Innovation Booms, Easy Financing, and Human Capital Accumulation*

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Abstract

Innovation booms are often fueled by easy financing that allows new technology firms to pay high wages that attracts skilled labor. Using the late 1990s Information and Communication Technology (ICT) boom as a laboratory, we show that skilled labor joining this new sector experienced sizeable long-term earnings losses. We show these earnings patterns are explained by faster skill obsolescence rather than either worker selection or the overall bust in the ICT sector. During the boom, financing flowed more to firms whose workers would experience the largest productivity declines, amplifying the negative effect of labor reallocation on aggregate human capital accumulation.

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1 Introduction

In quiet times, the economy efficiently allocates both capital and labor to productive and innovative firms, in a process that fosters economic growth (Acemoglu, Akcigit, Alp, Bloom, and Kerr 2018). But in periods of intense technological change, firms may benefit from high valuations and easy financing that is not fully justified based on their underlying productivity and innovation potential (e.g., Nanda and Rhodes-Kropf 2013, 2017; Scheinkman 2014; Haddad, Ho, and Loualiche 2022). This inflow of financial capital allows firms to pay high wages to compete for the scarce supply of necessary human capital, which can accelerate the reallocation of talent to the booming new technology sector. The current boom in AI and data science exemplifies this confluence of intense innovation, abundant financing, high wages, and inflow of skilled labor to new technology sectors.[1]

The ability of firms in booming tech sectors to access financial capital to attract talent implies that innovation booms may affect long-run economic growth not only through the introduction of new products and processes, but also through their impact on employment-based human capital accumulation. In this paper, we focus on this latter mechanism by asking two questions. First, how does joining a booming new technology sector affect skilled workers' long-run human capital accumulation (or depreciation)? And second, does financial capital amplify or mitigate the impact of labor reallocation on aggregate human capital?

The answers are not obvious. For the first question, a worker joining a booming innovative sector could perform tasks that embed the new, superior technologies and as a result, accumulate useful human capital for the long run, even if capital markets overvalue the industry during the boom and investors eventually lose money during a market correction. This argument echoes the assumption in speculative growth models that technology bubbles can be growth-enhancing because they promote investments that increase future productivity (Olivier 2000; Caballero, Farhi, and Hammour 2006).

1. See for instance "Amazon's shopping spree at business schools," *Financial Times,* March 2017.

However, the skills acquired by workers during innovation booms may also rapidly lose value, leaving these workers with lower value of human capital in the long run. This could happen because fast-paced technological change accelerates the obsolescence of technology vintage-specific skills or because firm overvaluation and lax financing conditions make workers more likely to acquire skills associated with low quality projects.

For the second question, the implications of capital flowing to booming innovative sectors for aggregate human capital accumulation depend not only on the *average* effect of joining the booming sector on workers' human capital, but also on the *covariance* between this effect and capital flows. If the value of workers' human capital appreciates more in firms that receive more capital, a financing boom will improve aggregate human capital accumulation, as more workers enjoy long-term productivity gains. Conversely, if workers' human capital depreciates more in innovative firms that receive more capital, a financing boom will worsen long-term aggregate human capital.

To shed empirical light on these questions, we study the late 1990s boom in the Information and Communications Technology (ICT) sector. This episode provides an ideal laboratory for three reasons. First, it is a large boom in a new technology sector that led to sizable high-skill labor reallocation (see Section 2.3 for France and Appendix C for the US). Second, it was accompanied by large capital flows, and plausibly by overvaluation.[2] Third, it is recent enough that rich administrative data exist for the boom period, and old enough to study its long-term effects.

We use annual French administrative matched employer-employee data for the period 1994–2015, which we link to the universe of firms' financial statements from tax filings.[3] The data contain high quality, longitudinal information on workers' wages and career paths and on firms' financial statements.

2. It is inherently difficult to demonstrate overvaluation, even ex post. See Ofek and Richardson (2003), Griffin, Harris, Shu, and Topaloglu (2011), and Campello and Graham (2013) for evidence of overvaluation during this period. See Pástor and Veronesi (2006) for a contrasting view.

3. The data are made available to researchers by the Secure Data Access Centre (see https://www.casd.eu/en/). All the results in the paper have been reproduced by the Certification Agency for Scientific Code And Data (see the reproducibility certificate at https://doi.org/10.5281/zenodo.7969175 and the replication package at https://johanhombert.github.io/TechBubble_ReplicationPackage.zip).

We have four sets of findings. Our first set of results documents the large reallocation of both capital and high-skill labor toward the ICT sector during the boom. The labor reallocation takes place almost exclusively at the extensive margin of the labor market, i.e., when workers take their first job. The share of high-skill labor market entrants starting in the ICT sector almost doubles during the boom, from 17% beforehand to 31% at the peak, and back down to 19% when the boom ends. By contrast, the flow of seasoned skilled workers from other sectors does not change significantly. This implies that seasoned workers outside the booming tech sector are poor substitutes for new workers and therefore that there are multiple vintages of human capital within existing occupations.[4]

In our second set of results, we examine how starting in the ICT sector during the boom affects workers' long-run human capital appreciation (or depreciation). We outline a two-sector model with overlapping cohorts, worker sectoral choice, and on-the-job human capital accumulation whose value can either appreciate or depreciate over time. The model provides an intuitive decomposition of the average wage in a sector-cohort into three components: the sector-level wage rate that reflects labor supply and demand in the sector; human capital accumulated since labor market entry that depends on the worker's cohort and sectoral choice (i.e., the component we want to estimate); and a selection term that depends on the endogenous sorting of workers across sectors. The model shows that we can control for sector-level shocks and selection effects by running regressions across cohorts and sectors, which allows us to isolate the effect of workers' initial sectoral choice on their human capital accumulation.

Empirically, the period of intense worker entry in the ICT sector is distinctly delineated in time, which allows us to conduct sharp cross-cohort comparisons. We define three cohorts of workers: a pre-boom, a boom, and a post-boom cohort. Each cohort has its human capital tightly linked to the technologies developed during its employment spell: pre-boom cohorts and boom cohorts are both exposed to the rapidly evolving technologies

4. This may be because younger employees are better fit for new businesses and new tasks because they have more recent education and possess more current technical skills (Ouimet and Zarutskie 2014).

during the boom while the post-boom cohort is exposed to stabilized technologies.

Our main specification includes cohort×year fixed effects, which ensure that we compare workers exposed to the same macroeconomic shocks at the same stage of their careers. For instance, cohort×year fixed effects absorb the well-documented impact of macroeconomic conditions at the time of labor market entry on long-term earnings.

We find that workers who enter in the ICT sector during the boom earn 5% higher entry wages on average but end up with 6% lower wages 15 years out relative to workers from the same cohort with the same characteristics starting in other sectors.

Workers from the post-boom cohort who start in ICT on the other hand exhibit the same wage dynamics as comparable workers from the same cohort who started in other sectors. Therefore, the long-term wage discount of the boom cohort cannot be explained by a sectoral-level decline in labor demand or oversupply of labor in the bubble's aftermath, since post-boom cohort workers in the ICT sector face similar sector-level shocks. Instead, lower long-term earnings concentrated on the boom cohort of ICT workers are consistent with steady depreciation of human capital accumulated in the ICT sector during the boom.[5]

We rule out that the long-run wage discount is explained by negative selection during the boom (i.e., the bubbly ICT sector attracts less able workers) using the pre-boom cohort as an additional comparison group. We show that the workers starting in the ICT sector during the pre-boom period experience a quantitatively similar long-run wage discount as workers from the boom cohort. Since the pre-boom cohort of workers sorted into jobs before the ICT boom starts, they constitute a group of workers whose human capital will be affected by the boom, but whose sorting decision is not. By construction, the wage dynamics of the pre-boom cohort cannot be explained by selection into the booming sector, which reinforces the interpretation that the long-run wage discount is due to human capital depreciation.

The granularity and richness of the data allow us to include a battery of additional

5. The pattern is similar for cumulative wages, implying that reverse backloading, whereby workers are paid below their productivity in the future in exchange for higher pay early in their career (Lazear 1981) does not explain the results.

fixed effects to control for other unobserved shocks that might correlate with the decision to start in the ICT sector during the boom. The baseline specification includes sector×year fixed effects that absorb sector-level shocks, due for instance to negative labor demand shocks or oversupply of labor in the bubble's aftermath. Thus, identification comes from across-cohort variation. Our results are quantitatively unchanged when we saturate the regression with controls that allow for time-varying shocks along local labor market, worker demographics and experience, entry wage bin, and sector. Our results are also robust to controlling for a host of firm-level characteristics, implying that human capital depreciation is not driven by a shift in the firm characteristics distribution, but is instead a within-firm phenomenon. We perform numerous additional robustness checks showing that the wage discount is similar if we remove the financial sector from the control group, if we include capital income in the total compensation of workers to account for stock grants and stock options, and if we focus on US companies with French operations.

Our third set of results examines the role of financial capital flows that allow firms to compete for the scarce supply of talent. We start by showing that larger capital flows during the boom are indeed associated with larger labor flows in the cross-section of firms. Then, we show that larger capital flows for firms is associated with higher human capital depreciation for these firms' workers, indicating that capital flows can worsen long-term aggregate human capital during episodes of intense technological change, since it both increases the number of workers exposed to a depreciation of their human capital and amplifies the depreciation each worker experiences.

Although this implication holds irrespective of whether capital flows cause worker-level human capital depreciation, we provide evidence that the relationship is causal. We compute the leave-one-out mean of firm equity issuance at the industry×commuting zone level, which allows us to measure capital flows net of firm idiosyncratic productivity, and to include industry×time and commuting zone×time fixed effects to absorb variation at the industry level (such as technology shocks) and at the commuting zone level (such as local innovation policies). We find that indeed capital flows have a direct negative effect on long-term wages.

In our fourth set of results, we examine the mechanisms inducing faster depreciation of human capital accumulated during the boom and amplification of this depreciation by easy financing. The first mechanism we consider is skill obsolescence. Accelerating technological change may result in faster obsolescence of skills tied to evolving technologies (Chari and Hopenhayn 1991; Deming and Noray 2020). Easy financing may exacerbate the problem by lowering the hurdle for innovative projects to be financed and exposing workers who start in capital-flushed firms to lower quality technologies that have a strong vintage component.

We find support for the skill obsolescence mechanism. The wage discount is larger for jobs with higher technological content, and particularly so in firms that benefit from large capital inflows. We proxy for the degree of technological content using the level of skill associated with an occupation, and we find that the wage discount is concentrated on high-skill workers. By contrast, low-skill workers in ICT firms have similar wage dynamics as low-skill workers in non-ICT firms. The difference is even starker when we focus on firms that experience large capital inflows during the boom.

We consider two other mechanisms and find no support for either. First, we rule out that heightened risk of job loss explains human capital depreciation by showing that the wage discount is quantitatively similar when we control for job termination.

Second, we rule out that the average long-term wage discount masks a winner-takes-all effect by estimating quantile regressions. This analysis allows for the possibility that specific parts of the wage distribution improve despite a negative average effect. Instead, we find that the wage discount is fairly uniform across the wage distribution and that the inflow of capital to innovative firms shifts the entire wage distribution to the left.

Related literature. We contribute to the literature that studies how financing cycles affect the trajectory of innovation such as the quantity of innovation (e.g., Kortum and Lerner 2000; Brown, Fazzari, and Petersen 2009; Bernstein 2015), the composition of innovation through changes in market discipline and appetite for experimentation (e.g., Nanda and Rhodes-Kropf 2013, 2017; Townsend 2015; Howell, Lerner, Nanda, and Townsend 2021; Bernstein, McQuade, Nanda, and Roth 2019), the financing structure of innovative firms (e.g. Ewens and Farre-Mensa 2020), and overvaluation of human capital (Fedyk and Hodson 2022). We add to this literature by showing that financing cycles affect the key input to innovation, namely, human capital, both by reallocating skilled workers across sectors and by modifying the long-run value of their human capital.

We therefore also contribute to the literature that studies how financing booms and wage premia across sectors affect the allocation of talents and long-run productivity growth. A strand of literature analyzes how the wage premium in the financial industry generated a brain drain to finance (Reshef and Philippon 2012; Gupta and Hacamo 2022), which may weigh on future productivity growth if finance jobs have a smaller social return than jobs skilled workers are reallocated away from (Baumol 1990; Murphy, Shleifer, and Vishny 1991; Philippon 2010). Another strand of literature analyzes how wage premia in low-skill sectors lure workers into these sectors, hindering human capital accumulation (e.g., Charles, Hurst, and Notowidigdo (2018) on the housing sector; Carrillo (2020) on agriculture; Choi, Lou, and Mukherjee (2022) on salient sectors). By contrast, we study labor reallocation to a high-skill, new technology sector, where workers may be able to accumulate useful knowledge.

The growth literature proposes that equity overvaluation in the innovative sector can enhance growth by promoting investments that increase future productivity (Olivier 2000; Caballero, Farhi, and Hammour 2006). We examine a natural channel through which this mechanism may operate—human capital accumulation of the large cohorts of high-skill individuals who enter the booming technology sector—and find that it actually has a negative impact on their future productivity.[6]

Our evidence of human capital depreciation connects our paper to the large literature on technological displacement, which studies how technological change affects the usage of tasks (Autor, Levy, and Murnane 2003; Goos, Manning, and Salomons 2014; Ma,

6. Of course, investments in the innovative sectors may have other positive effects such as knowledge externalities to other sectors that we do not study.

Ouimet, and Simintzi 2022), the value of human capital (Beaudry, Doms, and Lewis 2010; Beaudry, Green, and Sand 2016; Kogan, Schmidt, and Seegmiller 2022), and the implications of the induced income risk for asset prices (Gârleanu, Kogan, and Panageas 2012; Kogan, Papanikolaou, Schmidt, and Song 2019). We add to this literature by showing that a wave of innovation has a negative impact on the earnings of skilled workers who contribute to its development and diffusion because their vintage of human capital becomes obsolete. Thus, we also contribute to the literature on vintage human capital, which proposes that several vintages of knowledge can co-exist, and that technological change makes old vintages obsolete (Chari and Hopenhayn 1991; Violante 2002; Deming and Noray 2020; Kogan, Schmidt, and Seegmiller 2022; Ma 2022).

Finally, our contribution differs from the classic result that the aggregate state of the economy has persistent effects on labor market entrants (Oyer 2006; Kahn 2010; Oreopoulos, Wachter, and Heisz 2012; Altonji, Kahn, and Speer 2016; Schoar and Zuo 2017; Shu 2016; Nagler, Piopiunik, and West 2020). Instead, we compare labor market entrants joining the booming technology sector to same-cohort individuals joining other sectors in a setting that allows us to control for selection.

2 Sectoral Reallocation during the ICT Boom

2.1 Data

We use administrative data on French workers and firms. We describe the main databases used in the paper here and relegate the full list to Appendix A.

Workers. Linked employer-employee data are collected by the national statistical office based on a mandatory employer report of the gross earnings of each employee subject to payroll taxes. The data include all employed individuals in the private sector with information on the gross and net wage, dated employment periods, number of hours worked, occupation, and the individual's birth year and sex. The data also include unique firm and establishment identifiers that can be linked with other administrative data.

For a 1/24th subsample of the full employer-employee data (individuals born in October of even-numbered years), individuals are assigned a unique identifier that enables us to reconstruct their entire employment history.[7] Individuals are not present in this panel data during periods when they earn no wage, they exit the labor force, become unemployed, switch to self-employment and pay themselves only dividends, or move abroad.

We focus on the employer-employee panel from 1994 to 2015. Each observation corresponds to a unique firm-worker-year combination. We focus on job spells that are full time and last for at least six months in a given year. After we apply this filter, each individual has at most one job per year.[8] We obtain a panel at the worker-year level. Workers can have gap years in this panel when they earn no wage in the private sector, work part time or had jobs for periods of less than six months.

The employer-employee data include a two-digit classification of job occupations that maps into the skill content of the job. High-skill workers represent 16% of the labor force over 1994–2015. Among them, 42% are in a business (e.g., sales, general administration) occupation (two-digit code 37), 33% are in a STEM occupation (code 38), and 4% are heads of company with at least ten employees (code 23).[9] Appendix Table B.1 reports summary statistics for the sample of skilled workers. The median skilled worker is a man (mean 69%), is 43 years old (mean 43), and earns an annual wage of 41,000 euros (mean 50,000 euros), which corresponds to the 90th percentile of the wage distribution of full-time workers in France.[10] Finally, a 4/31 subsample of the employer-employee panel data (individuals born in the first four days of October) can be linked to census

7. The exhaustive employer-employee data do not include unique individual identifiers.

8. There are a few workers with full-time job spells of six months in two different firms in the same year. In these rare cases, we keep the observation with the higher wage.

9. Other high-skill occupations are mostly held by self-employed and public sector employees: 9% are teaching professionals (occupation code 34); 8% are public sector managers and professionals (code 33); 3% are cultural professionals (code 35); and 1% are health professionals and legal professionals (code 31).

10. Payroll taxes are split between the employer and the employee. In labor contracts, wages are stated net of payroll taxes paid by the employer, but gross of payroll taxes paid by the employee. We use this notion of wages. The employer's total labor cost is about 1.5 times this amount, and the employee's net wage is approximately 80% of it. We report wages in 2000 euros.

data, which contain demographics information. We use this smaller sample when we also retrieve information on education.

Firms. We retrieve information on firms from four sources. Firm accounting information is from tax-files, which cover all firms subject to the regular or simplified corporate tax regime. Information on firm ownership structure is from a yearly survey of business groups run by the statistical office and cross referenced with information from Bureau Van Dijk. The data include information on both direct and indirect stakes and cross-ownership, which allow us to reconstruct group structures even in the presence of pyramids. The data include information on the nationality of the ultimate owner, which allows us to identify subsidiaries of foreign companies. We retrieve the list of all new business registrations with the event date from the firm register, and use this information to measure firm age. Stock prices come from Eurofidai.

ICT sector. We use the OECD (2002) list of ICT industries to categorize industries. Appendix Table B.2 reports the shares of four-digit ICT industries in total employment and in skilled employment during the sample period. The overall ICT sector represents 5% of total employment and 15% of skilled employment, reflecting that ICT is intensive in skilled labor. The fraction of workers holding a master's degree is 14% over all industries, whereas it is 30% in the ICT sector. The ICT sector is more specifically intensive in STEM skills: the fraction of skilled workers in STEM occupations is 35% across all sectors and 70% in the ICT sector.

2.2 Capital Reallocation

We start by showing that fast-paced technological change in the ICT sector during the late 1990s France coincided with a dramatic run-up in equity valuations and an inflow of capital to the ICT sector followed by an abrupt correction, similar to the one experienced in the US (Brown, Fazzari, and Petersen 2009).

Figure 1 shows the stock price run-up in the ICT sector, using two different measures of equity valuation: the value-weighted cumulative stock return (Panel 1a) and the ratio of the stock price over sales per share (Panel 1b).[11] Both measures of equity valuation display a sharp increase in the ICT sector during the period 1997–2000, followed by an abrupt reversal.

Figure 2 shows that the run-up in equity valuations translates into an inflow of capital in the ICT sector that benefited both listed and private firms. We construct two measures of capital inflow using the administrative tax-files, which cover the universe of French firms. Panel 2a uses equity issuance, defined as the firm-level positive change in nominal equity scaled by lagged total assets averaged at the sector level. Panel 2b uses firm entry rate, defined as the number of new registered firms scaled by the stock of firms. For both measures, we observe the same boom-bust pattern as for equity valuation where capital reallocation peaks in 2000–2001, then sharply drops and returns to its pre-boom level around 2003.

2.3 Labor Reallocation

Consistent with the idea that the inflow of capital to the ICT sector allows firms in this sector to compete more aggressively for the scarce supply of talent, thereby attracting skilled workers, Figure 3a shows that the share of the ICT sector in total skilled employment features a sharp deviation from an increasing trend during the 1998–2001 period, with the share of the ICT sector going from 12.5% in 1996 up to 16.5% in 2001 and down to 15% in 2005.

Figure 3b unpacks this reallocation of human capital between individuals who recently entered the labor market (four years prior or fewer) and individuals who have been in the labor market for longer (for five years or more). It shows that the deviation from trend in the share of skilled workers in the ICT sector is entirely driven by labor market entrants. The ICT sector share among workers who have been in the labor force for five years or more exhibits a slight upward trend but no significant deviation from trend. By contrast,

11. Lewellen (2003) and Brunnermeier and Nagel (2004) use a similar measure to study the internet bubble. When stocks correspond to business groups, we consolidate sales at the business group level. To mitigate the role of outliers, we define the sector-level price-to-sales ratio as the median firm-level price-to-sales ratio in the sector.

the ICT sector share among new workers exhibits a sharp upward deviation from trend during the boom. This sharp difference in labor reallocation between cohorts points to the existence of different vintages of human capital within occupations. Workers with older vintages of human capital outside the ICT sector appear to be poor substitutes for new workers in the ICT sector during the development phase of new technologies.

Since sectoral reallocation of skilled labor induced by the boom mostly happens at the time of labor market entry, we focus on skilled workers who enter the labor market around the boom period in the rest of the paper. We define the entry year in the labor market as the year in which individuals take their first full-time job, conditional on not being older than 30 at that time.[12]

2.4 Taking Stock

Three main facts characterize the ICT boom. First, the ICT sector benefits from a capital supply shock characterized by an inflow of capital and high equity valuations, allowing ICT firms to aggressively compete with firms in other sectors for the scarce supply of talent, leading to a large inflow of skilled workers in the ICT sector. The interpretation that the inflow of capital translates into a labor demand shock is supported by the joint evidence of labor inflow (Figure 3) and high wages (see Figure 4 below) in the ICT sector during the boom.

Second, the large reallocation of skilled labor almost exclusively happens through the sectoral choice of labor market entrants. During the boom, the ICT sector absorbs one-third of skilled labor market entrants (Appendix Figure B.1). Therefore, the boom may have an impact on aggregate long-term labor productivity given the large number of skilled labor drawn to ICT, that depends on how exposure to new technologies during the boom impacts human capital accumulation, which we study in Sections 3, 4 and 5.

Third, the boom is sharply delimited over time, from 1997/98 to 2001, which allows us

12. We drop individuals who are older than 30 at entry. The results are robust to using a cutoff at 35 years old. Since the panel data start in 1976, there is no risk of mismeasuring entry because it would have happened before the first year of data.

to define the *boom cohort* of workers, that enters the labor market during the ICT boom, alongside with the *pre-boom cohort* and the *post-boom cohort* of workers, that enter the labor market in the period right before and right after the boom, respectively.

3 Human Capital Accumulation

We now estimate the long-term value of human capital accumulated during the ICT boom by skilled workers who start in the booming ICT sector. We start by outlining a simple model showing how this value can be inferred from the long-run wage dynamics of the different cohorts by comparing wages across sectors and cohorts.

3.1 Model

Human capital. Time is discrete and the horizon is infinite. At the beginning of each period, a mass one cohort of workers enters the labor market and chooses in which sector $k = 1, 2$ to work. In line with the evidence presented in Section 2.3 that sectoral reallocation occurs mostly through the sectoral choice of labor market entrants, we assume workers cannot switch sector after the initial sectoral choice made at the time of entry.[13] At the end of each period, a fraction δ of workers of every cohort exits the labor market.

We denote by $H_{i,c,k,t} = \log(h_{i,c,k,t})$ the human capital of worker i from cohort c in sector k in period t.[14] $H_{i,c,k,t}$ represents the number of efficiency units of labor supplied by the worker. A worker's human capital has two components:

$$h_{i,c,k,t} = \theta_{i,k} + h_{c,k,t}. \tag{1}$$

$\theta_{i,k}$ is a worker fixed effect reflecting time-invariant ability within the sector. $(h_{c,k,t})_{t \geq c}$ is

13. The assumption of no sectoral mobility can be derived as a result if human capital accumulated on-the-job is sector specific (Rogerson 2005) and is consistent with the limited reallocation of seasoned workers to the ICT sector that we document in Figure 3b.

14. Throughout the paper, we use lowercase letters to denote logs of uppercase variables.

a process driving post-entry human capital accumulation and depreciation given by:

$$h_{c,k,t=c} = 0, \tag{2}$$

$$h_{c,k,t} = h_{c,k,t-1} + dh_{c,k,t}, \qquad t > c, \tag{3}$$

where $dh_{c,k,t}$ is a shock to the period t-stock of human capital of individuals who work in sector k during period $t-1$. Human capital shocks follow the autoregressive process:

$$dh_{c,k,t} = \mu_h + \rho_h(dh_{c,k,t-1} - \mu_h) + \varepsilon^h_{k,t}, \qquad t > c, \tag{4}$$

where $\rho_h \in [0,1)$, $dh_{c,k,t=c} = \mu_h$, and $\varepsilon^h_{k,t}$ has zero mean. $\varepsilon^h_{k,t}$ is a human capital shock affecting all cohorts of workers in sector k in period $t-1$. It may reflect on-the-job learning, which increases human capital, or skill obsolescence, which decreases human capital. When $\rho_h > 0$, human capital shocks are serially correlated, implying that their effect builds up progressively over time.

Worker-level wages. A worker's wage in a given sector is equal to the product of the wage rate in the sector (i.e., the compensation per efficiency unit of labor) by the worker's human capital in that sector (i.e., the number of efficiency units of labor supplied by the worker). In log terms, and breaking down human capital into its two components, the wage of worker i from cohort c in sector k in period t is:

$$w_{i,c,k,t} = w_{k,t} + \theta_{i,k} + h_{c,k,t}, \tag{5}$$

where $w_{k,t}$ is the wage rate in sector k in period t. Equation (5) is the key equation for our empirical analysis. It shows that worker-level wages have three components: the sector-level wage rate ($w_{k,t}$), the fixed type of the worker ($\theta_{i,k}$), and human capital accumulated since entry ($h_{c,k,t}$). We show in Section 3.2 how we can use variation across years, cohorts, and sectors to identify the human capital component $h_{c,k,t}$.

In the rest of this section, we pin down the sector-level wage rate, which requires modeling workers' career choices (labor supply) and the corporate sector (labor demand).

Career choices. Workers have idiosyncratic preferences over their career choice. Worker i incurs a non-pecuniary cost $\gamma_{i,k}$ if she chooses sector k. Individuals derive log utility over per-period consumption with discount factor $\beta < 1$, and consumption is equal to the current wage. Worker i from cohort c chooses sector k that provides her with the higher expected utility given by:

$$\sum_{t=c}^{\infty} \beta^{t-c}\, \mathbb{E}_c[w_{i,c,k,t}] - \gamma_{i,k}, \tag{6}$$

where $\mathbb{E}_c[w_{i,c,k,t}]$ is time c-conditional expectation of the worker's wage in sector k in period t.[15]

Workers' sectoral choices depend on expectations of future wages. These choices and the resulting equilibrium outcomes do not depend on workers holding rational expectations or not. The only difference between the two cases is that if expectations are not rational, workers are systematically surprised by the realization of wages. Assessing whether workers' expectations are rational is outside the scope of this paper.

Corporate sector. We model the corporate sector with a final good sector, which purchases inputs from intermediate goods sectors, and in turn produces using labor.

Each sector $k = 1, 2$ hires workers to produce an intermediate good with constant returns to scale:

$$X_{k,t} = Z_{k,t} \sum_{c=-\infty}^{t} \int_{i \in \mathcal{I}_{c,k,t}} H_{i,c,k,t}\, di. \tag{7}$$

$Z_{k,t}$ is sectoral productivity and follows the autoregressive process $z_{k,t} = \rho_z z_{k,t} + \varepsilon^z_{k,t}$, where $\rho_z \in [0, 1]$ and $\varepsilon^z_{k,t}$ is a productivity shock with mean zero. The infinite sum in (7) is the efficient quantity of labor supplied in sector k in period t by all cohorts of workers $c = -\infty, \ldots, t$. The integral inside the sum is the efficient quantity of labor supplied by cohort c, which is equal to the efficient quantity of labor ($H_{i,c,k,t}$) supplied by the set of workers from cohort c who started in sector k and have not exited the workforce by time t (denoted by $\mathcal{I}_{k,c,t}$).

The final good is produced using the intermediate goods with CES production func-

15. The effect of workers' exit rate δ on expected utility is impounded in the discount factor β.

tion:

$$Y_t = \left(\sum_{k=1,2} A_k X_{k,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{8}$$

where $A_k > 0$ and $\sigma > 1$. The wage rate per efficiency unit of labor in sector k period t is determined by the marginal productivity of labor:[16]

$$w_{k,t} = a_k + z_{k,t} - \frac{1}{\sigma}(x_{k,t} - y_t). \tag{9}$$

The wage rate is not equalized across sectors because sectoral mobility is imperfect, for two reasons. First, workers do not switch sector after entry. Second, even workers from entering cohorts have non-pecuniary preferences over career choices, which implies that they do not necessarily go to the sector offering the higher wage.

Equations (1) to (9) describe labor supply and demand and the law of motion of human capital. They characterize a unique stationary equilibrium, which we describe in Appendix D.

3.2 Baseline Results

We present the empirical strategy and graphical results in this section. The empirical strategy allows us to incorporate additional controls and fixed effects to further tighten the identification. These refinements are presented in Section 3.3.

We start from the wage equation (5) from the model, where worker i from cohort c starting in sector k earns in period t the log wage:

$$w_{i,c,k,t} = w_{k,t} + \theta_{i,k} + h_{c,k,t}. \tag{5}$$

The log wage depends on the wage rate in the sector ($w_{k,t}$), the invariant ability of the worker ($\theta_{i,k}$), and human capital accumulated since entry ($h_{c,k,t}$). We now show how to identify the human capital accumulation component $h_{c,k,t}$ with wage regressions that

16. The right-hand side of (9) is obtained by taking the first order condition with respect to $H_{i,c,t,k}$ in (8), substituting $X_{k,t}$ using (7), and taking logs.

progressively add fixed effects for interactions between years, cohorts, and sectors.

3.2.1 Identification Across Sectors (Within Cohorts)

For each cohort, we compare the wage of workers who start in the ICT sector relative to workers from the same cohort who start outside the ICT sector over time. To make this comparison, we estimate the following regression at the individual-year level separately for three cohorts c: the *pre-boom* cohort, the *boom* cohort, and the *post-boom* cohort, which comprise workers who start between 1994 and 1996, 1998 and 2001, and 2003 and 2005, respectively.[17]

$$\log(Wage_{i,t}) = \sum_{t'} \beta^c_{t'} \cdot ICT_{i,0} \times (t = t') + \alpha_t \times X_{i,0} + e_{i,t} \tag{10}$$

$Wage_{i,t}$ is the annualized wage of individual i in year t. $ICT_{i,0}$ is a dummy equal to one if individual i starts in the ICT sector. It is interacted with year dummies. The baseline specification includes year fixed effects α_t, interacted with the vector $X_{i,0}$ of worker characteristics, which includes sex, age, entry year, and two-digit occupation at entry.

The regression coefficient β^c_t captures the average wage difference in year t between workers from cohort c who start in the ICT sector and workers from the same cohort and with the same characteristics in the same occupation, who start outside the ICT sector. We superscript β^c_t with c to emphasize that we estimate (10) separately for each cohort $c \in \{Pre, Boom, Post\}$. $e_{i,t}$ is an error term clustered at the individual level.

Figure 4 presents the estimated β^c_t for each cohort. Focusing first on the boom cohort, the figure shows that workers who start in the ICT sector during the boom earn an entry wage on average 5% higher than individuals from the same cohort and with the same characteristics, starting outside the ICT sector. Strikingly, the wage difference vanishes rapidly once the boom ends in 2001, and keeps falling after the bust so that the wage

17. We include a gap year between each successive cohort to have sharply delimited cohorts. The results are robust to including the gap years in either one of the adjacent cohorts.

difference becomes negative after 2004. By 2015, workers who started in the booming ICT sector earn on average 6% less than workers from the same cohort, same demographics, and same occupation, who started outside the ICT sector.

The wage decomposition (5) implied by the model shows that the 6% difference encompasses three economic forces: a sector-wide shock, the sorting of heterogeneous workers, and the accumulation of human capital.

To see this, notice that the regression coefficient β_t^c, which is equal to the difference in average wage between workers who started in ICT and workers who started in other sectors, can be exactly computed in the model. It requires averaging (5) over i at the cohort-year level and differencing by k between the ICT sector and other sectors, which yields:

$$\beta_t^c = \Delta \overline{w}_{c,t} = \Delta w_t + \Delta \overline{\theta}_c + \Delta h_{c,t} \tag{11}$$

where Δ denotes the difference operator between the average in the ICT sector and the average in other sectors, and $c \in \{Pre, Boom, Post\}$ is the cohort. $\Delta \overline{w}_{c,t}$ is the average wage in year t of workers from cohort c who start in the ICT sector minus that of workers who start outside the ICT sector. Δw_t is the wage rate in year t in the ICT sector minus that outside the ICT sector. $\Delta \overline{\theta}_c$ is the average type of workers from cohort c who start in the ICT sector minus that of workers who start outside the ICT sector. $\Delta h_{c,t}$ is human capital accumulated from entry until year t by workers from cohort c who start in the ICT sector minus that of workers who start outside the ICT sector.

Equation (11) shows that β_t^{Boom} can fall over time for two reasons. First, there may be a secular decline in the wage rate in the ICT sector relative to other sectors (i.e., Δw_t decreases over time). For example, labor demand in ICT may persistently decline after the bust. Second, human capital accumulated by the boom cohort in the ICT sector may depreciate over time compared to human capital accumulated in other sectors (i.e., $\Delta h_{Boom,t}$ decreases over time).

Note that the selection term within cohort across sectors $\Delta \overline{\theta}_c$ is time *invariant*, and therefore may shift the level of the wage difference β_t^{Boom} but cannot explain its variation over time.

3.2.2 Identification Across Sectors and Across Cohorts

As shown by equation (11), sectoral labor supply and demand shocks (Δw_t) affect all cohorts equally. Therefore, we can absorb the labor supply and demand component by comparing the wage dynamics of the boom cohort relative to that of the post-boom cohort, and thus isolate human capital accumulated in ICT during the boom ($\Delta h_{Boom,t}$). Differencing equation (11) between the two cohorts:

$$\begin{aligned} \beta_t^{Boom} - \beta_t^{Post} &= \left(\Delta\bar{\theta}_{Boom} - \Delta\bar{\theta}_{Post}\right) + \left(\Delta h_{Boom,t} - \Delta h_{Post,t}\right) \\ &= \left(\Delta\bar{\theta}_{Boom} - \Delta\bar{\theta}_{Post}\right) + \sum_{\tau<2003} \frac{1-\rho^{t-\tau+1}}{1-\rho}\Delta\varepsilon_\tau^h, \end{aligned} \tag{12}$$

where the second equality follows from calculating $h_{c,t}$ using equations (2) to (4). The first term on the right side of (12) is time invariant and reflects selection that impacts average wage levels. The second term captures the long-run evolution of human capital accumulated in the ICT sector during the boom.

Figure 4 shows that, in sharp contrast to the boom cohort, the post-boom cohort of workers who start in ICT shows no downward trend in the wage dynamics. Therefore, the long-run wage discount of ICT boom-cohort workers is not explained by a secular decline in labor demand or over-supply of skilled workers in the wake of the ICT bust. If it were, the post-boom cohort would also experience the long-term wage decline and therefore we should not see any change in the gap between β_t^{Boom} and β_t^{Post}. The wage dynamics are instead consistent with human capital accumulated during the boom depreciating over time, i.e., the second term of equation (12).

We estimate this cross-cohort comparison with a specification that compares the wage dynamics of workers who start in ICT relative to workers who start in other sectors, for workers of the boom cohort relative to workers of the post-boom cohort. We include both cohorts in regression (10) and interact each right-hand side variable with a boom cohort dummy variable equal to one if the worker belongs to the boom cohort. The regression equation becomes:

$$\log(Wage_{i,t}) = \sum_{t'} \beta_{t'} \cdot ICT_{i,0} \times BoomCohort_i \times (t = t') \\ + \delta_t \times ICT_{i,0} + \alpha_{c,t} \times X_{i,0} + e_{i,t} \quad (13)$$

We now include a starting-sector×year fixed effect ($\delta_t \times ICT_{i,0}$) to compare workers exposed to the same sectoral shocks such as the slowdown of the ICT sector in the aftermath of the boom, and a cohort×year fixed effect ($\alpha_{c,t}$) to compare workers from the same cohort.[18]

Figure 5 Panel A plots the regression coefficients. The downward trend indicates that there is a progressive depreciation of human capital accumulated by the boom cohort in the ICT sector during the boom relative to similar boom cohort-workers starting in other sectors, relative to the same comparison for the post-boom cohort. These coefficients capture the difference in the estimated coefficients for the boom and post-boom cohorts from Figure 4.

3.2.3 Selection

We now examine whether these estimates are explained by negative selection into ICT during the boom. This would happen if the booming ICT sector attracts a disproportionate share of low productivity workers or if large expansion in the share of new workers joining the sector increases the risk of mismatch between workers and sectors.[19]

Our baseline starting-sector×year fixed effect ($\delta_t \times ICT_{i,0}$) adequately controls for selection if unobserved heterogeneity shifts the wage profile by a time-invariant term, as $\theta_{i,k}$ does in the wage equation (5), effectively acting as a worker fixed effect (Abowd, Kra-

18. We also interact the worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) with the cohort×year fixed effect to allow these controls to affect wages differently for different cohorts and in different years.

19. In the sectoral choice model laid out in Section 3.1, higher entry in a sector may increase or decrease the average type in the sector. Selection based on sector-specific type $\theta_{i,k}$ tends to decrease the average type. Selection based on non-pecuniary preferences $\gamma_{i,k}$ may increase or decrease the average type depending on the joint distribution of non-pecuniary preferences and types.

marz, and Margolis 1999; Babina, Ma, Moser, Ouimet, and Zarutskie 2022). However, the starting-sector×year fixed effect fails to control for selection if unobserved heterogeneity is correlated with wage *growth* and not just with the wage level. In this case, the downward trend in the boom cohort's wage dynamics could be explained by a more subtle form of negative selection: the booming ICT sector might draw workers who would experience lower wage growth even if they had started in another sector.

To account for selection correlated with wage growth, we bring into the analysis the pre-boom cohort. Individuals entering the labor market before the ICT boom experience the same human capital shocks and sectoral productivity shocks as individuals from the boom cohort. However, as shown in Figure 3, the boom in the ICT sector was sudden, making it unlikely that anticipation of the boom led to negative selection among individuals who started in ICT a few years before the boom. Therefore, the pre-boom cohort would not experience a long-term wage decline caused by negative selection during the boom, but it would experience a long-term wage decline caused by human capital depreciation.

Figure 4 shows that the pre-boom cohort's wage dynamics has a downward trend very similar to that of the boom cohort. The difference-in-differences regression (13) estimated using the pre-boom cohort and the boom cohort shows that the difference in wage dynamics between the two cohorts is statistically insignificant (Panel B of Figure 5), consistent with human capital depreciation but not with negative selection during the boom.

3.3 Ruling out Additional Confounders

Our setting allows us to further deal with unobserved shocks and non-random allocation of workers to sectors, places, and firms by conditioning on an extensive set of fixed effects in equation (13). For the sake of exposition, we replace the year dummies in the triple-interaction terms $ICT_{i,0}$×cohort-dummy×year-dummy with dummies for the three time periods 2003–2005, 2006–2010, and 2011–2015. The specification is otherwise identical to equation (13):

$$\log(Wage_{i,t}) = \sum_{\substack{\text{period}=2003\text{-}05,\\ 2006\text{-}10,2011\text{-}15,}} \beta_{period} \cdot ICT_{i,0} \times BoomCohort_i \times (t \in period)$$
$$+ \delta_t \times ICT_{i,0} + \alpha_{c,t} \times X_{i,0} + e_{i,t} \quad (14)$$

The baseline specification controls for worker demographic characteristics and experience (sex, age dummies, entry year dummies) gathered in vector $X_{i,0}$, interacted with cohort×year fixed effects (α_{ct}) to account for potential changes in return to experience (e.g., Buchinsky, Fougère, Kramarz, and Tchernis 2010) and in the gender gap (e.g., Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon 2022). We also control for potential differences in on-the-job learning and human capital depreciation across occupations (e.g., Kogan, Schmidt, and Seegmiller 2022) by including two-digit occupation at entry in the vector of worker characteristics $X_{i,0}$.[20]

Column 1 of Table 1 reports the result of the baseline specification. The result reflects the dynamics in Panel A of Figure 5. During the 2003–2005 period, individuals from the boom cohort who started in the ICT sector have similar wages as individuals from the post-boom cohort who also started in the ICT sector (relative to the same comparison for individuals who started in other sectors). However, as time passes, individuals who started in ICT during the boom experience slower wage growth such that their wage is 7.3% lower over the 2011–2015 period.

In column 2, we add individual fixed effects, which ensure that we identify wage changes off individual wage trajectories and not off changes in the pool of workers induced by attrition. The inclusion of individual fixed effects implies that the β coefficients are identified relative to a reference time period that we fix to 2003–2005. The coefficients for the period 2006–2015 relative to the reference period are very similar to those in

20. We construct the fixed effect using the occupation in the first job rather than the current occupation because the current occupation is endogenous to human capital accumulation. For the same reason, all the other fixed effects described in this section and constructed using the commuting zone, sector, and firm characteristics, are measured in the first job.

column 1, implying that non-random attrition does not explain the wage discount.[21] We provide additional evidence that attrition does not explain our results in Section 3.4.

Our results could still be biased if workers are exposed to unobserved shocks across sectors, space, and firms, which correlate with the choice of sector at entry. We address this possibility by progressively saturating the regression with high-dimensional fixed effects. In column 3, we include commuting zone×cohort×year fixed effects. This removes any correlation rising from spatial sorting of productive workers that would expose them to different local shocks such as local tax shocks that interact with technological change (Hombert and Matray 2018; Babina and Howell 2022), local demand shocks (Adelino, Ma, and Robinson 2017), and local credit shocks (Guiso, Pistaferri, and Schivardi 2012; Barrot, Martin, Sauvagnat, and Vallée 2019).

In column 4, we add entry wage quintile×cohort×year fixed effects. This ensures that we compare workers with the same entry wage and therefore accommodates the possibility that workers with different ex-ante productivity are on different wage trends. In column 5, we include four-digit sector×year fixed effects to control for worker sorting that might correlate with sector-level differences in wage trajectories such as differences in return to talent and rent sharing (Philippon and Reshef 2012; Célérier and Vallée 2019) and differences in unionization and collective bargaining rules that affect innovation and wage dynamics (Bena, Ortiz-Molina, and Simintzi 2021). In this case, the coefficient on $ICT_{i,0} \times BoomCohort_i \times$ 2011-15 remains identified off variation across workers starting in the same four-digit sector from the boom cohort relative to those from the post-boom cohort. In all cases, we find quantitatively similar effects.

Despite the tight identification strategy, it could still be the case that within occupations, narrowly defined sectors, and local labor markets, the composition of firm characteristics in the ICT sector changes during the boom. This could pose a problem for identification since workers' long-term outcomes have been shown to be associated with firm characteristics.[22] Ideally, we would like to add fixed effects for the worker's

21. For instance, the coefficient for 2011–2015 is -0.077 in column 2, close to the same coefficient relative to 2003–2005, $-0.073 - 0.001 = -0.074$ in column 1.

22. For instance: size and differences in rent sharing and ability to insure workers (Bloom, Guvenen,

initial employer interacted with year fixed effects and compare workers from different cohorts starting in the same firm. Because of the way the data are sampled, whereby individuals are randomly selected to be part of the panel irrespective of their employer, we cannot implement this strategy as few firms beyond the large ones hire sampled high-skill workers from several cohorts. However, it is still possible to absorb much of the potential endogeneity coming from the correlation between firm characteristics and worker productivity by creating "pseudo firms" based on firm characteristics.

Given the importance of firm size, firm age, firm productivity, and affiliation with a conglomerate for workers' wage dynamics emphasized in the literature, we create pseudo firms based on the combination of quintiles of employment, firm age, labor productivity, and a dummy for whether the firm belongs to a conglomerate (i.e., $5 \times 5 \times 5 \times 2 = 250$ pseudo firms). In column 6, we include the worker's (pseudo) employer fixed effect interacted with year fixed effects. This ensures that we compare workers within the same narrowly defined type of firms.

While these fixed effects hold constant the distribution of firms' ex-ante characteristics, variation in firms' future performance may remain and explain wage dynamics. In column 7, we address this possibility by adding the quintiles of five-year future sales growth in the set of variables used to construct pseudo firms.[23] Finally, we include in column 8 all the high-dimensional fixed effects used in columns 3 to 5 and the pseudo-firm fixed effects used in column 7. The result is quantitatively robust across specifications.

3.4 Robustness

Excluding the financial sector. Compensation of high-skill workers in the financial sector grew faster than in other sectors during the 2000s (see Philippon and Reshef (2012) for the US; Célérier and Vallée (2019) for France), which could partially drive the wage

Smith, Song, and Wachter 2018; Hartman-Glaser, Lustig, and Xiaolan 2019), connection to a business group (Tate and Yang 2015; Cestone, Kramarz, and Fumagalli 2018), firm age (Ouimet and Zarutskie 2014; Babina, Ma, Moser, Ouimet, and Zarutskie 2022), productivity (Abowd, Kramarz, and Margolis 1999), and workforce composition (D'Acunto, Tate, and Yang 2020).

23. We use the mid-point growth rate defined as $[S_{t+5} - S_t]/[(S_{t+5} + S_t) \times 0.5]$ to account for firm exit. Using different time windows leads to quantitatively similar results.

discount in the ICT sector relative to the other sectors that include the financial sector. In column 1 of Table 2, we show that our results are robust to excluding workers starting in the financial sector.

Excluding French firms. While France fully embraced the ICT revolution and produced successful ICT firms, the wage discount might be specific to employees of French firms. As a first pass to testing for external validity, we leverage the fact that many large US firms have offices across the world, including in France, so their employees located in France appear in our data. We use ownership data to identify subsidiaries of US companies defined as firms that are 100% owned by a US company.[24] In column 2 of Table 2, we re-estimate the baseline regression for this subset of firms and find a similar effect as on the entire sample of firms. These results show that the long-term wage decline is not a French firm phenomenon and extends to US firms with high-skill workers in France.

Capital income. We may under-estimate workers' earnings because the matched employer-employee data report labor income but not capital income. Capital income can be significant for entrepreneurs and high-skill employees when they are granted shares or options in their employer's stock (e.g., Kim and Ouimet 2014; Eisfeldt, Falato, and Xiaolan 2022). To account for capital income, we link the employer-employee data with employers' financial statements from tax filings. Since we do not have information on stock grants and stock options, we calculate capital income under two scenarios.

In the first scenario (column 3 of Table 2), we assume the CEO holds all cash flow rights. We add the firm's net income to the CEO's earnings.[25] In the second scenario (column 4), we assume employees receive ownership stakes when they join startup companies. During the first eight years of a firm's life, we allocate one-third of its net income to the skilled employees who joined the firm within three years of firm creation.[26]

24. Examples of US employers in the ICT sector include Microsoft and IBM.

25. We identify the CEO as one-digit occupation code 2. When the firm reports several CEOs, we split the net income equally among them. Results are similar when we use dividends instead of net income. We prefer net income because it includes capital gains resulting from undistributed profits.

26. We assume that this one-third fraction of net income is shared between the early joiners of the startup in proportion to their wage. We use a profit share of one-third because it is unlikely capital providers would not claim at least two-thirds of the profits (Eisfeldt, Falato, and Xiaolan 2022). Results

For both measures, we calculate workers' total earnings as wage plus capital income and use log of total earnings as the dependent variable. In both cases, accounting for capital income has little effect on the magnitude of the long-run wage discount.

Cumulative earnings. The long-term wage would not accurately reflect long-term productivity if there is reverse backloading, i.e., if workers earn high upfront wages in exchange for lower wages later on (Lazear 1981). In this case, individuals starting in the booming ICT sector might still earn the same cumulative earnings as individuals starting in other sectors despite slower wage growth.

To test whether this is the case, in Appendix B.1 we estimate equation (10) using cumulative earnings from labor market entry up to each year t post-entry as the dependent variable, discounted back to the entry year at a rate of 5% per year. We find that high-skill workers starting in ICT during the boom earn cumulative earnings from entry to 2015 that are 4.1% (significant at 5%) lower than that of similar workers starting in other sectors. A specification in levels instead of logs shows that the discounted cumulative earnings loss is 19,600 euros (significant at 1%). Therefore, the long-term wage discount is not driven by backloading practices, but instead reflects that high-skill workers starting in the ICT sector during the technology boom are worse off in the long-run.

Other robustness. We run two additional tests to confirm that selection is unlikely to explain our results. First, using workers that we can link to education outcomes, we show there is no evidence that the pool of workers going to the ICT sector during the boom is of lower quality based on their education achievements (see Appendix B.2). Second, looking at the correlation between wage growth and attrition, we show that cohorts of workers joining the ICT sector during the boom are neither more likely to leave the sample when they are on a high wage growth trajectory (e.g., because they move to the Silicon Valley) nor when they are on a low wage growth trajectory (e.g., inducing them to drop out of the labor force; see Appendix B.3).

are robust to using different profit shares and different time horizons at which we assume ownership stakes are granted to employees.

3.5 Taking Stock

The results in Sections 2 and 3 have implications for the evolution of aggregate human capital, since this evolution depends on the change in each worker's human capital multiplied by the number of workers experiencing this change. The large inflow of skilled workers to the ICT sector during the boom (Section 2) combined with the sizable long-run human capital depreciation experienced by these workers (Section 3), implies a negative employment-based effect of the tech boom on aggregate human capital. In the next section, we examine how this effect interacts with financial capital flows.

4 Capital Flows and Human Capital Depreciation

The finding that workers who start in the ICT sector during the boom experience sizable long-run human capital depreciation could imply that financing booms that accompany periods of rapid technological change weigh on aggregate human capital, and ultimately on aggregate labor productivity and economic growth. This occurs if the capital flows during the boom are directed towards firms whose workers will experience larger depreciation of their human capital, as more workers would lose human capital in the long run.[27] Conversely, if the capital flows during the boom are directed towards firms whose workers will experience smaller depreciation of their human capital, capital flows tend to mitigate aggregate human capital depreciation. Therefore, which case prevails depends on the *correlation* between human capital depreciation and capital flow during the boom. We study this correlation in Section 4.1.

While the above implication does not depend on whether the correlation is causal, financing booms might play an additional role on aggregate human capital by causally accelerating the human capital depreciation of workers in firms that benefited from easy financing. We examine this question in Section 4.2.

27. In Appendix B.4, we show that capital flows are indeed strongly correlated with labor flows in a panel regression at the industry×geography×year level with industry, geography, and year fixed effects.

4.1 Correlation Between Capital Availability and Human Capital Depreciation

To understand how human capital depreciation correlates with capital availability during the innovation boom, we augment equation (14) with interactions with the three proxies of capital availability that we introduced in Section 2.2.[28] The first two proxies measure overvaluation at the four-digit industry level using stock prices: value-weighted stock return during the year 1999 (ICT stocks peak in March 2000); and the mean ratio of stock price over company sales per share (P/S) at the end of 1999.

The third proxy measures capital inflow using all public and private firms. We take net equity issuance defined as the mid-point growth rate in nominal equity at the firm level from the tax filings, and calculate the leave-one-out mean at the four-digit industry×commuting zone×year level. The leave-one-out mean ensures that capital availability is not endogenous to the firm's intrinsic productivity. An advantage of this proxy is that it varies across industries and geographies, which allows us to augment the specification with a rich set of fixed effects.

Table 3 reports the results. In all columns, the coefficient of interest is the interaction of $ICT_{i,0} \times BoomCohort_i \times$ 2011-15 with the dummy $Capital\ availability_i$ that takes the value one if the proxy for capital availability is above the sample median.

Columns 1 and 2 use the proxies based on stock price valuations. In both cases, the wage discount for workers who started in the ICT sector during the technology boom is concentrated in the four-digit sectors that experienced the largest overvaluation, and the point estimates are consistent across both proxies. The magnitudes are large, with workers facing an additional 11.3% to 12.9% long-term wage discount in these sectors.

Starting from column 3, the proxy for capital availability is the leave-one-out mean of equity issuance at the four-digit industry×commuting zone×year level. Here again, we find that the human capital depreciation is concentrated in ICT industries that experienced the largest capital inflow.

28. As for other firm characteristics used in previous specifications, capital availability is measured for the firm at which the worker takes her first job and is thus time-invariant for each worker.

Results in columns 1 to 3 imply that the large inflow of capital to the ICT sector during the boom contributed to reduce aggregate labor productivity. Indeed, rather than flowing to firms in which workers accumulate useful skills, capital was directed towards firms whose workers subsequently experienced the largest human capital depreciation and therefore more workers lose human capital in the long run. In that sense, the positive cross-sectional covariance between capital flow and human capital depreciation contributes negatively to aggregate labor productivity, in the spirit of Hsieh and Klenow (2009).

4.2 Does Capital Availability Cause Human Capital Depreciation?

If the relationship between capital availability and human capital depreciation is causal, capital inflows have an additional impact on aggregate human capital by accelerating the human capital depreciation that the average worker experiences. This may occur if greater capital availability lowers the hurdle for innovative projects to be financed and if, in turn, workers exposed to lower quality projects develop skills more prone to obsolescence. Alternatively, the relationship may not be causal. For instance, sectors receiving large capital inflows during the boom may be sectors experiencing fast-paced technological change, which would be the true driver of the depreciation of human capital exposed to technological change.

To estimate the impact of capital availability, we study how the wage discount varies with capital inflow when we hold fixed technological change. To do so, we use the fact that our measure of capital availability in column 3 is defined at the four-digit sector$\times$commuting zone$\times$year level, which allows us to augment the specification with four-digit sector$\times$cohort$\times$year fixed effects. This implies that we now compare the wage discount in a given year for workers from the same cohort, who start in the *same four-digit sector*, across geographies. To the extent that the technological frontier moves at the same pace for all firms within a four-digit sector, this specification estimates the impact of capital flows on the wage discount, holding fixed technological change that could be a driver of capital flows and thus a confounding factor.

Column 4 reports the results when we include four-digit sector×cohort×year fixed effects. The point estimate remains strongly negative and statistically significant, implying that even in the same narrowly defined sector and same cohort, workers more exposed to a large inflow of capital experience a larger depreciation of their human capital. Column 5 shows that the effect of capital inflow on human capital depreciation remains similar when we include commuting zone×cohort×year fixed effects, which account for time-varying unobserved shocks at the commuting zone level, such as differences in business dynamism and local productivity shocks. Taken together, these results show that capital inflows uncorrelated with firm productivity, industry productivity, and local labor market productivity, lead to a larger depreciation of human capital for workers starting in the ICT sector. In the next section, we investigate the mechanism behind this pattern.

5 Mechanisms for Human Capital Depreciation

We now examine what drives the human capital depreciation of high-skill workers starting in ICT during the boom and why this depreciation is amplified by capital availability during the boom. We study three potential mechanisms: (i) obsolescence of technology vintage-specific skills; (ii) heightened risk of job termination; (iii) winner-take-all effect.

5.1 Skill Obsolescence

The first mechanism is rooted in the notion that skills are not only sector specific but also vintage specific (Chari and Hopenhayn 1991). In this case, accelerating technological change during the boom leads to skill obsolescence because new technologies require new vintages of skills, rendering old vintages of skills obsolete. Easy financing exacerbates the problem by lowering the hurdle for innovative projects to be financed such that workers' human capital is tied to lower quality technologies that are more likely to have a strong vintage component.

We test the skill obsolescence mechanism by studying whether the wage discount is larger for jobs with higher technological content in which human capital accumulation is more likely to be tied to those technologies. We proxy for the degree of technological content of a job by leveraging the fact that the occupation classification in the data maps directly into three broad levels of skill: high-skill, middle-skill, and low-skill.[29] This allows us to compare the obsolescence of human capital when new technologies appear between the three groups of workers classified according to the skill level corresponding to their first job. To do so, we re-run the baseline regression (14) separately for each group of workers, as well as the specification augmented with interactions with capital flow to the worker's four-digit sector×commuting zone in the year in which she starts.

Columns 1, 3 and 5 of Table 4 show the unconditional (to capital availability) long-term wage discount for each of the three skill levels. High-skill workers starting in the ICT sector during the boom experience a larger long-run wage discount (column 1) than middle-skill workers (column 3), while the effect is insignificant for low-skill workers (column 5).

The difference in wage discount across skill levels is even starker when we focus on four-digit sector×commuting zones that experience large capital inflow during the boom. The additional long-term wage discount when capital flow at entry is high is 8.1% for high-skill workers (column 2), while it is insignificant for middle-skill workers (column 4) and low-skill workers (column 6).

Therefore, the wage decline is the largest in occupations where human capital embeds more technological content, particularly so in firms that benefit from the largest inflow of capital. This pattern is consistent with the notion that skills are vintage specific (e.g., Chari and Hopenhayn 1991; Deming and Noray 2020) and that the combination of easy financing and technological change accelerates their obsolescence.

29. High-skill occupation codes are 23 and those starting with 3. Middle-skill occupations start with 4. Low-skill occupations start with 5 or 6. We exclude those starting with 6 because they correspond to manual low-skill occupations, which are rare in the ICT sector.

5.2 Job Termination

Accelerated obsolescence of human capital may also be driven by heightened risk of job termination if skills acquired on-the-job have limited portability across firms. Excessive inflow of capital can further amplify future job termination risk, which would explain why capital flow during the boom inflates the long-run wage discount.

We examine this hypothesis by controlling directly for job termination in the wage regression (14). Job termination is a dummy equal to one if the worker experiences a forced job change within the first four years after entry. We proxy for a forced job change as a change in employer such that either (i) employment at the worker's initial employer decreases by 10% or more in the year of the job change or (ii) the transition to the next job leads to a wage cut for the worker.[30]

Column 1 of Table 5 reproduces the baseline wage discount without controlling for job termination. Column 2 controls for job termination interacted with the five-year period dummies.[31] This barely changes the long-term wage discount, which decreases from 7.7% to 7.6%.

Job termination during a sectoral bust might have a disproportionate impact on long-term earnings. To account for this possibility, in column 3, we include the interaction term between job termination and all the interactions between $ICT_{i,0}$ and $BoomCohort$ and the five-year period dummies. This specification allows job termination to have a different effect on workers starting in the booming ICT sector than on workers from other cohorts and starting in other sectors. In this case, the coefficient on $ICT_{i,0} \times BoomCohort \times$ 2011-15 represents the long-term wage discount for a worker starting in the ICT sector during the boom and experiencing no job termination. The discount in this case is only slightly reduced, by about one-tenth, and remains large and significant.

A back-of-the-envelop calculation explains why job termination accounts for only a negligible part of the wage discount. In Appendix B.5, we show that the probability of

30. Results are robust to using condition (i) only or condition (ii) only to define a forced job change.

31. The coefficients on the interactions with job termination are omitted in Table 5 to save space. We report them in Appendix Table B.7.

job termination increases by 6.6 percentage points for high-skill workers starting in ICT during the boom, and that job termination is associated with a long-term wage decline of 3.3 percentage points on average. These estimates imply that heightened job termination explains $0.066 \times 0.033 = 0.2$ percentage points of the overall 7.7 percentage points wage discount.

Column 4 reproduces the wage discount in sector×commuting zones experiencing high capital inflow during the boom, without controlling for job termination (this is the same specification as in column 3 of Table 3). Column 5 controls for job termination and its interaction with capital flow (and all the interactions with the five-year period dummies). In column 6, we also include the interactions between job termination, capital flow, $ICT_{i,0}$, and $BoomCohort$. In all specifications, the additional wage discount in firms experiencing high capital flow is stable between 8.1% and 8.3%.

5.3 Winner-Take-All

The average long-term wage discount may mask a winner-take-all effect due to right-skewed returns to starting in technology sectors flushed with capital during periods of rapid technological change. Indeed, fast-paced technological change creates uncertainty regarding which firms and technologies will prevail in the long run (Kerr, Nanda, and Rhodes-Kropf 2014). High inflow of capital can further amplify this risk if capital is provided by investors whose business model is to finance projects with a small probability of a large success, such as venture capitalists and angel investors.[32] In this case, akin to patterns documented in the literature on the return to entrepreneurship (Hamilton 2000; Kerr, Nanda, and Rhodes-Kropf 2014; Kisseleva, Mjøs, and Robinson 2022), low average earnings may conceal positive skewness and high earnings in the right tail of the distribution.

To test for this possibility, we estimate quantile regressions for the baseline specifica-

32. See Kerr and Nanda (2015) and Janeway, Nanda, and Rhodes-Kropf (2021) for surveys on financing innovation and VC financing. Nanda and Rhodes-Kropf (2013) show that financing booms lower the discipline of VC investors, but increase their willingness to experiment, increasing the quality of innovation produced at the top of the distribution.

tion (14) as well as for the specification augmented with interactions with capital flow. This allows us to examine the distribution of the long-term wage discount and determine if the discount turns into a premium in the right tail of the distribution.

Table 6 reports estimates of quantile regressions for the 10th, 25th, 50th, 75th and 90th percentiles. Panel A shows that the discount experienced by individuals starting in the booming ICT sector is fairly uniform across the long-term wage distribution, ranging from 7.1% at the 90th percentile to 9.0% at the 10th percentile. Panel B shows that higher capital availability amplifies the discount across the board, shifting the entire long-term wage distribution to the left. If anything, the coefficient on the interaction with capital availability is more negative in the right tail of the distribution, inconsistent with the hypothesis that the inflow of capital to innovative firms during the technology boom creates a winner-take-all effect among workers joining these firms.

6 Concluding Remarks

Theories of endogenous growth and speculative growth posit that reallocation of resources to new technology sectors enhances future productivity and growth through spillovers, even if reallocation is fostered by a bubble in the technology sector and investors over-invest and end up losing money. In this paper, we focus on one natural channel for such spillovers, namely, on the human capital embedded in the large cohort of skilled workers who are hired in the technology sector during the bubble.

Using the Internet Bubble as a laboratory, during which one-third of a cohort of skilled individuals started in the ICT sector, we find that these workers experience a significant wage discount fifteen years later, after controlling for selection and job losses in the bubble's aftermath. The wage decline hits workers holding higher-skill jobs harder, consistent with obsolescence of skills acquired during the bubble. Furthermore, the discount is larger for workers hired by firms that receive larger inflows of capital, highlighting a detrimental impact of easy financing during innovation booms on aggregate productivity as large cohorts of skilled labor are attracted to firms where their human capital depreciate in the long run.

These results do not necessarily imply that the excessive growth of the ICT sector during the boom (from the perspective of investors value maximization) did not benefit the economy through other channels. Such benefits may include faster adoption of new information and communication technologies in the rest of the economy, relative to a counterfactual with no bubble and slower growth of the ICT sector. We leave this important question for future research.

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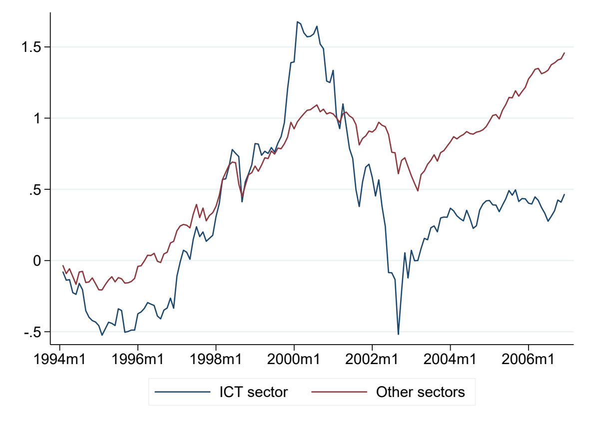
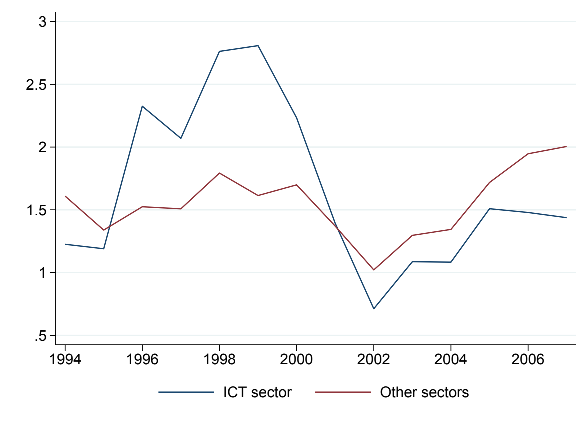
Figure 1: Equity Valuation

(a) Cumulative stock return



(b) Stock price over sales



Panel (a) plots cumulative value-weighted return in the ICT sector and in non-ICT sectors. Panel (b) plots the median ratio of stock price over sales per share within the ICT sector and within non-ICT sectors.

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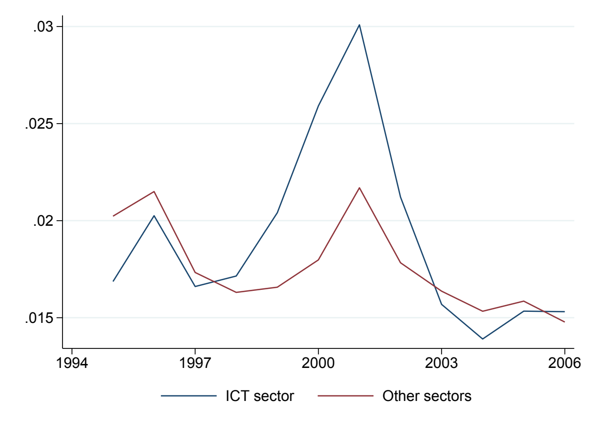
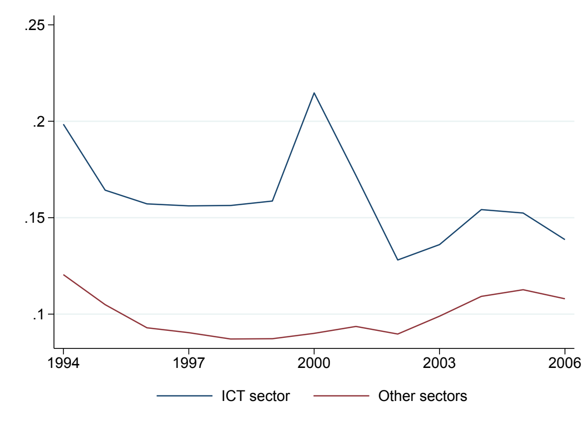
Figure 2: Capital Reallocation

(a) Equity issuance



(b) Firm entry



Panel (a) plots equity issuance scaled by lagged total assets in the ICT sector and in non-ICT sectors. Panel (b) plots new firm registrations scaled by the total number of firms in the ICT sector and in non-ICT sectors.

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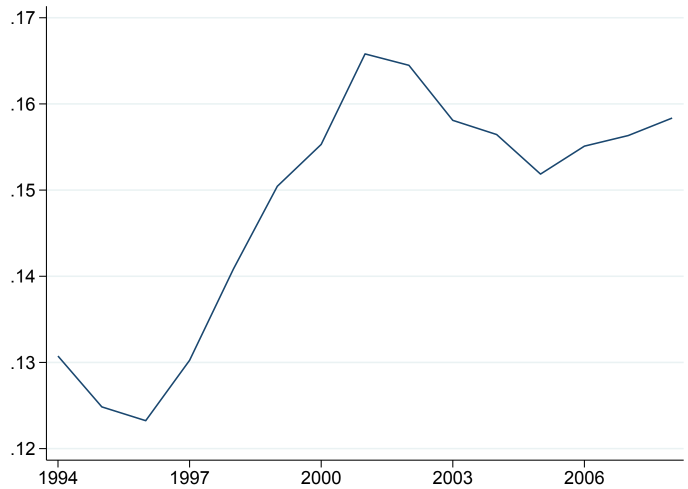
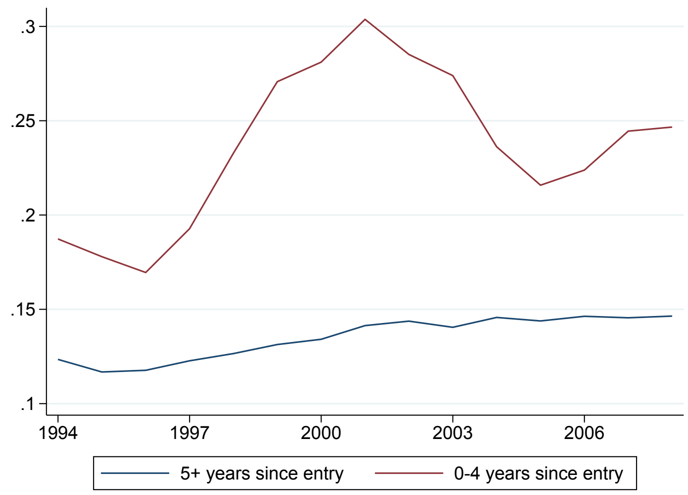
Figure 3: Labor Reallocation

(a) ICT sector share among all skilled workers



(b) ICT sector share among skilled workers: recent entrants vs. older workers



Panel (a) plots the share of the ICT sector in high-skill employment. Panel (b) shows the share of the ICT sector in high-skill employment separately for workers who entered the labor market five years ago or more (blue line) and for workers who entered four years ago or less (red line).

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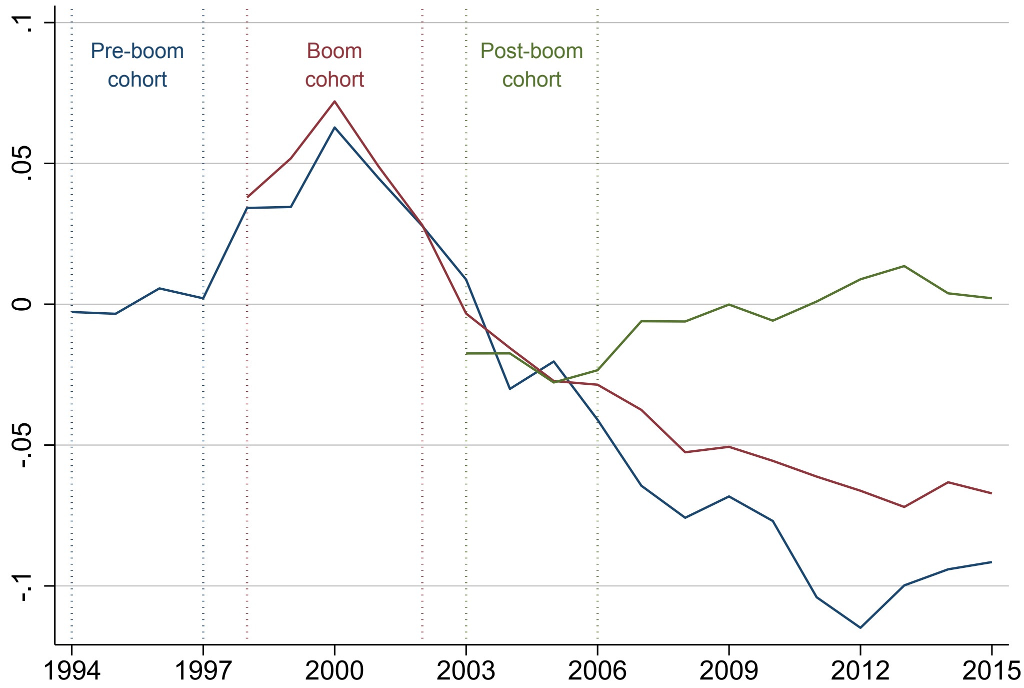
Figure 4: Wage Dynamics of Workers Starting in the ICT Sector Relative to Workers Starting in Other Sectors



The figure displays the estimates of β_t^c in the simple-difference specification (10). β_t^c reflects the wage premium in a given year t of high-skill workers from cohort c who started in the ICT sector relative to similar workers of the same cohort who started in other sectors, for the pre-boom cohort 1994–1996 (blue), boom cohort 1998–2001 (red), and post-boom cohort 2003–2005 (green).

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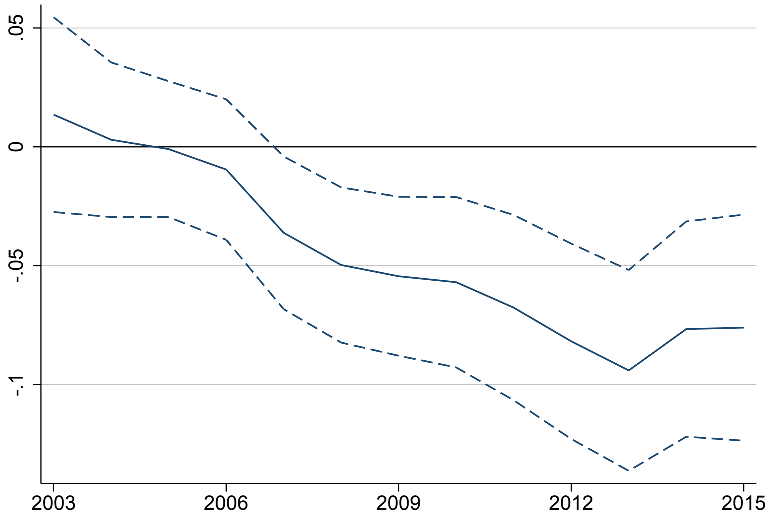
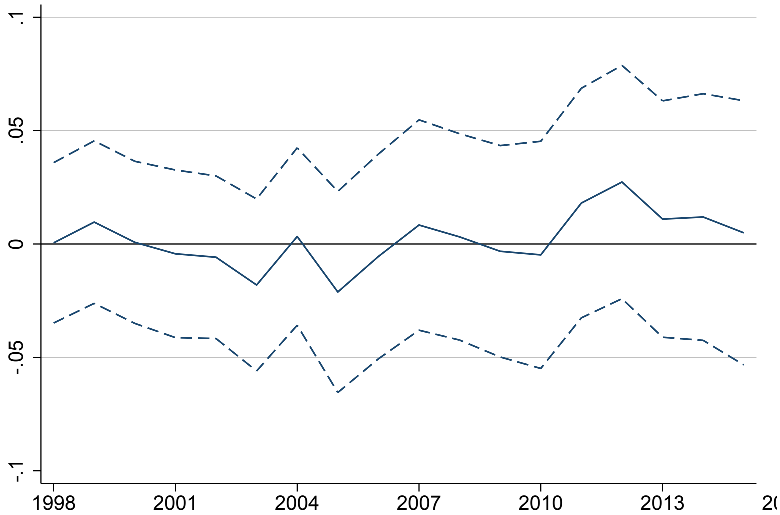
Figure 5: Wage Dynamics of Workers Starting in the ICT Sector Relative to Workers Starting in Other Sectors

(a) Boom cohort relative to post-boom cohort



(b) Boom cohort relative to pre-boom cohort



The figure displays the estimates of β_t^{Boom} in the difference-in-differences specification (13). β_t^{Boom} reflects the wage premium in a given year t of skilled workers from the boom cohort 1998–2001 who started in the ICT sector relative to similar workers of who started in other sectors (first difference) and relative to workers from the post-boom cohort 2003–2005 (in Panel A) or relative to workers from the pre-boom cohort 1994–1996 (in Panel B) (second difference).

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Table 1: Wage Regressions

	log(Wage)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT_0 × Boom cohort × 2003-05	0.001 (0.013)							
ICT_0 × Boom cohort × 2006-10	-0.035** (0.014)	-0.048*** (0.010)	-0.041*** (0.011)	-0.043*** (0.010)	-0.045*** (0.013)	-0.037*** (0.011)	-0.039*** (0.012)	-0.034** (0.016)
ICT_0 × Boom cohort × 2011-15	-0.073*** (0.019)	-0.077*** (0.015)	-0.067*** (0.016)	-0.075*** (0.015)	-0.078*** (0.019)	-0.065*** (0.016)	-0.070*** (0.018)	-0.074*** (0.024)
Adjusted-R2	.3	.84	.84	.84	.84	.84	.84	.84
Observations	93,304	92,901	92,719	92,901	91,343	92,714	90,473	88,586
ICT_0×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Worker FE	—	✓	✓	✓	✓	✓	✓	✓
Commuting zone×Cohort×Year FE	—	—	✓	—	—	—	—	✓
Entry wage quintile×Cohort×Year FE	—	—	—	✓	—	—	—	✓
Four-digit sector×Year FE	—	—	—	—	✓	—	—	✓
Pseudo firm FE×Year FE	—	—	—	—	—	✓	✓	✓
Sales growth ($t \to t+5$) Quintile FE×Year FE	—	—	—	—	—	—	✓	✓

The table presents the OLS estimates of equation (14) for high-skill entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2002–05, 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Column 2 adds two-digit occupation at entry×cohort×year fixed effects. Column 3 includes commuting zone at entry×cohort×year fixed effects. Column 4 includes initial wage quintile at entry×cohort×year fixed effects. Column 5 includes four-digit sector at entry×year fixed effects. Column 6 includes initial employer's pseudo firm (based on employment, firm age, labor productivity, affiliation with a conglomerate)×year fixed effects. Column 7 adds five-year futures sales growth in the set of variables used to construct pseudo firms. Column 8 includes all the controls and fixed effects together, using the same definition of pseudo firms as in column 7. All specifications include ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 2: Robustness

	log(Wage)		log(Wage+Cap.income)	
	Excl. finance	US firms	Capital income assigned to CEOs	Capital income assigned to Skilled workers
	(1)	(2)	(3)	(4)
ICT_0 × Boom cohort × 2006-10	-0.049***	-0.033	-0.051***	-0.052***
	(0.010)	(0.032)	(0.011)	(0.011)
ICT_0 × Boom cohort × 2011-15	-0.079***	-0.074*	-0.076***	-0.081***
	(0.015)	(0.044)	(0.015)	(0.016)
Adjusted-R2	.83	.83	.82	.82
Observations	87,522	11,359	92,901	92,901
ICT_0×Year FE	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓

The table presents the OLS estimates of equation (14) for skilled entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. In columns 1 and 2, the dependent variable is log wage of worker i in year t. In column 1, we exclude workers who started in the financial sector. In column 2, the sample is restricted to workers who started in the subsidiary of a US firm. In columns 3 and 4, the dependent variable is log wage plus capital income. In column 3, capital income is equal to the employer's profits if the worker is the CEO of the firm. In column 4, capital income is equal to one-third of the employer's profits times the share of the worker's wage in the firm's total high-skill wage bill, if the firm is eight year old or less. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 3: Capital Availability and Human Capital Depreciation

	log(Wage)				
Proxy of capital availability:	1999 return (sector level)	1999 P/S (sector level)	Equity issuance (sector×geo×entry year level)		
	(1)	(2)	(3)	(4)	(5)
ICT_0 × Boom cohort × 2006-10	0.011	0.008	-0.024		-0.027
	(0.030)	(0.030)	(0.017)		(0.018)
ICT_0 × Boom cohort × 2011-15	0.022	0.007	-0.029		-0.033
	(0.044)	(0.042)	(0.025)		(0.027)
ICT_0 × Capital availability × Boom cohort × 2006-10	-0.062*	-0.063*	-0.033	-0.030	-0.022
	(0.033)	(0.033)	(0.021)	(0.024)	(0.022)
ICT_0 × Capital availability × Boom cohort × 2011-15	-0.129***	-0.113**	-0.081***	-0.083**	-0.067**
	(0.049)	(0.047)	(0.031)	(0.035)	(0.033)
Adjusted-R2	.84	.84	.84	.84	.84
Observations	60,420	60,420	85,128	77,556	83,366
ICT_0×Year FE	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Each variable is interacted with a proxy of capital availability in the sector (and geography and time for the third proxy) at which the worker takes her first job. In column 1, the proxy of capital availability is the value-weighted stock return in 1999 at the four-digit sector level. In column 2, it is the median ratio of stock price over company sales at the end of 1999 at the four-digit sector level. In columns 3 to 5, it is net equity issuance at the four-digit sector×commuting zone×year level. All specifications include worker fixed effects, ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 4: Heterogeneity Across Skill Levels and Capital Availability

	log(Wage)					
	High-skill		Middle-skill		Low-skill	
	(1)	(2)	(3)	(4)	(5)	(6)
ICT_0 × Boom cohort × 2006-10	-0.048***	-0.024	-0.048***	-0.024	-0.028*	-0.025
	(0.010)	(0.017)	(0.011)	(0.017)	(0.015)	(0.027)
ICT_0 × Boom cohort × 2011-15	-0.077***	-0.029	-0.068***	-0.039*	-0.022	-0.027
	(0.015)	(0.025)	(0.014)	(0.023)	(0.020)	(0.040)
ICT_0 × Capital availability × Boom cohort × 2006-10		-0.033		-0.025		-0.012
		(0.021)		(0.022)		(0.030)
ICT_0 × Capital availability × Boom cohort × 2011-15		-0.081***		-0.033		-0.004
		(0.031)		(0.029)		(0.041)
Adjusted-R2	.84	.84	.83	.83	.8	.81
Observations	92,901	85,128	206,918	186,477	250,620	218,927
ICT_0×Year FE	✓	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t. In columns 1 and 2, the sample is workers with a high-skill occupation at entry. In columns 3 and 4, the sample is workers with a intermediate-skill occupation at entry. In columns 5 and 6, the sample is workers with a low-skill occupation at entry. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. Capital availability is net equity issuance in the four-digit sector×commuting zone×year at which the worker takes her first job. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

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Table 5: Controlling for Job Termination

	log(Wage)					
Control for:	—	Job loss	Job termination $\times$ICT$_0$ $\times$BoomCoh.	—	Job termination	Job termination $\times$ICT$_0$ $\times$BoomCoh.
	(1)	(2)	(3)	(4)	(5)	(6)
ICT$_0$ $\times$ Boom cohort $\times$ 2006-10	-0.048***	-0.046***	-0.042***	-0.024	-0.021	-0.022
	(0.010)	(0.010)	(0.012)	(0.017)	(0.017)	(0.020)
ICT$_0$ $\times$ Boom cohort $\times$ 2011-15	-0.077***	-0.076***	-0.069***	-0.029	-0.026	-0.019
	(0.015)	(0.015)	(0.017)	(0.025)	(0.025)	(0.028)
ICT$_0$ $\times$ Capital availability $\times$ Boom cohort $\times$ 2006-10				-0.033	-0.035*	-0.028
				(0.021)	(0.021)	(0.025)
ICT$_0$ $\times$ Capital availability $\times$ Boom cohort $\times$ 2011-15				-0.081***	-0.082***	-0.083**
				(0.031)	(0.031)	(0.035)
Adjusted-R2	.84	.84	.84	.84	.84	.84
Observations	92,901	92,901	92,901	85,128	85,128	85,128
ICT$_0$$\times$Year FE	✓	✓	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t. ICT$_0$ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. ICT$_0$ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Capital availability is net equity issuance in the four-digit sector$\times$commuting zone$\times$year at which the worker takes her first job. Column 1 reproduces the specification in column 2 of Table 1. In column 2, we control for a job termination dummy equal interacted with the five-year period dummies. Job termination equals one if the worker experiences forced job change within the first four years after entry, where forced job change is defined as a change in employer such that either (i) employment at the worker's initial employer decreases by 10% or more in the year of the job change or (ii) the transition to the next job leads to a wage cut for the worker. In column 3, we include the interaction term between job termination and all the interactions between ICT$_0$, BoomCohort, and the five-year period dummies. Column 4 reproduces the specification in column 3 of Table 3. In column 5, we control for job termination and its interaction with capital availability and with the five-year period dummies. In column 6, we include the interaction term between job termination and all the interactions between ICT$_0$, BoomCohort, capital availability, and the five-year period dummies. All specifications include worker fixed effects, ICT$_0$ interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort$\times$year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 6: Quantile Regressions

Panel A: Unconditional Wage Discount	log(Wage)				
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT_0 × Boom cohort × 2006-10	-0.053***	-0.053***	-0.053***	-0.053***	-0.053***
	(0.016)	(0.011)	(0.009)	(0.012)	(0.016)
ICT_0 × Boom cohort × 2011-15	-0.090***	-0.086***	-0.080***	-0.075***	-0.071***
	(0.017)	(0.012)	(0.009)	(0.012)	(0.017)
Observations	93,306	93,306	93,306	93,306	93,306
ICT_0×Year FE	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓

Panel B: Conditional on Capital Availability	log(Wage)				
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT_0 × Boom cohort × 2006-10	-0.033	-0.030*	-0.026**	-0.023	-0.020
	(0.025)	(0.018)	(0.013)	(0.016)	(0.022)
ICT_0 × Boom cohort × 2011-15	-0.053**	-0.045**	-0.033**	-0.022	-0.014
	(0.027)	(0.019)	(0.014)	(0.017)	(0.024)
ICT_0 × Capital availability × Boom cohort × 2006-10	-0.028	-0.034	-0.042**	-0.050**	-0.056*
	(0.034)	(0.024)	(0.017)	(0.022)	(0.030)
ICT_0 × Capital availability × Boom cohort × 2011-15	-0.056	-0.065**	-0.077***	-0.089***	-0.098***
	(0.036)	(0.026)	(0.018)	(0.023)	(0.032)
Observations	87,114	87,114	87,114	87,114	87,114
ICT_0×Year FE	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓

The table presents quantile regressions of equation (14) for skilled entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variables in columns 1 through 5 are the 10th, 25th, 50th, 75th and 90th percentiles of the log wage. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. Capital availability is net equity issuance in the four-digit sector×commuting zone×year at which the worker takes her first job. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Internet Appendix

A Data

All the results in the paper have been reproduced by the Certification Agency for Scientific Code And Data (cascad-CASD) using the code in this replication package. The reproducibility certificate is available at https://doi.org/10.5281/zenodo.7969175 and the replication package at https://johanhombert.github.io/TechBubble_ReplicationPackage.zip.

The administrative data used in the paper are made available to researchers by CASD (Secure Data Access Centre; see https://www.casd.eu/en/). The administrative databases used in the paper are:

1. *DADS All-Employees Database, Job Position Data:* Exhaustive employer-employee cross-sectional data, from social security filings.

   See https://www.casd.eu/en/source/all-employees-databases-job-position-data/

2. *DADS All-Employees Panel:* 1/24th employer-employee panel data (individuals born in October of even-numbered years), from social security filings.

   See https://www.casd.eu/en/source/all-employee-panel/

3. *DADS-EDP Matched Panel:* 4/30th subsample of the employer-panel data (individuals born in the first four days of October) linked with census data.

   See https://www.casd.eu/en/source/dads-panel-with-matched-data-from-edp/

4. *Corporate Tax Filings (FICUS-FARE):* Financial statements for the universe of French firms, from tax filings.

   See https://www.casd.eu/en/source/annual-structural-statistics-of-companies-from-the-suse-scheme/ and https://www.casd.eu/en/source/annual-structural-statistics-of-companies-from-the-esane-scheme/.

5. *Ownership Links between Enterprises Survey (LIFI):* Firm ownership structure, from Bureau van Dijk and survey run by the statistical office.

   See https://www.casd.eu/en/source/financial-links-between-enterprises-survey/

6. *Business Startups Register (SIRENE):* Universe of new business registration, from firm register.

   See https://www.casd.eu/en/source/business-start-ups/

7. *Firm and Establishment Register (SIRENE):* Universe of stock of firms and establishments, from firm register.

   See https://www.casd.eu/en/source/company-and-establishment-inventory/ and https://www.casd.eu/en/source/company-inventory/

The other databases used in the paper are:

8. *Eurofidai:* Stock market data.

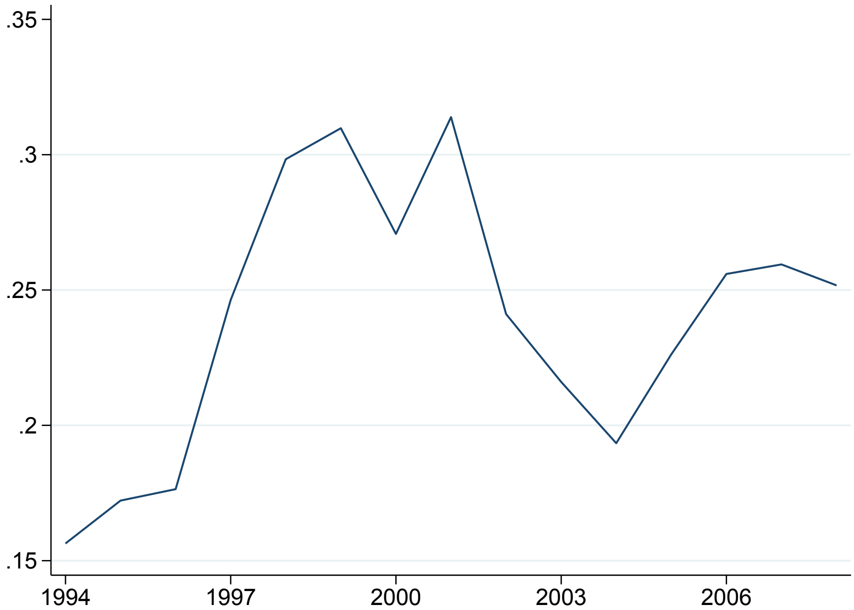
   See https://www.eurofidai.org/

9. *Current Population Survey:* For evidence on the US in Appendix C.

   See https://cps.ipums.org/cps/

B Additional Figures and Tables

Figure B.1: ICT Sector Share Among New Skilled Workers



The figure shows the share skilled workers joining the ICT sectors among all skilled workers taking their first full-time job in the current year.

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Table B.1: Summary Statistics

Panel A shows summary statistics at the worker-year level for the period 1994–2015 for the sample of skilled workers in the linked employer-employee panel who hold a full-time job. Panel B reports summary statistics for the subsample of skilled workers who enter the labor force over 1994–2005.

	N	Mean	P25	P50	P75
	Panel A: All skilled workers				
Annual wage	1,980,097	50,406	32,137	41,414	56,468
Male	1,980,097	0.69	0	1	1
Age	1,980,097	43	35	43	51
	Panel B: Skilled workers entering the labor force over 1994–2005				
Annual wage	244,120	44,767	29,769	38,330	50,960
Male	244,120	0.68	0	1	1
Age at entry	244,120	26	25	26	27

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Table B.2: ICT Industries

List of ICT industries from OECD (2002). The third (fourth) column reports the 1994–2008 average share in total employment (in skilled employment) of each ICT industry.

ICT industries	ISIC rev 3.1 codes	Share of total employment (%)	Share of skilled employment (%)
ICT: Services		**1.8**	**7.6**
IT consultancy	*7210*	0.7	3.4
Software	*7220*	0.7	3.1
Data processing	*7230*	0.3	0.8
Maintenance computers	*7250*	0.1	0.2
Other data/computer-related services	*7123,7240,7290*	0.1	0.2
ICT: Telecommunications		**1.2**	**2.1**
Telecommunications	*6420*	1.2	2.1
ICT: Manufacturing		**1.6**	**3.7**
Electronic/communication equipment	*3210,3220,3230*	0.8	1.7
Measurement/navigation equipment	*3312,3313*	0.5	1.2
Accounting/computing equipment	*3000*	0.2	0.7
Insulated wire and cable	*3130*	0.1	0.1
ICT: Wholesale		**0.5**	**1.2**
Computers, electronics, telecom	*5151,5152*	0.5	1.2
ICT: Total		**5.1**	**14.6**

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B.1 Cumulative Earnings

We estimate equation (10) using as the dependent variable cumulative earnings (including from part-time and short job spells, which were excluded from the previous regressions) from labor market entry up to each year t post-entry, discounted back to the entry year at a rate of 5% per year. We do not use the difference-in-differences specification (14) that estimates the wage relative to the post-boom cohort, because we want to estimate cumulative earnings starting from the entry year of the boom cohort, which precedes the post-boom cohort. We also do not include individual fixed effects because we are interested in cumulative earnings in level, not in difference relative to a reference period. Finally, we replace the five-year time period dummies by year dummies, so that the cumulative earnings is defined from the entry year to a specific year t.

The dependent variable is the log of cumulative earnings in column 1 of Appendix Table B.3. High-skill workers starting in the ICT sector during the boom earn cumulative earnings from entry to 2015 that are 4.1% (significant at 5%) lower than that of similar workers starting in other sectors.

Column 2 shows the cumulative earnings in level instead of log. The discounted cumulative earnings loss from entry to 2015 is 19,600 euros (significant at 1%).

In column 3, we account for unemployment benefits in the calculation of cumulative earnings. Since unemployment benefits (UB) are only reported starting in 2008, we assign estimated UB when an individual has no earnings reported in the data in a given year. In France, individuals are entitled to UB if the job is terminated or not renewed by the employer, but not if they resign, and UB are paid for a period of time roughly equal to that of their pre-unemployment job spell and no longer than two years (Cahuc and Prost, 2015). Since the data do not report the motive for job termination, we assume in the baseline scenario that all job terminations give rise to one year of UB equal to the average replacement rate in France of 60% of the total wage earned in the previous year.[33] If anything, accounting for unemployment benefits increases slightly the

33. We obtain an UB-adjusted cumulative earnings loss that varies within a range of 500 euros of that of the baseline scenario when we use a more conservative replacement rate of 30% to account for the fact

cumulative earnings loss.

Table B.3: Cumulative Earnings

	Cumulative Earnings		
	Log	Level (in Euro)	Level incl. UB (in Euro)
	(1)	(2)	(3)
$ICT_0 \times 2001$	.041***	2093***	2244***
	(.01)	(660)	(641)
$ICT_0 \times 2005$	.0086	74	-288
	(.014)	(1874)	(1854)
$ICT_0 \times 2010$	-.021	-8924**	-9558**
	(.018)	(3749)	(3713)
$ICT_0 \times 2015$	-.041**	-19596***	-20650***
	(.02)	(6049)	(6029)
Adjusted-R2	.56	.41	.43
Observations	120,457	120,457	120,457
$ICT_0\times$Year FE	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓

The table presents OLS estimates for high-skill entrants of the boom cohort 1998–2001 over the period 1998–2015. In column 1, the dependent variable is the log of cumulative wage of worker i from entry up to year t. In column 2, the dependent variable is the level of cumulative wage of worker i from entry up to year t. In column 3, the dependent variable is the level of cumulative wage plus unemployment benefits of worker i from entry up to year t. The sample is restricted to the worker's entry year and the years 1998–2001, 2005, 2010, and 2015. ICT_0 is a dummy equal to one if the worker started in the ICT sector. All specification include ICT_0 interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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that not all job terminations give rise to UB, and when we use a more aggressive UB length of two years if the pre-unemployment job spell lasts for at least two years.

B.2 Education

A subsample of individuals in the employer-employee panel can be linked to education information from Census data (individuals born in the first four days of October). For these individuals, we define a dummy equal to one if the individual holds a Master's degree or more. Master's degrees correspond to at least five years of higher education and include degrees from French elite *Grandes Ecoles*, university masters, and doctorates. Using skilled workers from the boom cohort and post-boom cohort, we regress Master's degree on $ICT_{i,0}$ and its interaction with the boom cohort dummy. We progressively include the same set of of fixed effects as in Table 1 (without the interaction with year fixed effects since the time dimension is now collapsed). The results are in Table B.4. Across the different specifications, we find no evidence that the pool of workers going in the ICT sector during the boom has lower education achievement.

Table B.4: Education

	=1 if Master's degree				
	(1)	(2)	(3)	(4)	(5)
ICT_0	-0.004	-0.023		-0.011	
	(0.034)	(0.034)		(0.032)	
ICT_0 × BoomCohort	-0.016	-0.020	-0.019	-0.014	0.018
	(0.041)	(0.043)	(0.053)	(0.040)	(0.063)
Constant	0.902***	0.915***	0.912***	0.797***	0.846***
	(0.011)	(0.011)	(0.018)	(0.030)	(0.045)
Adjusted-R2	.02	.029	.055	.041	.032
Observations	1,138	1,097	1,009	1,083	902
Commuting zone×Cohort FE		✓			✓
Four-digit sector FE			✓		✓
Pseudo-firm FE				✓	✓

The table presents OLS estimates of cross-sectional regressions for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. The dependent variable is a dummy equal to one if the worker holds a Master's degree. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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B.3 Attrition

Our main specification in Table 1 already controls for composition effects by including individual fixed effects, which ensure that we identify wage changes off individual wage trajectories and not off changes in the pool of workers induced by attrition. Differential attrition across cohorts could still bias the results if attrition is correlated with systematically better or worse wage trajectories, i.e., not just with the wage level but also with wage growth. In this case, the counterfactual wage that individuals would have earned if they had not dropped out of the data is on average different from that of individuals who do not drop out of the data even after controlling for worker fixed effects. This bias cannot be estimated directly but we can take a clue from the wage dynamics before individuals drop out of the data.

We define an exit dummy that equals one if the individual permanently exits from the employer-employee data in the next year. The last year of data is 2015, so we define the exit dummy until 2010 to reduce truncation bias. We regress the exit dummy on the worker's wage growth over the past two years interacted with the ICT dummy and the boom cohort dummy, controlling for the same set of fixed effects as in equation (14). Results are reported in Table B.5. In column 1, the negative coefficient on wage growth implies that workers who exit from the data tend to have slower wage growth on average. In column 2, the negative coefficient on wage growth interacted with $ICT_{i,0}$ implies that workers who started in ICT are on average more likely to exit the sample when they are on a growing wage trajectory. The key result is in column 3, showing that this relation is not specific to the boom cohort. The coefficient on wage growth interacted with $ICT_{i,0}$ and the boom cohort dummy is statistically insignificant and the point estimate is essentially zero. It implies that there is no differential pre-exit wage growth between workers who started in ICT during the boom relative to workers who started outside of ICT and relative to workers who started after the boom. Therefore, the results on the wage dynamics of the boom cohort of ICT workers are unlikely to be biased by variation in the determinants of attrition.

Table B.5: Attrition

	=1 if exits in $t+1$		
	(1)	(2)	(3)
Wage growth$_{i,t-2\to t}$	-0.010*	-0.018**	-0.009
	(0.006)	(0.007)	(0.012)
Wage growth$_{i,t-2\to t}$ × ICT$_0$		0.025*	0.032
		(0.013)	(0.022)
Wage growth$_{i,t-2\to t}$ × BoomCohort			-0.014
			(0.015)
Wage growth$_{i,t-2\to t}$ × ICT$_0$ × BoomCohort			-0.009
			(0.025)
Constant	0.034***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)
Adjusted-R2	.01	.01	.01
Observations	44,773	44,773	44,773
ICT$_0$×Year FE	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓
Worker FE	✓	✓	✓
Four-digit sector×Year FE	✓	✓	✓

The table presents the OLS estimates on the sample of skilled entrants from the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is a dummy equal to one if worker i permanently exits the employer-employee data in year $t+1$. Wage growth$_{i,t-2\to t}$ is the worker's wage growth from year $t-2$ to year t ICT$_0$ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. All the specifications include ICT$_0$ interacted with year fixed effects, and worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort×year fixed effects. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[Back to Section 3.4]

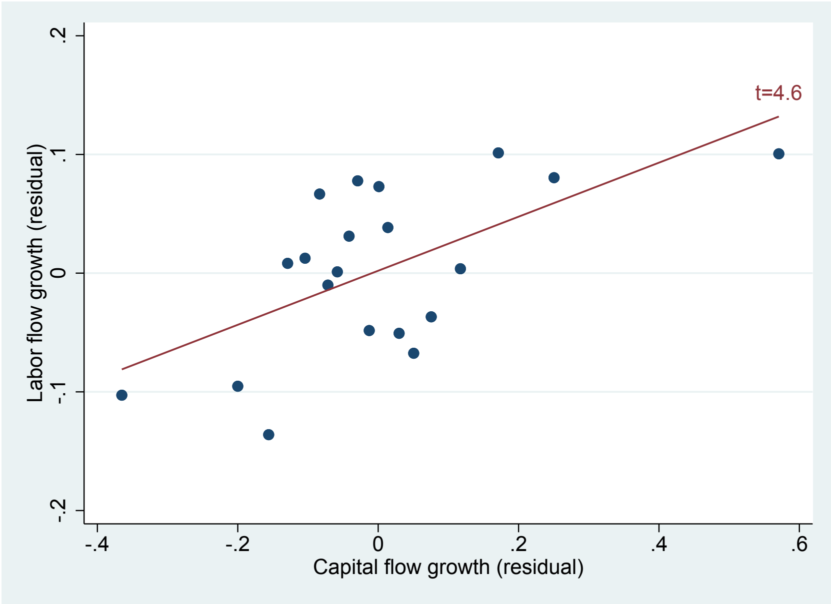
B.4 Correlation between Capital Flows and Labor Flows

In this appendix, we show that capital flows are correlated with labor flows. We construct capital flow at the four-digit sector×commuting zone×year level as the average firm-level equity issuance normalized by the mid-point of equity between current and previous year. We construct labor flow at the same level as the number of high-skill labor market entrants at that level, normalized by the time-series average of the same variable.

We regress labor flow on capital flow at the four-digit sector×commuting zone×year level for the years 1998 to 2005, controlling for four-digit sector fixed effects, commuting zone fixed effects, and year fixed effects. To visualize the results, in Figure B.2, we take out the fixed effects from both labor flow and capital flow, group the residual of capital flow into 20 quantiles, and plot the mean labor flow residual for each quantile. The relationship is positive and statistically significant (t-stat 4.6). The magnitude is large: Moving from the bottom quantile to the top quantile of capital flow leads to a 20% increase in labor flow.

Table B.6 reports the results in a regression format. Consistent with Figure B.2, we find a positive and significant relation. In column 2, we interact capital flow with the ICT sector dummy and find that the relation is even stronger in the ICT sector.

Figure B.2: Capital Flows and Labor Flows



The figure shows average labor flow by 20 quantiles of capital flow at the four-digit sector×commuting zone×year. Both variables are residuals of regressions on four-digit sector, commuting zone, and year fixed effects. See the text for details.

Table B.6: Capital Flows and Labor Flows

	Labor flow	
	(1)	(2)
Capital flow	0.26**	0.13**
	(0.08)	(0.05)
Capital flow × ICT_0		0.34***
		(0.08)
Adjusted-R2	.57	.57
Observations	5,464	5,464
Year FE	✓	✓
Sector FE	✓	✓
Commuting zone FE	✓	✓

We regress labor flow on capital flow at the four-digit sector×commuting zone×year level. Variables are defined in the text. In column 2, the non-interacted ICT dummy is absorbed by the sector fixed effects.

[Back to Section 4]

B.5 Job Loss

Table B.7 reports the coefficients on the interactions with job termination, which were not omitted from Table 5 for the sake of space.

In Table B.8, we test if workers who start in the ICT sector during the boom are more likely to experience a subsequent job termination. This test is also a way to validate that our measure of forced job termination used in Table 5/B.7 captures meaningful variation.

We build our preferred measure of forced job termination step-by-step, by defining four successive variables of job termination. The first one does not aim at distinguishing between voluntary versus forced job termination: it is a dummy variable equal to one if the worker experiences any job termination within the first four years after entry. The other measures aim at capturing forced job termination. The second one is a dummy equal to one if the worker experiences a job termination within the first four years and employment at the worker's employer declines by more than 10% in the year of the job termination. The third one is a dummy equal to one if the worker experiences a job termination within the first four years and the transition to the next job leads to a wage cut for the worker. The fourth measure combines both criteria used to identify forced termination: it is equal to one if the worker experiences a job termination within the first four years and either employment at the worker's employer declines by more than 10% in the year of the job termination or the transition to the next job leads to a wage cut for the worker.

We collapse the data at the worker level because the measures of early career job termination are time-invariant. We regress job termination on the same set of explanatory variables as in the baseline difference-in-differences specification (but without the time dimension.) In column 1 of Table B.8, we find that while workers who start in the ICT sector during the boom are more likely to experience any job change, there is no differential effect for the cohort that starts during the boom relative to the cohort that starts during the post-boom period. The coefficient on $ICT_{i,0} \times BoomCohort$ is statistically insignificant and the point estimate is essentially zero.

When we focus on forced job termination in columns 2 to 4, we find that workers starting in ICT during the boom are more likely to experience early career forced termination than workers starting in ICT after the boom. The estimated effect is the strongest when using the measure that combines both criteria used to identify forced termination (column 4). This is the reason why we choose this variable to control for job termination in the wage regressions in Table 5/B.7.

A back-of-the-envelop calculation helps understand why heightened risk of job termination explains only a negligible part of the wage discount. The probability of job termination increases by 6.6 percentage points for high-skill workers starting in ICT during the boom (column 4 of Table B.8). Job termination is associated with a long-term wage decline of 3.3 percentage points on average (column 2 of Table B.7).[34] Put together, these estimates imply that heightened job termination explains $0.066 \times 0.033 = 0.2$ percentage points of the 7.7 percentage points wage discount. This is consistent with the magnitude of the reduction in the estimated wage discount from 7.7 percentage points when we do not control for job termination (column 1 of Table B.7) to 7.6 percentage points when we control for job termination (column 2).

34. This long-term wage effect is in the range of estimates in the job displacement literature (e.g., Dustmann and Meghir, 2005).

Table B.7: Controlling for Job Losses

	log(Wage)					
Control for:		Job loss	Job loss $\times ICT_0$ $\times$BoomCoh.		Job loss	Job loss $\times ICT_0$ $\times$BoomCoh.
	(1)	(2)	(3)	(4)	(5)	(6)
ICT_0 × Boom cohort × 2011-15	-0.077***	-0.076***	-0.069***	-0.029	-0.026	-0.019
	(0.015)	(0.015)	(0.017)	(0.025)	(0.025)	(0.028)
Job loss × 2011-15		-0.033***	-0.064***		-0.046***	-0.070***
		(0.007)	(0.015)		(0.011)	(0.023)
Job loss × ICT_0 × 2011-15			0.045			0.055
			(0.028)			(0.042)
Job loss × Boom cohort × 2011-15			0.034*			0.013
			(0.019)			(0.029)
ICT_0 × Job loss × Boom cohort × 2011-15			-0.027			-0.028
			(0.033)			(0.050)
ICT_0 × Capital availability × Boom cohort × 2011-15				-0.081***	-0.082***	-0.083**
				(0.031)	(0.031)	(0.035)
ICT_0 × Capital availability × 2011-15				0.065**	0.064**	0.070**
				(0.025)	(0.025)	(0.029)
Capital availability × 2011-15				-0.014	-0.015	-0.011
				(0.014)	(0.014)	(0.016)
Capital availability × Boom cohort × 2011-15				0.010	0.010	0.001
				(0.018)	(0.018)	(0.020)
Capital availability × Job loss × 2011-15					0.010	-0.004
					(0.016)	(0.033)
ICT_0 × Capital availability × Job loss × 2011-15						-0.024
						(0.058)
Capital availability × Job loss × Boom cohort × 2011-15						0.034
						(0.042)
ICT_0 × JCapital availability × ob loss × Boom cohort × 2011-15						0.004
						(0.070)
Adjusted-R2	.84	.84	.84	.84	.84	.84
Observations	92,901	92,901	92,901	85,128	85,128	85,128
ICT_0×Year FE	✓	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

The table reports the same regressions as in Table 5, showing the coefficients on the interactions with job termination that were omitted from Table B.7 for the sake of space.

Table B.8: Early Career Job Losses

	=1 if Job termination			
	All	Employment decline	Wage cut	Both
	(1)	(2)	(3)	(4)
ICT_0 × Boom cohort	.0072	.04***	.04**	.066***
	(.022)	(.015)	(.017)	(.02)
ICT_0	.065***	-.0023	-.012	-.0069
	(.018)	(.012)	(.014)	(.016)
Adjusted-R2	.008	.0021	.001	.0022
Observations	11,312	11,312	11,312	11,312
Worker controls×Cohort FE	✓	✓	✓	✓

The table presents OLS estimates of cross-sectional regressions for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. The dependent variable is a dummy equal to one if the worker experiences job termination in the first four years of her career. In column 1, job termination is defined as any change in employer. In column 2, job termination is defined as a change in employer while employment at the initial employer declines by more than 10% in the year of the transition. In column 3, job termination is defined as a change in employer such that the transition to the next job leads to a wage cut for the worker. In column 4, job termination is defined as a change in employer such that either employment at the initial employer declines by more than 10% in the year of the transition or the transition to the next job leads to a wage cut for the worker. ICT_0 is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. All the specifications include worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels respectively.

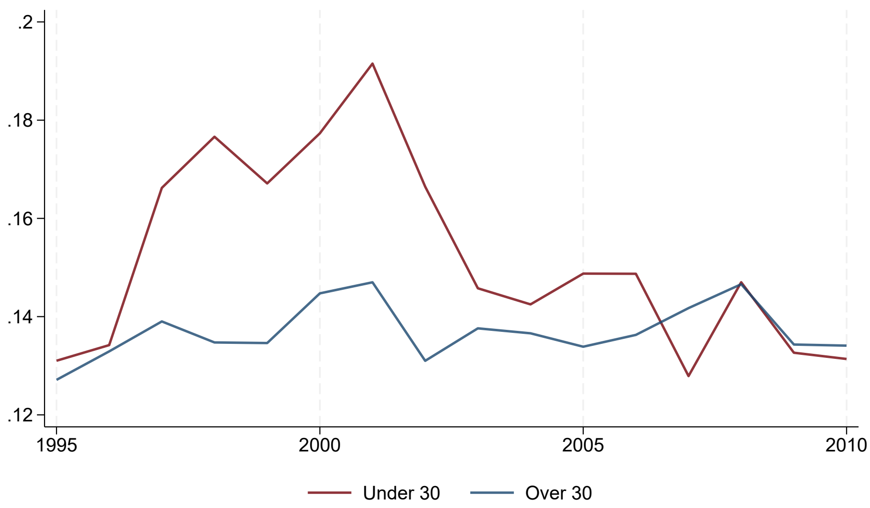
[Back to Section 5.2]

C Employment Share of ICT in the US

We estimate the evolution of the share of skilled employment in the ICT sector in the US using the Current Population Survey for the years 1995–2010. We apply the following filtering: we restrict the data to individuals who are between 20 and 65 year old and who are in the labor force. We defined skilled workers as individuals with some college education. We flag ICT sectors using the variable $ind1990$ and manually match it to the OECD list of ICT sectors.

Figure C.1 plots the ICT sector share of the skilled workforce separately for recent labor market entrants (aged below 30) and for incumbent workers (aged 30 or above). Similar to the pattern for France, the share of skilled labor market entrants joining in the ICT sector sharply deviates from trend during the period 1996–2001. By contrast, the share of skilled incumbents workers in the ICT sector is mostly flat over the period.

Figure C.1: Employment Share of the ICT Sector: United States



The figure shows the share of the ICT sector in the skilled workforce aged 30 or less (red) and in the skilled workforce aged above 30 (blue). Source: CPS.

[Back to Section 1]

D Equilibrium of the Model

We make a few stationarity and normalization assumptions to obtain a stationary equilibrium. First, we assume that the joint distribution of worker type and worker preference $(\theta_{i,1}, \theta_{i,2}, \gamma_{i,1}, \gamma_{i,2})$ across workers is the same in every cohort, with mean normalized to zero.

Second, it follows from equation (6) that the set of workers from cohort c going to sector $k = 1$ is:

$$\mathcal{I}_{1,c,c} = \left\{ i : \sum_{t=c}^{\infty} \beta^{t-c}\, \mathbb{E}_c[w_{i,c,k,1}] - \gamma_{i,1} > \sum_{t=c}^{\infty} \beta^{t-c}\, \mathbb{E}_c[w_{i,c,k,2}] - \gamma_{i,2} \right\},$$

where $\mathbb{E}_c[w_{i,c,k,t}] = \mathbb{E}_c[w_{k,t}] + \theta_{k,1} + \mathbb{E}_c[h_{c,k,t}]$ by equation (5). Since expected human capital accumulation $\mathbb{E}_c[h_{c,k,t}] = (t-c)\mu_h$ is the same in both sectors by equations (2)–(3), sectoral allocation of cohort c can be rewritten as:

$$\mathcal{I}_{1,c,c} = \left\{ i : \sum_{t=c}^{\infty} \beta^{t-c} \left(\mathbb{E}_c[w_{k,1} - w_{k,2}] + \theta_{i,1} - \theta_{i,2} \right) > \gamma_{i,1} - \gamma_{i,2} \right\}. \tag{D.1}$$

We denote by $E_{k,c}$ the share of cohort c going to sector k:

$$E_{k,c} = \int_{i \in \mathcal{I}_{1,c,c}} di \tag{D.2}$$

Our next assumption is that, when expected wage rates are equalized across sectors, the sectoral allocation of new workers is proportional to the sector weights in the final good production function, that is, the mass of $\{i : \theta_{i,1}/(1-\beta) - \gamma_{i,1} > \theta_{i,2}/(1-\beta) - \gamma_{i,2}\}$ is equal to A_1^{σ}, where we have normalized the sum of the sector weights $A_1^{\sigma} + A_2^{\sigma} = 1$ wlog.

Third, we assume $\mu_h < -\log(1-\delta)$ to ensure that the aggregate supply of efficient labor remains bounded almost surely (see equation (D.9)).

We can now solve for a stationary equilibrium using a first-order approximation when productivity shocks and human capital shocks are small. Proposition 1 states that the equilibrium can be characterized in difference between sector $k = 1$ and sector $k = 2$, which we denote using the operator Δ, e.g., $\Delta w_t = w_{1,t} - w_{2,t}$. The state of the economy can be summarized by three variables: the (exogenous) sectoral difference in productivity, Δz_t, the (exogenous) sectoral difference in average human capital shock, $\Delta\overline{dh}_t$, and the (endogenous) sectoral difference in the efficient quantity of labor supplied by old workers, $\Delta\ell_t = \log(L_{1,t}) - \log(L_{2,t})$, where $L_{k,t} = \sum_{c=-\infty}^{t-1}(1-\delta)^{t-c}\int_{i\in\mathcal{I}_{k,c,c}} H_{i,c,k,t}\,di$. We denote steady state values with *.

Proposition 1 *At the stationary equilibrium:*

$$\begin{aligned} \Delta w_t &\simeq \Delta w^* + w_z\,.\,\Delta z_t + w_\ell\,.\,\big(\Delta\ell_t - \Delta\ell^*\big) + w_h\,.\,\Delta\overline{dh}_t, && \text{(D.3)}\\ \Delta E_t &\simeq \Delta E^* + E_z\,.\,\Delta z_t + E_\ell\,.\,\big(\Delta\ell_t - \Delta\ell^*\big) + E_h\,.\,\Delta\overline{dh}_t, && \text{(D.4)} \end{aligned}$$

where $w_z \in (0,1)$, $w_\ell < 0$, $w_h \geq 0$, $E_z > 0$, $E_\ell < 0$, $E_h \leq 0$, and $\Delta\ell_t$ evolves according to:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq (1-\delta)e^{\mu_h}\,.\,\big(\Delta\ell_t - \Delta\ell^*\big) + \ell_E\,.\,\big(\Delta E_t - \Delta E^*\big) + \Delta\overline{dh}_{t+1}, \quad \text{(D.5)}$$

where $\ell_E > 0$, and $\Delta\overline{dh}_{t+1}$ is a weighted average of human capital shocks $\Delta dh_{c,t+1}$ across all cohorts $c \leq t$.

Consider first the effect of a positive productivity shock in sector 1 relative to sector 2: $\Delta z_t > 0$. Higher productivity increases the demand for labor in sector 1. Since old workers cannot switch sector, sectoral reallocation takes place through the sectoral choice of labor market entrants. The wage rate increases in sector 1 relative to sector 2 ($w_z > 0$ in (D.3)) in order to induce more entry in sector 1 ($E_z > 0$ in (D.4)). Therefore, a positive productivity shock in the ICT sector in the late 1990s can explain the high entry rate (see Figure B.1) and the concomitant high wages (Figure 4) in ICT during the period.

Next, consider the effect of there being an excess mass of old workers in sector 1 relative to sector 2: $\Delta\ell_t - \Delta\ell^* > 0$. Higher labor supply lowers the wage rate in sector 1 ($w_\ell < 0$ in (D.3)), which reduces entry in sector 1 ($E_\ell < 0$ in (D.4)).

Finally, consider the effect of a positive human capital shock to old workers in sector 1 relative to sector 2: $\Delta\overline{dh}_t > 0$. If human capital shocks are persistent ($\rho_h > 0$), old workers are expected to become more productive in the future, increasing labor supply and reducing the wage rate in the future. This makes entry less attractive in the current period ($E_h < 0$), which pushes the current wage rate up ($w_h > 0$).

Equation (D.5) describes how the efficient quantity of labor supplied by old workers evolves over time. The first term on the RHS reflects that a fraction δ of old workers exit the labor market in each period, while those who do not exit experience an expected increase in human capital e^{μ_h}. Thus, the efficient quantity of labor by old workers mean reverts at rate $(1-\delta)e^{\mu_h}$. The second term shows that entry of new workers adds to the stock of old workers ($\ell_E > 0$). The third term is a shock to old workers' human capital, which affects the efficient quantity of labor they supply. This shock is a weighted average of the shocks received by all cohorts of old workers.

D.1 Proof of Proposition 1

Law of motion of old labor. Let

$$L_{k,t}^{new} = \int_{i\in\mathcal{I}_{k,t,t}} H_{i,t,k,t}\, di \tag{D.6}$$

denote the efficient quantity of labor supplied by new workers in sector k in period t. (D.1) implies that $L_{k,t}^{new}$ is a function of the expected intertemporal wage differential between the two sectors:

$$L_{k,t}^{new} = \mathcal{L}_k^{new}\Big(\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}[\Delta w_\tau]\Big), \tag{D.7}$$

where

$$\mathcal{L}_1^{new}(\mathcal{W}) = \int_{\mathcal{W}+\Delta\theta_i>\Delta\gamma_i} e^{\theta_{i,1}}\, di, \qquad \mathcal{L}_2^{new}(\mathcal{W}) = \int_{\mathcal{W}+\Delta\theta_i\leq\Delta\gamma_i} e^{\theta_{i,2}}\, di. \tag{D.8}$$

The law of motion of the efficient quantity of labor supplied by old workers in sector k is:

$$L_{k,t+1} = (1-\delta)e^{\mu_h}\big(L_{k,t} + L_{k,t}^{new}\big) + \sum_{c=-\infty}^{t-1}(1-\delta)^{t+1-c}\Big(\int_{i\in\mathcal{I}_{k,c,c}} H_{i,c,k,t}\, di\Big)\big(dH_{c,k,t+1} - e^{\mu_h}\big) + (1-\delta)L_{k,t}^{new}\big(dH_{t,k,t+1} - e^{\mu_h}\big). \quad \text{(D.9)}$$

Steady state. We define the steady state as the equilibrium when $\varepsilon^h = \varepsilon^z = 0$ and denote steady state quantities with *. The steady state intertemporal wage differential between the two sectors is $\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}[\Delta w^*] = \Delta w^*/(1-\beta)$. The efficient quantity of labor supplied by new workers in sector k is:

$$L_k^{new*} = \mathcal{L}_k^{new}\left(\frac{\Delta w^*}{1-\beta}\right).$$

(D.9) at steady state implies:

$$L_k^* = g(L_k^* + L_k^{new*}) = \frac{g}{1-g}L_k^{new*}, \quad \text{(D.10)}$$

where $g \equiv (1-\delta)e^{\mu_h} < 1$. Substituting into the labor demand function (9), we obtain:

$$\Delta w^* = \Delta a - \frac{1}{\sigma}\log\left(\frac{\mathcal{L}_1^{new}\left(\frac{\Delta w^*}{1-\beta}\right)}{\mathcal{L}_2^{new}\left(\frac{\Delta w^*}{1-\beta}\right)}\right). \quad \text{(D.11)}$$

Since $(\mathcal{L}_1^{new}/\mathcal{L}_2^{new})(.)$ is an increasing function going to zero at $-\infty$ and going to infinity at $+\infty$, (D.11) uniquely pins down Δw^*.

Small deviation from steady state. We consider small deviations from the steady state. We guess that:

$$\Delta w_t - \Delta w^* \simeq w_z.\Delta z_t + w_\ell.\big(\Delta\ell_t - \Delta\ell^*\big) + w_h.\Delta\overline{dh}_t, \quad \text{(D.12)}$$

where $\overline{dh}_{k,t} = \sum_{c=-\infty}^{t} q_{t-c}(dh_{c,k,t+1} - \mu_h)$ is a weighted average of the human capital shocks, and the weights $q_{t,c}$ are to be determined.

Labor demand. We take log in the production function for intermediate good k, given by (7), and write the total efficient quantity of labor as the sum over old workers and new workers:

$$x_{k,t} = z_{k,t} + \log\left(L_{k,t} + L_{k,t}^{new}\right). \tag{D.13}$$

We linearize the log efficient quantity of labor:

$$\begin{aligned}\log\left(L_{k,t} + L_{k,t}^{new}\right) - \log\left(L_{k,t}^{*} + L_{k,t}^{new*}\right) &\simeq \frac{L_{k,t}^{*}\left(\ell_{k,t} - \ell_k^{*}\right) + L_{k,t}^{new*}\left(\ell_{k,t}^{new} - \ell_k^{new*}\right)}{L_{k,t}^{*} + L_{k,t}^{new*}} \\ &= g.\left(\ell_{k,t} - \ell_k^{*}\right) + (1-g).\left(\ell_{k,t}^{new} - \ell_k^{new*}\right), \end{aligned} \tag{D.14}$$

where the latter equality follows from (D.10). We calculate the difference between (D.13) for $k = 1$ and (D.13) for $k = 2$, and use (D.14) to substitute $\log(L_{k,t} + L_{k,t}^{new})$. We obtain:

$$\Delta x_t \simeq \Delta z_t + \log\left(\frac{L_{1,t}^{*} + L_{1,t}^{new*}}{L_{2,t}^{*} + L_{2,t}^{new*}}\right) + g.\left(\Delta\ell_t - \Delta\ell^{*}\right) + (1-g).\left(\Delta\ell_t^{new} - \Delta\ell^{new*}\right). \tag{D.15}$$

Using (D.10) and (D.11), the term in big parenthesis in (D.15) is equal to $\sigma\Delta a - \sigma\Delta w^{*}$. Plugging (D.15) into the labor demand function (9), we obtain:

$$\Delta w_t - \Delta w^{*} \simeq \frac{\sigma - 1}{\sigma}\Delta z_t - \frac{g}{\sigma}\left(\Delta\ell_t - \Delta\ell^{*}\right) - \frac{1-g}{\sigma}\left(\Delta\ell_t^{new} - \Delta\ell^{new*}\right). \tag{D.16}$$

We combine (D.12) and (D.16) to obtain:

$$\Delta\ell_t^{new} - \Delta\ell^{new*} \simeq \frac{\sigma - 1 - \sigma w_z}{1-g}\Delta z_t - \frac{g + \sigma w_\ell}{1-g}\left(\Delta\ell_t - \Delta\ell^{*}\right) - \frac{\sigma w_h}{1-g}\Delta\overline{dh}_t. \tag{D.17}$$

Expected future wages. We consider (D.12) evaluated at time $t+\tau$, and take expectations conditional on beginning of period t information. We obtain:

$$\mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] \simeq w_z \mathbb{E}_t\big[\Delta z_{t+\tau}\big] + w_\ell \mathbb{E}_t\big[\Delta \ell_{t+\tau} - \Delta \ell^*\big] + w_h \mathbb{E}_t\big[\Delta \overline{dh}_t\big]. \tag{D.18}$$

We linearize the law of motion of the efficient quantity of labor supplied by old workers, given by (D.9):

$$\ell_{k,t+1} - \ell_k^* \simeq g.\big(\ell_{k,t} - \ell_k^*\big) + (1-g).\big(\ell_{k,t}^{new} - \ell_k^{new^*}\big) + \overline{dh}_{k,t+1}, \tag{D.19}$$

where

$$\begin{aligned}\overline{dh}_{k,t+1} = \sum_{c=-\infty}^{t-1} \frac{(1-\delta)^{t+1-c} e^{\mu_h} \int_{i\in\mathcal{I}_{k,c,c}} H_{i,c,k,t}\, di}{L_k^*}\big(dh_{c,k,t+1} - \mu_h\big) \\ + \frac{(1-\delta)e^{\mu_h} L_{k,t}^{new}}{L_k^*}\big(dh_{t,k,t+1} - \mu_h\big) \equiv \sum_{c=-\infty}^{t} q_{t-c}\big(dh_{c,k,t+1} - \mu_h\big).\end{aligned} \tag{D.20}$$

A first-order approximation of the weights is:

$$q_{t-c} \simeq \frac{(1-\delta)^{t+1-c}(e^{\mu_h})^{t+1-c} L_k^{new*}}{L_k^*} = (1-g)g^{t-c}. \tag{D.21}$$

Autoregressive human capital shocks $dh_{c,k,t} = \mu_h + \rho_h(dh_{c,k,t-1} - \mu_h) + \varepsilon_{k,t}^h$ implies:

$$\overline{dh}_{k,t+1} = g\rho_h \overline{dh}_{k,t} + g\varepsilon_{k,t+1}^h. \tag{D.22}$$

We calculate the difference between (D.19) for $k=1$ and (D.19) for $k=2$:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq g.\big(\Delta\ell_t - \Delta\ell^*\big) + (1-g).\big(\Delta\ell_t^{new} - \Delta\ell^{new*}\big) + \Delta\overline{dh}_{t+1}. \tag{D.23}$$

Using (D.17) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (D.23), we obtain:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq -\sigma w_\ell\big(\Delta\ell_t - \Delta\ell^*\big) + (\sigma - 1 - \sigma w_z)\Delta z_t + \Delta\overline{dh}_{t+1}. \tag{D.24}$$

Therefore:

$$\Delta\ell_{t+\tau} - \Delta\ell^* \simeq (-\sigma w_\ell)^\tau \big(\Delta\ell_t - \Delta\ell^*\big) + \sum_{s=0}^{\tau-1} (-\sigma w_\ell)^{\tau-1-s} \Big[(\sigma - 1 - \sigma w_z)\Delta z_{t+s} + \Delta\overline{dh}_{t+s+1}\Big]. \tag{D.25}$$

We use (D.25) to substitute $\Delta\ell_{t+\tau} - \Delta\ell^*$ in (D.18), and we use $\mathbb{E}_t[z_{k,t+s}] = \rho_z^s z_{k,t}$ and $\mathbb{E}_t[\overline{dh}_{k,t+s+1}] = (g\rho_h)^{s+1}\overline{dh}_{k,t}$ for $s \geq 0$, to obtain:

$$\begin{aligned} \mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] \simeq & \left[w_z\rho_z^\tau + w_\ell(\sigma - 1 - \sigma w_z)\frac{(-\sigma w_\ell)^\tau - \rho_z^\tau}{(-\sigma w_\ell) - \rho_z}\right]\Delta z_t \\ & + w_\ell(-\sigma w_\ell)^\tau\big(\Delta\ell_t - \Delta\ell^*\big) + \left[w_h(g\rho_h)^{\tau+1} + w_\ell g\rho_h\frac{(-\sigma w_\ell)^\tau - (g\rho_h)^\tau}{(-\sigma w_\ell) - g\rho_h}\right]\Delta\overline{dh}_t \end{aligned} \tag{D.26}$$

if $(-\sigma w_\ell) \neq \rho_z$ and $(-\sigma w_\ell) \neq g\rho_h$. The fraction on the first line of (D.26) is equal to $\tau\rho_z^{\tau-1}$ if $(-\sigma w_\ell) = \rho_z$. The fraction on the second line of (D.26) is equal to $\tau(g\rho_h)^{\tau-1}$ if $(-\sigma w_\ell) = g\rho_h$.

We use (D.26) to calculate the intertemporal wage difference between the two sectors:

$$\begin{aligned} \sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*] \simeq & \left[\frac{w_z}{1-\beta\rho_z} + w_\ell(\sigma - 1 - \sigma w_z)\frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta\rho_z)}\right]\Delta z_t \\ & + \frac{w_\ell}{1+\beta\sigma w_\ell}\big(\Delta\ell_t - \Delta\ell^*\big) + \left[\frac{w_h g\rho_h}{1-\beta g\rho_h} + w_\ell g\rho_h\frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta g\rho_h)}\right]\Delta\overline{dh}_t, \end{aligned} \tag{D.27}$$

where we require $\beta\sigma|w_\ell| < 1$.

Labor supply. We denote by $\sigma\eta$ the (positive) derivative of the share of entrants in a sector with respect to the expected wage differential between the two sectors:

$$E_{1,t} - E_1^* = -\big(E_{2,t} - E_2^*\big) \simeq \sigma\eta\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*]. \tag{D.28}$$

We linearize the efficient quantity of labor supplied by new workers in sector k, given by (D.6):

$$\big(\ell_{k,t}^{new} - \ell_k^{new*}\big)L_k^{new*} \simeq \big(E_{k,t} - E_k^*\big)\mathbb{E}\big[e^{\theta_{i,k}}|\gamma_i = \Delta^* + \Delta\theta_i\big]. \tag{D.29}$$

We use (D.28) to substitute $E_{k,t} - E_k^*$ in (D.29), and we use $L_1^{new*} + L_2^{new*} = \mathbb{E}\big[e^{\theta_i}\big]$. We obtain:

$$\Delta\ell_t^{new} - \Delta\ell^{new^*} \simeq \sigma\eta\alpha \sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*], \tag{D.30}$$

where

$$\alpha = \frac{\mathbb{E}\big[e^{\theta_{i,1}}|\gamma_i = \Delta^* + \Delta\theta_i\big]}{L_1^{new*}} + \frac{\mathbb{E}\big[e^{\theta_{i,2}}|\gamma_i = \Delta^* + \Delta\theta_i\big]}{L_2^{new*}} \tag{D.31}$$

and the intertemporal sectoral wage difference in (D.30) is given by (D.27).

Solving for (w_z, w_ℓ, w_h)**.** Equalizing (D.17) and (D.30), we obtain that the sectoral wage differential is given by (D.3). Equalizing the term in front of $(\Delta\ell_t - \Delta\ell^*)$, we obtain that $(-\sigma w_\ell)$ is the unique root with absolute value smaller than $1/\beta$ of the quadratic function $f(x) = \beta x^2 - (1 + \beta g + (1-g)\alpha\eta)x + g$. Since $f(0) > 0$, $f'(0) < 0$, and $f'' > 0$, the two roots of f are positive. Since $f(1/\beta) < 0$, then $(-\sigma w_\ell)$ is the smallest root of f. Since $f(g) < 0$, then $(-\sigma w_L) < g$. Therefore, $w_\ell \in (-g/\sigma, 0)$.

Equalizing the term in front of Δz_t, we obtain that w_z is the unique solution to:

$$w_z = \left[\frac{1-\beta\rho_z}{\alpha\eta(1-g)} + \frac{-\beta\sigma w_\ell}{1+\beta\sigma w_\ell}\right]\left(\frac{\sigma-1}{\sigma} - w_z\right) \tag{D.32}$$

The term in large brackets on the RHS is positive, therefore $w_z \in (0, (\sigma-1)/\sigma)$.

Equalizing the term in front of $\Delta\overline{dh}_t$, we obtain that:

$$w_h = \frac{-w_\ell\beta g\rho_h\alpha\eta(1-g)}{(1+\beta\sigma w_\ell)(1-\beta g\rho_h + (1-g)g\rho_h\alpha\eta)}. \tag{D.33}$$

Since $w_\ell < 0$, then $w_h \geq 0$, and $w_h > 0$ if $\rho_h > 0$.

Solving for (E_z, E_ℓ, E_h)**.** Combining (D.28) and (D.30), we obtain:

$$\Delta E_t - \Delta E^* \simeq \frac{2}{\alpha}\big(\Delta\ell_t^{new} - \Delta\ell^{new*}\big). \tag{D.34}$$

Using (D.17) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (D.34), we obtain that entry is given by (D.4), where

$$E_z = \frac{2\sigma}{\alpha(1-g)}\left(\frac{\sigma-1}{\sigma} - w_z\right) > 0, \tag{D.35}$$

since $w_z \in (0, (\sigma-1)/\sigma)$;

$$E_\ell = -\frac{2(g+\sigma w_\ell)}{\alpha(1-g)} < 0, \tag{D.36}$$

since $w_\ell \in (-g/\sigma, 0)$; and

$$E_h = -\frac{2\sigma w_h}{\alpha(1-g)} \leq 0, \tag{D.37}$$

since $w_h \geq 0$, and $E_h < 0$ if $\rho_h > 0$.

Solving for ℓ_E. Using (D.34) to substitute $\ell_{k,t}^{new} - \ell_k^{new*}$ in (D.23), we obtain that the law of motion of efficient quantity of old labor is given by (D.5), where

$$\ell_E = \frac{1}{2}\alpha(1-g) > 0, \tag{D.38}$$

and the law of motion of $\Delta\overline{dh}_t$ is given by (D.22).