Innovation Booms, Easy Financing, and Human Capital Accumulation*

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Abstract

Innovation booms are often fueled by easy financing, allowing new technology firms to pay high wages that attract skilled labor. Studying the Information and Communication Technology (ICT) boom in the late 1990s, we show that high-skill workers who joined the ICT sector during the boom experienced sizeable long-term earnings losses. These earnings patterns stem from accelerated skill obsolescence rather than worker selection or the subsequent bust in the ICT sector. Moreover, during the boom, financing disproportionately flowed to firms whose workers would later experience the largest productivity declines, amplifying the negative effect of labor reallocation on aggregate human capital accumulation.

Replication package available at:

https://johanhombert.github.io/TechBubble_ReplicationPackage.zip

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1 Introduction

Technological change does not progress at a constant rate. Instead, it evolves by jumps, where breakthroughs trigger a period of intense experimentation, followed by a long period of stabilization of the mature technologies (e.g., Callander, 2011; Bowen, Frésard, and Hoberg, 2023). The period of experimentation is often marked by an inflow of capital to innovative firms, allowing them to pay high wages and attract talents. This, coupled with easy financing, further accelerates the process of experimentation and development of frontier technologies (e.g., Nanda and Rhodes-Kropf, 2013; Kerr and Nanda, 2015; Janeway, Nanda, and Rhodes-Kropf, 2021). The current boom in AI exemplifies this confluence of intense innovation, abundant financing, high wages, and an inflow of skilled labor to new technology sectors.

How the booming technology sector, flush with easy financing, affects the human capital of skilled workers drawn to it will shape long-term growth. Specifically, if (a) capital-fueled technology booms lead to a reallocation of skilled workers across sectors, which (b) affects their human capital, then these events will have a long-run impact on aggregate labor productivity—a key driver of economic growth. Despite its potential importance, this channel has been largely overlooked. Our paper aims to fill this gap by investigating how the human capital of skilled workers drawn to the innovative sector during a technological and financial boom evolves after embedding the new technologies.

The effect on human capital is not obvious a priori. Workers who join the effervescent, innovative sector and contribute to developing superior technologies may accumulate human capital valuable in the long-run, even if capital markets overvalue these innovative firms during the boom and later undergo a sharp correction. However, the technologies developed during the boom may quickly become obsolete, and workers' human capital depreciate over time. This depreciation could happen either because fast-paced innovation accelerates the obsolescence of older technology vintages, or because firm overvaluation and lax financing conditions make workers more likely to be employed on lower-quality projects.

Empirically assessing how human capital evolves in this context raises several challenges. On the measurement side, it requires identifying workers exposed to different technology vintages and quantifying the value of their human capital. Neither of them is directly observable by the econometrician. On the identification front, we need to isolate the impact of on-the-job exposure to new technologies from that of the business cycle, industry cycles, and selection.

To address both measurement and identification challenges, we study the boom in Information and Communications Technology (ICT) in the late 1990s (a.k.a. the dotcom boom). During this period, the ICT sector experienced a large expansion, clearly delineated in time, triggered by technological breakthroughs followed by a rapid phase of experimentation and trial-and-error, fueled by an inflow of capital and possibly overvaluation.[1] The episode is recent enough to be covered by rich administrative data yet distant enough to study long-term effects. We use French administrative matched employer-employee data from 1994 to 2015, linked to the universe of firms' financial statements from tax filings.[2]

The fact that the ICT boom is distinctly delineated in time allows us to adopt a cohort-based design to identify the workers more likely to have participated in the experimentation and development of new technologies. We define three cohorts of workers: pre-boom (1994–1996), boom (1998–2001), and post-boom (2003–2005). The assumption is that each cohort builds human capital shaped by the technologies developed during their careers while all workers, irrespective of their cohorts, are exposed to aggregate and sectoral shocks. As such, the boom cohort is exposed to the evolving technologies from that concentrated period of rapid technological change. By contrast, the post-boom cohort is exposed to the downturn in the ICT sector after 2001, but not to the early technologies developed and experimented during the boom.

We show that workers who start in the ICT sector during the boom earn significantly

1. For the US, see for instance Brown, Fazzari, and Petersen, (2009) and Cunningham, Foster, Grim, Haltiwanger, and Wolf, (2021).

2. In Appendix C, we show that the pattern of labor reallocation to the ICT sector during the late 1990s in France is similar to that in the US.

lower long-term wages than workers with similar characteristics from the same cohort who started in different sectors, despite higher entry wages. Fifteen years out, the wage discount is around 7%, which is equivalent to losing about two years of on-the-job human capital accumulation. Because this comparison is within cohort, it controls for the well-documented impact of macroeconomic conditions at the time of labor market entry on long-term earnings.

The pattern is similar for the discounted sum of wages from labor market entry to the end of the sample period, which accounts for the higher wage during the boom. The effect is also robust to accounting for capital income that captures potential gains from stock grants, as well as to rich sets of fixed effects that account for worker heterogeneity and worker sorting across firms and places.

Our preferred interpretation of the long-term wage discount is that human capital tied to the rapidly evolving technologies during the ICT boom quickly depreciate. Consistent with this interpretation, when we re-run the same analysis on the post-boom cohort—whose human capital, by design, was not exposed to the technological experimentation of the boom years—we find that workers who started in ICT exhibit the same wage dynamics as comparable workers from the same (post-boom) cohort who started in other sectors. This result holds when we include high-dimensional fixed effects for firms' ex-ante characteristics and ex-post performance. These fixed effects ensure we are comparing workers at the same type of firms, only separated by a few years of entry, which precisely correspond to the period of intense technological change. This within-firm characteristics, across-cohorts comparison implies that the long-term wage discount for boom-cohort ICT workers cannot be explained by a sector-wide decline in labor demand or an oversupply of labor in the bubble's aftermath. Post-boom cohort ICT workers at similar firms face similar firm-specific shocks but do not experience the discount.

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 while 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 technologies developed during the boom, but whose sorting decision, by construction, is not.

Turning to the interplay between the financing boom (a recurrent pattern during periods of technological change) and human capital depreciation, we find that firms enjoying large inflows of financial capital during the boom are those whose workers' human capital depreciates the most in the long run. Since the inflow of financial capital both increases the number of workers exposed to human capital depreciation and amplifies the depreciation each worker experiences, it worsens aggregate human capital. This conclusion relies on the negative covariance between financial capital flows and subsequent human capital value, but not on whether the covariance is causal (as in Hsieh and Klenow, 2009).

We examine two potential mechanisms for the human capital depreciation of ICT workers who contributed to the technological boom, and for its correlation with capital flows during the boom. The first mechanism relies on skill obsolescence, whereas the second one focuses on the consequences of the ICT sector bust. We find strong support for the skill obsolescence channel, but no evidence for the ICT bust channel.

The skill obsolescence channel builds on Chari and Hopenhayn, (1991) and Deming and Noray, (2020), who argue that economies have overlapping vintages of technologies, where human capital tied to older vintages progressively becomes obsolete as newer ones are introduced. This effect is particularly pronounced during periods of technological change marked by intense experimentation and fast-paced innovation.

The skill obsolescence channel therefore implies that the pace of human capital depreciation should increase with (i) the intensity of experimentation in the sector in which the worker operates during the period of technological change, and (ii) the degree to which workers' human capital is tied to technologies.

Consistent with (i), we find that the ICT boom wage discount is present only among industries with high technological experimentation, that we proxy with an above-median share of STEM workers. Consistent with (ii), we find a similar dichotomy when comparing

STEM workers with non-STEM workers, even within the same type of firms. The wage discount is concentrated among STEM workers (e.g., software developers), while non-STEM workers whose human capital is less tied to firms' technologies (e.g., CFOs) have similar wage trajectories as non-STEM workers who started outside the ICT sector.

The skill obsolescence channel also explains why human capital depreciates more among firms that received greater inflows of capital during the boom. Indeed, we show that capital flowed more toward firms and sectors that experimented more and where the early technologies developed become obsolete faster, in line with other episodes of technological change.

Finally, we run several tests, but find no evidence for the main alternative explanation that can rationalize our results, namely that the ICT sector experienced a severe bust after the boom that had a large scarring effect on workers.

First, in line with technological and financing booms producing winners and losers quantile regressions of firm performance show that ICT firms under-perform non-ICT firms in the bottom half of the distribution, and outperform in the top quartile. In sharp contrast to what happens for firms, quantile regressions for long-run wages show that the wage discount is uniform across the wage distribution, even at the 90th percentile. Zooming in on the range of the distribution of firm performance where ICT firms outperformed non-ICT firms, we still find a wage discount for the boom cohort of similar magnitude.

Second, we examine whether workers who started in ICT during the boom are more likely to experience job losses, and hence might suffer from job loss scarring effect. We show that while ICT-boom workers are indeed more likely to experience job termination, the effects are an order of magnitude too small to explain the wage discount, and cannot account for the asymmetric discount between STEM and non-STEM workers.

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). Blank and Maghzian, (2023) show that credit booms lead to labor flows and subsequent slow human capital accumulation. By contrast, we study financing flows and 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.[3]

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

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, Ouimet, and Simintzi, 2022), the value of human capital (Beaudry, Doms, and Lewis, 2010; Beaudry, Green, and Sand, 2016; Kogan, Schmidt, and Seegmiller, 2024), 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, 2024; Ma, 2023).

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 The ICT Boom

2.1 Data

Our analysis relies on several comprehensive administrative datasets covering French workers and firms from 1994 to 2015. We describe here the main databases used in the paper 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 $1/24^{\text{th}}$ representative subsample of the full employer-employee data (specifically, individuals born in October of even-numbered years), individuals are assigned a unique identifier that enables us to reconstruct their entire employment history. 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 applying this filter, each individual has at most one job per year.[4] 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, 41% are in a business occupation (e.g., sales, general administration – two-digit code 37), 32% are in a STEM occupation (code 38), and 4% are heads of company with at least ten employees (code 23).[5] 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 42,000 euros (mean 51,000 euros), which corresponds to the 90th percentile of the wage distribution

4. In rare cases where workers have two six-month full-time job spells at different firms in the same year, we retain only the higher-wage observation.

5. Other high-skill occupations are mostly held by self-employed and public sector employees: 12% are teaching professionals (occupation code 34); 8% are public sector managers and professionals (code 33); 2% are cultural professionals (code 35); and 1% are health professionals and legal professionals (code 31).

of full-time workers in France.[6] Finally, a $4/31^{\text{th}}$ subsample of the employer-employee panel data (individuals born in the first four days of October) can be linked to census 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 allows 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 5.0% of total employment and 14.4% of skilled employment, reflecting that ICT is intensive in skilled labor. The ICT sector is more specifically intensive in STEM skills: the fraction of skilled workers in STEM occupations is 71% in the ICT sector versus 26% in other sectors.

2.2 Capital Flow

We start by showing that fast-paced technological change in the ICT sector during the late 1990s France coincided with a run-up in equity valuations and an inflow of capital

6. The amounts in the paper are all expressed in 2000 constant euros. 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.

to the ICT sector, similar to the US experience (Brown, Fazzari, and Petersen, 2009). Panel A of Figure 1 shows the stock price run-up in the ICT sector during the period 1997–2000, measured as the value-weighted cumulative stock return.

Panel B 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. To measure capital flow for the universe of firms, we use the administrative tax-files and compute the net change in equity issuance, defined as the firm-level change in nominal equity scaled by lagged total assets averaged at the sector level. The measure features the same boom as equity valuation that peaks in 2000–2001.

2.3 Labor Flow

Consistent with the idea that the inflow of capital allows firms in the ICT sector to compete more aggressively for the scarce supply of talent, Panel A of Figure 2 shows that the share of the ICT sector in total skilled employment deviates sharply upward from its pre-existing 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. The interpretation that the inflow of capital translates into a labor demand shock is supported by the fact that the inflow of labor coincides with high wages (see Figure 3 below) in the ICT sector.

Panel B breaks down this reallocation of skilled labor into young workers (defined as workers who have been in the labor market for four years or less) and seasoned workers (defined as workers who have been in the labor market for five years or more). It shows that the large inflow of skilled labor in the ICT sector is entirely driven by young workers. The ICT sector share among seasoned workers exhibits a slight upward trend but no significant deviation from trend. By contrast, the ICT sector share among young workers exhibits a sharp upward deviation from trend during the boom.

This fact motivates our analysis by cohort of labor market entrants. 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.[7] Panel C plots the share of labor market entrants who start in the ICT sector by labor market entry year. It shows that, during the boom, the ICT sector absorbs one-third of entering cohorts of skilled workers. The effect of this large labor reallocation on aggregate long-term labor productivity depends on how exposure to rapidly evolving technologies impacts the human capital accumulation—or depreciation—of the large cohort of skilled workers who are drawn to ICT during the ICT boom to develop and diffuse these new technologies.

3 Wage Dynamics

We now estimate the long-term value of human capital accumulated during the ICT boom by skilled workers who started in the booming ICT sector. Our identification strategy relies on comparing long-run wage dynamics across sectors and across cohorts. It is motivated by an overlapping generations model with sectoral choice and human capital accumulation presented in Appendix D. We summarize the key implications of the model below.

3.1 Motivating Evidence: Wage Dynamics Across Sectors for the Boom Cohort

We focus, first, on the *boom cohort*, defined as skilled workers who enter the labor market between 1998 and 2001. We define the boom period as 1998-2001, corresponding to the sharp increase in ICT sector valuations and capital and labor flows documented in Section 2. We estimate the following regression at the individual-year level:

$$\log(Wage_{i,t}) = \sum_{t'=1998}^{2015} \beta_{t'}^{boom} ICT_{i,0} \times (t = t') + \alpha_t \times X_{i,0} + \epsilon_{i,t} \tag{1}$$

7. 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.

$Wage_{i,t}$ 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. $\epsilon_{i,t}$ is the error term. We cluster standard errors at the individual level to account for serial correlation in individual wages.

The regression coefficient β_t^{boom} estimates the average wage difference in year t between two groups of workers from the boom cohort. The first group consists of workers who start their career in the ICT sector. The second group comprises workers who start outside the ICT sector. Importantly, both groups include workers with the same characteristics and in the same occupation. This comparison allows us to isolate the effect of starting in the ICT sector during the boom period. We superscript β_t^{boom} with *boom* to emphasize that we estimate (1) for the boom cohort. We later estimate (1) for other cohorts.

Figure 3 presents the estimates of β_t^{boom} (red line). It 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. The initial 5% wage premium shrinks rapidly after the boom ends in 2001. Strikingly, the wage difference keeps falling and eventually turns negative. 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.

3.2 A Framework to Interpret Wage Dynamics

In Appendix D, we outline a model in which overlapping cohorts of workers choose in which sector to work when they enter the labor market. 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.

The productivity of worker i from cohort c working in sector k at date t has two components. The first component, $\theta_{i,k}$, is a fixed effect reflecting innate productivity and education. The second component, $h_{i,c,k,t}$, is time-varying and reflects on-the-job human capital accumulation or skill obsolescence and other potential losses of human capital from labor market entry until the current year t. Sector-specific labor demand shocks shift the equilibrium wage rate $w_{k,t}$ in each sector k. The key equation of the model determines the log wage of worker i from cohort c in sector k in year t as a function of the worker's fixed type, human capital accumulated since labor market entry, and the sector wage rate:

$$\log(Wage_{i,c,k,t}) = \theta_{i,k} + h_{i,c,k,t} + w_{k,t} \tag{2}$$

The regression equation (1) maps directly into the model equation (2). In the model, the regression coefficient β_t^c estimated on a given cohort c can be calculated exactly as the difference in average log wage between workers from cohort c who started in ICT and workers who started in other sectors. Averaging (2) over i at the cohort-sector-year level, and taking the difference between the ICT sector and other sectors, we obtain

$$\beta_t^c = \Delta\theta_c + \Delta h_{c,t} + \Delta w_t \tag{3}$$

where Δ denotes the difference operator between the cohort-year-level average in the ICT sector and that in other sectors. $\Delta\theta_c$ is the average type of workers from cohort c who start in the ICT sector minus that of workers who start in other sectors. $\Delta h_{c,t}$ 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 in other sectors. Δw_t is the wage rate in year t in the ICT sector minus that in other sectors.

Equation (3) shows that the 6% long-term relative earnings decline experienced by workers who started in the booming ICT sector can be explained by three economic forces—working out the three terms on the right-hand side of (3) in reverse order: (1) a secular decline in ICT sector wage rates, (2) depreciation of human capital accumulated in ICT relative to other sectors, and (3) negative selection into ICT during the boom.

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). This decline may stem from a labor market imbalance due to a persistent decline in labor demand or excess entry of workers in the ICT sector. 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). Third, there may be negative selection into the ICT sector during the boom, namely workers who started in ICT during the boom were of worse quality. Note, however, that the selection term $\Delta\overline{\theta}_{boom}$ is time-invariant, and therefore may shift the level of the wage difference β_t^{boom} but cannot explain its variation over time.

3.3 Identification Across Sectors and Across Cohorts

3.3.1 Baseline Cross-Cohort Comparison

According to our theoretical framework (Equation (3)), sectoral labor supply and demand shocks (Δw_t) affect all cohorts equally. Therefore, if the long-run wage discount of ICT boom-cohort workers is explained by a persistent decline in labor demand or over-supply of skilled workers in the ICT sector, skilled workers who enter the labor market after the ICT boom should also experience the long-term wage decline. By contrast, if the wage discount is explained by the fast depreciation of human capital accumulated during the boom in the ICT sector ($\Delta h_{boom,t}$), workers who start in ICT after the boom period should not experience the discount.

We estimate equation (1) on the *post-boom cohort*, defined as skilled workers who enter the labor market between 2003 and 2005.[8] Figure 3 (green line) shows that, in sharp contrast to the boom cohort, the post-boom cohort of workers who start in ICT experience no downward trend in the wage dynamics. Therefore, the long-run wage discount of ICT boom-cohort workers cannot be explained by a secular labor market imbalance in the ICT sector. To address the concern that the post-boom cohort may be an imperfect control group and be exposed to different sector-specific shocks, in Sections 3.4 and 4.1 we consider additional sources of variation *within* the boom cohort and reach a similar

8. We include a gap year between the boom cohort (1998-2001) and the post-boom cohort (2003-2005) to have sharply delimited cohorts. The results are robust to including the gap years in either one of the adjacent cohorts.

conclusion.

To formally compare the boom and post-boom cohorts, we stack both cohorts and estimate the regression in difference between the two cohorts by interacting each right-hand side variable with a boom cohort dummy:

$$\log(Wage_{i,t}) = \sum_{t'=2003}^{2015} \beta_{t'}\, ICT_{i,0} \times BoomCohort_i \times (t = t') \\ + \delta_t \times ICT_{i,0} + \alpha_{c,t} \times X_{i,0} + \epsilon_{i,t} \quad (4)$$

where $BoomCohort_i$ is a dummy variable equal to one for workers from the 1998-2001 cohort. We also include a starting-sector×year fixed effect ($\delta_t \times ICT_{i,0}$) to compare workers exposed to the same sectoral shocks, and a cohort×year fixed effect ($\alpha_{c,t}$) to compare workers from the same cohort.[9]

Panel A of Figure 4 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 3.

3.3.2 Selection

We now examine whether these estimates are explained by negative selection into ICT during the boom. This would happen if either (1) the booming ICT sector attracted a disproportionate share of low-productivity workers, or (2) the rapid expansion in ICT hiring increased worker-sector mismatches.

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

9. 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.

$\theta_{i,k}$ does in the wage equation (2), effectively acting as a worker fixed effect (Abowd, Kramarz, 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 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 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 2, the sudden nature of the ICT boom makes it unlikely that workers who entered the sector just a few years earlier selected into ICT in anticipation of 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. Consequently, comparing the boom cohort to the pre-boom cohort absorbs the component of the wage equation (2) reflecting the differences in worker type starting in the ICT sector, and thus isolates the long-run evolution of human capital accumulated in ICT during the boom net of selection effect.

We start by returning to Figure 3, where we also plot the pre-boom cohort's wage dynamics (the blue line). Three key patterns emerge. First, workers who started in the ICT sector prior to the boom experience the same wage pattern as similar workers in other sectors during the years 1994–1998. This is consistent with the assumption that both groups of workers have similar intrinsic productivity. Second, their wage during the boom period (1998–2001) increases by the same magnitude as workers who started during the boom. This suggests that the ICT premium is driven by heightened labor demand rather than a shift in workers' types joining the ICT sector. Third, the pre-boom cohort experiences the same downward trend as the boom cohort. This is evidence that the wage discount is driven by a deterioration of the human capital of workers who were exposed to the technologies developed by the booming ICT sector (since both cohorts' human capital embedded these new technologies), rather than by a worsening of the pool of workers joining the ICT sector during the boom (the selection component of equation (2)).

To formally test the similarity of the wage pattern between the pre-boom and boom cohorts, we use the same strategy as in Section 3.3.1 and stack both cohorts of workers. The coefficients of the difference-in-differences regression (4) capture the difference in the estimated coefficients for the pre-boom and boom cohorts from Figure 3. We find that the difference in wage dynamics between the two cohorts is statistically insignificant (panel B of Figure 4). This result confirms that the wage decline that follows the boom period in the ICT sector is consistent with human capital depreciation but not with negative selection during the boom.

3.3.3 Baseline Specification and Additional Controls

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 (4). For 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 (4):

$$\log(Wage_{i,t}) = \sum_{\substack{\text{period=2003-05,}\\ \text{2006-10, 2011-15}}} \beta_{period} \cdot ICT_{i,0} \times BoomCohort_i \times (t \in period) + \delta_t \times ICT_{i,0} + \alpha_{c,t} \times X_{i,0} + e_{i,t} \quad (5)$$

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 changes in the returns to experience over time (e.g., Buchinsky, Fougère, Kramarz, and Tchernis, 2010) and evolving gender wage gaps (e.g., Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon, 2022). We also control for occupation-specific patterns in skill accumulation and depreciation (e.g., Kogan, Schmidt, and Seegmiller, 2024) by including two-digit occupation at entry in the vector of worker characteristics $X_{i,0}$.[10]

Column 1 of Table 1 reports the results without individual fixed effects. The estimates mirror the dynamics in panel A of Figure 4. 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 6.9% lower over the 2011–2015 period.

Column 2 is our baseline specification. It includes individual fixed effects, ensuring identification comes from within-worker wage trajectories rather than changes in sample composition due to attrition. The inclusion of individual fixed effects implies that the β coefficients are identified relative to a reference time period which we fix to 2003–2005. The coefficients for the period 2006–2015 relative to the reference period are very similar to those in column 1, implying that non-random attrition does not explain the wage discount. We provide additional evidence that attrition does not explain our results in Appendix B.6.

The 7.4% long-term wage discount is economically significant. It amounts to approximately two years of experience. We obtain this number by estimating the return to experience in our sample to be in the range of 3.2% to 4.4% per year of experience (see Appendix B.1).

To address potential bias from unobserved sector-, location-, and firm-specific shocks that might correlate with workers' initial sector choices, we progressively saturate the regression with high-dimensional fixed effects. We address this possibility by progressively saturating the regression with high-dimensional fixed effects.

10. 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, unless otherwise specified.

In column 3, we start by including pseudo-firm fixed effects interacted with year to account for the well-documented relationship between employer characteristics and long-run wage trajectories.[11] Since the composition of firm characteristics in the ICT sector might change during the boom due to easy financing, the wage discount for workers starting in the ICT sector during the boom might partially reflect changes in their first employer's characteristics.

The ideal specification would include worker's initial employer fixed effects interacted with year fixed effects, allowing us to compare workers from different cohorts who started at the same firm. However, the sampling design—which randomly selects individuals regardless of employer—makes this impractical. Since few firms except the largest ones hire multiple sampled high-skill workers across cohorts, firm×year fixed effects would absorb most of the identifying variation. Instead, we address the potential endogeneity arising from firm characteristic-worker productivity correlations by constructing "pseudo firms" based on key firm attributes.

Drawing on the literature that identifies firm size, age, and productivity as crucial determinants of wage dynamics, we create combinations of quintiles of employment, firm age, and labor productivity (i.e., $5 \times 5 \times 5 = 125$ pseudo firms) that we interact with year fixed effects. These fixed effects ensure that we compare similar workers across sectors and cohorts, who started in firms of comparable size, age, and productivity profiles.

While in column 3 we make comparisons within ex-ante firm characteristics, ICT-boom cohort workers may be disproportionately hired by firms who perform poorly ex-post. In column 4, we augment the pseudo-firm definition to include ex-post performance, measured by five-year forward sales growth quintiles, alongside the previous ex-ante characteristics.

While the similar wage dynamics between boom and pre-boom cohorts (Section 3.3.2) suggest otherwise, one might worry that ICT-boom workers differed in initial productivity.

11. For instance: firm size (Tate and Yang, 2015; Bloom, Guvenen, Smith, Song, and Wachter, 2018; Hartman-Glaser, Lustig, and Xiaolan, 2019), firm age (Ouimet and Zarutskie, 2014; Babina, Ma, Moser, Ouimet, and Zarutskie, 2022), firm productivity (Abowd, Kramarz, and Margolis, 1999), and workforce composition (D'Acunto, Tate, and Yang, 2020).

To further ensure that we compare workers with the same initial productivity, in column 6 we include entry wage quintile×cohort×year fixed effects.[12]

In column 6, 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 (e.g., 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). Across all specifications, the long-term wage discount from starting in the ICT sector during the boom is quantitatively robust.

We discuss in depth in Section 4.2 why our results cannot be explained by the fact the ICT sector experienced a bust after the boom. As a simple first approach, we include in columns 2 and 3 of Table B.5 pseudo-firm fixed effects for the current employer in addition to the initial employer and find a similar wage discount. It implies that the result is not explained by the fact that boom-cohort ICT workers end up in different or worst types of firms than post-boom cohort ICT workers.

3.4 Capital Flows

Periods of intense technological change are typically accompanied by a large inflow of speculative capital to the innovative sector (e.g., Janeway, Nanda, and Rhodes-Kropf, 2021). As we show in Section 2.2, the ICT revolution in France was no exception. In this section, we explore the interplay between the financing boom and subsequent human capital depreciation.

Implications for Aggregate Human Capital. Our results so far show that workers exposed to the ICT revolution experience a wage discount, which can be interpreted as human capital depreciation (Section 3.3). This *average effect* would particularly weigh on aggregate human capital (and, consequently, on aggregate labor productivity and economic growth) if the capital flows during the boom are directed towards firms whose

12. A similar argument and empirical strategy is made in Michelacci and Schivardi, (2020) or Kogan, Schmidt, and Seegmiller, (2024).

workers are likely to experience greater depreciation of their human capital. In such a scenario, more workers would face long-term losses in their human capital.[13]

If instead capital flowed primarily to firms whose workers maintained their human capital value, the aggregate impact would be less severe. Therefore, whether financing booms amplify or mitigate the aggregate productivity impact depends on the *covariance* between human capital depreciation and capital flow during the boom.

Importantly, whether financing booms amplify or mitigate aggregate human capital depreciation neither depends on whether the covariance is causal, nor does it depend on the exact channel through which financing booms might accelerate the human capital depreciation of workers. Nonetheless, we discuss the possible causal effect of financing booms on heightened human capital depreciation in this section, and provide an in-depth analysis of which channels might account for this effect in Section 4.

Empirical analysis. To examine how human capital depreciation correlates with capital availability during the boom, we extend our baseline specification (equation (5)) by incorporating interactions with the two measures of capital availability introduced in Section 2.2.[14] The first one proxies for overvaluation at the four-digit industry level using value-weighted stock return during the year 1999 (ICT stocks peak in March 2000).

The second proxy measures capital inflow using all public and private firms. We take net equity issuance defined as the mid-point growth rate in share equity at the firm level from the tax filings, and calculate the leave-one-out mean at the four-digit industry$\times$commuting zone$\times$year level. The leave-one-out mean ensures that capital availability is not mechanically tied to the firm's 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.[15]

13. In Appendix B.2, we show that capital flows are indeed strongly correlated with labor flows in a panel regression at the industry$\times$geography$\times$year level with industry, geography, and year fixed effects.

14. 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.

15. The top three ICT industries in terms of capital flow are "Other telecommunications activities", "Database activities", and "Computer systems consulting", while the bottom three are "Rental of office machinery and computer equipment", "Manufacture of radio and television transmission equipment", and "Manufacture of office machinery".

Results. Table 2 reports the results. We focus on the interaction term $ICT_{i,0} \times CapitalAvailability_i \times BoomCohort_i \times$ 2011-15, where $CapitalAvailability_i$ is a dummy variable indicating above-median values for each capital availability measure. We find that the wage discount for workers who started in the ICT sector during the technology boom is concentrated in four-digit industries with high capital availability, and the point estimates are consistent across both proxies (columns 1 and 2). The magnitudes are large, with workers facing an additional 8 to 10 percentage points long-term wage discount in these sectors.

The negative covariance between capital flow and human capital depreciation implies that the financing boom contributed to reduce aggregate labor productivity. Indeed, rather than flowing to firms where workers accumulate useful skills, capital was directed towards firms whose workers subsequently experienced large human capital depreciation. Therefore, in aggregate, more workers lost human capital in the long run. Consequently, 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).

Causal effect of financing booms. While the aggregate productivity implications we identified above hold regardless of causality, understanding whether capital flows causally affect human capital depreciation provides important insights into the mechanisms at work.

A causal impact may occur if greater capital availability spurs experimentation and exposes workers to the risk of failure and loss of project-specific human capital. 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 in turn be the true driver of the depreciation of human capital exposed to technological change.

As a first pass to distinguish between these explanations, we exploit the granular nature of our capital flow measure (varying at the four-digit industry×commuting zone×year level) by adding four-digit industry×cohort×year fixed effects. This approach allows us to examine how the wage discount varies with capital flow while holding constant the pace of technological change within each detailed industry. When we include these fixed effects, equation (5) compares the wage discount in a given year for workers from the same cohort, who start in the *same four-digit industry*, across geographies. Since technological progress likely advances similarly for all firms within a narrowly-defined industry, this approach helps isolate the effect of capital flows from technological change that could be a driver of capital flows and thus a confounding factor.

Column 3 reports the results with four-digit industry×cohort×year fixed effects. The point estimate remains strongly negative and statistically significant, implying that even within the same detailed industry and cohort, workers more exposed to large capital inflows face a larger depreciation of their human capital. Column 4 shows that the effect of capital flow on human capital depreciation remains similar when we include commuting zone×cohort×year fixed effects, which account for local time-varying factors like business dynamism and productivity shocks.

Taken together, these results show that capital flows 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.

3.5 Robustness

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 5 of Table B.5), we assume the CEO holds all cash flow rights. We add the firm's net income to the CEO's earnings.[16] In the second scenario (column 6), 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.[17]

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.4 we estimate equation (1) 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 6.4% 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 26,000 euros. 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

16. 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.

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

lower quality based on their education achievements (see Appendix B.5). 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.6).

Excluding sectors one-by-one. Compensation of high-skill workers in the financial sector grew faster than in other sectors during the 2000s (e.g., Philippon and Reshef, 2012), which could partially drive the wage discount in the ICT sector relative to the other sectors that include the financial sector. In column 4 of Table B.5, we show that our results are robust to excluding workers starting in the financial sector. In Figure B.2, we show the distribution of coefficients when we estimate the regression excluding two-digit sectors one-by-one, resulting in 26 distinct regressions. The point estimates and t-statistics are tightly distributed around the baseline point estimate and t-statistic. Therefore, the results are not driven by any particular industry in the control group.

4 Mechanism

Why do workers who developed the innovations of the ICT sector during its technological boom experience a substantial depreciation of their human capital, while similar workers hired in the same firms just a few years later face no such depreciation? And why is this depreciation concentrated among workers hired in firms that benefited from large capital inflow, while workers in firms outside the ICT sector with similar large capital inflow face no such depreciation?

We examine two potential mechanisms. The first relies on skill obsolescence, whereas the second focuses on the consequences of the ICT sector bust.

4.1 Skill Obsolescence

Innovation booms are characterized by a period of intense experimentation and fast-paced introduction of multiple versions of the new technologies, before they stabilize. After this period, the economy contains overlapping vintages of technology, with old vintages rendered obsolete by newer ones, while still co-existing with them (Chari and Hopenhayn, 1991). As a result, the human capital that embeds the older vintages of experimentation becomes obsolete as well. Such obsolescence could explain the long-run wage discount of workers who were exposed to the booming ICT sector as they develop human capital specific to early technology versions. For example, while many developers specialized in building static websites using early early versions of HTML during the late 1990s, database-driven technologies like CSS3 became the norms by the mid-2000s. IT consultants faced similar challenges, with on-premise CRM systems being rendered obsolete by cloud-based solutions.

The skill obsolescence channel generates two predictions. First, the pace of human capital depreciation should increase with the intensity of experimentation because this human capital is more likely to embed vintages of technologies that quickly became obsolete after the boom. Second, human capital depreciation should be stronger for workers with technology skills than for workers with management or general skills, since engineers' human capital for example is tied to specific technology implementations, while CFO's human capital remains valuable across technology vintages.

To test the first prediction, we estimate the wage regression separately for industries with high experimentation and for industries with low experimentation. We proxy for the pace of experimentation using the share of STEM workers among the workforce at the four-digit industry level and split industries at the sample median.

Table 3 presents the results. In all specifications, the long-run wage discount is concentrated in ICT industries with above-median STEM share (panel A), in line with accelerating skill obsolescence in those industries. In contrast, the effect in ICT industries with low STEM intensity is statistically and economically insignificant (panel B).

To test the second prediction, we estimate the wage regressions separately for STEM workers and for non-STEM workers. Table 4 presents the results. Once again, a clear pattern emerges. The wage discount within the ICT sector is concentrated among STEM workers (panel A), supporting the technological skill obsolescence hypothesis. Meanwhile, non-STEM workers whose human capital is more generalist and less tied to firms' technologies have similar wage trajectories as non-STEM workers who started outside the ICT sector (panel B).

One potential concern is that STEM workers and non-STEM workers might sort into different types of firms during the boom, driving the divergent wage patterns. We address this possibility in column 3, where we control for the characteristics of the initial employer by including pseudo-firm fixed effects as described in Section 3.3.3. The effect of starting in ICT during the boom remains close to the baseline effect for STEM workers (-7.0% versus -6.0%), while it is close to zero for non-STEM workers (-1.7% not statistically significant). This result is robust to additionally controlling for initial wage quintile$\times$year fixed effects (to restrict the comparison to workers with similar starting wages) and for commuting zones$\times$year fixed effects (to focus on within geographies comparison).

The interaction with capital flows. The skill obsolescence channel may also explain why human capital depreciates more among firms that received greater inflows of capital during the boom (Table 2). During innovation booms, capital tends to flow more toward ICT firms and sectors that engage in more experimentation (e.g., Kerr and Nanda, 2015; Janeway, Nanda, and Rhodes-Kropf, 2021), and hence where the early technologies developed are likely to become obsolete faster.

We provide evidence for this mechanism in Table 5 using the STEM share as a proxy for experimentation and greater exposure to obsolescence risk. In the four-digit industry$\times$commuting zone$\times$ year panel over the boom period 1998–2001, we regress capital flow on the STEM share. The positive coefficient on the interaction between the STEM share and the ICT dummy in columns 3 and 4 implies that capital flows to ICT firms that are more STEM intensive. This result is consistent with the idea that capital is particularly attracted to firms pushing the technological frontier during an innovation boom and with the notion that innovative firms need equity financing due to their high levels of intangible assets.[18]

Taking stock, capital flows to firms that experiment and innovate intensively, which leads to a larger number of technology vintage and, as a result, faster skill obsolescence. This mechanism generates the positive covariance between capital flow during the boom and future human capital depreciation of workers employed by firms receiving the additional capital. Consequently, the financing boom amplified the aggregate human capital depreciation by directing more workers toward firms where their skills would become obsolete more quickly.

4.2 ICT Bust

The main alternative explanation that can rationalize our results is that the ICT sector experienced a severe bust after the boom that had a large scarring effect on workers. Our previous results already suggest this channel is unlikely. The post-boom cohort displays no ICT wage discount (Figure 3), the boom discount is similar when we control for firms' ex-ante characteristics and ex-post performance (column 4 of Table 1), and finally, the discount is concentrated among STEM occupations (Table 4), while a sectoral bust should affect all occupations in the sector.

4.2.1 Firm Performance

Firm-level analysis. First, we examine the performance of ICT firms in the period following the ICT boom. We regress firm-level sales growth from 2001 to 2005 on an ICT dummy, controlling for log of sales in 2001 to account for mean reversion. Column 1 of Table 6 shows that the average ICT firm present during the boom performs only marginally worse during the bust, with the difference being statistically insignificant.

18. For a discussion and evidence on the role of intangible assets and financing frictions, and the importance of equity, see among many others: (Eisfeldt and Papanikolaou, 2013; Crouzet and Eberly, 2019; Begenau and Palazzo, 2021; Falato, Kadyrzhanova, Sim, and Steri, 2022; Crouzet, Eberly, Eisfeldt, and Papanikolaou, 2022; Beaumont, Hombert, and Matray, 2024).

This marginally lower average sales growth could mask substantial skewness because technological change creates uncertainty regarding which firms and technologies will prevail in the long run. We examine the dispersion in firm performance by running quantile regressions, which we report in columns 2 to 6 of Table 6. At the median and below, ICT firms experience lower performance than firms outside the ICT sector in the aftermath of the ICT bust, e.g., 6.3% smaller growth at the median. But this difference then turns positive, and at the 75th percentile ICT firms experience 5.7% faster growth than non-ICT firms.

To further evaluate the bust explanation, we examine whether workers at successful ICT firms fared better. If the bust drove our results, we would expect workers at top quartile ICT firms—those that performed better than non-ICT firms—to avoid the wage discount, as these firms successfully weathered the downturn. Instead, we find that workers who started in top quartile ICT firms during the boom also experience a large wage discount relative to workers starting in top quartile non-ICT firms (column 1 of Table B.9).

In column 2 of the same table, we rule out a related version of the under-performing sector channel, namely that the ICT-boom discount was specific to French firms. We use ownership data to identify subsidiaries of US companies defined as firms that are 100% owned by a US company and re-estimate the wage equation on this subsample.[19] Here again, we find the same ICT-boom discount as in the whole sample.

All in all, differences in firm quality are unlikely to explain the wage discount for workers who started in the ICT sector during the boom. On the other hand, the skewed distribution of ICT firm performance suggests that the average ICT wage discount might also mask substantial heterogeneity in worker outcomes. We explore this possibility next.

Worker-level analysis. We re-estimate the wage equation using quantile regressions instead of OLS to see if we observe a skewed distribution that could explain the negative average wage discount. Table 7 presents the results. In stark contrast to the results for firm performance, there is no evidence of a winner-take-all effect among ICT workers that

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

started during the boom. Instead, the entire long-term wage distribution of individuals starting in the booming ICT sector is shifted uniformly to the left, with a discount ranging from 7.4% at the 90th percentile to 8.1% at the 10th percentile.

4.2.2 Job Losses

While many ICT firms performed well after the boom, they may have withstood the bust by firing *en masse* boom-cohort workers, who then suffered from the well-documented scarring effects of job losses (e.g., Huckfeldt, 2022).

We rule out this hypothesis in two ways. First, we show that scarring effects are an order of magnitude too small to explain the wage discount, and cannot account for the asymmetric discount between STEM and non-STEM workers. Second, controlling for job losses in the wage regression does not affect the point estimate.

Magnitude of scarring effects. We define three different proxies for workers facing a job loss: the worker experiences a job transition and (i) the transition leads to a wage cut for the worker; (ii) employment at the worker's initial employer decreases by 10% or more in the year of the job transition; (iii) either happens. We impose these conditions to capture job termination and not any, potentially voluntary, job transition.

In Panel A of Table 8, we report the results when we estimate whether starting in ICT during the boom affects the probability of any job transition and the probability of job termination in the four years following entry. We find that while ICT boom workers are not more likely to change job than non-ICT boom workers (column 1), they are more likely to lose their job by 4.0 to 6.8 percentage points (columns 2–4).

Moreover, Table 9 shows that job termination is associated with a long-term wage decline of 3.4 to 5.2 percentage points on average depending on the proxy of job termination. These wage effects are in line with previous estimates.[20] Therefore, heightened job termination can explain at best $0.068 \times 0.052 = 0.35$ percentage points of the overall 7.4 percentage points wage discount.

20. For instance, Gibbons and Katz, (1991) finds wage losses between 1.1% and 5.4%, Burdett, Carrillo-Tudela, and Coles, (2020) report wage losses around 5%, and Huckfeldt, (2022) around 5.5%.

In panels B and C of Table 8, we re-estimate the job termination regression separately for STEM workers and for non-STEM workers. While the wage discount is concentrated among STEM workers, we find that if anything, boom-cohort non-STEM workers face a higher rate of job termination than boom-cohort STEM workers (9.5 p.p. vs. 5.8 p.p. when we measure job termination using either proxies in column 4). This sharp asymmetry between which workers experience the wage discount vs. which workers experience higher job termination rate is consistent with heightened skill obsolescence for workers whose human capital is tightly connected to the technologies developed during the boom, and inconsistent with a large scarring effect of job losses.

Controlling for scarring effects. In Table 9, we re-estimate the baseline wage regression and directly control for the dummy *Job termination* that equals one if the worker experiences a job termination within the first four years after entry, using the three different proxies of job termination defined previously. This barely changes the long-term wage discount, which decreases from 7.4% to 7.2%.

Job termination during a sectoral bust might have a disproportionate impact on long-term earnings. To address this possibility, in Table B.10, we re-estimate the regression by controlling for the full interaction of *Job termination* with $ICT_{i,0}$, *Boom cohort* and $ICT_{i,0} \times$ *Boom cohort*. 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 is only slightly reduced, by about one-tenth, and remains large and significant at 1%.

Workers who are not laid-off might still experience lower wage growth when job losses spike in their local labor market, because outside options worsen. To examine this possibility, we split the sample along the intensity of job termination in the worker's local labor market. We compute the average yearly termination rate at the commuting zone×occupation level over the post post-boom period 2002–2005. In Table B.11, we estimate the baseline wage regression, as well as the specifications that control for each proxy of job termination, separately for local labor markets with above median job termination rate and for those below median. We find that if anything, the wage discount is higher in local labor markets that faced a lower termination rate, inconsistent with job losses explaining the discount.

5 Concluding Remarks

Theories of growth highlight that reallocation of capital and talent to innovative sectors can enhance productivity and growth, even when this reallocation is amplified by speculative financing where investors over-invest and end up losing money. However, the impact on the human capital of workers drawn to these sectors during periods of intense technological change and easy financing remains understudied.

Using the late 1990s ICT boom as a laboratory, during which one-third of skilled labor market entrants joined the ICT sector, we find that these workers experience a significant wage discount fifteen years later, even after controlling for selection, firm performance, and job losses. This wage decline is concentrated among STEM workers and in sectors with high technological experimentation, consistent with faster obsolescence of skills acquired during periods of rapid innovation. Moreover, the human capital depreciation is larger for workers hired by firms that received greater capital inflows during the boom. Since capital flowed disproportionately to firms and sectors where workers' skills would later become obsolete more quickly, the financing boom amplified the negative effect on aggregate human capital by both increasing the number of workers exposed to skill obsolescence and magnifying the depreciation each worker experienced.

These findings highlight an important but overlooked channel through which innovation booms and the associated financing cycles can affect long-run productivity growth—namely through their impact on the human capital of the large cohorts of skilled workers drawn to these sectors. However, our results do not imply that the rapid expansion of the ICT sector during the boom was necessarily detrimental to aggregate welfare. The faster development and diffusion of new technologies throughout the economy may have generated benefits that outweighed the costs we identify. Understanding this broader welfare calculation remains an important avenue for future research.

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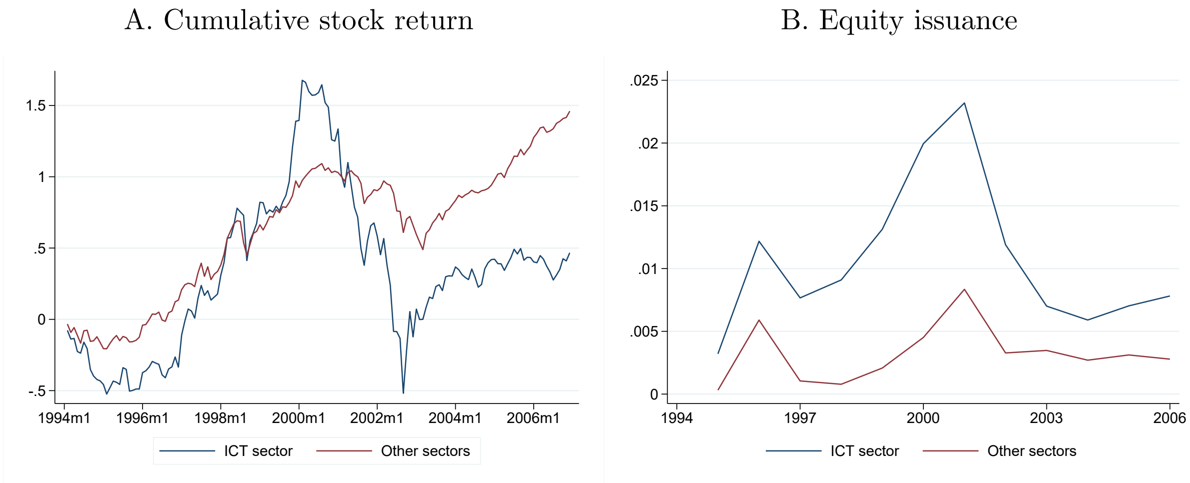
Figure 1: Valuation and Flow of Capital



Note. Panel A plots cumulative value-weighted return in the ICT sector and in non-ICT sectors. Panel B plots net equity issuance scaled by lagged total assets in the ICT sector and in non-ICT sectors.

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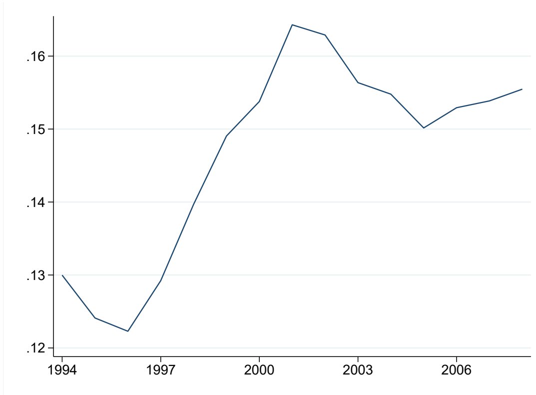
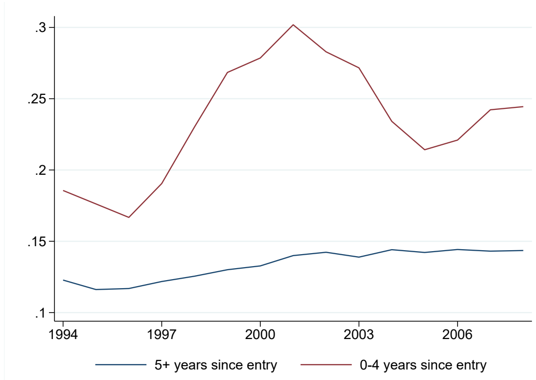
Figure 2: Labor Reallocation: ICT Sector Share Among Skilled Workers

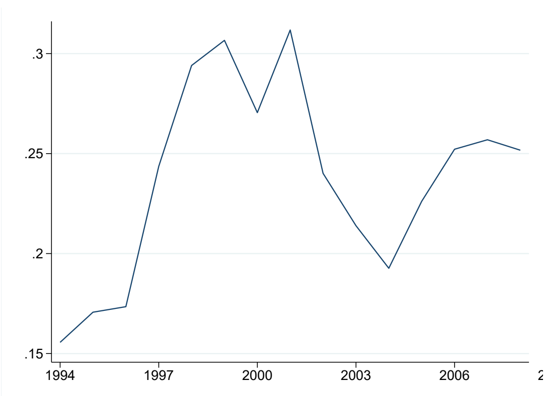
A. All skilled workers



B. Recent entrants vs. older workers



C. Labor market entrants



Note. 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). Panel C plots the plots the share of the ICT sector among high-skill labor market entrants.

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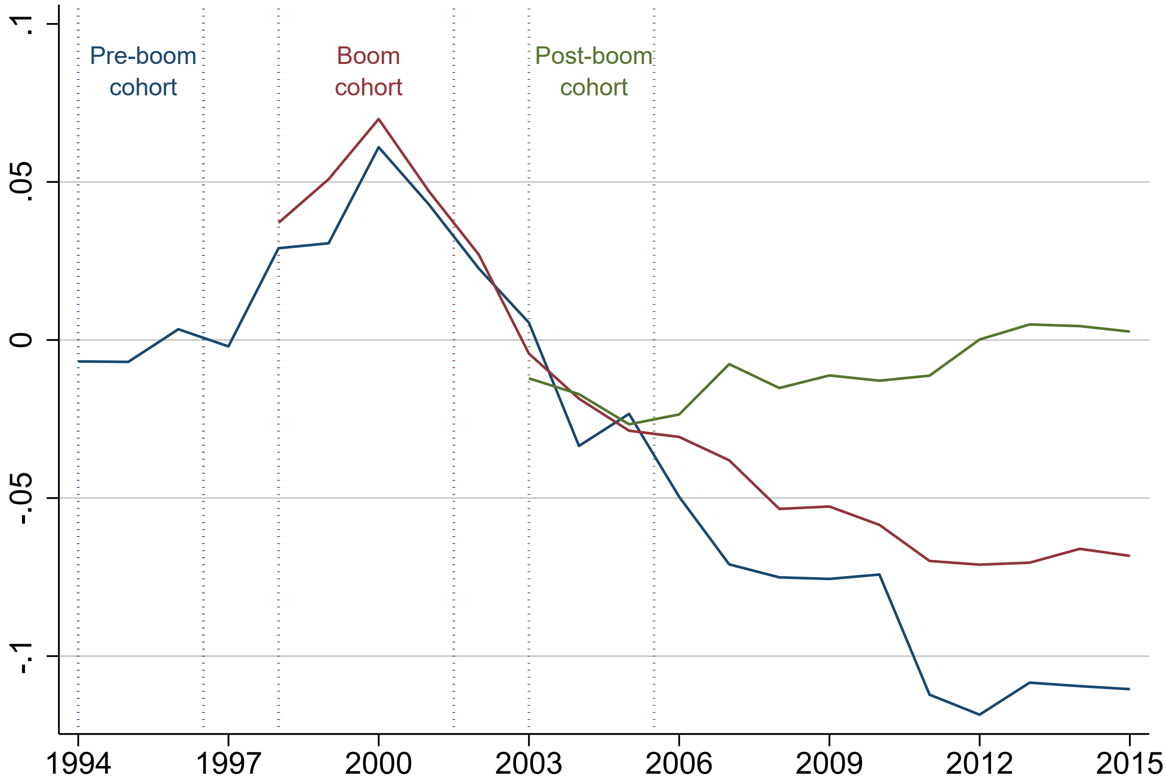
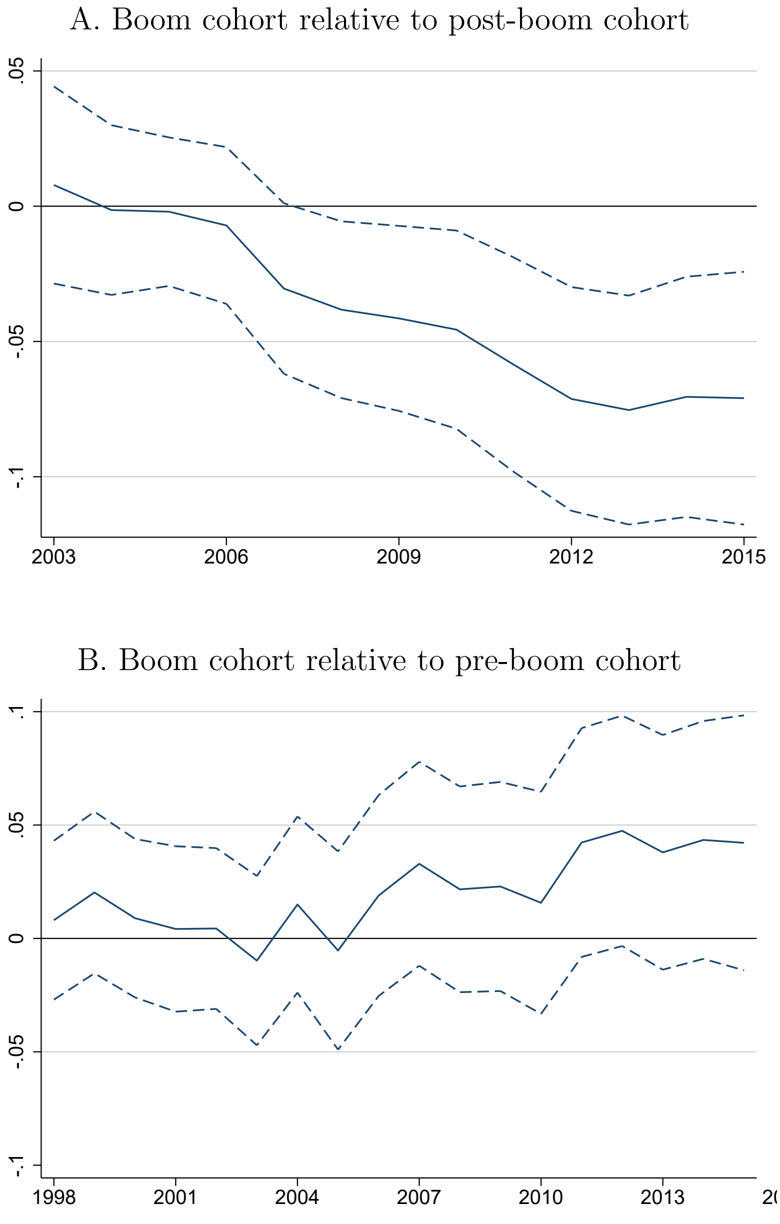
Figure 3: Wage Dynamics of Workers Starting in the ICT Sector Relative to Workers Starting in Other Sectors



Note. The figure displays the estimates of β_t^c in the simple-difference specification (1). 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).

[Back to Motivating Evidence]
[Back to Discussion of Post-Boom Cohort]
[Back to Section on Selection]

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



Note. The figure displays the estimates of β_t^{Boom} in the difference-in-differences specification (4). 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)
ICT_0×Boom cohort×2003-05	0.000					
	(0.013)					
ICT_0×Boom cohort×2006-10	-0.032**	-0.044***	-0.030***	-0.034***	-0.032***	-0.027**
	(0.014)	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
ICT_0×Boom cohort×2011-15	-0.069***	-0.074***	-0.060***	-0.062***	-0.062***	-0.056***
	(0.020)	(0.015)	(0.016)	(0.018)	(0.018)	(0.018)
Observations	95,091	94,710	94,710	93,940	93,940	93,747
Fixed Effects						
ICT_0×Year	✓	✓	✓	✓	✓	✓
Worker controls×Cohort×Year	✓	✓	✓	✓	✓	✓
Worker	—	✓	✓	✓	✓	✓
Pseudo firm×Year	—	—	✓	✓	✓	✓
Sales growth ($t \to t+5$) quintile×Year	—	—	—	✓	✓	✓
Entry wage quintile×Cohort×Year	—	—	—	—	✓	✓
Commuting zone×Cohort×Year	—	—	—	—	—	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. Column 2 adds worker fixed effects. Column 3 includes initial employer's pseudo-firm fixed effects based on ex-ante characteristics and include combinations of quintiles of employment, firm age, and labor productivity (i.e., $5 \times 5 \times 5 = 125$ pseudo firms) interacted with year fixed effects. Column 4 augments the pseudo-firm definition to include ex-post performance, measured by five-year forward sales growth quintiles, alongside the previous ex-ante characteristics. Column 5 includes entry wage quintile×cohort×year fixed effects. Column 6 includes commuting zone×cohort×year fixed effects. 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: Capital Availability and Human Capital Depreciation

	log(Wage)			
Proxy of capital availability:	1999 return (sector level)	Equity issuance (sector×geo×entry year level)		
	(1)	(2)	(3)	(4)
ICT_0×Boom cohort×2006-10	0.013	-0.014		-0.017
	(0.028)	(0.016)		(0.019)
ICT_0×Boom cohort×2011-15	0.011	-0.023		-0.023
	(0.041)	(0.022)		(0.027)
ICT_0×Capital availability×Boom cohort×2006-10	-0.056*	-0.042**	-0.036	-0.026
	(0.031)	(0.021)	(0.025)	(0.023)
ICT_0×Capital availability×Boom cohort×2011-15	-0.097**	-0.080***	-0.088**	-0.071**
	(0.046)	(0.030)	(0.036)	(0.033)
Observations	61,667	88,299	79,108	84,917
Fixed Effects				
ICT_0×Year	✓	✓	✓	✓
Worker controls×Cohort×Year	✓	✓	✓	✓
Worker	✓	✓	✓	✓
Industry×Cohort×Year	—	—	✓	—
Commuting zone×Cohort×Year	—	—	—	✓

Note. 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. *Boom cohort* 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 a dummy that takes the value one if the proxy of capital availability is above the sample median. 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 industry level at which the worker takes her first job. In columns 2 to 4, it is net equity issuance at the four-digit industry×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 3: Wage Regression by Sector-Level STEM Intensity

	log(Wage)				
	(1)	(2)	(3)	(4)	(5)
			Panel A: STEM sectors		
$\text{ICT}_0 \times$Boom cohort$\times$2006-10	-0.055***	-0.040***	-0.030	-0.032*	-0.033*
	(0.014)	(0.015)	(0.018)	(0.018)	(0.019)
$\text{ICT}_0 \times$Boom cohort$\times$2011-15	-0.104***	-0.091***	-0.078***	-0.082***	-0.087***
	(0.020)	(0.022)	(0.026)	(0.026)	(0.028)
Observations	47,139	47,123	45,331	45,331	44,989
			Panel B: Non-STEM sectors		
$\text{ICT}_0 \times$Boom cohort$\times$2006-10	0.007	0.011	0.004	0.003	0.010
	(0.026)	(0.027)	(0.034)	(0.034)	(0.037)
$\text{ICT}_0 \times$Boom cohort$\times$2011-15	0.019	0.024	0.034	0.036	0.029
	(0.039)	(0.042)	(0.053)	(0.054)	(0.056)
Observations	42,579	42,541	40,417	40,417	39,935
Fixed Effects					
$\text{ICT}_0 \times$Year	✓	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓	✓	✓
Worker	✓	✓	✓	✓	✓
Pseudo firm$\times$Year	—	✓	✓	✓	✓
Sales growth ($t \to t+5$) quintile$\times$Year	—	—	✓	✓	✓
Entry wage quintile$\times$Cohort$\times$Year	—	—	—	✓	✓
Commuting zone$\times$Cohort$\times$Year	—	—	—	—	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. The table estimates specification (5) on two separate samples. We compute the share of STEM workers among the workforce at the four-digit industry level and split industries at the sample median. Panel A reports the results for sectors above the sample median, and Panel B reports the results for the sectors below the sample median (i.e., sectors with lower share of STEM workers). The fixed effects used are the same as for Table 1, and progressively includes employer's pseudo firm using ex-ante characteristics, ex-post performance, work entry wage, and commuting zone, interacted with year and cohort fixed effects. 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 4: Wage Regression by Worker-Level STEM

	log(Wage)				
	(1)	(2)	(3)	(4)	(5)
			Panel A: STEM workers		
$\text{ICT}_0\times$Boom cohort$\times$2006-10	-0.046***	-0.033***	-0.037***	-0.035***	-0.026*
	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)
$\text{ICT}_0\times$Boom cohort$\times$2011-15	-0.076***	-0.065***	-0.070***	-0.070***	-0.062***
	(0.016)	(0.017)	(0.019)	(0.019)	(0.020)
Observations	63,016	63,012	61,479	61,479	61,240
			Panel B: Non-STEM workers		
$\text{ICT}_0\times$Boom cohort$\times$2006-10	-0.031	-0.017	-0.018	-0.019	-0.020
	(0.028)	(0.030)	(0.042)	(0.042)	(0.043)
$\text{ICT}_0\times$Boom cohort$\times$2011-15	-0.066	-0.040	-0.017	-0.017	-0.036
	(0.043)	(0.046)	(0.065)	(0.065)	(0.066)
Observations	31,236	31,200	28,414	28,414	27,854
Fixed Effects					
$\text{ICT}_0\times$Year	✓	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓	✓	✓
Worker	✓	✓	✓	✓	✓
Pseudo firm$\times$Year	—	✓	✓	✓	✓
Sales growth ($t \to t+5$) quintile$\times$Year	—	—	✓	✓	✓
Entry wage quintile$\times$Cohort$\times$Year	—	—	—	✓	✓
Commuting zone$\times$Cohort$\times$Year	—	—	—	—	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. The table estimates specification (5) on two separate samples. The first sample conditions on workers with a STEM occupation, and the second sample conditions on workers with a non-STEM occupation. The fixed effects used are the same as for Table 1, and progressively includes employer's pseudo firm using ex-ante characteristics, ex-post performance, work entry wage, and commuting zone, interacted with year and cohort fixed effects. 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 5: Capital Flow to STEM-Intensive Sectors

	Equity growth			
	(1)	(2)	(3)	(4)
STEM share	.025**	.011	.017*	-.0026
	(0.01)	(0.02)	(0.01)	(0.01)
STEM share×ICT			.093**	.12***
			(0.04)	(0.04)
ICT			.027**	.0099
			(0.01)	(0.01)
Observations	115,647	115,647	115,647	115,647
Fixed effects				
Year	✓	✓	✓	✓
Commuting zone	✓	✓	✓	✓
Broad sector	—	✓	—	✓

Note. The table presents OLS estimates for a panel at the four-digit industry×commuting zone×year, over the period 1998–2001. The dependent variable is the yearly growth rate of equity in the industry×commuting zone×year. *STEM Share* is the share of STEM workers in the cell, and *ICT* is a dummy equal to one if the industry belongs to the ICT sector. Columns 1 and 3 include year fixed effects and commuting zones fixed effects. Columns 2 and 4 additionally include broad sector fixed effects.

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Table 6: Firm Outcomes

	Sales growth					
	OLS	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)	(6)
ICT	-0.028	-0.245***	-0.165***	-0.063***	0.057***	0.178***
	(0.025)	(0.022)	(0.009)	(0.006)	(0.007)	(0.011)
Observations	95,091	94,710	94,710	93,940	93,940	93,747
Controls						
Firm sales	✓	✓	✓	✓	✓	✓

Note. The table presents OLS and quantile regressions of firm-level sales growth from 2001 to 2005 on ICT_0, a dummy equal to one if the firm is in the ICT sector, controlling for log of sales in 2001. Column 1 shows OLS, while columns 2 through 6 show quantile regressions for the 10th, 25th, 50th, 75th and 90th percentiles of sales growth. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 7: Quantile Wage Regressions

	log(Wage)				
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT$_0$×Boom cohort×2006-10	-0.051***	-0.050***	-0.049***	-0.048***	-0.047***
	(0.016)	(0.012)	(0.009)	(0.011)	(0.015)
ICT$_0$×Boom cohort×2011-15	-0.081***	-0.079***	-0.077***	-0.076***	-0.074***
	(0.017)	(0.012)	(0.009)	(0.012)	(0.016)
Observations	95,093	95,093	95,093	95,093	95,093
Fixed effects					
ICT$_0$×Year	✓	✓	✓	✓	✓
Worker controls×Cohort×Year	✓	✓	✓	✓	✓
Worker	✓	✓	✓	✓	✓

Note. The table presents quantile regressions of equation (5) 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. *Boom cohort* 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 8: Job Losses

	log(Wage)			
Job loss proxy:	Any transition	$\text{Wage}_t < \text{Wage}_{t_0}$	$\Delta Emp < -10\%$	Either (2) or (3)
	(1)	(2)	(3)	(4)
		Panel A: All workers		
$\text{ICT}_0 \times$Boom cohort	.0076	.044**	.04***	.068***
	(.022)	(.017)	(.014)	(.02)
Observations	11,374	11,374	11,374	11,374
		Panel B: STEM workers		
$\text{ICT}_0 \times$Boom cohort	-.0013	.032*	.034**	.058***
	(.024)	(.019)	(.016)	(.022)
Observations	7,260	7,260	7,260	7,260
		Panel C: Non-STEM workers		
$\text{ICT}_0 \times$Boom cohort	.054	.076*	.056*	.096**
	(.05)	(.04)	(.033)	(.047)
Observations	4,053	4,053	4,053	4,053
Fixed effects				
ICT_0	✓	✓	✓	✓
Worker controls×Cohort	✓	✓	✓	✓

Note. The table presents presents OLS estimates of cross-sectional regressions for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. The data is collapsed at the worker level. The dependent variable is a dummy that takes the value one if the worker has experienced a job loss in the four years following entry, and columns 1 through 4 use different proxies of job loss. In column 1, we use the probability of any job transition. In column 2 we use transitions that lead to a wage cut for the cut. In column 3 we use transition associated with employment at the worker's initial employer decreasing by 10% or more in the year of the transition. In column 4 we use transitions whether either condition happen. In Panel A, we use all the workers. In Panels B and C, we estimate the regression using only workers who started in a STEM occupation and in a non-STEM occupation, respectively. ICT_0 is a dummy equal to one if the worker started in the ICT sector. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. Worker controls include sex, age dummies, and two-digit occupation at entry. Robust standard errors are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table 9: Controlling for Job Losses

	log(Wage)			
Job loss proxy:	Any transition	$\text{Wage}_t < \text{Wage}_{t_0}$	$\Delta Emp < -10\%$	Either (2) or (3)
	(1)	(2)	(3)	(4)
$\text{ICT}_0\times$Boom cohort$\times$2006-10	-0.044***	-0.042***	-0.043***	-0.042***
	(0.010)	(0.010)	(0.010)	(0.010)
$\text{ICT}_0\times$Boom cohort$\times$2011-15	-0.074***	-0.072***	-0.074***	-0.072***
	(0.015)	(0.015)	(0.015)	(0.015)
	(0.015)	(0.015)	(0.015)	(0.015)
Job loss$\times$2006-10		-0.046***	-0.008	-0.035***
		(0.006)	(0.007)	(0.005)
Job loss$\times$2011-15		-0.052***	-0.006	-0.034***
		(0.009)	(0.010)	(0.008)
Observations	94,710	94,710	94,710	94,710
Fixed effects				
$\text{ICT}_0\times$Year	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓	✓
Worker	✓	✓	✓	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. *Job loss* is a dummy that takes the value one if the worker experienced a job termination within the first four years after entry, using three different proxies of job termination: the worker experiences a job transition and (i) the transition leads to a wage cut for the worker (column 2); (ii) employment at the worker's initial employer decreases by 10% or more in the year of the job transition (column 3); (iii) either happens (column 4). Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Online Appendix

A Data

The replication package is available 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

Table B.1: Summary Statistics

	N	Mean	P25	P50	P75
			Panel A: All skilled workers		
Annual wage	2,015,188	51,081	32,765	42,321	57,705
Male	2,015,188	0.69	0	1	1
Age	2,015,188	42.8	35	43	51
			Panel B: Skilled workers entering the labor force over 1994–2005		
Annual wage	249,577	45,942	29,985	39,080	52,824
Male	249,577	0.68	0	1	1
Age at entry	249,577	26.0	25	26	27

Note. 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.

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Table B.2: ICT Industries

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	3.0
Data processing	*7230*	0.3	0.8
Maintenance computers	*7250*	0.1	0.1
Other data/computer-related services	*7123,7240,7290*	0.1	0.2
ICT: Telecommunications		**1.2**	**2.0**
Telecommunications	*6420*	1.2	2.0
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		**0.4**	**1.2**
Computers, electronics, telecom	*5151,5152*	0.4	1.2
ICT: Total		**5.0**	**14.4**

Note. 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.

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B.1 Return to Experience

To estimate the return to experience in our sample, we use the same sample of high-skill workers from the boom and post-boom cohorts as in our main regressions. We regress the log real wage on age. As is standard, it is not possible to identify jointly the effects of age, cohorts, and time, because each variable is the sum or subtraction of the two other variables. It implies that it is not possible to control for both cohort fixed effects and time fixed effects in the wage regression on age.

We therefore consider two specifications that control either for cohort effects or for time effects. In column 1 of Table B.3, we include an individual fixed effect, which account for cohort effects as well as any other time-invariant individual characteristics. In column 2, we include year fixed effects, as well as time-invariant individual characteristics (sex, occupation at entry, and sector at entry).

The point estimates imply that one additional year of experience leads to a 3.2% to 4.4% wage increase.

Table B.3: Return to Experience

	log(Wage)	
	(1)	(2)
Age	0.044***	0.032***
	(0.000)	(0.001)
Observations	94,712	95,088
Fixed Effects		
Worker	✓	✓
Year	✓	✓
Worker controls	✓	✓

Note. 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 real wage of worker i in year t. Standard errors are clustered at the individual level. Worker controls include sex, two-digit occupation at entry, and industry at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

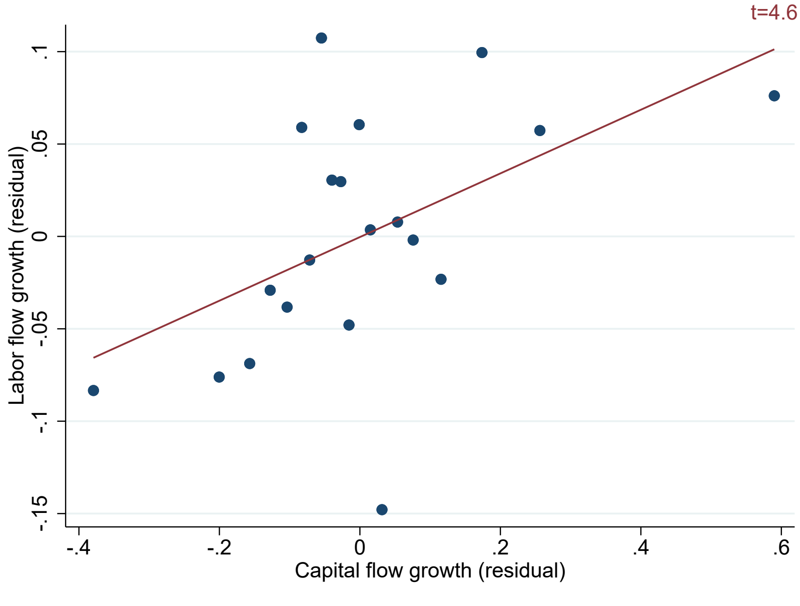
B.2 Correlation between Capital Flows and Labor Flows

In this appendix, we show that capital flows are correlated with labor flows. We construct capital flow at the four-digit industry×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 industry×commuting zone×year level for the years 1998 to 2005, controlling for four-digit industry fixed effects, commuting zone fixed effects, and year fixed effects. To visualize the results, in Figure B.1, 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 15% increase in labor flow.

Table B.4 reports the results in a regression format. Consistent with Figure B.1, 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.1: Capital Flows and Labor Flows



Note: The figure shows average labor flow by 20 quantiles of capital flow at the four-digit industry×commuting zone×year over the period 1998–2001. Capital flow is defined as the mid-point growth rate of share equity. Labor growth is defined as the mid-point growth rate of the number of skilled labor market entrants. Both variables are residuals of regressions on four-digit industry, commuting zone, and year fixed effects. Standard errors are clustered at the industry×commuting zone level.

Table B.4: Capital Flows and Labor Flows

	Labor flow	
	(1)	(2)
Capital flow	0.22***	0.18**
	(0.07)	(0.08)
Capital flow×ICT		0.10
		(0.16)
Observations	5,541	5,541
Fixed Effects		
Year	✓	✓
Sector	✓	✓
Commuting zone	✓	✓

Note. The table presents OLS estimates for yearly labor flow regressed on yearly capital flow at the four-digit industry×commuting zone×year level over the period 1998–2001. Capital flow is defined as growth of net equity issuance. In column 2, the non-interacted ICT dummy is absorbed by the sector fixed effects. Standard errors are clustered at the industry×commuting zone level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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B.3 Additional Robustness

Table B.5: Robustness

	log(Wage)				log(Wage+Cap.income)	
	Baseline			Excl. finance	Capital income assigned to CEOs	Skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ICT}_0 \times$Boom cohort$\times$2006-10	-0.044***	-0.044***	-0.039***	-0.045***	-0.047***	-0.047***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
$\text{ICT}_0 \times$Boom cohort$\times$2011-15	-0.074***	-0.070***	-0.066***	-0.076***	-0.072***	-0.078***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)
Observations	94,710	94,700	94,700	89,344	94,710	94,710
Fixed effects						
$\text{ICT}_0 \times$Year	✓	✓	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓	✓	✓	✓
Worker	✓	✓	✓	✓	✓	✓
Pseudo current employer$\times$Year	—	✓	✓	—	—	—

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. Column 1 is the baseline regression (column 2 of Table 1). In column 2, we add pseudo-firm fixed effect for the worker's current employer based on combinations of quintiles of employment, firm age, and labor productivity, interacted with year fixed effects. In column 4, we exclude workers starting in the financial sector. In columns 5 and 6, the dependent variable is log wage plus capital income. In column 5, capital income is equal to the employer's profits if the worker is the CEO of the firm. In column 6, 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. 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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B.4 Cumulative Earnings

We estimate equation (1) 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 (5) 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 cumulative earnings are defined from the entry year to a specific year t.

The dependent variable is the log of cumulative earnings in column 1 of Table B.6. High-skill workers starting in the ICT sector during the boom earn cumulative earnings from entry to 2015 that are 6.4% 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 26,000 euros.

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. 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.[21] If anything, accounting

21. 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 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.

for unemployment benefits increases slightly the cumulative earnings loss.

Table B.6: Cumulative Earnings

	Cumulative Earnings		
	Log	Level (in Euro)	Level incl. UB (in Euro)
	(1)	(2)	(3)
$\text{ICT}_0 \times 2001$	.037***	1593**	1844**
	(.01)	(764)	(735)
$\text{ICT}_0 \times 2005$	-.0028	-1597	-1791
	(.014)	(1962)	(1934)
$\text{ICT}_0 \times 2010$	-.04**	-13095***	-13462***
	(.018)	(3777)	(3739)
$\text{ICT}_0 \times 2015$	-.064***	-26026***	-27079***
	(.02)	(6040)	(6025)
Observations	121,285	121,285	121,285
Fixed effects			
$\text{ICT}_0 \times$Year	✓	✓	✓
Worker controls×Year	✓	✓	✓

Note. 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 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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B.5 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. 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.7: Education

	=1 if Master's degree		
	(1)	(2)	(3)
ICT_0	0.001	-0.008	-0.041
	(0.031)	(0.034)	(0.034)
$\text{ICT}_0 \times$Boom cohort	0.012	-0.001	0.011
	(0.038)	(0.040)	(0.041)
Observations	1,221	1,220	1,180
Fixed effects			
Worker controls×Cohort	✓	✓	✓
Occupation	—	✓	✓
Commuting zone	—	—	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. All specifications include worker controls (sex, age and entry year dummies) interacted with cohort fixed effects. Columns 2 add occupation at entry fixed effects. Columns 3 add commuting zone 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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B.6 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 (5).

Results are reported in Table B.8. 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.8: Attrition

	=1 if exits in $t+1$		
	(1)	(2)	(3)
Wage growth$_{i,t-2\rightarrow t}$	-0.005	-0.013*	-0.001
	(0.006)	(0.007)	(0.011)
Wage growth$_{i,t-2\rightarrow t}\times$ICT$_0$		0.026**	0.022
		(0.013)	(0.021)
Wage growth$_{i,t-2\rightarrow t}\times$Boom cohort			-0.018
			(0.014)
Wage growth$_{i,t-2\rightarrow t}\times$ICT$_0\times$Boom cohort			0.007
			(0.023)
Observations	45,453	45,453	45,453
Fixed effects			
ICT$_0\times$Year	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓
Worker	✓	✓	✓
Industry$\times$Year	✓	✓	✓

Note: 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$_{i,t-2\rightarrow t}$ 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. *Boom cohort* 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.

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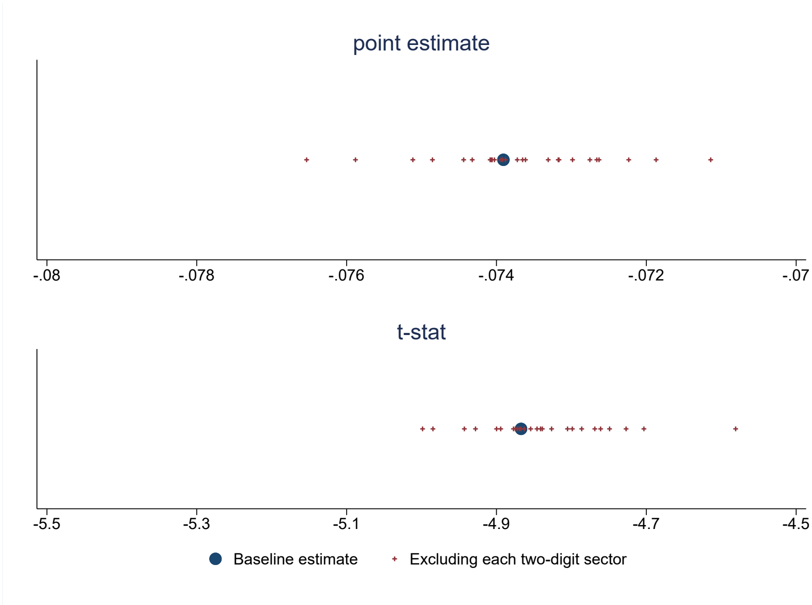
To check that the results are not driven by the wage dynamics in any of the non-ICT sectors in the control group, we re-run the baseline regression in column 2 of Table B.5 excluding workers starting in each of the two-digit non-ICT sectors, resulting in 26 different regressions. Figure B.2 plots the distribution of the point estimate and t-statistic for the coefficient of interest on $ICT_{i,0} \times BoomCohort_i \times$ 2011-15. The blue dot is the baseline result in the full sample. The results are consistent across subsamples.

Figure B.2: Excluding Sectors One By One



Note. The figures reports the point estimate and t-stat for each 26 different regressions when we estimate our baseline regression (5) excluding workers starting in each of the two-digit non-ICT sectors.

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Table B.9: Subsample Analysis: High Growth Firms and US Firms

	log(Wage)	
Sample:	Firm growth top 75^{th}	US subsidiaries
	(1)	(2)
$\text{ICT}_0 \times$Boom cohort$\times$2006-10	-0.058**	-0.038
	(0.023)	(0.038)
$\text{ICT}_0 \times$Boom cohort$\times$2011-15	-0.066**	-0.096*
	(0.033)	(0.051)
Observations	16,694	8,077
Fixed effects		
$\text{ICT}_0 \times$Year	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓
Worker	✓	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. Column 1 restricts the sample to workers who start in firms that belong to the top quartile of five-year forward sales growth, where the quartiles are defined by year. Column 2 restricts the sample to workers who start in the subsidiary of a US firm. These establishments are identified by using the ownership data, and we defined a firm as "American" if it is 100% owned by a US company. 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 B.10: Controlling for Job Losses

	log(Wage)			
Job loss proxy:	Any transition	$\text{Wage}_t < \text{Wage}_{t_0}$	$\Delta Emp < -10\%$	Either (2) or (3)
	(1)	(2)	(3)	(4)
$\text{ICT}_0 \times$Boom cohort$\times$2006-10	-0.044***	-0.037***	-0.042***	-0.037***
	(0.010)	(0.011)	(0.011)	(0.012)
$\text{ICT}_0 \times$Boom cohort$\times$2011-15	-0.074***	-0.068***	-0.070***	-0.066***
	(0.015)	(0.017)	(0.016)	(0.017)
Job termination$\times$2006-10		-0.103***	0.004	-0.066***
		(0.012)	(0.016)	(0.011)
Job loss$\times$2011-15		-0.118***	0.022	-0.066***
		(0.017)	(0.022)	(0.016)
Job loss$\times\text{ICT}_0\times$2006-10		0.040*	0.022	0.039**
		(0.021)	(0.027)	(0.019)
Job loss$\times\text{ICT}_0\times$2011-15		0.037	0.031	0.046*
		(0.029)	(0.041)	(0.028)
Job loss$\times$Boom cohort$\times$2006-10		0.074***	-0.026	0.034**
		(0.016)	(0.020)	(0.014)
Job loss$\times$Boom cohort$\times$2011-15		0.091***	-0.050*	0.032
		(0.022)	(0.028)	(0.020)
Job loss $\times$ $\text{ICT}_0\times$Boom cohort$\times$2006-10		-0.029	-0.009	-0.019
		(0.025)	(0.031)	(0.023)
Job loss $\times$ $\text{ICT}_0\times$Boom cohort$\times$2011-15		-0.029	-0.021	-0.026
		(0.037)	(0.048)	(0.034)
Observations	94,710	94,710	94,710	94,710
Fixed effects				
$\text{ICT}_0\times$Year	✓	✓	✓	✓
Worker controls$\times$Cohort$\times$Year	✓	✓	✓	✓
Worker	✓	✓	✓	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *2003–05*, *2006–10*, and *2011–15* are dummies equal to one if year t belongs to the corresponding time period. *Job loss* is a dummy that takes the value one if the worker experienced a job termination within the first four years after entry, using three different proxies of job termination: the worker experiences a job transition and (i) the transition leads to a wage cut for the worker (column 2); (ii) employment at the worker's initial employer decreases by 10% or more in the year of the job transition (column 3); (iii) either happens (column 4). 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 B.11: Wage Discount in Local Labor Markets with High vs. Low Job Losses

	log(Wage)			
Job loss proxy:	Any transition	$\text{Wage}_t < \text{Wage}_{t_0}$	$\Delta Emp < -10\%$	Either (2) or (3)
	(1)	(2)	(3)	(4)
	Panel A: Labor markets with high job losses			
ICT_0×Boom cohort×2006-10	-0.053***	-0.051***	-0.053***	-0.051***
	(0.014)	(0.014)	(0.014)	(0.014)
ICT_0×Boom cohort×2011-15	-0.080***	-0.078***	-0.080***	-0.079***
	(0.020)	(0.020)	(0.020)	(0.020)
Job termination×2006-10		-0.044***	-0.011	-0.037***
		(0.007)	(0.010)	(0.007)
Job termination×2011-15		-0.056***	-0.004	-0.039***
		(0.011)	(0.014)	(0.010)
Observations	45,593	45,593	45,593	45,593
	Panel B: Labor markets with low job losses			
ICT_0×Boom cohort×2006-10	-0.025*	-0.023	-0.025	-0.023
	(0.015)	(0.015)	(0.015)	(0.015)
ICT_0×Boom cohort×2011-15	-0.052**	-0.050**	-0.051**	-0.049**
	(0.022)	(0.022)	(0.022)	(0.022)
Job termination×2006-10		-0.055***	-0.010	-0.039***
		(0.009)	(0.009)	(0.008)
Job termination×2011-15		-0.058***	-0.016	-0.040***
		(0.013)	(0.014)	(0.011)
Observations	48,519	48,519	48,519	48,519
Fixed effects				
ICT_0×Year	✓	✓	✓	✓
Worker controls×Cohort×Year	✓	✓	✓	✓
Worker	✓	✓	✓	✓

Note. 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. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. *Job loss* is a dummy that takes the value one if the worker experienced a job termination within the first four years after entry, using three different proxies of job termination: the worker experiences a job transition and the transition leads to a wage cut for the worker (column 2); employment at the worker's initial employer decreases by 10% or more in the year of the job transition (column 3); either happens (column 4). Regressions are estimated in split samples. We compute local market job losses as the average yearly termination rate at the commuting zone×occupation level over 2002–2005, and split along the median sample. 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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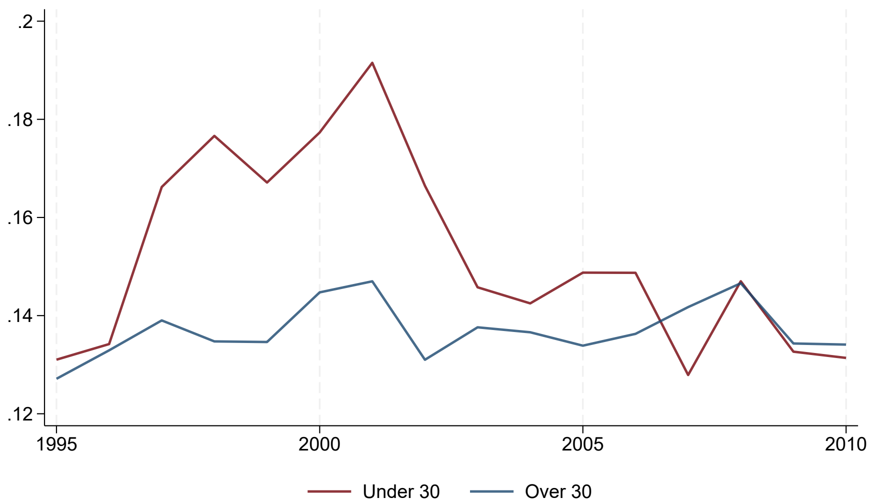
C Employment Share of ICT in the US

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 in Figure 2b for France, the share of skilled labor market entrants joining 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



Note. 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.

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D A Model of Wage Dynamics with On-the-job Human Capital Accumulation

D.1 Setup and Key Dynamics

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.[22] 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.[23] $H_{i,c,k,t}$ represents the number of efficiency units of labor supplied by the worker. A worker's human capital has two components:

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

$\theta_{i,k}$ is a worker fixed effect reflecting time-invariant ability within the sector. $(h_{c,k,t})_{t \geq c}$ is a process driving post-entry human capital accumulation and depreciation given by:

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

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

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:

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

22. The assumption of no sectoral mobility can be derived as a result if human capital accumulated on-the-job is sector specific and is consistent with the limited reallocation of seasoned workers to the ICT sector that we document in Figure 2b.

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

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:

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

where $w_{k,t}$ is the wage rate in sector k in period t. Equation (D.5) is equation (2) in the main text; it is the key equation for our empirical analysis. It shows that worker-level wages have three components: the fixed type of the worker ($\theta_{i,k}$), human capital accumulated since entry ($h_{c,k,t}$), and the sector-level wage rate ($w_{k,t}$). We show in Section 3.3 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).

D.2 Labor Supply and 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:

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

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.[24]

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:

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

$Z_{k,t}$ 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 (D.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 function:

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

where $A_k > 0$ and $\sigma > 1$. The wage rate per efficiency unit of labor in sector k period t

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

is determined by the marginal productivity of labor:[25]

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

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

D.3 Solving for the 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 (D.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 (D.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 (D.2)–(D.3), sectoral allocation of cohort c can be rewritten as:

$$\mathcal{I}_{1,c,c} = \left\{ i : \sum_{t=c}^{\infty} \beta^{t-c} \left(\mathbb{E}_c[w_{k,1} - w_{k,2}] + \theta_{i,1} - \theta_{i,2}\right) > \gamma_{i,1} - \gamma_{i,2} \right\}. \tag{D.10}$$

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

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

$$E_{k,c} = \int_{i \in \mathcal{I}_{1,c,c}} di \tag{D.11}$$

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.18)).

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:*

$$\begin{aligned} \Delta w_t &\simeq \Delta w^* + w_z \,.\, \Delta z_t + w_\ell \,.\, \big(\Delta \ell_t - \Delta \ell^*\big) + w_h \,.\, \Delta \overline{dh}_t, && \text{(D.12)} \\ \Delta E_t &\simeq \Delta E^* + E_z \,.\, \Delta z_t + E_\ell \,.\, \big(\Delta \ell_t - \Delta \ell^*\big) + E_h \,.\, \Delta \overline{dh}_t, && \text{(D.13)} \end{aligned}$$

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:

$$\Delta \ell_{t+1} - \Delta \ell^* \simeq (1-\delta) e^{\mu_h} \,.\, \big(\Delta \ell_t - \Delta \ell^*\big) + \ell_E \,.\, \big(\Delta E_t - \Delta E^*\big) + \Delta \overline{dh}_{t+1}, \tag{D.14}$$

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.12)) in order to induce more entry in sector 1 ($E_z > 0$ in (D.13)). Therefore, a positive productivity shock in the ICT sector in the late 1990s can explain the high entry rate (see Figure 2c) and the concomitant high wages (Figure 3) 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.12)), which reduces entry in sector 1 ($E_\ell < 0$ in (D.13)).

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.14) 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.4 Proof of Proposition 1

Law of motion of old labor. Let

$$L_{k,t}^{new} = \int_{i \in \mathcal{I}_{k,t,t}} H_{i,t,k,t}\, di \tag{D.15}$$

denote the efficient quantity of labor supplied by new workers in sector k in period t. (D.10) implies that $L^{new}_{k,t}$ is a function of the expected intertemporal wage differential between the two sectors:

$$L^{new}_{k,t} = \mathcal{L}^{new}_k\Big(\sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}[\Delta w_\tau]\Big), \tag{D.16}$$

where

$$\mathcal{L}^{new}_1(\mathcal{W}) = \int_{\mathcal{W}+\Delta\theta_i > \Delta\gamma_i} e^{\theta_{i,1}}\, di, \qquad \mathcal{L}^{new}_2(\mathcal{W}) = \int_{\mathcal{W}+\Delta\theta_i \leq \Delta\gamma_i} e^{\theta_{i,2}}\, di. \tag{D.17}$$

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

$$\begin{aligned} L_{k,t+1} = (1-\delta)e^{\mu_h}\big(L_{k,t} + L^{new}_{k,t}\big) + \sum_{c=-\infty}^{t-1}(1-\delta)^{t+1-c}\Big(\int_{i\in\mathcal{I}_{k,c,c}} H_{i,c,k,t}\, di\Big)\big(dH_{c,k,t+1} - e^{\mu_h}\big) \\ + (1-\delta)L^{new}_{k,t}\big(dH_{t,k,t+1} - e^{\mu_h}\big). \end{aligned} \tag{D.18}$$

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:

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

(D.18) at steady state implies:

$$L^*_k = g(L^*_k + L^{new*}_k) = \frac{g}{1-g}L^{new*}_k, \tag{D.19}$$

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

$$\Delta w^* = \Delta a - \frac{1}{\sigma}\log\left(\frac{\mathcal{L}^{new}_1\left(\frac{\Delta w^*}{1-\beta}\right)}{\mathcal{L}^{new}_2\left(\frac{\Delta w^*}{1-\beta}\right)}\right). \tag{D.20}$$

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.20) uniquely pins down Δw^*.

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

$$\Delta w_t - \Delta w^* \simeq w_z.\Delta z_t + w_\ell.\big(\Delta \ell_t - \Delta \ell^*\big) + w_h.\Delta \overline{dh}_t, \tag{D.21}$$

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 (D.7), and write the total efficient quantity of labor as the sum over old workers and new workers:

$$x_{k,t} = z_{k,t} + \log\left(L_{k,t} + L_{k,t}^{new}\right). \tag{D.22}$$

We linearize the log efficient quantity of labor:

$$\begin{aligned}\log\left(L_{k,t} + L_{k,t}^{new}\right) - \log\left(L_{k,t}^* + L_{k,t}^{new*}\right) &\simeq \frac{L_{k,t}^*\big(\ell_{k,t} - \ell_k^*\big) + L_{k,t}^{new*}\big(\ell_{k,t}^{new} - \ell_k^{new*}\big)}{L_{k,t}^* + L_{k,t}^{new*}} \\ &= g.\big(\ell_{k,t} - \ell_k^*\big) + (1-g).\big(\ell_{k,t}^{new} - \ell_k^{new*}\big), \end{aligned} \tag{D.23}$$

where the latter equality follows from (D.19). We calculate the difference between (D.22) for $k=1$ and (D.22) for $k=2$, and use (D.23) to substitute $\log(L_{k,t} + L_{k,t}^{new})$. We obtain:

$$\Delta x_t \simeq \Delta z_t + \log\left(\frac{L_{1,t}^* + L_{1,t}^{new*}}{L_{2,t}^* + L_{2,t}^{new*}}\right) + g.\big(\Delta \ell_t - \Delta \ell^*\big) + (1-g).\big(\Delta \ell_t^{new} - \Delta \ell^{new*}\big). \tag{D.24}$$

Using (D.19) and (D.20), the term in big parenthesis in (D.24) is equal to $\sigma \Delta a - \sigma \Delta w^*$. Plugging (D.24) into the labor demand function (D.9), we obtain:

$$\Delta w_t - \Delta w^* \simeq \frac{\sigma - 1}{\sigma}\Delta z_t - \frac{g}{\sigma}\big(\Delta \ell_t - \Delta \ell^*\big) - \frac{1-g}{\sigma}\big(\Delta \ell_t^{new} - \Delta \ell^{new*}\big). \tag{D.25}$$

We combine (D.21) and (D.25) to obtain:

$$\Delta\ell_t^{new} - \Delta\ell^{new*} \simeq \frac{\sigma - 1 - \sigma w_z}{1-g}\Delta z_t - \frac{g + \sigma w_\ell}{1-g}\big(\Delta\ell_t - \Delta\ell^*\big) - \frac{\sigma w_h}{1-g}\Delta\overline{dh}_t. \tag{D.26}$$

Expected future wages. We consider (D.21) evaluated at time $t+\tau$, and take expectations conditional on beginning of period t information. We obtain:

$$\mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] \simeq w_z\mathbb{E}_t\big[\Delta z_{t+\tau}\big] + w_\ell\mathbb{E}_t\big[\Delta\ell_{t+\tau} - \Delta\ell^*\big] + w_h\mathbb{E}_t\big[\Delta\overline{dh}_t\big]. \tag{D.27}$$

We linearize the law of motion of the efficient quantity of labor supplied by old workers, given by (D.18):

$$\ell_{k,t+1} - \ell_k^* \simeq g.\big(\ell_{k,t} - \ell_k^*\big) + (1-g).\big(\ell_{k,t}^{new} - \ell_k^{new^*}\big) + \overline{dh}_{k,t+1}, \tag{D.28}$$

where

$$\begin{aligned}\overline{dh}_{k,t+1} = \sum_{c=-\infty}^{t-1} &\frac{(1-\delta)^{t+1-c}e^{\mu_h}\int_{i\in\mathcal{I}_{k,c,c}} H_{i,c,k,t}\,di}{L_k^*}\big(dh_{c,k,t+1} - \mu_h\big) \\ &+ \frac{(1-\delta)e^{\mu_h}L_{k,t}^{new}}{L_k^*}\big(dh_{t,k,t+1} - \mu_h\big) \equiv \sum_{c=-\infty}^{t} q_{t-c}\big(dh_{c,k,t+1} - \mu_h\big).\end{aligned} \tag{D.29}$$

A first-order approximation of the weights is:

$$q_{t-c} \simeq \frac{(1-\delta)^{t+1-c}(e^{\mu_h})^{t+1-c}L_k^{new*}}{L_k^*} = (1-g)g^{t-c}. \tag{D.30}$$

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

$$\overline{dh}_{k,t+1} = g\rho_h\overline{dh}_{k,t} + g\varepsilon_{k,t+1}^h. \tag{D.31}$$

We calculate the difference between (D.28) for $k=1$ and (D.28) for $k=2$:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq g.\big(\Delta\ell_t - \Delta\ell^*\big) + (1-g).\big(\Delta\ell_t^{new} - \Delta\ell^{new*}\big) + \Delta\overline{dh}_{t+1}. \tag{D.32}$$

Using (D.26) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (D.32), we obtain:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq -\sigma w_\ell\big(\Delta\ell_t - \Delta\ell^*\big) + (\sigma - 1 - \sigma w_z)\Delta z_t + \Delta\overline{dh}_{t+1}. \tag{D.33}$$

Therefore:

$$\Delta\ell_{t+\tau} - \Delta\ell^* \simeq (-\sigma w_\ell)^\tau\big(\Delta\ell_t - \Delta\ell^*\big) + \sum_{s=0}^{\tau-1}(-\sigma w_\ell)^{\tau-1-s}\Big[(\sigma - 1 - \sigma w_z)\Delta z_{t+s} + \Delta\overline{dh}_{t+s+1}\Big]. \tag{D.34}$$

We use (D.34) to substitute $\Delta\ell_{t+\tau} - \Delta\ell^*$ in (D.27), 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:

$$\begin{aligned}\mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] &\simeq \left[w_z\rho_z^\tau + w_\ell(\sigma - 1 - \sigma w_z)\frac{(-\sigma w_\ell)^\tau - \rho_z^\tau}{(-\sigma w_\ell) - \rho_z}\right]\Delta z_t \\ &+ w_\ell(-\sigma w_\ell)^\tau\big(\Delta\ell_t - \Delta\ell^*\big) + \left[w_h(g\rho_h)^{\tau+1} + w_\ell g\rho_h\frac{(-\sigma w_\ell)^\tau - (g\rho_h)^\tau}{(-\sigma w_\ell) - g\rho_h}\right]\Delta\overline{dh}_t \end{aligned} \tag{D.35}$$

if $(-\sigma w_\ell) \neq \rho_z$ and $(-\sigma w_\ell) \neq g\rho_h$. The fraction on the first line of (D.35) is equal to $\tau\rho_z^{\tau-1}$ if $(-\sigma w_\ell) = \rho_z$. The fraction on the second line of (D.35) is equal to $\tau(g\rho_h)^{\tau-1}$ if $(-\sigma w_\ell) = g\rho_h$.

We use (D.35) to calculate the intertemporal wage difference between the two sectors:

$$\begin{aligned}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*] &\simeq \left[\frac{w_z}{1-\beta\rho_z} + w_\ell(\sigma - 1 - \sigma w_z)\frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta\rho_z)}\right]\Delta z_t \\ &+ \frac{w_\ell}{1+\beta\sigma w_\ell}\big(\Delta\ell_t - \Delta\ell^*\big) + \left[\frac{w_h g\rho_h}{1-\beta g\rho_h} + w_\ell g\rho_h\frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta g\rho_h)}\right]\Delta\overline{dh}_t, \end{aligned} \tag{D.36}$$

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:

$$E_{1,t} - E_1^* = -\big(E_{2,t} - E_2^*\big) \simeq \sigma\eta\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*]. \tag{D.37}$$

We linearize the efficient quantity of labor supplied by new workers in sector k, given by (D.15):

$$\big(\ell_{k,t}^{new} - \ell_k^{new*}\big) L_k^{new*} \simeq \big(E_{k,t} - E_k^*\big) \mathbb{E}\big[e^{\theta_{i,k}} | \gamma_i = \Delta^* + \Delta\theta_i\big]. \tag{D.38}$$

We use (D.37) to substitute $E_{k,t} - E_k^*$ in (D.38), and we use $L_1^{new*} + L_2^{new*} = \mathbb{E}\big[e^{\theta_i}\big]$. We obtain:

$$\Delta\ell_t^{new} - \Delta\ell^{new^*} \simeq \sigma\eta\alpha \sum_{\tau=t}^{\infty} \beta^{\tau-t} \mathbb{E}_t[\Delta w_\tau - \Delta w^*], \tag{D.39}$$

where

$$\alpha = \frac{\mathbb{E}\big[e^{\theta_{i,1}} | \gamma_i = \Delta^* + \Delta\theta_i\big]}{L_1^{new*}} + \frac{\mathbb{E}\big[e^{\theta_{i,2}} | \gamma_i = \Delta^* + \Delta\theta_i\big]}{L_2^{new*}} \tag{D.40}$$

and the intertemporal sectoral wage difference in (D.39) is given by (D.36).

Solving for (w_z, w_ℓ, w_h)**.** Equalizing (D.26) and (D.39), we obtain that the sectoral wage differential is given by (D.12). 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:

$$w_z = \left[\frac{1 - \beta\rho_z}{\alpha\eta(1-g)} + \frac{-\beta\sigma w_\ell}{1 + \beta\sigma w_\ell}\right] \left(\frac{\sigma - 1}{\sigma} - w_z\right) \tag{D.41}$$

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:

$$w_h = \frac{-w_\ell \beta g \rho_h \alpha\eta(1-g)}{(1 + \beta\sigma w_\ell)(1 - \beta g\rho_h + (1-g)g\rho_h\alpha\eta)}. \tag{D.42}$$

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.37) and (D.39), we obtain:

$$\Delta E_t - \Delta E^* \simeq \frac{2}{\alpha}\big(\Delta\ell_t^{new} - \Delta\ell^{new*}\big). \tag{D.43}$$

Using (D.26) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (D.43), we obtain that entry is given by (D.13), where

$$E_z = \frac{2\sigma}{\alpha(1-g)}\left(\frac{\sigma-1}{\sigma} - w_z\right) > 0, \tag{D.44}$$

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

$$E_\ell = -\frac{2(g+\sigma w_\ell)}{\alpha(1-g)} < 0, \tag{D.45}$$

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

$$E_h = -\frac{2\sigma w_h}{\alpha(1-g)} \leq 0, \tag{D.46}$$

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

Solving for ℓ_E. Using (D.43) to substitute $\ell_{k,t}^{new} - \ell_k^{new*}$ in (D.32), we obtain that the law of motion of efficient quantity of old labor is given by (D.14), where

$$\ell_E = \frac{1}{2}\alpha(1-g) > 0, \tag{D.47}$$

and the law of motion of $\Delta\overline{dh}_t$ is given by (D.31).