (0.148) implies that deregulation of international capital flows by one unit is associated with an increase of relative skilled wages and the excess wage in finance by more than one third of a standard deviation. To put it differently so it will be comparable with other results, a one standard deviation increase in international capital flow index (0.65) increases relative skilled wages and the excess wage in finance by about a 0.3 standard deviation. The effect of international capital flows restrictions is similar in magnitude to that of domestic credit but larger than the effect of ICT on relative skilled wages. These findings are consistent with finance jobs becoming more complex and with an increase in the threat of moral hazard (Philippon and Reshef (2012)) when international capital flows become larger.

Lower entry barriers are associated with lower relative wages and lower excess wage in finance. This supports the idea that more competition leads financial institutions to minimize their costs, including cutting down rents given to labor. This message is echoed in regressions using bank concentration in the later period. We also find that privatization has a negative effect on relative skill intensity in finance, which suggests that banks cut down their expensive labor costs.

[29] In column 10 and 11 of Table 6, when we only include deregulation indices, we find that deregulation of international capital flows are significantly and positively correlated with relative skill intensity in finance. In Table 7, when we allow for non-linear effect of deregulation, we find a positive association between lower restrictions on international capital flows and relative skill intensity in finance, even in the presence of other explanatory variables.

Finally, we find a positive, robust and significant effect of banking supervision on all dependent variables. The increase in demand for skill may be due to the need to hire more skilled workers in order to conform to tighter supervision and to allocate credit more profitably under Basle convention capital requirements and other supervisions. Another Reason for a positive relationship is regulatory capture (Stigler (1971) and Peltzman (1976)); if so, then regulation may be more beneficial to incumbents. A close examination of the sub-components of the banking supervision measure reveals that this type of supervision is particularly detrimental to new entrants. If some of the additional rents that accrue to banks are passed on to workers, then this can explain the positive relationship. Lower restrictions on interest rates increase relative wages in finance but do not have a robust impact on relative skilled wages in finance. This may be due to the fact that simple loans are administered by lower level bank employees.

In Table 7 we allow for a nonlinear effect of deregulation. Indicator variables for financial deregulation are constructed as follows: $I\{v=0\}$, $I\{v=1 \text{ or } v=2\}$, $I\{v=3\}$, where v indicates the value of the linear variable. We group 1 and 2 together to avoid unnecessary multicollinearity when we use all six dimensions together as explanatory variables. This keeps the regression specifications parsimonious without sacrificing much flexibility. The nonlinearity allows different effects at initial stages versus more advanced stages of deregulation. Overall, the results in Table 7 are similar to Table 6. The main difference is that when allowing for non-linear effects, the magnitude of the coefficient to relative ICT use in finance declines substantially and loses statistical insignificant in all regressions. In light of the theoretical discussion above, this supports the notion that the *differential* investment in ICT in finance became profitable because of lower regulatory restrictions, rather than falling prices of ICT. Moreover, Table 7 shows that deregulation of international capital flows both at the initial stages and the more advanced stages positively affect skilled wages and the excess wage in finance. The magnitudes of the effect is larger when a country goes from partially regulated to completely deregulated (rather than going from regulated to partially deregulated). However, its effect on skill intensity is only present at initial stages of deregulation.

Variation in different types of credit may have different effects on demand for skill and wages in finance. We examine this in Table 8. Specifically, we investigate the impact of bank versus non-bank, household versus corporate, and mortgage versus non-mortgage credit. The main result is that non-bank credit is robustly associated with all dependent variables. Bank credit also drives relative skilled wages in finance, and all the splits of bank credit have some explanatory power. Thus, all types of credit benefit skilled workers, whose skills are scarce, and who are likely to be in positions to leverage their skills more when demand for credit is high. In contrast, only non-bank credit and bank credit to corporations have an effect on the excess wage.

The effect of bank and non-bank credit on relative skilled wages is both large, and similar in magnitude. The estimates in column 6 suggest that a one standard deviation increase in bank credit and non-bank credit increases relative skilled wage in finance by about 0.4 and 0.5 of a standard deviation, respectively. Moreover, the results in columns 7 and 8 imply that within bank credit, an increase of one standard deviation of either household credit or corporate credit increases relative skilled wages in finance by about 0.3 of a standard deviation. In contrast, a one standard deviation increase in mortgage lending increases finance relative skilled wages by 0.5 of a standard deviations, which is about three times as large as the effect of non-mortgage lending. This is an interesting (and perhaps surprising) result, which could be explained by the following observations. Most of the increase in the ratio of bank credit to GDP since 1970 in advanced economies has been driven by the dramatic rise in mortgage lending relative to GDP (Jordà, Taylor, and Schularick (2014)). This increase in mortgage lending made the creation and marketing of mortgage-backed securities and securitization more appealing, which subsequently led to higher demand for skill and higher skilled wages in finance as these activities are rather complex and require specific skills.

Finally, as the last analysis in level regressions, we examine whether the relationships we find above are different across countries with different financial systems. In particular, Anglo-Saxon countries have financial systems that are much more reliant on markets than on banks. We add to the specification in Table 6 interactions of relative ICT intensity in finance, domestic credit and financial globalization with a dummy for Anglo-Saxon countries (Australia, Canada, United Kingdom, United States). Our prior is that financial globalization should be more important in Anglo-Saxon countries, whereas domestic credit may have a lower effect on these countries. We do not expect to find a differential effect of ICT in Anglo-Saxon countries as the effect of technology should be the same across countries. We do not report results using interaction of regulation indicators with the Anglo-Saxon dummy because it is difficult to identify so many coefficients separately, and the interaction terms are not robust across different specifications.

Table 9 reports the results. The interaction of financial globalization with the Anglo-Saxon dummy has a large and statistically significant effect on all dependent variables; adding it diminishes the effect of financial globalization on other countries. These differential effects are economically large. For instance, column 6 shows that the impact of financial globalization on relative skill intensity in finance in Anglo-Saxon countries is 75% (= 0.0261/0.0346) larger than on other countries. The interaction terms for relative ICT use in finance and domestic credit appear with negative sign but are only marginally significant in one specification. We test whether the overall effects of relative ICT and domestic credit in Anglo-Saxon countries is zero; we cannot reject this hypothesis at conventional levels of significance. When the effect of financial globalization is larger, the effect of ICT and domestic credit is smaller. In unreported regressions we did not find differential effects for bank versus non-bank credit in Anglo-Saxon countries.

2.5 Predictive regressions, 1973–1998

We now turn to the predictive regressions (12). As explained before, these regressions are much more demanding as we are explaining (within each country) the future 3-year changes in the dependent variables based on the past 3-year changes in the right hand side variables—over and above country-specific trends. As a result, these regression are less subject to omitted variable problem or endogeneity concerns. Table 10 shows that the only robust predictors for changes in relative wages and the excess wage in finance are changes in *de facto* financial globalization and in *de jure* regulatory restrictions on international capital flows. Changes in relative skill intensity in finance are explained by financial globalization and reductions in entry barriers. These results are in line with what was found in the level regressions. [30] These results remain unchanged when using the nonlinear regulation specification or when splitting domestic credit into its components; see Table A2 and Table A3 in the appendix.

In order to better establish causality, we use instrumental variables to investigate the causal effect of technology and financial deregulation on relative wages and skill intensity in finance. Table 11 reports TSLS estimates of (12) using separately the instrument for reductions in regulatory restrictions on international capital flows, and for changes in relative ICT intensity in finance. In all these we find very large first stage partial F-stats, so we are not worried about weak instruments. In Table A4 in the appendix we report the first stage regressions, where, as expected, regulation of capital markets in levels is negatively correlated with deregulation (changes) in this dimension. In addition, the relative price of ICT investment is negatively correlated with the change in relative ICT capital intensity in finance. We cannot simultaneously instrument for both endogenous variables, despite very high first stage partial F-stats and partial R-squared when doing so. The Shea (1997) partial R-squared are very small and much smaller than the standard partial R-squared; this indicates that our instruments do not separately identify both coefficients of interest. Instrumenting for only one endogenous variable at a time is not problematic here because of the weak correlation across all explanatory variables in changes; see Table A5 in the appendix.

In columns 1 to 4 in Table 11 we find that the causal effect of reductions in regulatory restrictions on international capital flows is concentrated on relative skilled wages, which also affects the excess wage—not on the overall relative wage or on relative skill intensity in finance. The coefficients

[30] However, we find that changes in domestic credit—over and above country-specific trends—are associated with reductions in relative skilled wages, in contrast with the level regressions.

grow in magnitude and maintain statistical significance. Specifically, the coefficient of international capital flows on relative skilled wage regressions increases from 0.07 to 0.12, and from 0.09 to 0.14 in the excess wage regressions. In contrast, whether we instrument for ICT or not, its effect is nil.

Finally, we investigate differential effects for Anglo-Saxon countries in the predictive regressions. We simplify the regressions and include only the five variables that are statistically significant in full specifications in Table 10: relative ICT intensity in finance, domestic credit, financial globalization, and regulation of international capital markets and entry. We interact these five with a dummy for Anglo-Saxon countries (Australia, Canada, United Kingdom, United States). We report the results in Table 12. We do not find any differential effect of ICT and domestic credit in Anglo-Saxon countries. In contrast, we find large and highly significant additional impact of financial globalization on all relative wage concepts in these countries (columns 2, 4 and 8). These effects are present for both *de facto* measure of financial globalization and *de jure* regulatory restrictions on international capital flows. Finally, columns 4 and 8 show that lowering entry barriers has a larger negative effect on skilled wages and the excess wage in finance of Anglo-Saxon countries. This suggest that when competition is low, skilled workers in Anglo-Saxon countries receive a larger rent compared to their peers in other countries.

We perform several robustness checks that are not reported here. First, we control for some macro variables that might be related to our dependent variables such as GDP growth and interest rate. Second, we drop the top and bottom percentiles of the distribution of our dependent variables from the regressions. Third, we run the regressions without one country from the sample while keeping the rest; we do this for each country separately. The main results of the paper are robust to these robustness checks.

To sum up, using several specifications and estimators, we find that financial globalization and financial market structure and regulation (specially restrictions on international capital flows) are the most important factors driving relative wages and skill intensity in finance.

2.6 Level regressions, 1997–2005

So far we have investigated the determinants of wages and skill intensity in finance across countries up to the late 1990s. The reason, as explained above, is that variation in the regulatory variables in our sample all but vanishes after 1995. To provide some results on the later part of the sample, we use measures of bank concentration that are available in 1997–2005. Larger banks in concentrated markets have more market power and hence have larger rents to be shared with their workers.

We use similar level regressions as in the 1973–1998 sample, while replacing financial regulatory variables with bank concentration. The measure of bank concentration is the log share of three largest banks in each country from the World Bank, and is available from 1997. Due to the small number of observations, we report regression results using only country fixed effects; adding year fixed effects reduces precision, but has little effect on magnitudes. We have reported descriptive statistics of variables used in these regressions in Table 5.

The results in Table 13 show that the most robust determinant of average relative wages, relative skilled wages, and the excess wage in finance in this period is bank concentration. These results are also economically large. The results of column 1 suggest that a one standard deviation increase in our measure of bank concentration increases average relative wages in finance by 0.2 of a standard deviation. The same increase in bank concentration leads to even a larger increase—of 0.3 of a standard deviation—in relative skilled wages in finance (column 5). Not surprisingly, bank concentration has no effect on relative demand for skill in finance. In contrast to results in the earlier period, ICT has little explanatory power for any of our dependent variables. In fact, the point estimates are negative.

We now focus on the impact of total domestic credit as well as different types of credit on measures of relative wages and skill in finance. Total domestic credit has a positive and significant effect on relative skilled wages in finance (column 5). Column 6 shows that both bank and non-bank credit contribute to this positive association. Although non-bank credit appears to be statistically significant only at the 10% level, the economic magnitude of it's effect is more than twice as large as that of bank credit—0.32 versus 0.14 standard deviations, respectively. When we split bank credit to household and corporate credit (columns 3, 7, 11, and 16), we find a positive association between household bank credit and measures of relative wage and the excess wage. In contrast, the association is negative for corporate credit in this period. The economic magnitudes of these effects are also quite large. A one standard deviation increase in household credit (corporate credit) leads to an increase (decrease) of average relative wages in finance by about a 0.6 (0.3) standard deviation. Similar as in the previous period, we find that mortgage credit is an important determinant of wages (and the excess wage) in finance.

Finally, the only variable that appears to have explanatory power in explaining relative skill intensity in finance in this period is *de facto* measure of financial globalization. This is also in line with the results from 1973–1998 sample. The effect of financial globalization on demand for skill in finance is large: A one standard deviation increase in financial globalization increases relative skill intensity in finance by about 0.35 of a standard deviation.

Overall, the results of these regressions suggest that bank concentration and domestic credit are the important factors explaining relative wages and the excess wage in finance, whereas financial globalization is the most important variable behind increased relative skill intensity in finance.

This is in line with the results from the earlier period, in the following sense: market structure (regulation and bank concentration) drive wages, while other demand shifters are more important for explaining relative demand for skill.

3 Finance wages and brain drain

Given the findings above, it is natural to ask whether high wages in finance attract talent from other parts of the economy. Addressing the effects of drawing talented workers to finance, and making the distinction between social and private returns are beyond the scope of this paper. It is very difficult to empirically characterize allocative effects between activities within an economy. Instead, in this section we ask whether high wages in finance lure qualified workers from other countries. We restrict attention to immigration within a sample of 15 industrialized countries, where remittances and backward knowledge spillovers to the country of origin are not likely to be large. Here, it is relatively clear that attracting skilled workers from other countries has detrimental effects on the country of origin—i.e. brain drain.[31]

We find that variation in skilled wages in finance—over and above overall skilled wages—predict skilled immigration and employment in finance and therefore affect the allocation of immigration. We do not find evidence for this for unskilled immigrants in finance, or for skilled immigrants in other sectors of the economy. This raises concerns that high wages in finance cause brain drain across borders.

3.1 Immigration data

Unfortunately, to the best of our knowledge there are no comprehensive data sets that provide information on employment both before and after immigration. Moreover, data on immigration flows, rather than stocks are also scant. Therefore, we rely on data on bilateral immigration *stocks* for 15 OECD countries in 2000.[32] We restrict attention to immigration flows within this group of countries in order to stay close to the concept of luring qualified workers. Moreover, this way we restrict the incidence of remittances and backward knowledge spillovers to the country of origin. All wages are calculated from the EU KLEMS database. Migration stocks in a given sector in a destination country are classified by source country and education level. We focus on highly educated workers (attaining a bachelors degree from a four year college or from university), but we also compare our results to lower levels of education.

[31] See Nyarko (2011) on net gains from brain drain for one developing country, Ghana.

[32] The countries are: Australia, Austria, Canada, Denmark, Spain, Finland, France, Hungary, Ireland, Italy, Luxemburg, Portugal, Sweden, United Kingdom, United States. See appendix for more details on the sample. Data downloaded from: http://stats.oecd.org/Index.aspx?DatasetCode=MIG#

Table 14 shows that there is considerable heterogeneity in immigration stocks by destination. Panel A reports statistics for skilled workers. The first set of columns report the statistics on immigrants who work in finance in destination countries (where they moved to), while the latter set of columns report the distribution of those same immigrants by source country (where they came from). Panel A documents very high skill intensity of immigrants in finance as a share in total immigrants working in finance (except for France). Panel B documents similar statistics for all immigrants. Destination country size plays a role, as seen in the shares of skilled immigrants in total finance immigration. But attracting more skilled immigrants to finance across countries in the sample is virtually uncorrelated with their share of skilled employment in finance (0.01), and only weakly correlated to their share in overall skilled immigration to the destination (0.35). This indicates that finance-specific forces help predict skilled immigration employment in finance. The same correlations for overall immigrant employment in finance in Panel B are markedly higher (0.26 and 0.65, respectively), which indicates that finance-specific forces are less important for unskilled workers.

3.2 Finance wages cause brain drain

We start by fitting the following regression, which resembles a trade gravity equation (for example, see Ortega and Peri (2012)):

$$\ln m_{od}^{H,fin} = \alpha_o + \beta \ln w_d^{H,fin} + \gamma \ln w_d^{H,nonfin} + \delta' X_{od} + \varepsilon_{od} \ . \tag{13}$$

Here m_{od} denotes immigration stock in destination d from origin o, H denotes skilled workers, fin denotes employment in finance, and $nonfin$ denotes employment outside finance and agriculture. Here X are standard "gravity" control variables: Common language and contiguity (common border) indicators, and the log of distance between origin and destination capital cities.[33] α_o are origin fixed effects. Since we wish to estimate the effect of wages in the destination, we cannot add destination fixed effects. To help address reverse causality we fit these regressions using one-year lagged explanatory variables (there is no time dimension in X); results are qualitatively similar for longer lags. We add overall skilled wages in non-finance non-agriculture sectors in the destination $w_d^{H,nonfin}$ in order to see whether conditions that are correlated with average wages predict finance immigration, rather than finance wages *per se*. Descriptive statistics for the variables are reported in Table 15.

Regression results of fitting (13) to data are reported in Table 16, columns 1 and 2. The

[33] Data from CEPII, downloaded from: http://www.cepii.fr/anglaisgraph/bdd/distances.htm#. Using different measures of distance from the CEPII dataset hardly affects the results.

message from Panel A is that high skilled wages in finance predict more skilled immigration into finance, even after controlling for skilled wages elsewhere in the destination country. In contrast, low skilled immigration does not respond to low skilled wages in finance, as seen in Panel B. In column (2) in Panel A we estimate (13) and find an elasticity of 2.3 between finance wages and immigration, controlling for aggregate wages. A one standard deviation increase in log finance wages increases finance immigration by 0.54 log points, which is 23% of the standard deviation of log skilled immigration (2.32; see Table 15).

We compare this result to a similar regression for unskilled workers in Panel B (replace all H superscripts with L in (13)). We find that unskilled wages in finance do not predict low skilled immigration to finance once low skilled wages elsewhere are controlled for. The coefficient to $\ln w_d^{L,fin}$ is small and statistically insignificant. This is somewhat surprising: If unskilled workers do not have specific human capital and operate in a competitive environment, then differences in industry wages should have larger effects for them—but this is not the case in the data.[34] It seems that for immigration, it is the skilled workers who respond more to industry wage differentials. This finding is strengthened in the next specification, which we find more appealing.

In the next specification we replace $m_{od}^{H,fin}$ by its share in the overall skilled immigration flow of skilled immigration $m_{od}^{H,fin}/m_{od}^{H}$

$$\left(\frac{m_{od}^{H,fin}}{m_{od}^{H}}\right) = \alpha_o + \beta \ln w_d^{H,fin} + \gamma \ln w_d^{H,nonfin} + \delta' X_{od} + \varepsilon_{od} \ . \tag{14}$$

This specification is preferable for estimating the effect of finance wages on the attractiveness of the sector. It also alleviates the concern that wages in finance may be correlated with overall attractiveness of the country, thus creating a concern for endogeneity in (13).

In columns 3 and 4 of Table 16 we find a similar pattern as in columns 1 and 2: Finance wages increase skilled finance immigration even as a share of overall skilled immigration. A one standard deviation increase in log finance wages increases the share of finance immigration by 3.2 percent points, compared to a standard deviation of 7 percent points, i.e. 46% of the variation. As before, when we compare this to the corresponding regression for unskilled workers in Panel B (replace all H superscripts with L in (14)), we find that unskilled wages in finance have no predictive power for low skilled immigration in finance once overall low skilled wages are controlled for.

Our third specification asks whether the relative skilled wage within finance has an effect on immigrant skill intensity in finance over and above the relative skilled wage in the rest of the

[34] In Table A8 in the appendix we find that this pattern is common to other sectors as well.

economy:

$$\left(\frac{m_{od}^{H,fin}}{m_{od}^{L,fin}}\right) = \alpha_o + \beta\left(\frac{w_d^{H,fin}}{w_d^{L,fin}}\right) + \gamma\left(\frac{w_d^{H,nonfin}}{w_d^{L,nonfin}}\right) + \delta' X_{od} + \varepsilon_{od} \ , \qquad (15)$$

In column 6 we see that relative skilled wages within finance ($w_d^{H,fin}/w_d^{L,fin}$) have a stronger effect on the skill intensity of finance immigration ($m_{od}^{H,fin}/m_{od}^{L,fin}$) relative to the effect of relative skilled wages outside of farm and finance ($w_d^{H,nonfin}/w_d^{L,nonfin}$). A one standard deviation increase in $w_d^{H,fin}/w_d^{L,fin}$ increases $m_{od}^{H,fin}/m_{od}^{L,fin}$ by 0.34, compared to a standard deviation of 1.24, i.e. 28% of the variation—this compared to 20% for $w_d^{H,nonfin}/w_d^{L,nonfin}$.

Finally, we ask whether immigration stocks in other sectors follows similar patterns as in finance. We fit equations (13)–(15) to data on skilled and unskilled immigrants in other sectors, using corresponding wages. We report results on skilled immigration in Table 17. Results for unskilled immigrants are relegated to the appendix (Table A8).

The relationships between wages and immigrant employment in other sectors differ from those in finance. First, skilled wages in Real Estate and Business Services have no predictive power for skilled immigration there. Second, although in the simple "gravity" specification (13) we find similar results to finance in Health Services and Manufacturing, in the normalized gravity specification (14) the coefficients to sector wages turn negative. This justifies our approach to normalize sector-specific immigration flows by overall immigration, thus addressing concerns for endogeneity. Third, although relative skilled wages in health services predict skill intensity of immigrant employment—they do not for manufacturing or for real estate and business services.

Overall, we find compelling evidence that high skilled wages in finance predict skilled immigration employment in finance and affect the allocation of immigration. We do not find strong evidence for this for unskilled immigrants in finance, or for skilled immigrants in other sectors of the economy. This raises concerns that high wages in finance cause brain drain across borders, with detrimental effects on the countries of origin.

4 Concluding remarks

We study the evolution of wages and human capital in the finance industry in a set of developed economies in 1970–2005. Relative wages and skill intensity in finance are generally increasing, but there is wide variation across countries. We find that half of the countries in our sample see increases, while the remainder are split between decreases and mixed trends. We find similar results for skill intensity, but these changes in composition do not explain relative wages in finance. Most of the variation is driven by within-group wage changes, in particular skilled wages in finance relative to skilled wages in the rest of the private sector.

We then seek to explain these patterns. We find that financial deregulation, financial globalization and concentration are the most important determinants of relative wages and skill intensity in finance. In addition, we find that although relative ICT intensity in finance is correlated with the allocation and compensation of human capital in finance, this relationship is not causal.

We also document that increasing wages in finance affect the cross border allocation of talent. We find that when finance pays higher wages, it attract more skilled immigrants. This seems to suggest a negative externality that countries with high finance wages imposes on those with lower wages in finance. We do not find comparable effects for unskilled workers or other industries.

Can high power incentives explain the rise of relative wages in finance? Some theory and evidence suggest that the answer is yes. Axelson and Bond (forthcoming) present an equilibrium theory in which the threat of moral hazard is associated with high wages in finance, and that these problems are exacerbated in booms. Efing, Hau, Kampkötter, and Steinbrecher (2014) find that incentive pay (bonuses) are positively correlated with trading volume and volatility, and that this has diminished somewhat after 2008. Bolton, Santos, and Scheinkman (2011) present a theory of informational rents in opaque "over the counter" markets that drive high wages for traders in these markets. Cheng, Hong, and Scheinkman (2010) find that residual compensation chief executive officers (CEOs) and risk-taking are positively correlated across finance firms in 1992–2008. In contrast, Philippon and Reshef (2012) show that scale effects explain little of the wage differential of CEOs in finance versus CEOs in other sectors after 1990, the period of financial deregulation. Understanding and identifying the mechanisms through which deregulation and financial globalization affect wages in finance is an important field of future research.

Although we have shown that financial deregulation and globalization leads to higher skill intensity and wages in the finance sector, we cannot provide evidence on whether these are socially optimal. This requires a structural model far beyond the scope of this paper.[35] The work of Kneer (2013b), Martinsson (2013), Cecchetti and Kharroubi (2012) and Arcand, Berkes, and Panizza (2012) suggests that higher wages in finance, through their effect on talent absorption, may cause potential harm to some industries. However, these studies only estimate difference-in-difference effects on some sectors versus others, and their results are hard to interpret. 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.

[35] 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 a symmetric way.

Appendix

A EU KLEMS database

All data are available from www.euklems.net. We use the 2008 release. The overall sample covers 22 countries: Australia (1970–2005), Austria (1970–2005), Belgium (1970–2005), Canada (1970–2004), Czech Republic (1995–2005), Denmark (1970–2005), Spain (1970–2005), Finland (1970–2005), France (1970–2005), Germany (1970–2005), Hungary (1991–2005), Ireland (1970–2005), Italy (1970–2005), Japan (1970–2005), Korea (1970–2005), Luxembourg (1970–2005), Netherlands (1970–2005), Portugal (1970–2005), Slovenia (1995–2005), Sweden (1970–2005), United Kingdom (1970–2005), United States (1970–2005). For the United States we use NAICS based data (1977–2005) and complete it with SIC based data (1970–2005) when NAICS based data are missing. Differences in series that we use between NAICS and SIC based methodology are not significant. Not all series are available for all countries and years.

B Derivation of benchmark wage

The finance relative wage can be written as

$$\omega_{fin,t} = \frac{\overline{w}_{fin,t}}{\overline{w}_{nffp,t}} = \frac{w_{fin,t}\left(1-h_{fin,t}\right)+s_{fin,t}h_{fin,t}}{w_{nffp,t}\left(1-h_{nffp,t}\right)+s_{nffp,t}h_{nffp,t}} = \frac{w_{fin,t}}{w_{nffp,t}} \cdot \frac{1+h_{fin,t}\left(\frac{s_{fin,t}}{w_{fin,t}}-1\right)}{1+h_{nffp,t}\left(\frac{s_{nffp,t}}{w_{nffp,t}}-1\right)} ,$$

where h is the employment share of skilled labor, w and s are unskilled and skilled wages. If $w_{fin,t} = w_{nffp,t}$ and $s_{fin,t} = s_{nffp,t}$, then we get the expression for the benchmark wage in the text,

$$\widehat{\omega}_{fin,t} = \frac{1+h_{fin,t}\pi_{nffp,t}}{1+h_{nffp,t}\pi_{nffp,t}} ,$$

where $\pi_{nffp,t} = s_{nffp,t}/w_{nffp,t} - 1$.

C Quantity indices for non-farm, non-finance private sector (NFFP)

Capital quantity indices for the non-farm, non-finance private sector (NFFP) are given by

$$Q_{nffp,t} = \frac{Q_{agg,t} * v_{agg,1995} - \sum_{i\in\{farm,fin,public\}} Q_{i,t} * v_{i,1995}}{v_{agg,1995} - \sum_{i\in\{farm,fin,public\}} v_{i,1995}} ,$$

where $Q_{i,t}$ is the quantity index for sector i, $v_{i,1995}$ is the nominal value of the capital stock in 1995. This preserves the properties of the quantity indices since each quantity index is conceptually given by

$$Q_{i,t} = 100 \cdot \frac{q_{i,t}}{q_{i,1995}} = 100 \cdot \frac{q_{i,t}p_{i,1995}}{q_{i,1995}p_{i,1995}} = 100 \cdot \frac{q_{i,t}p_{i,1995}}{v_{i,1995}} ,$$

where q and p are real quantity and price, respectively. In particular, $Q_{nffp,1995} = 100$.

D Domestic credit data and corrections

Our measure of overall domestic credit is *Domestic credit provided by financial sector (% of GDP)*, from the World Bank: "Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations where data are available (including corporations that do not accept transferable deposits but do incur such liabilities as time and savings deposits). Examples of other financial corporations are finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies."

The bank credit measure from the World Bank is *Domestic credit to private sector by banks (% of GDP)*: "Domestic credit to private sector by banks refers to financial resources provided to the private sector by other depository corporations (deposit taking corporations except central banks), such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises." This is very similar to the definitions in Jordà, Taylor, and Schularick (2014) (JST), who split bank credit to household versus corporate credit, and to mortgage versus non-mortgage credit.

When examining the World Bank domestic credit series (both overall and bank credit), we detected a few breaks. In order to correct these breaks we spliced series based on the following criterion. In most years bank credit data from JST and from the World Bank are almost identical. Breaks in the World Bank data are invariably deviations from JST data. Therefore, we adjust all observations in which we observe large deviations from JST bank credit data. The source of the breaks is likely the denominator (GDP), because breaks appear both in the *Domestic credit provided by financial sector (% of GDP)* series and in the *Domestic credit to private sector by banks (% of GDP)* series, in the same proportion.

Here we list all corrections made to the *Domestic credit provided by financial sector (% of GDP)* series, as well as one correction to *Domestic credit to private sector by banks (% of GDP)* series for Korea:

- Belgium 1991/1992 break: multiply all years before 1992 by the 1992/1991 ratio.
- Canada 2000/2001 break: divide all years after 2000 by the 2001/2000 ratio.
- Denmark 1999/2000 break: multiply all years before 2000 by the 2000/1999 ratio.
- France 1976/1977/1978 and 1984/1985 breaks: we correct in two steps, in the following sequence:

1. Replace the value for 1977 from 0.381 to 0.881. In 1976 the value is 0.880, so we assume that "3" was an "8" that got botched up.

2. deduct from 1978–1984 years the average of the difference between 1984 and 1985 and the new difference between 1977 and 1978.

- Korea 2000/2001 break: we divide all years after 2000 by the 2001/2000 ratio—for both credit concepts.
- Netherlands 1985/1986 break: divide all years before 1986 by the 1985/1986 ratio.
- Sweden 1982/1983 and 2000 break: multiply all years before 1983 by the 1983/1982 ratio; we drop the observation for year 2000.
- United Kingdom 1986/1987 break: multiply all years before 1987 by the 1987/1986 ratio.

Our main source for bank credit is JST data. We use the World Bank data whenever JST does not have it (Korea, Austria, Portugal, Czech Republic, Slovenia). This gives a maximum of 16 countries with bank credit data: Australia, Austria, Canada, Czech Republic, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Portugal, Sweden, United States, Slovenia. The intersection of this set of countries before 1995 with ICT data leaves us with only 13 countries: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. When we split bank credit before 1995 we lose Austria and Korea because the split is unavailable for these countries. In the sample after

1997 we have the maximal set of countries (16). When we split bank credit after 1997 we lose four countries—Austria, Czech Republic, Korea and Slovenia—because the split is unavailable for these countries.

E Immigration data and sample

Data on immigration stocks in a sample of 15 countries in 2000 by country of origin and sector of employment in the destination country were downloaded from the OECD *StatExtracts* website: http://stats.oecd.org/Index.aspx?DatasetCode=MIG#. Sectors of immigrants' employment in Belgium and The Netherlands are not coded and therefore we cannot distinguish immigrants in different sectors in these two countries, so they are not part of our data. The data does not include Germany at all. Thus, the sample covers 15 countries: Australia, Austria, Canada, Denmark, Spain, Finland, France, Hungary, Ireland, Italy, Luxemburg, Portugal, Sweden, United Kingdom, United States.

There are potentially 210 bilateral observations ($15 \times 15 - 15 = 210$). There are 17 missing observations for skilled immigrants in finance, and another 17 missing observations for unskilled immigrants in finance (skilled have tertiary education; unskilled are all the rest). These missing observations are zeros and since we cannot employ them in our estimation, they are dropped. This gives us 193 bilateral observations of immigration stocks in working in finance, either skilled or unskilled. The 17 missing observations on each type of worker only partially overlap. Therefore, in specifications that use data on both we lose 10 additional observations because only 7 missing observations are common. In appendix Table A7 we report the incidence of missing observations.

When we estimate migration gravity equations using TSLS, we lose 14 additional observations because deregulation data for Luxemburg are missing; this gives us 179 observations in those regressions ($193 - 14 = 179$).

Samples for immigration stocks employed in other sectors of the economy vary in similar ways.

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Table 1: Decomposition of Changes in Wages

A. Decomposition of Finance Relative Wage

Country	Sample	Change in finance relative wage	Within share	Between share
Australia	1982 - 2005	1.30	0.87	0.13
United States	1970 - 2005	0.78	0.65	0.35
Spain	1980 - 2005	0.52	0.76	0.24
Netherlands	1979 - 2005	0.45	0.52	0.48
Canada	1970 - 2004	0.43	0.64	0.36
Luxemburg	1992 - 2005	0.42	0.76	0.24
Finland	1970 - 2005	0.40	0.50	0.50
Hungary	1995 - 2005	0.38	0.56	0.44
Denmark	1980 - 2005	0.36	0.78	0.22
France	1980 - 2005	0.32	0.57	0.43
Czech Republic	1995 - 2005	0.32	0.59	0.41
Sweden	1981 - 2005	0.30	0.61	0.39
Portugal	1992 - 2005	0.29	0.67	0.33
Japan	1973 - 2005	0.26	0.10	0.90
Ireland	1988 - 2005	0.26	0.04	0.96
Germany	1991 - 2005	0.12	0.81	0.19
United Kingdom	1970 - 2005	-0.02	16.39	-15.39
Austria	1980 - 2005	-0.04	4.70	-3.70
Belgium	1980 - 2005	-0.11	2.42	-1.42
Slovenia	1995 - 2005	-0.21	1.49	-0.49
Korea	1970 - 2005	-0.52	1.18	-0.18
Italy	1970 - 2005	-1.20	1.03	-0.03

Notes: Countries are sorted by the change in finance relative wage. The decomposition for each country is based on equation (2) in the text. The within share captures the contribution of wage changes within skill groups (high skilled, low skilled); the between share captures the contribution of changes of skill composition. Data: EU KLEMS.

B. Decomposition of Changes in Skilled Relative Wage

Country	Sample	Change in skilled relative wage	Within share	Between share	Finance share
United States	1980 - 2005	0.58	0.98	0.02	0.22
Luxemburg	1992 - 2005	0.55	0.87	0.13	0.65
Portugal	1992 - 2005	0.33	0.98	0.02	0.19
Canada	1980 - 2004	0.33	0.98	0.02	0.30
Hungary	1995 - 2005	0.32	1.03	-0.03	0.01
Ireland	1988 - 2005	0.28	0.91	0.09	0.56
Germany	1991 - 2005	0.26	1.00	0.00	0.10
Italy	1980 - 2005	0.20	1.19	-0.19	-0.61
Czech Republic	1995 - 2005	0.08	1.05	-0.05	0.16
Australia	1982 - 2005	0.08	1.05	-0.05	1.57
Japan	1980 - 2005	-0.04	0.80	0.20	0.73
Sweden	1981 - 2005	-0.08	1.02	-0.02	-0.33
Spain	1980 - 2005	-0.10	1.05	-0.05	-0.48
Slovenia	1995 - 2005	-0.12	1.04	-0.04	0.11
Belgium	1980 - 2005	-0.14	1.03	-0.03	0.10
Finland	1980 - 2005	-0.15	0.98	0.02	0.23
Austria	1980 - 2005	-0.19	1.15	-0.15	-0.22
United Kingdom	1980 - 2005	-0.23	1.00	0.00	-0.08
Denmark	1980 - 2005	-0.32	1.03	-0.03	-0.13
Netherlands	1980 - 2005	-0.44	1.07	-0.07	-0.19
France	1980 - 2005	-0.55	1.01	-0.01	-0.03
Korea	1980 - 2005	-0.74	1.01	-0.01	0.07

Notes: Countries are sorted by the change in skilled relative wage, which is defined as the wage of university-educated workers divided by the wage other workers, both in the nonfarm private sector (including finance). The decomposition for each country is based on equations 6 and 7 in the text. The within share captures the contribution of wage changes within skill groups (high skilled, low skilled); the between share captures the contribution of changes of skill composition; the finance share captures the overall contribution of finance, whether from within-finance changes or changes in the allocation of skilled workers to finance. Data: EU KLEMS.

Table 2: Finance Relative ICT Capital Share

	Finance Relative ICT Share				Changes			
	1975	1985	1995	2005	1975-1985	1985-1995	1995-2005	Total
Australia	0.008	0.019	0.061	0.391	0.012	0.042	0.330	0.383
Austria		0.016	0.048	0.178		0.032	0.130	0.162
Belgium								
Canada*	-0.054	-0.015	0.012	-0.043	0.039	0.027	-0.055	0.011
Czech Republic			0.168	0.293			0.125	0.125
Denmark	0.006	0.041	0.125	0.592	0.035	0.085	0.466	0.586
Finland	0.075	0.146	0.350	0.836	0.071	0.204	0.486	0.761
France								
Germany			0.077	0.194			0.117	0.117
Hungary								
Ireland								
Italy	-0.005	0.004	0.014	0.137	0.009	0.010	0.122	0.141
Japan	0.046	0.047	0.122	0.306	0.001	0.075	0.184	0.260
Korea		0.085	0.153	0.186		0.069	0.033	0.102
Luxemburg								
Netherlands	0.008	0.019	0.066	0.300	0.011	0.047	0.234	0.292
Portugal			0.112	0.101			-0.010	-0.010
Slovenia			-0.027	0.284			0.311	0.311
Spain								
Sweden			0.163	0.276			0.113	0.113
United Kingdom	0.035	0.015	0.129	0.303	-0.020	0.114	0.174	0.268
United States	0.014	0.054	0.146	0.355	0.040	0.092	0.209	0.341
Average	0.015	0.039	0.107	0.293	0.022	0.072	0.186	0.248

Notes: The table reports ICT (Information and Communication Technology) shares in real capital stock in finance minus the ICT share in the nonfarm, non-finance private sector (NFFP) in different years and the changes between those years. The Total change is the sum of changes in the preceding three columns. * Data for Canada in 2005 is missing and is replaced in this table by data for Canada in 2004. Data: EU KLEMS.

Table 3: Financial Regulation

A. Indicators

	Directed Credit		Interest Rate Controls		Entry Barriers, Activity		Banking Supervision		Privatization		International Capital Flows	
	1973*	1995	1973*	1995	1973*	1995	1973*	1995	1973*	1995	1973*	1995
Australia	0	3	0	3	0	2	0	3	0	3	0	3
Austria	1	1	0	3	0	3	0	1	0	2	1	3
Belgium	2	3	1	3	1	3	1	2	2	2	0	3
Canada	2	3	3	3	0	3	0	3	3	3	2	3
Czech Republic*	1	1	0	3	3	2	0	1	0	2	0	0
Denmark	2	2	0	3	1	3	0	3	2	3	1	3
Finland	2	3	1	3	2	3	0	1	1	1	0	3
France	0	3	1	3	1	3	0	3	1	2	1	3
Germany	3	3	3	3	1	3	1	3	1	1	2	3
Hungary*	1	1	3	3	2	2	0	1	0	0	0	2
Ireland	1	3	1	3	3	3	0	3	3	3	1	3
Italy	0	2	1	3	0	3	0	2	0	1	1	3
Japan	1	2	0	3	0	3	0	1	2	2	2	3
Korea	0	3	0	3	0	2	0	1	1	0	1	2
Luxemburg**												
Netherlands	3	3	3	3	3	3	0	2	3	3	0	3
Portugal	0	1	0	3	0	3	0	2	1	1	1	3
Slovenia**												
Spain	1	3	1	3	1	3	1	3	2	2	1	3
Sweden	0	3	0	3	1	3	0	2	3	3	1	3
United Kingdom	2	3	2	3	1	3	0	2	2	3	1	3
United States	2	3	0	3	1	1	1	3	3	3	3	3

B. Changes in Indicators

	Directed Credit	Interest Rate Controls	Entry Barriers, Activity	Banking Supervision	Privatization	International Capital Flows
Australia	3	3	2	3	3	3
Austria	0	3	3	1	2	2
Belgium	1	2	2	1	0	3
Canada	1	0	3	3	0	1
Czech Republic*	0	3	-1	1	2	0
Denmark	0	3	2	3	1	2
Finland	1	2	1	1	0	3
France	3	2	2	3	1	2
Germany	0	0	2	2	0	1
Hungary*	0	0	0	1	0	2
Ireland	2	2	0	3	0	2
Italy	2	2	3	2	1	2
Japan	1	3	3	1	0	1
Korea	3	3	2	1	-1	1
Luxemburg**						
Netherlands	0	0	0	2	0	3
Portugal	1	3	3	2	0	2
Slovenia**						
Spain	2	2	2	2	0	2
Sweden	3	3	2	2	0	2
United Kingdom	1	1	2	2	1	2
United States	1	3	0	2	0	0

Notes: The table reports financial regulation indicators and changes. Higher values indicate less restrictions or financial liberalization, except for Banking Supervision. For Banking Supervision higher values indicate adopting a capital adequacy ratio based on the Basle standard; banking supervisory agency independence; and whether the banking supervisory agency covers all financial institutions without exception. * Data for the Czech Republic and Hungary start in 1990. ** Data for Luxemburg and Slovenia are not available. Source: Abiad, Detragiache and Tressel (2008) and authors' calculations.

Table 4: ICT and complementarity with high skilled workers

	Dependent variable: Wage bill share of skilled workers					
	Finance	Aggregate	NFFP	Finance	Aggregate	NFFP
ln(wH/wL)	0.254***	-0.0266	-0.0116	0.229***	0.0543***	0.0355**
	(0.0314)	(0.0237)	(0.0241)	(0.0252)	(0.0133)	(0.0158)
ln(ICT/Q)	0.0562***	0.0472***	0.0465***	0.0409***	0.0227***	0.0273***
	(0.00234)	(0.00129)	(0.00263)	(0.00291)	(0.00212)	(0.00331)
ln(NonICT/Q)	-0.0946***	0.00367	-0.0475***	-0.0671***	0.0636***	0.0686***
	(0.00901)	(0.0224)	(0.00656)	(0.00628)	(0.0171)	(0.0137)
ln(Q)				0.0751***	0.120***	0.0898***
				(0.00923)	(0.00919)	(0.0104)
Observations	456	456	353	456	456	353
Number of countries	22	22	16	22	22	16
Test of equality of ln(ICT/Q) coefficient with finance						
Chi-squared		11.45	7.61		25.59	9.55
p-value		0.001	0.006		0.000	0.002

Notes: All regressions are estimated with two stage least squares, and include country fixed effects. Here wH and wL are wages of skilled and all other workers, respectively; ICT and NonICT are quantity indices for ICT and non-ICT capital, respectively; and Q is the output quantity index. See text for details on the construction of quantity indices for the NFFP sector. The sample for NFFP reduces due to data limitations. Data: EU KLEMS. Test statistics are obtaied by pooling data series for aggregate or NFFP with finance. Robust standard errors in parentheses. *** p<0.01.

Table 5: Descriptive Statistics for Level, Predictive, and Bank Concentration Regressions

A. For level regressions

	Mean	S.D.	Min	p10	p25	p50	p75	p90	Max
Finance relative wage (t)	1.51	0.35	0.61	1.18	1.29	1.47	1.67	2.02	3.01
Finance skilled relative wage (t)	1.44	0.42	0.61	0.99	1.2	1.39	1.57	1.94	3.62
Finance relative skill intensity (t)	0.07	0.06	-0.03	-0.01	0.01	0.06	0.1	0.17	0.23
Finance excess wage (t)	0.5	0.35	-0.43	0.12	0.3	0.45	0.66	1.03	2.01
Finance relative ICT intensity (t-3)	0.06	0.07	-0.05	0	0.01	0.04	0.1	0.14	0.48
Domestic credit/GDP (t-3)	1.07	0.53	0.38	0.5	0.71	0.98	1.23	1.7	2.92
Non-bank domestic credit/GDP (t-3)	0.42	0.44	0.02	0.07	0.17	0.27	0.41	1.19	1.92
Bank domestic credit/GDP (t-3)	0.65	0.24	0.21	0.39	0.46	0.61	0.83	1	1.29
Household bank credit/GDP (t-3)	0.32	0.17	0.06	0.11	0.18	0.3	0.45	0.54	0.7
Corporate bank credit/GDP (t-3)	0.34	0.2	0.11	0.14	0.17	0.25	0.48	0.65	0.84
Mortgage bank credit/GDP (t-3)	0.29	0.18	0.07	0.14	0.18	0.24	0.32	0.59	0.81
Non-mortgage bank credit/GDP (t-3)	0.36	0.15	0.14	0.17	0.27	0.34	0.46	0.55	0.8
Financial globalization (t-3)	0.09	0.68	-1.55	-0.77	-0.4	0.08	0.53	1.02	1.73

B. For predictive regressions

	Mean	S.D.	Min	p10	p25	p50	p75	p90	Max
Change in finance relative wage (t,t+3)	0	0.18	-1.01	-0.16	-0.03	0.02	0.08	0.14	0.75
Change in finance skilled relative wage (t,t+3)	0.02	0.17	-0.76	-0.13	-0.03	0.02	0.09	0.15	0.7
Change in finance relative skill intensity (t,t+3)	0.01	0.01	-0.03	-0.01	0	0.01	0.02	0.02	0.04
Change in finance excess wage (t,t+3)	0.01	0.16	-0.58	-0.14	-0.03	0.02	0.08	0.14	0.74
Change in finance relative ICT intensity (t-3,t)	0.02	0.02	-0.02	0	0	0.01	0.02	0.04	0.17
Change in domestic credit/GDP (t-3,t)	0.06	0.11	-0.34	-0.06	0	0.06	0.13	0.18	0.37
Change in financial globalization (t-3,t)	0.14	0.17	-0.61	-0.05	0.06	0.15	0.24	0.34	0.59

Notes: Statistics are computed for 241 observations for 13 countries. The range for t is 1976-1998. This is due to our choice to use financial regulation variables in 1973-1995. Wage, skill and ICT variables are calculated based on EU KLEMS data. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Bank domestic credit data are from Jorda, Schularick and Taylor (2014), except for Austria and Korea where the data are from the Bank World Development Indicators databse. Non-bank domestic credit is total domestic credit minus bank credit. The split of bank domestic credit to households versus corporations, and to mortgage versus non-mortgage lending is given in Jorda, Schularick and Taylor (2014). Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). Statistics on the financial reform indices are reported in Table 5.

C. For Bank Concentration Regressions

	Mean	S.D.	Min	p10	p25	p50	p75	p90	Max
Finance relative wage (t)	1.72	0.33	1.3	1.41	1.53	1.61	1.89	2.08	2.74
Finance skilled relative wage (t)	1.47	0.23	0.98	1.16	1.19	1.5	1.64	1.76	1.88
Finance relative skill intensity (t)	0.12	0.09	-0.01	0.02	0.04	0.13	0.16	0.26	0.3
Finance excess wage (t)	0.63	0.27	0.2	0.3	0.44	0.55	0.79	0.93	1.36
Finance relative ICT intensity (t-3)	0.27	0.18	-0.06	0.1	0.18	0.25	0.3	0.5	0.84
Domestic credit/GDP (t-3)	1.32	0.67	0.42	0.48	0.99	1.22	1.58	2.18	3.19
Non-bank domestic credit/GDP (t-3)	0.43	0.66	-0.31	0.03	0.1	0.2	0.39	1.76	2.38
Bank domestic credit/GDP (t-3)	0.89	0.36	0.28	0.4	0.65	0.87	1.07	1.39	1.63
Household bank credit/GDP (t-3)	0.51	0.2	0.24	0.25	0.32	0.49	0.68	0.8	0.84
Corporate bank credit/GDP (t-3)	0.44	0.19	0.15	0.16	0.25	0.5	0.58	0.7	0.79
Mortgage bank credit/GDP (t-3)	0.5	0.22	0.22	0.27	0.32	0.47	0.57	0.91	1.05
Non-mortgage bank credit/GDP (t-3)	0.45	0.14	0.13	0.3	0.37	0.47	0.53	0.63	0.7
Financial globalization (t-3)	1.12	0.58	0.05	0.43	0.6	1.26	1.51	2.06	2.17
Bank concentration (t-3)	-0.42	0.4	-1.46	-1.05	-0.53	-0.34	-0.13	0	0

Notes: Bank concentration is the log of the share of the largest three banks; data from the World Bank. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Bank domestic credit data are from Jorda, Schularick and Taylor (2014), except for Austria and Korea where the data are from the Bank World Development Indicators databse. Non-bank domestic credit is total domestic credit minus bank credit. The split of bank domestic credit to households versus corporations, and to mortgage versus non-mortgage lending is given in Jorda, Schularick and Taylor (2014). Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). Statistics are computed for 60 observations for 16 countries. The range for t is 2000-2005. The sample of 16 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Czech Republic, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Portugal, Sweden, United States, Slovenia. We lose Austria, Czech Republic, Korea and Slovenia when we split bank credit due to data unavailability.

Table 6: Finance Relative Wage and Relative Skill Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent Variable:	Finance relative wage				Finance skilled relative wage				Finance relative skill intensity				Finance excess wage			
Finance relative share of ICT in capital stock, t-3	0.917*			0.185	1.486**			1.215**	0.139***			0.120***	1.081**			0.362
	(0.529)			(0.451)	(0.625)			(0.558)	(0.0362)			(0.0420)	(0.522)			(0.463)
Domestic credit/GDP, t-3	0.00980			0.135	0.257*			0.559***	0.0282***			0.0342***	0.0267			0.202**
	(0.108)			(0.0903)	(0.135)			(0.117)	(0.00781)			(0.00884)	(0.113)			(0.0973)
Financial globalization, t-3	0.449***			0.221***	0.242***			-0.0694	0.0430***			0.0412***	0.349***			0.134**
	(0.0585)			(0.0525)	(0.0774)			(0.0691)	(0.00448)			(0.00520)	(0.0647)			(0.0573)
International capital restrictions, t-3		0.134***	0.174***	0.133***		0.105***	0.154***	0.148***		0.0133***	0.00801**	-0.000337		0.146***	0.178***	0.149***
		(0.0220)	(0.0249)	(0.0247)		(0.0263)	(0.0330)	(0.0328)		(0.00322)	(0.00315)	(0.00247)		(0.0219)	(0.0267)	(0.0272)
Privatization, t-3		-0.00777	-0.0587	-0.0399		-0.0146	-0.0483	-0.00865		-0.0156***	-0.0187***	-0.0136***		-0.0213	-0.0557	-0.0351
		(0.0360)	(0.0432)	(0.0409)		(0.0389)	(0.0525)	(0.0496)		(0.00476)	(0.00501)	(0.00373)		(0.0324)	(0.0425)	(0.0411)
Entry barriers, t-3		-0.0286	-0.117***	-0.145***		-0.0630**	-0.0815*	-0.122***		0.00194	0.00649	3.49e-06		-0.119***	-0.126***	-0.154***
		(0.0258)	(0.0333)	(0.0315)		(0.0308)	(0.0434)	(0.0411)		(0.00377)	(0.00414)	(0.00309)		(0.0257)	(0.0351)	(0.0340)
Banking supervision, t-3		0.142***	0.196***	0.175***		0.133***	0.171***	0.221***		0.0106***	0.00999***	0.00818***		0.156***	0.185***	0.181***
		(0.0249)	(0.0298)	(0.0299)		(0.0272)	(0.0372)	(0.0376)		(0.00332)	(0.00355)	(0.00283)		(0.0226)	(0.0301)	(0.0311)
Directed credit, t-3		-0.0406*	0.00644	0.0480*		0.0279	0.0314	0.0744**		-0.00927***	-0.00546	0.00315		-0.0215	-0.00147	0.0367
		(0.0212)	(0.0282)	(0.0283)		(0.0236)	(0.0369)	(0.0365)		(0.00289)	(0.00352)	(0.00274)		(0.0197)	(0.0298)	(0.0302)
Interest rate control, t-3		0.0614***	0.0902***	0.0481**		0.0388*	0.0637**	0.0233		0.00522*	0.00618**	-0.00197		0.0415**	0.0694***	0.0353
		(0.0192)	(0.0214)	(0.0213)		(0.0228)	(0.0274)	(0.0270)		(0.00279)	(0.00261)	(0.00203)		(0.0190)	(0.0221)	(0.0224)
Sample	Full	Full	1∩2	1∩2	Full	Full	5∩6	5∩6	Full	Full	9∩10	9∩10	Full	Full	13∩14	13∩14
Observations	265	404	241	241	238	324	226	226	238	324	226	226	238	324	226	226
R-squared, within	0.333	0.283	0.480	0.553	0.215	0.233	0.310	0.413	0.742	0.474	0.533	0.753	0.279	0.366	0.434	0.494
Number of countries	13	20	13	13	13	20	13	13	13	20	13	13	13	20	13	13

Note: All regressions include country fixed effects and year fixed effects. The right hand side variables are lagged 3 periods. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 1998. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Finance Relative Wage and Relative Skill Intensity, Nonlinear Effects of Financial Reform

	(1)	(2)	(3)	(4)
Dependent Variable:	Finance relative wage	Finance skilled relative wage	Finance relative skill intensity	Finance excess wage
Finance relative share of IT in capital stock, t-3	-0.0208	0.360	0.0827*	-0.0158
	(0.503)	(0.612)	(0.0457)	(0.515)
Domestic credit/GDP, t-3	0.0616	0.445***	0.0261***	0.144
	(0.0878)	(0.114)	(0.00848)	(0.0956)
Financial globalization, t-3	0.228***	-0.0473	0.0421***	0.137**
	(0.0495)	(0.0648)	(0.00484)	(0.0546)
International capital restrictions == 1, t-3	0.291***	0.359***	0.0125**	0.358***
	(0.0472)	(0.0708)	(0.00529)	(0.0596)
International capital restrictions == 2, t-3	0.375***	0.474***	0.00604	0.451***
	(0.0504)	(0.0734)	(0.00548)	(0.0618)
Privatization == 1, t-3	0.0363	-0.160**	0.00553	0.0168
	(0.0647)	(0.0780)	(0.00582)	(0.0656)
Privatization == 2, t-3	0.0462	0.0229	-0.0136*	0.0545
	(0.0809)	(0.0971)	(0.00725)	(0.0818)
Entry barriers == 1, t-3	-0.0407	-0.0150	0.0119***	-0.0468
	(0.0401)	(0.0529)	(0.00395)	(0.0445)
Entry barriers == 2, t-3	-0.245***	-0.226***	0.00937	-0.273***
	(0.0611)	(0.0816)	(0.00609)	(0.0687)
Banking supervision == 1, t-3	0.135***	0.191***	0.00499	0.156***
	(0.0369)	(0.0470)	(0.00351)	(0.0395)
Banking supervision == 2, t-3	0.412***	0.406***	0.0185***	0.409***
	(0.0600)	(0.0737)	(0.00551)	(0.0621)
Directed credit == 1, t-3	-0.155***	-0.193***	-0.0175***	-0.152***
	(0.0490)	(0.0602)	(0.00449)	(0.0506)
Directed credit == 2, t-3	-0.0595	-0.0248	-0.00683	-0.0700
	(0.0578)	(0.0725)	(0.00541)	(0.0610)
Interest rate control == 1, t-3	0.0988***	0.106**	-0.00481	0.0916**
	(0.0360)	(0.0470)	(0.00351)	(0.0396)
Interest rate control == 2, t-3	0.107***	0.0602	-0.00489	0.0901**
	(0.0399)	(0.0510)	(0.00381)	(0.0429)
Observations	241	226	226	226
R-squared, within	0.643	0.542	0.810	0.593
Number of country_id	13	13	13	13

Note: All regressions include country fixed effects and year fixed effects. The right hand side variables are lagged 3 periods. The right hand side deregulation dummies are constructed as follows: We create a dummy variable corresponding with each value for each index. We drop the category 0 for each deregulation variable. The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 1998. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Finance Relative Wage and Relative Skill Intensity, Breakdown of Domestic Credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent Variable:	Finance relative wage				Finance skilled relative wage				Finance relative skill intensity				Finance excess wage			
Finance relative share of ICT in capital stock, t-3	0.185	0.149	0.497	0.152	1.215**	1.247**	1.941***	1.382**	0.120***	0.114***	0.0772*	0.0930**	0.362	0.345	0.625	0.231
	(0.451)	(0.451)	(0.504)	(0.470)	(0.558)	(0.557)	(0.684)	(0.619)	(0.0420)	(0.0410)	(0.0465)	(0.0421)	(0.463)	(0.463)	(0.521)	(0.491)
Financial globalization, t-3	0.221***	0.215***	0.192**	0.238***	-0.0694	-0.0653	0.0743	0.0735	0.0412***	0.0406***	0.0305***	0.0326***	0.134**	0.132**	0.126	0.151*
	(0.0525)	(0.0525)	(0.0798)	(0.0764)	(0.0691)	(0.0690)	(0.115)	(0.108)	(0.00520)	(0.00508)	(0.00781)	(0.00736)	(0.0573)	(0.0573)	(0.0876)	(0.0857)
Domestic credit/GDP, t-3	0.135				0.559***				0.0342***				0.202**			
	(0.0903)				(0.117)				(0.00884)				(0.0973)			
Non-bank domestic credit/GDP, t-3		0.214**	0.265**	0.216**		0.460***	0.546***	0.413***		0.0501***	0.0424***	0.0394***		0.253**	0.294**	0.259**
		(0.107)	(0.111)	(0.109)		(0.135)	(0.157)	(0.148)		(0.00994)	(0.0107)	(0.0101)		(0.112)	(0.120)	(0.117)
Bank domestic credit/GDP, t-3		0.00973				0.732***				0.00621				0.113		
		(0.128)				(0.166)				(0.0122)				(0.138)		
Household bank credit/GDP, t-3			-0.145				0.868***				0.0201				-0.0609	
			(0.191)				(0.263)				(0.0179)				(0.201)	
Corporate bank credit/GDP, t-3			0.652**				0.692*				0.0376				0.643**	
			(0.271)				(0.367)				(0.0250)				(0.280)	
Mortgage bank credit/GDP, t-3				0.0406				1.335***				0.0501*				0.111
				(0.284)				(0.375)				(0.0255)				(0.297)
Non-mortgage bank credit/GDP, t-3				0.230				0.498*				0.000318				0.320
				(0.209)				(0.278)				(0.0190)				(0.221)
International capital restrictions, t-3	0.133***	0.144***	0.122***	0.109***	0.148***	0.137***	0.105**	0.106***	-0.000337	0.00143	0.00134	-0.000789	0.149***	0.155***	0.131***	0.127***
	(0.0247)	(0.0258)	(0.0309)	(0.0278)	(0.0328)	(0.0335)	(0.0426)	(0.0388)	(0.00247)	(0.00247)	(0.00290)	(0.00264)	(0.0272)	(0.0279)	(0.0324)	(0.0308)
Privatization, t-3	-0.0399	-0.0173	0.0123	-0.0402	-0.00865	-0.0394	-0.00880	-0.0675	-0.0136***	-0.00863**	-0.0178***	-0.0190***	-0.0351	-0.0192	0.0162	-0.0351
	(0.0409)	(0.0440)	(0.0495)	(0.0486)	(0.0496)	(0.0536)	(0.0662)	(0.0631)	(0.00373)	(0.00395)	(0.00450)	(0.00430)	(0.0411)	(0.0446)	(0.0505)	(0.0500)
Entry barriers, t-3	-0.145***	-0.143***	-0.188***	-0.166***	-0.122***	-0.129***	-0.120**	-0.164***	3.49e-06	0.00109	-0.00628	-0.00257	-0.154***	-0.150***	-0.178***	-0.165***
	(0.0315)	(0.0315)	(0.0421)	(0.0348)	(0.0411)	(0.0412)	(0.0571)	(0.0476)	(0.00309)	(0.00303)	(0.00389)	(0.00324)	(0.0340)	(0.0343)	(0.0435)	(0.0377)
Banking supervision, t-3	0.175***	0.176***	0.213***	0.167***	0.221***	0.221***	0.286***	0.198***	0.00818***	0.00808***	0.00703**	0.00439	0.181***	0.181***	0.207***	0.165***
	(0.0299)	(0.0298)	(0.0357)	(0.0336)	(0.0376)	(0.0375)	(0.0483)	(0.0449)	(0.00283)	(0.00276)	(0.00329)	(0.00306)	(0.0311)	(0.0311)	(0.0368)	(0.0356)
Directed credit, t-3	0.0480*	0.0533*	0.146***	0.123***	0.0744**	0.0654*	0.122**	0.111**	0.00315	0.00459*	0.00472	0.00634**	0.0367	0.0413	0.136***	0.111***
	(0.0283)	(0.0285)	(0.0364)	(0.0331)	(0.0365)	(0.0369)	(0.0518)	(0.0459)	(0.00274)	(0.00271)	(0.00352)	(0.00312)	(0.0302)	(0.0306)	(0.0395)	(0.0364)
Interest rate control, t-3	0.0481**	0.0446**	0.00805	0.0337	0.0233	0.0269	0.00255	-0.00432	-0.00197	-0.00255	-0.00178	0.00106	0.0353	0.0334	0.00240	0.0214
	(0.0213)	(0.0214)	(0.0330)	(0.0296)	(0.0270)	(0.0271)	(0.0455)	(0.0400)	(0.00203)	(0.00199)	(0.00310)	(0.00272)	(0.0224)	(0.0225)	(0.0347)	(0.0317)
Observations	241	241	187	204	226	226	176	190	226	226	176	190	226	226	176	190
R-squared, within	0.553	0.558	0.661	0.629	0.413	0.420	0.495	0.478	0.753	0.766	0.821	0.816	0.494	0.496	0.603	0.563
Number of countries	13	13	11	11	13	13	11	11	13	13	11	11	13	13	11	11

Note: All regressions include country fixed effects and year fixed effects. The right hand side variables are lagged 3 periods. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance are calculated from EU KLEMS database. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Bank domestic credit data are from Jorda, Schularick and Taylor (2014), except for Austria and Korea where the data are from the Bank World Development Indicators databse. Non-bank domestic credit is total domestic credit minus bank credit. The split of bank domestic credit to households versus corporations, and to mortgage versus non-mortgage lending is given in Jorda, Schularick and Taylor (2014). Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 1998. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. We lose Austria and Korea when we split bank credit due to data unavailability. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Finance Relative Wage and Relative Skill Intensity, Anglo-Saxon versus Other Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Finance relative wage		Finance skilled relative wage		Finance relative skill intensity		Finance excess wage	
Finance relative share of ICT in capital stock, t-3 to t	0.185	0.908**	1.215**	2.501***	0.120***	0.166***	0.362	1.046**
	(0.451)	(0.448)	(0.558)	(0.507)	(0.0420)	(0.0487)	(0.463)	(0.444)
Domestic credit/GDP, t-3 to t	0.135	0.203**	0.559***	0.717***	0.0342***	0.0475***	0.202**	0.248**
	(0.0903)	(0.0967)	(0.117)	(0.113)	(0.00884)	(0.0109)	(0.0973)	(0.0992)
Financial globalization, t-3 to t	0.221***	0.100*	-0.0694	-0.247***	0.0412***	0.0346***	0.134**	0.0284
	(0.0525)	(0.0516)	(0.0691)	(0.0610)	(0.00520)	(0.00586)	(0.0573)	(0.0533)
International capital restrictions, t-3 to t	0.133***	0.133***	0.148***	0.121***	-0.000337	-0.00282	0.149***	0.147***
	(0.0247)	(0.0239)	(0.0328)	(0.0290)	(0.00247)	(0.00279)	(0.0272)	(0.0254)
Privatization, t-3 to t	-0.0399	-0.0961***	-0.00865	-0.0800*	-0.0136***	-0.0125***	-0.0351	-0.104***
	(0.0409)	(0.0362)	(0.0496)	(0.0408)	(0.00373)	(0.00392)	(0.0411)	(0.0357)
Entry barriers, t-3 to t	-0.145***	-0.136***	-0.122***	-0.0651**	3.49e-06	0.00145	-0.154***	-0.115***
	(0.0315)	(0.0267)	(0.0411)	(0.0326)	(0.00309)	(0.00313)	(0.0340)	(0.0286)
Banking supervision, t-3 to t	0.175***	0.141***	0.221***	0.143***	0.00818***	0.00830***	0.181***	0.117***
	(0.0299)	(0.0265)	(0.0376)	(0.0311)	(0.00283)	(0.00299)	(0.0311)	(0.0272)
Directed credit, t-3 to t	0.0480*	-0.0829***	0.0744**	-0.0719**	0.00315	0.00163	0.0367	-0.0735***
	(0.0283)	(0.0284)	(0.0365)	(0.0321)	(0.00274)	(0.00309)	(0.0302)	(0.0281)
Interest rate control, t-3 to t	0.0481**	0.00652	0.0233	-0.0520**	-0.00197	-0.00414*	0.0353	-0.0129
	(0.0213)	(0.0195)	(0.0270)	(0.0230)	(0.00203)	(0.00221)	(0.0224)	(0.0201)
<u>Interactions with Anglo-Saxon dummy</u>								
Finance relative share of ICT in capital stock, t-3 to t		-0.757		-2.140*		-0.0497		-1.025
		(1.006)		(1.149)		(0.110)		(1.005)
Domestic credit/GDP, t-3 to t		-0.0280		-0.454*		-0.0363		-0.181
		(0.200)		(0.235)		(0.0226)		(0.206)
Financial globalization, t-3 to t		0.547***		1.075***		0.0261**		0.719***
		(0.0864)		(0.115)		(0.0111)		(0.101)
<u>P-values for test of coef(X) + coef(X*AngloSaxon) = 0</u>								
X = Finance relative share of ICT in capital stock, t-3 to t		0.87		0.73		0.25		0.98
X = Domestic credit/GDP, t-3 to t		0.30		0.19		0.56		0.70
Observations	241	241	226	226	226	226	226	226
R-squared, within	0.553	0.690	0.413	0.651	0.753	0.761	0.494	0.665
Number of countries	13	13	13	13	13	13	13	13

Note: All regressions include country fixed effects and year fixed effects. The right hand side variables are lagged 3 periods. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 1998. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Anglo-Saxon countries are: Australia, Canada, United Kingdom, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Finance Relative Wage and Relative Skill Intensity, Predictive Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent Variable:	Change in finance relative wage, t to t+3				Change in finance skilled relative wage, t to t+3				Change in finance relative skill intensity, t to t+3				Change in finance excess wage, t to t+3			
Finance relative share of ICT in capital stock, t-3 to t	0.504			0.531	0.0210			0.210	0.0140			0.0288	-0.139			0.119
	(0.541)			(0.484)	(0.496)			(0.512)	(0.0449)			(0.0485)	(0.463)			(0.477)
Domestic credit/GDP, t-3 to t	-0.139			-0.0691	-0.201**			-0.190**	-0.00728			-0.00873	-0.167*			-0.123
	(0.101)			(0.0875)	(0.0948)			(0.0951)	(0.00860)			(0.00901)	(0.0886)			(0.0886)
Financial globalization, t-3 to t	0.348***			0.139***	0.164***			0.112**	0.0109**			0.00978*	0.167***			0.118**
	(0.0500)			(0.0514)	(0.0513)			(0.0557)	(0.00465)			(0.00527)	(0.0480)			(0.0518)
International capital restrictions, t-3 to t		0.0810***	0.103***	0.106***		0.0524***	0.0676***	0.0691***		0.00478**	0.000304	0.000499		0.0716***	0.0869***	0.0869***
		(0.0183)	(0.0227)	(0.0229)		(0.0193)	(0.0244)	(0.0248)		(0.00233)	(0.00230)	(0.00235)		(0.0193)	(0.0227)	(0.0231)
Privatization, t-3 to t		0.0168	0.00911	0.0109		0.00495	-0.0170	-0.0166		-0.00160	-0.00458	-0.00445		0.000192	-0.0155	-0.0132
		(0.0217)	(0.0278)	(0.0277)		(0.0224)	(0.0295)	(0.0294)		(0.00271)	(0.00277)	(0.00279)		(0.0224)	(0.0274)	(0.0274)
Entry barriers, t-3 to t		-0.0215	-0.0242	-0.0260		0.00855	0.00903	0.00634		-0.00422*	-0.00583**	-0.00598**		-0.0250	-0.0257	-0.0281
		(0.0186)	(0.0246)	(0.0244)		(0.0195)	(0.0260)	(0.0258)		(0.00236)	(0.00244)	(0.00244)		(0.0195)	(0.0242)	(0.0240)
Banking supervision, t-3 to t		0.0437**	0.0199	0.0193		0.00105	0.00382	-0.00156		0.00629***	0.00338	0.00320		0.0109	0.00238	-6.75e-05
		(0.0178)	(0.0218)	(0.0218)		(0.0187)	(0.0233)	(0.0234)		(0.00226)	(0.00219)	(0.00221)		(0.0187)	(0.0216)	(0.0218)
Directed credit, t-3 to t		-0.00359	0.00355	-0.00432		-0.0109	-0.00328	-0.00785		0.00148	0.00251	0.00202		-0.0206	-0.0148	-0.0217
		(0.0181)	(0.0236)	(0.0239)		(0.0186)	(0.0248)	(0.0252)		(0.00224)	(0.00233)	(0.00238)		(0.0186)	(0.0230)	(0.0234)
Interest rate control, t-3 to t		-0.0114	0.0190	0.0176		-0.0221	-0.0133	-0.0149		-8.82e-05	0.00153	0.00138		-0.00802	0.0145	0.0120
		(0.0145)	(0.0171)	(0.0170)		(0.0154)	(0.0181)	(0.0181)		(0.00186)	(0.00171)	(0.00172)		(0.0154)	(0.0169)	(0.0169)
Sample	Full	Full	1∩2	1∩2	Full	Full	5∩6	5∩6	Full	Full	9∩10	9∩10	Full	Full	13∩14	13∩14
Observations	265	404	241	241	238	324	226	226	238	324	226	226	238	324	226	226
R-squared	0.165	0.070	0.096	0.129	0.054	0.032	0.042	0.073	0.025	0.047	0.059	0.077	0.059	0.051	0.078	0.105
Number of countries	13	20	13	13	13	20	13	13	13	20	13	13	13	20	13	13

Note: All regressions include country fixed effects. The right hand side deregulation variables are the three-year changes (from t-3 to t) for each index. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit is normalized by GDP, data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 2000. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Finance Relative Wage and Relative Skill Intensity, Predictive Regressions, TSLS

Instrumented:	Change in International capital restrictions, t-3 to t				Change in Finance relative share of ICT in capital stock, t-3 to t			
Instrument:	International capital restrictions, t-3				Relative Price of ICT in the Economy, t-3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Changes from t to t+3 in	Relative Wage	Relative Skilled Wage	Relative Skill Intensity	Excess Wage	Relative Wage	Relative Skilled Wage	Relative Skill Intensity	Excess Wage
Change in finance relative share of ICT in capital stock, t-3 to t	0.294	0.422	0.0135	0.346	0.938	-0.499	0.106	-0.609
	(0.425)	(0.453)	(0.0445)	(0.441)	(0.808)	(0.766)	(0.0795)	(0.655)
Change in domestic credit/GDP, t-3 to t	-0.0619	-0.193***	-0.00851	-0.126**	-0.0899	-0.199***	-0.0103	-0.138**
	(0.0575)	(0.0643)	(0.00756)	(0.0583)	(0.0593)	(0.0621)	(0.00778)	(0.0571)
Change in financial globalization, t-3 to t	0.141*	0.110	0.00993*	0.115	0.146*	0.110	0.0108**	0.117
	(0.0792)	(0.0830)	(0.00534)	(0.0820)	(0.0788)	(0.0830)	(0.00521)	(0.0819)
Change in international capital restrictions, t-3 to t	0.0505	0.116**	-0.00287	0.137***	0.111***	0.0617**	0.00134	0.0793***
	(0.0502)	(0.0466)	(0.00352)	(0.0427)	(0.0302)	(0.0290)	(0.00179)	(0.0265)
Change in privatization, t-3 to t	0.00940	-0.0135	-0.00467*	-0.00989	0.00823	-0.0140	-0.00481*	-0.0106
	(0.0193)	(0.0223)	(0.00262)	(0.0199)	(0.0215)	(0.0210)	(0.00253)	(0.0190)
Change in entry barriers, t-3 to t	-0.0216	0.00292	-0.00574***	-0.0318	-0.0251	0.00512	-0.00583***	-0.0293
	(0.0184)	(0.0229)	(0.00184)	(0.0201)	(0.0186)	(0.0229)	(0.00186)	(0.0199)
Change in banking supervision, t-3 to t	0.0222	-0.00331	0.00333	-0.00193	0.0161	-0.00146	0.00288	-0.000638
	(0.0175)	(0.0199)	(0.00225)	(0.0193)	(0.0180)	(0.0189)	(0.00220)	(0.0185)
Change in directed credit, t-3 to t	-0.00425	-0.00675	0.00194	-0.0205	-0.00364	-0.0127	0.00234	-0.0271
	(0.0304)	(0.0282)	(0.00218)	(0.0294)	(0.0301)	(0.0276)	(0.00213)	(0.0286)
Change in interest rate control, t-3 to t	0.0184	-0.0155	0.00142	0.0114	0.0173	-0.0183	0.00149	0.00795
	(0.0168)	(0.0201)	(0.00191)	(0.0167)	(0.0168)	(0.0212)	(0.00197)	(0.0178)
Observations	241	226	226	226	237	223	223	223
R-squared	0.290	0.357	0.312	0.339	0.312	0.364	0.318	0.352
Number of countries	13	13	13	13	13	13	13	13
First stage partial F-stat	33.53	31.07	31.07	31.07	18.12	19.73	19.73	19.73

Note: All regressions include country fixed effects. The right hand side deregulation variables are the three-year changes (from t-3 to t) for each index. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit is normalized by GDP, data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 2000. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Finance Relative Wage and Relative Skill Intensity, Predictive Regressions, Anglo-Saxon versus Other Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Change in finance relative wage, t to t+3		Change in finance skilled relative wage, t to t+3		Change in finance relative skill intensity, t to t+3		Change in finance excess wage, t to t+3	
Finance relative share of ICT in capital stock, t-3 to t	0.536	0.226	0.247	0.171	0.0158	0.0292	0.119	0.0655
	(0.473)	(0.469)	(0.501)	(0.502)	(0.0480)	(0.0499)	(0.467)	(0.468)
Domestic credit/GDP, t-3 to t	-0.0749	-0.111	-0.190**	-0.194**	-0.00955	-0.00810	-0.122	-0.112
	(0.0863)	(0.0870)	(0.0932)	(0.0952)	(0.00894)	(0.00946)	(0.0869)	(0.0886)
Financial globalization, t-3 to t	0.140***	0.0869*	0.107**	0.0621	0.0116**	0.0124**	0.115**	0.0722
	(0.0501)	(0.0514)	(0.0541)	(0.0552)	(0.00519)	(0.00548)	(0.0504)	(0.0514)
International capital restrictions, t-3 to t	0.108***	0.0562**	0.0696***	0.0362	0.000843	0.00123	0.0881***	0.0504*
	(0.0228)	(0.0259)	(0.0246)	(0.0283)	(0.00236)	(0.00281)	(0.0229)	(0.0264)
Entry barriers, t-3 to t	-0.0237	-0.0154	0.00477	0.0296	-0.00563**	-0.00481*	-0.0318	-0.0119
	(0.0238)	(0.0266)	(0.0252)	(0.0286)	(0.00242)	(0.00285)	(0.0235)	(0.0267)
<u>Interactions with Anglo-Saxon dummy</u>:								
Finance relative share of ICT in capital stock, t-3 to t		2.798		1.418		-0.211		0.569
		(1.976)		(2.227)		(0.221)		(2.073)
Domestic credit/GDP, t-3 to t		0.401		0.0179		-0.0263		-0.103
		(0.293)		(0.338)		(0.0336)		(0.315)
Financial globalization, t-3 to t		0.354**		0.542***		-0.00732		0.484***
		(0.147)		(0.189)		(0.0187)		(0.176)
International capital restrictions, t-3 to t		0.174***		0.113**		-0.00224		0.121**
		(0.0496)		(0.0550)		(0.00546)		(0.0512)
Entry barriers, t-3 to t		-0.0659		-0.131**		-0.00312		-0.113**
		(0.0553)		(0.0600)		(0.00596)		(0.0559)
Observations	241	241	226	226	226	226	226	226
R-squared, within	0.121	0.213	0.068	0.139	0.047	0.057	0.098	0.169
Number of countries	13	13	13	13	13	13	13	13

Note: All regressions include country fixed effects. The right hand side deregulation variables are the three-year changes (from t-3 to t) for each index. Deregulation data are from Abiad, Detragiache and Tressel (2008). The dependent variables as well as relative ICT use in finance is calculated from EU KLEMS database. Domestic credit is normalized by GDP, data from the World Bank World Development Indicators databse. Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 2000. Out of original 22 countries, we do not have sufficient data for Slovenia, and we drop Luxemburg as an outlier. The sample of 13 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Sweden, United States. Anglo-Saxon countries are: Australia, Canada, United Kingdom, United States. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Finance Relative Wage and Relative Skill Intensity, 2000-2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent Variable:	Finance relative wage				Finance skilled relative wage				Finance relative skill intensity				Finance excess wage			
Finance relative share of ICT in capital stock, t-3	-0.118	-0.120	-0.204	-0.104	-0.142	-0.127	-0.536**	-0.0992	-0.0434	-0.0362	-0.0371	-0.0580	-0.0391	-0.0363	-0.160	-0.0234
	(0.170)	(0.174)	(0.159)	(0.161)	(0.212)	(0.217)	(0.230)	(0.286)	(0.0495)	(0.0504)	(0.0707)	(0.0645)	(0.173)	(0.177)	(0.174)	(0.183)
Financial globalization, t-3	0.0874	0.0868	0.0678	0.0741	-0.00556	0.000350	-0.105	0.0231	0.0552***	0.0581***	0.0605*	0.0478	0.0487	0.0498	0.00732	0.0287
	(0.0599)	(0.0617)	(0.0737)	(0.0799)	(0.0748)	(0.0769)	(0.107)	(0.142)	(0.0175)	(0.0178)	(0.0328)	(0.0320)	(0.0610)	(0.0628)	(0.0811)	(0.0907)
Domestic credit/GDP, t-3	0.121				0.396**				0.0219				0.0929			
	(0.132)				(0.165)				(0.0386)				(0.135)			
Non-bank domestic credit/GDP, t-3		0.111	-0.114	-0.0259		0.490*	0.0521	0.352		0.0678	0.0992	0.0904		0.110	-0.150	-0.0406
		(0.226)	(0.182)	(0.190)		(0.282)	(0.264)	(0.337)		(0.0653)	(0.0812)	(0.0761)		(0.230)	(0.200)	(0.216)
Bank domestic credit/GDP, t-3		0.122				0.379**				0.0138				0.0898		
		(0.138)				(0.172)				(0.0399)				(0.140)		
Household bank credit/GDP, t-3			0.992***				2.029***				0.0594				1.030***	
			(0.292)				(0.422)				(0.130)				(0.321)	
Corporate bank credit/GDP, t-3			-0.513**				-0.589**				-0.0740				-0.517**	
			(0.195)				(0.282)				(0.0868)				(0.214)	
Mortgage bank credit/GDP, t-3				0.794**				0.755				0.147				0.708**
				(0.296)				(0.524)				(0.118)				(0.336)
Non-mortgage bank credit/GDP, t-3				-0.287				0.149				-0.0930				-0.241
				(0.178)				(0.316)				(0.0713)				(0.202)
Bank concentration, t-3	0.148**	0.148**	0.147***	0.173***	0.171**	0.171**	0.136**	0.183**	-0.00521	-0.00518	-0.00456	-0.00246	0.147**	0.147**	0.143***	0.170***
	(0.0552)	(0.0559)	(0.0423)	(0.0445)	(0.0689)	(0.0696)	(0.0613)	(0.0790)	(0.0161)	(0.0161)	(0.0188)	(0.0178)	(0.0562)	(0.0569)	(0.0465)	(0.0506)
Observations	60	60	46	46	60	60	46	46	60	60	46	46	60	60	46	46
R-squared, within	0.296	0.296	0.700	0.658	0.325	0.328	0.659	0.416	0.254	0.269	0.252	0.310	0.237	0.237	0.625	0.544
Number of countries	16	16	12	12	16	16	12	12	16	16	12	12	16	16	12	12

Note: All regressions include country fixed effects, but no year fixed effects. The right hand side variables are lagged 3 periods. Bank concentration is the log of the share of the largest three banks; data from the World Bank. The dependent variables as well as relative ICT use in finance are calculated from EU KLEMS database. Domestic credit covers all forms of credit to the non-financial sector on a gross level, except for credit to the government, which is on a net basis; data from the World Bank World Development Indicators databse. Bank domestic credit data are from Jorda, Schularick and Taylor (2014), except for Austria and Korea where the data are from the Bank World Development Indicators databse. Non-bank domestic credit is total domestic credit minus bank credit. The split of bank domestic credit to households versus corporations, and to mortgage versus non-mortgage lending is given in Jorda, Schularick and Taylor (2014). Financial globalization is log(foreign assets + liabilities/GDP), data are from Lane and Milesi-Ferretti (2007). The sample ends in 1998. The sample of 16 countries is determined by ICT data availability in the EU KLEMS data; these countries are: Australia, Austria, Canada, Czech Republic, Germany, Denmark, Finland, United Kingdom, Italy, Japan, Korea, Netherlands, Portugal, Sweden, United States, Slovenia. We lose Austria, Czech Republic, Korea and Slovenia when we split bank credit due to data unavailability. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Immigration and Employment in Finance

A. Skilled workers

	Employed in finance by destination					Employed in finance in destination, by source			
	Number of skilled immigrants	Skill intensity (skilled/all immigrants) (%)	Share in sample finance skilled immigration (%)	Share in finance skilled employment in destination (%)	Share in total skilled immigration to destination (%)	Number	Skill intensity (skilled/all immigrants) (%)	Share in total finance skilled immigration (%)	Share in total skilled immigration from source (%)
Australia	10458	38.1	8.22	10.97	3.67	6697	62.6	5.27	8.50
Austria	347	33.7	0.27	2.74	2.53	1744	51.3	1.37	5.43
Canada	19450	51.0	15.29	10.61	4.55	17580	59.0	13.82	6.14
Denmark	221	33.2	0.17	3.07	1.92	1710	54.9	1.34	6.03
Spain	2060	58.5	1.62	1.55	2.06	5195	24.2	4.08	6.82
Finland	132	49.6	0.10	0.57	1.37	1628	47.3	1.28	4.14
France	9429	11.9	7.41	6.59	11.36	12929	67.4	10.17	6.80
Hungaria	58	67.4	0.05	0.27	2.08	1790	51.4	1.41	4.34
Ireland	4145	62.3	3.26	19.03	4.44	8354	45.9	6.57	6.78
Italy	1343	35.8	1.06	1.69	2.57	12154	31.2	9.56	8.00
Luxemburg	2261	49.3	1.78	29.44	9.00	232	32.4	0.18	8.04
Portugal	568	47.0	0.45	2.55	1.69	5525	11.0	4.34	9.58
Sweden	775	32.9	0.61	3.04	1.63	2735	64.7	2.15	6.73
United Kingdom	24131	62.5	18.97	10.55	6.29	37454	49.0	29.45	5.57
United States	51804	56.2	40.73	1.98	5.37	11455	71.1	9.01	5.89
Total	127182	42.5	100			127182	42.5	100	
Correlation with Share in sample finance skilled immigration				0.01	0.35				

B. All workers

	Employed in finance by destination				Employed in finance in destination, by source		
	Number of immigrants	Share in sample finance immigration (%)	Share in finance employment in destination (%)	Share in total immigration to destination (%)	Number	Share in total finance immigration (%)	Share in total immigration from source (%)
Australia	27450	9.17	8.55	3.67	10692	3.57	7.24
Austria	1030	0.34	0.91	2.53	3399	1.13	4.56
Canada	38130	12.73	6.32	4.55	29785	9.94	5.30
Denmark	666	0.22	0.84	1.92	3112	1.04	4.82
Spain	3520	1.18	1.08	2.06	21483	7.17	8.71
Finland	266	0.09	0.65	1.37	3440	1.15	2.65
France	79074	26.40	11.33	11.36	19177	6.40	4.38
Hungary	86	0.03	0.12	2.08	3481	1.16	3.41
Ireland	6649	2.22	10.07	4.44	18194	6.07	5.00
Italy	3752	1.25	0.72	2.57	38993	13.02	6.06
Luxemburg	4589	1.53	15.30	9.00	715	0.24	7.62
Portugal	1209	0.40	1.51	1.69	50271	16.78	7.42
Sweden	2355	0.79	2.51	1.63	4230	1.41	5.00
United Kingdom	38626	12.90	3.92	6.29	76431	25.52	4.83
United States	92107	30.75	1.54	5.37	16106	5.38	5.08
Total	299509	100			299509	100	
Correlation with Share in sample finance immigration			0.26	0.65			

Notes: Data are immigration stocks of workers that are employed in financial intermediation in the destination country, regardless of their past employment sector or employment status in the source country. Panel A reports statistics for skilled workers, which are consistently defined as having a college or university Bachelors' degree. In this panel all statistics, except for the skill intensity, are relative to skilled workers. Panel B reports statistics for all types of workers. The first set of columns in each panel report the distribution of immigrants in their destination countries (where they moved to), while the latter set of columns report the distribution of those immigrants by source country (where they came from). Data source: OECD.

Table 15: Summary Statistics

	Mean	S.D.	Min	Median	Max
A. Migration flows					
Log(mH_fin)	4.15	2.32	0.0	4.09	9.62
(mH_fin/mH)*100	6.47	6.99	0.75	4.30	46.26
mH_fin/mL_fin	1.46	1.24	0.05	1.06	6.50
Log(mL_fin)	4.12	2.32	0.0	4.01	10.53
mL_fin/mL	5.05	7.26	0.26	2.58	43.33
B. Wages					
Log(wH_fin)	4.39	0.23	3.97	4.41	4.84
Log(wH_nonfin)	4.06	0.19	3.53	4.10	4.32
wH_fin/wL_fin	1.62	0.35	1.07	1.62	2.55
wH_nonfin/wL_nonfin	1.88	0.53	1.29	1.84	3.66
Log(wL_fin)	3.95	0.29	3.03	3.97	4.36
Log(wL_nonfin)	3.47	0.25	2.59	3.54	3.71
C. Gravity controls					
Contiguous countries	0.09	0.29	0.0	0.0	1.0
Common language	0.16	0.36	0.0	0.0	1.0
Log(distance)	7.84	1.11	5.37	7.53	9.8

Notes: 193 observations. m denotes imgration stocks in 2000, n denotes employment in 2000, and w denotes wages in 1999. H denotes high-skill and L denotes low-skill workers, where high-skill is consistently defined as four-year college or university degree. "fin" denotes employment in finance and "nonfin" denotes employment outside of finance and agriculture.

Table 16: Immigration Stocks Employed in Finance and Wages in Finance

	(1)	(2)	(3)	(4)	(5)	(6)
A. Skilled immigration						
Dependent variable:	log(mH_fin)		(mH_fin/mH)*100		mH_fin/mL_fin	
Log(wH_fin)	3.783***	2.335***	16.52***	13.91***		
	(0.570)	(0.789)	(3.005)	(3.023)		
Log(wH_nonfin)		2.735***		4.912**		
		(0.789)		(1.912)		
wH_fin/wL_fin					0.968***	0.983***
					(0.298)	(0.302)
wH_nonfin/wL_nonfin						0.487***
						(0.141)
Observations	193	193	193	193	183	183
R-squared	0.511	0.540	0.359	0.369	0.232	0.272

B. Unskilled immigration				
Dependent variable:	log(mL_fin)		(mL_fin/mL)*100	
Log(wL_fin)	2.562***	0.374	6.442***	3.411
	(0.398)	(0.592)	(2.247)	(2.322)
Log(wL_nonfin)		3.712***		5.141**
		(0.702)		(2.032)
Observations	193	193	193	193
R-squared	0.444	0.518	0.149	0.163

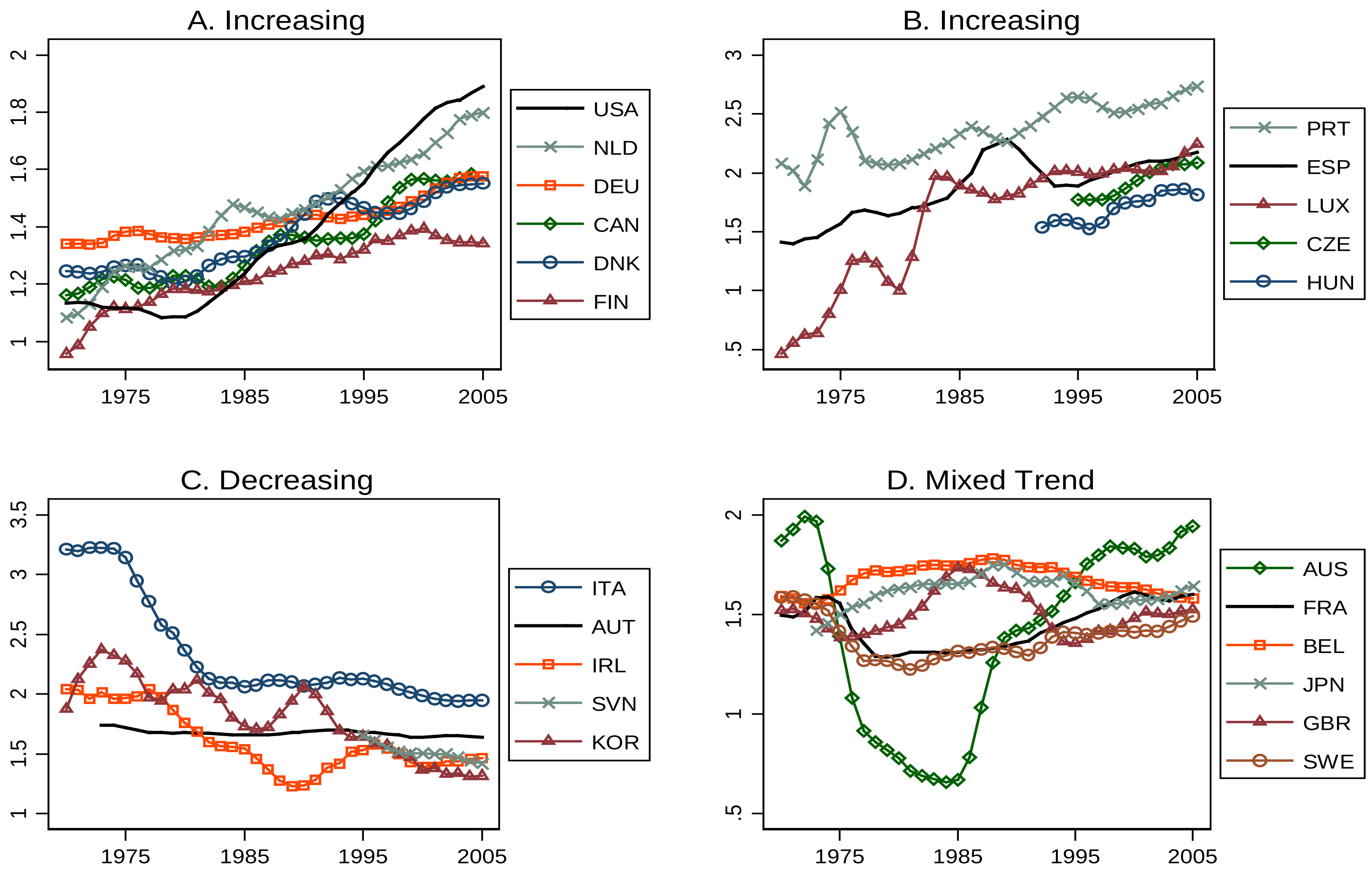
Notes: m denotes imgration stocks in 2000, and w denotes wages in 1999. H denotes high-skill and L denotes low-skill workers, where high-skill is consistently defined as four-year college or university degree. "fin" denotes employment in finance and "nonfin" denotes emploiyment outside of finance and agriculture. All regressions include source country fixed effects and the following gravity variables: contiguity indicator, commonlanguage indicator, and log distance between capital cities. Although regressions in both panels have the same number of observations, the sample varies slightly due to data availability. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: migration data from OECD and wage data from EU KLEMS. Distance between capital cities, common language and contiguity indicators are from the CEPII dataset.

Table 17: Immigration Stocks and Wages in Other Sectors -- Skilled Immigrants

	(1)	(2)	(3)	(4)	(5)	(6)
A. Skilled immigration in Health Services						
Dependent variable:	log(mH_health)		(mH_health/mH)*100		mH_health/mL_health	
Log(wH_health)	2.050***	1.862***	-2.405	-6.377***		
	(0.511)	(0.704)	(1.893)	(2.130)		
Log(wH_nonhealth)		0.327		6.912*		
		(1.198)		(3.748)		
wH_health/wL_health					0.817***	0.778***
					(0.209)	(0.197)
wH_nonhealth/wL_nonhealth						0.0462
						(0.282)
Observations	203	203	203	203	195	195
R-squared	0.430	0.430	0.187	0.202	0.304	0.304
B. Skilled immigration in Manufacturing						
Dependent variable:	log(mH_manuf)		(mH_manuf/mH)*100		mH_manuf/mL_manuf	
Log(wH_manuf)	2.221***	3.240***	-9.230***	-5.274***		
	(0.542)	(0.718)	(1.835)	(2.023)		
Log(wH_nonmanuf)		-1.597*		-6.205**		
		(0.823)		(2.719)		
wH_manuf/wL_manuf					0.172*	0.294
					(0.103)	(0.364)
wH_nonmanuf/wL_nonmanuf						-0.131
						(0.337)
Observations	188	188	188	188	187	187
R-squared	0.457	0.469	0.248	0.271	0.269	0.270
C. Skilled immigration in Real Estate and Business Services						
Dependent variable:	log(mH_rebus)		(mH_rebus/mH)*100		mH_rebus/mL_rebus	
Log(wH_rebus)	0.647	0.463	-2.430	-0.987		
	(0.492)	(0.481)	(2.810)	(2.655)		
Log(wH_nonrebus)		1.411***		-11.09***		
		(0.526)		(2.228)		
wH_rebus/wL_rebus					0.339*	0.274
					(0.174)	(0.323)
wH_nonrebus/wL_nonrebus						0.0707
						(0.291)
Observations	191	191	191	191	189	189
R-squared	0.420	0.447	0.148	0.261	0.176	0.176

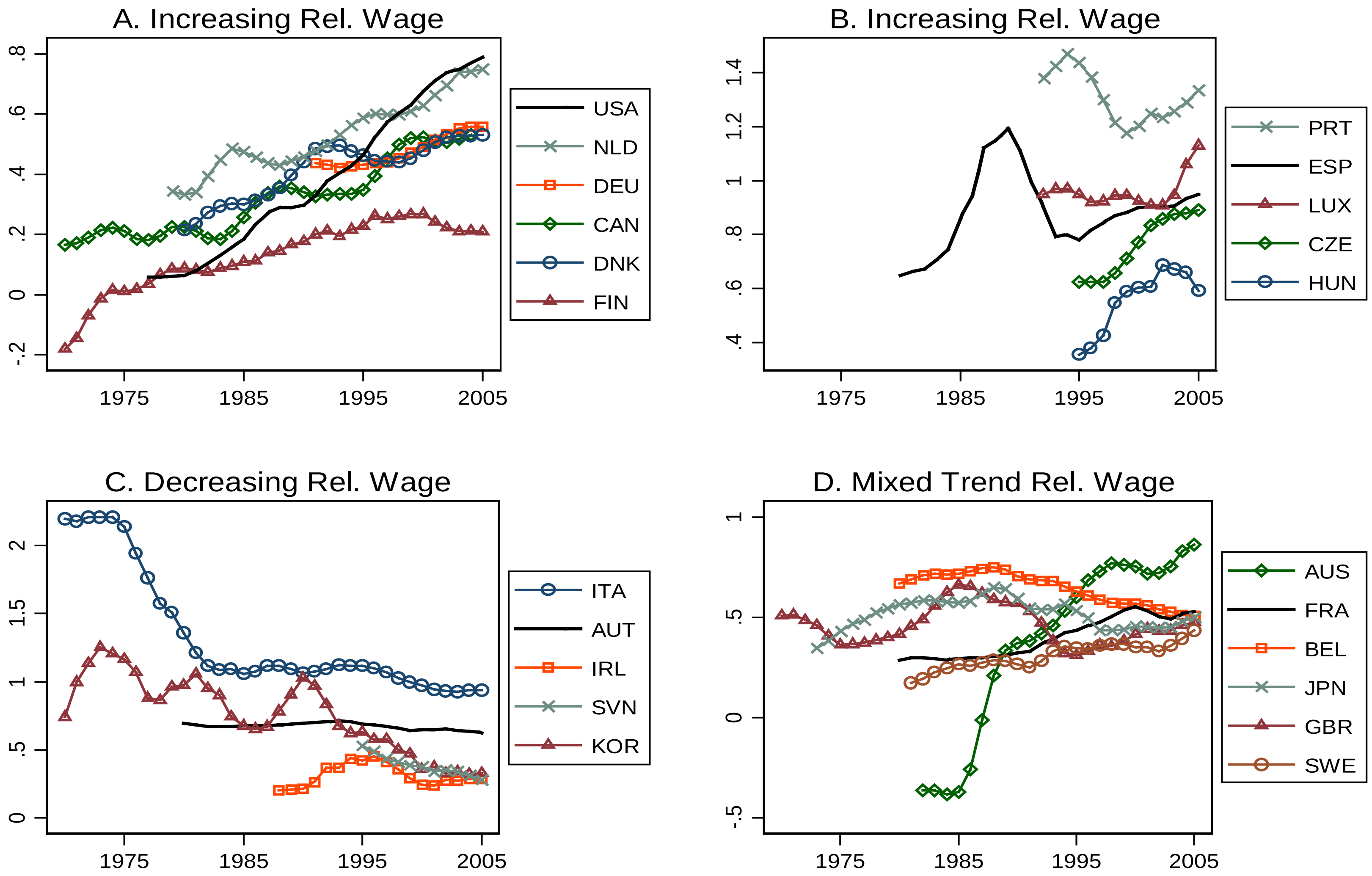
Notes: m denotes imgration stocks in 2000, and w denotes wages in 1999. H denotes high-skill and L denotes low-skill workers, where high-skill is consistently defined as four-year college or university degree. "health" denotes employment in health and social works and "nonhealth" denotes employment outside of health and social works and agriculture. "manuf" denotes employment in manufacturing and "nonmanuf" denotes employment outside of manufacturing and agriculture. "rebus" denotes employment in real estate, renting and business activities and "nonrebus" denotes employment outside of real estate, renting and business activities and agriculture. All regressions include source country fixed effects and the following gravity variables: contiguity indicator, commonlanguage indicator, and log distance between capital cities. Samples vary slightly due to data availability. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: migration data from OECD and wage data from EU KLEMS. Distance between capital cities, common language and contiguity indicators are from the CEPII dataset.

Figure 1: Finance Relative Wage



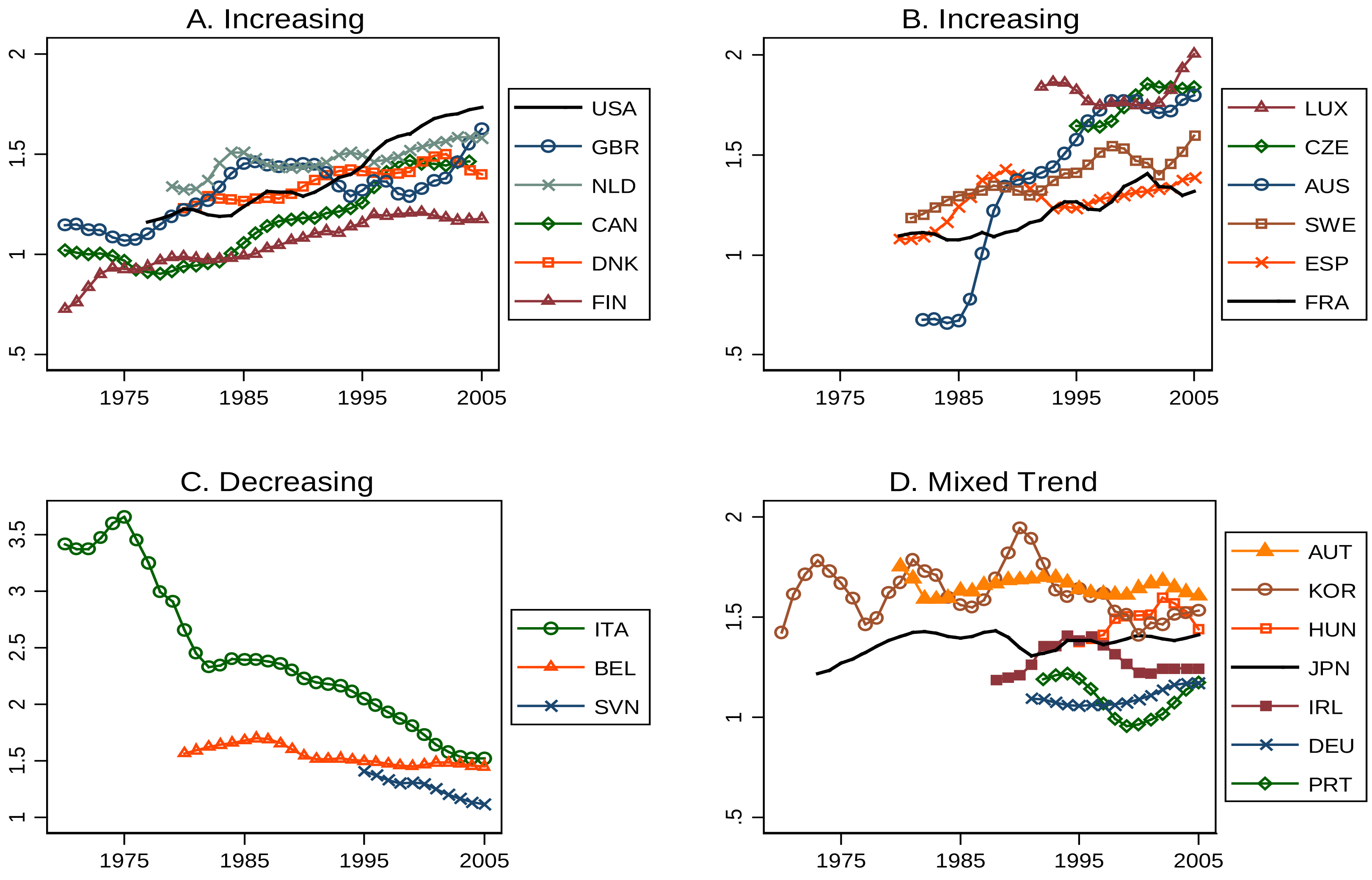
Notes: Finance relative wage is the average wage in finance relative to the averagre wage in the the non-farm, non-finance private sector. Average wages are computed by dividing employee compensation by hours worked. Data: EU KLEMS. Series are three-year moving averages. Panels A and B groups countries that exhibit an increasing trend. Panel C groups countries that exhibit decreasing trend and Panel D groups countries that exhibit mixed trends.

Figure 2: Finance Excess Wage



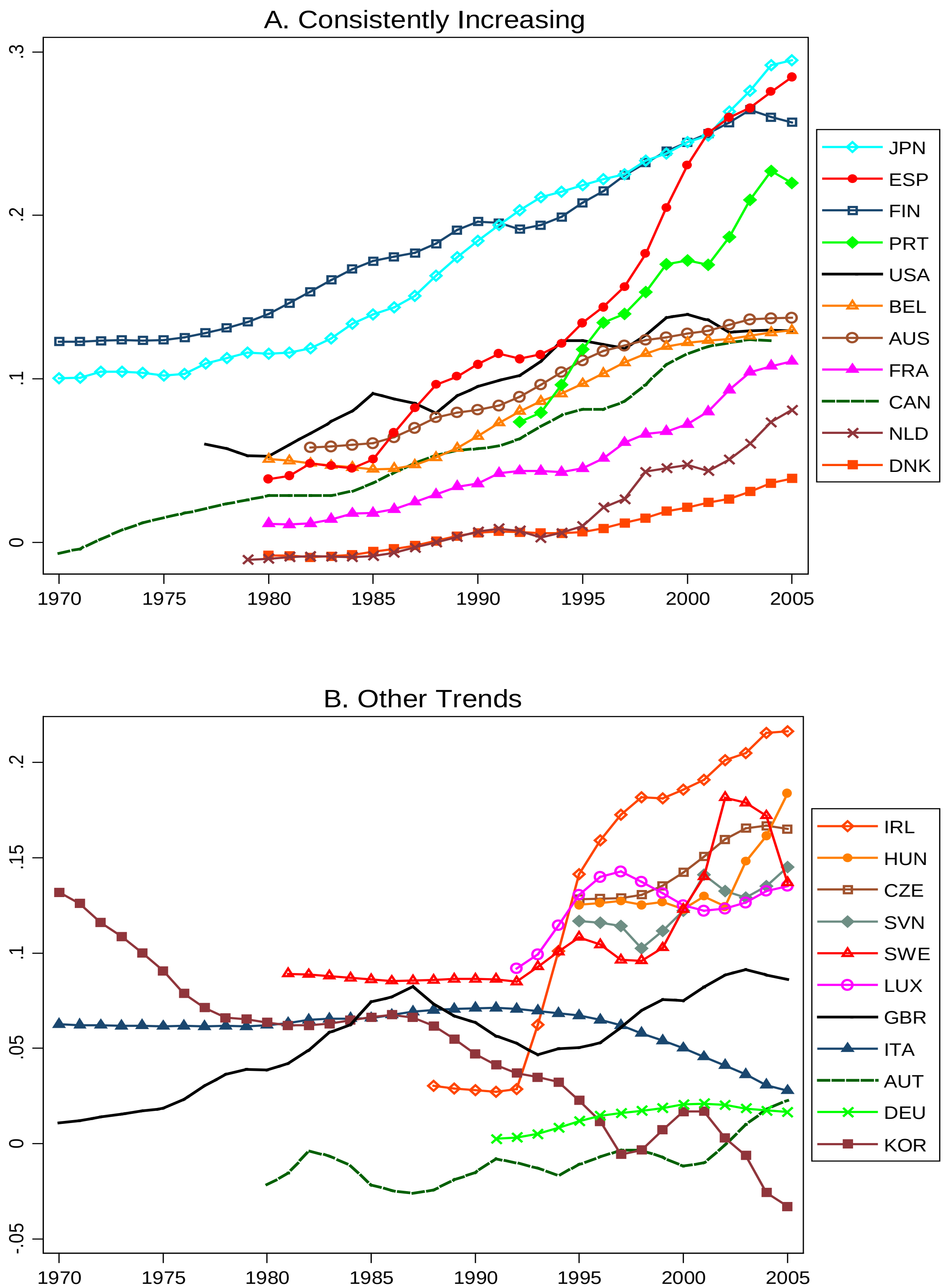
Notes: Finance ecess wage is the finance relative wage minus the benchmark wage. The benchmark assumes equal skilled and unskilled wages in finance and in the non-farm, non-finance private sector (NFFP), and allows for skill differences in finance versus NFFP. Data: EU KLEMS. Series are three-year moving averages. Panels A and B groups countries that exhibit an increasing trend in the finance relative wage. Panel C groups countries that exhibit decreasing finance relative wage and Panel D groups countries that exhibit mixed trends in finance relative wages.

Figure 3: Finance Relative Skilled Wage



Notes: Finance relative skilled wage is the average wage of skilled workers in finance relative to the averagre wage of skilled workers in the rest of the non-farm, non-finance private sector. Average wages are computed by dividing employee compensation by hours worked. Data: EU KLEMS. The definition of skilled workers in the EU KLEMS is consistent across countries, and implies a university-equivalent bachelors degree. Series are three-year moving averages. Panels A and B groups countries that exhibit an increasing trend. Panel C groups countries that exhibit decreasing trend and Panel D groups countries that exhibit mixed trends.

Figure 4: Finance Relative Skill Intensity



Notes: Finance relative skill intensity is the share of college-educated workers in finance relative to the share of college-educated workers in the rest of the non-farm, non-finance private sector. These shares are computed using hours worked. Data: EU KLEMS. The definition of skilled workers in the EU KLEMS is consistent across countries, and implies a university-equivalent bachelors degree. Series are three-year moving averages. Panel A groups countries that exhibit an increasing trend. Panel B groups countries that exhibit mixed trends.