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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.

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Key words: innovation, human capital, financing

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1 Introduction

Technological change evolves not at a constant rate but by jumps, where breakthroughs trigger a period of intense experimentation, followed by a long period of stabilization as technologies mature (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 talent, which accelerates experimentation and development of frontier technologies (e.g., Kerr and Nanda, 2015). 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.

If capital-fueled technology booms reallocate skilled workers across sectors in ways that affect their human capital, these events will have lasting effects on aggregate labor productivity—a channel largely overlooked. We investigate how the human capital of skilled workers who join the innovative sector during a technological and financial boom evolves after they embed 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 firms during the boom and later undergo a sharp correction. However, the technologies developed during the boom may quickly become obsolete, depreciating workers' human capital. 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 two challenges: neither workers' exposure to different technology vintages nor the value of their human capital is directly observable; and we must 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 Communication 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, it featured 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

1. Using USPTO patents, we confirm in Appendix B.9 that ICT-related technologies displayed an increase in technological experimentation and overvaluation during this period. See also Brown, Fazzari,

distant enough to study long-term effects. We use French matched employer-employee data from 1994 to 2015, linked to firms' financial statements from tax filings.[2]

Because the ICT boom is distinctly delineated in time, we 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 during the boom.

We show that workers who start in the ICT sector during the boom earn significantly 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%—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, accounting 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 rapidly evolving technologies during the ICT boom quickly depreciates. Consistent with this, we find that the magnitude of the wage discount increases with the duration of exposure to the ICT boom: within the boom cohort, workers who entered the ICT sector earlier experience larger long-term human capital depreciation than those who entered later. As the technologies stabilize, workers who start in ICT post-boom—whose human capital, by design, was not exposed to the technological experimentation of the boom years—exhibit the same wage dynamics as comparable workers who started in other sectors. This result holds when we include high-dimensional fixed effects for firms' ex-ante

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.

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 comparison, within firm characteristics and across cohorts, 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.

Using the pre-boom cohort as an additional comparison group, we rule out the possibility that the long-run wage discount is explained by negative selection during the boom (i.e., the bubbly ICT sector attracts less able workers). We show that the workers starting in the ICT sector during the pre-boom period experience a long-run wage discount quantitatively similar to that of workers from the boom cohort. Since the pre-boom cohort of workers sorted into jobs before the ICT boom started, 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 and human capital depreciation, we find that firms receiving large inflows of financial capital during the boom are those whose workers' human capital depreciates most. The inflow of financial capital both increases the number of workers exposed to human capital depreciation and amplifies the depreciation each worker experiences, reducing 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 models of embedded technological change, which argue that economies have overlapping vintages of technologies that are embodied in workers (e.g., Chari and Hopenhayn, 1991; Deming and Noray, 2020; Braxton and Taska, 2023). New workers introduce newer technology vintages, making human capital tied to older vintages obsolete. 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.

To test prediction (i), we measure the pace of technological experimentation and obsolescence using patent data from the USPTO. We construct three measures: the average age of cited patents, the dispersion of citations received, and a text-based measure of novel language. These measures confirm that ICT technologies developed during the boom displayed higher levels of experimentation and obsolescence—ICT patents cited younger patents, showed greater variance in citation impact, and employed more novel terminology. The wage discount is concentrated among workers who started in sectors where technologies became obsolete faster, while workers in sectors with slower obsolescence experience little to no wage discount.

We test prediction (ii) in two ways. First, using the share of STEM workers as a proxy for experimentation intensity, we find that the ICT boom wage discount is present only among industries with high technological experimentation, while the effect in industries with low STEM intensity is economically insignificant. Second, 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 to non-STEM workers who started outside the ICT sector.

We further show that the wage discount is larger for workers who started in firms that subsequently rejuvenated their workforce by hiring younger workers during the post-boom period. Consistent with theories where technological change is embodied in firm-worker matches, the wage discount is concentrated among workers at firms with above-median hiring of young workers post-boom, while workers at firms with below-median hiring—where existing technology vintages remain in use longer—experience little to no wage discount. Notably, firms with above-median absolute growth in young workers show the largest wage discount, indicating that poor firm performance does not drive the result.

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 technologies developed early on became obsolete faster, in line with other episodes of technological change. Specifically, we show that capital flowed disproportionately toward ICT firms with higher STEM intensity and toward sectors displaying faster technological obsolescence as measured by our patent-based proxies. This generates the positive covariance between capital flow during the boom and future human capital depreciation: the financing boom amplified aggregate human capital depreciation by directing more workers toward firms where skills would quickly become obsolete.

Finally, we test if an increase in job termination and its associated wage discount could explain our results and find that the magnitude of job termination after the ICT bust accounts for only a small fraction of the long-run wage discount, ruling out scarring as the main alternative explanation.

Quantile regressions of firm performance show that ICT firms underperform 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 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 effects. 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; Nanda and Rhodes-Kropf, 2017), 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). 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 subsequently slower 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]

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, 2025), the value of human capital (Beaudry, Doms, and Lewis, 2010; Beaudry, Green, and Sand, 2016), and the implications of the induced income risk for asset prices (Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, Schmidt, and Song, 2020). 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; Deming and Noray, 2020; Kogan, Papanikolaou, Schmidt, and Seegmiller, 2023; Braxton and Taska, 2023; Ma, 2025).

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.

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.

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, 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 restrict the sample to 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 have 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, 8% are in a business occupation (e.g., sales, general administration – two-digit code 37), 29% are in a STEM occupation (code 38), and 3% are heads of companies 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

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: 15% are teaching professionals (occupation code 34); 7% are public sector managers and professionals (code 33); 7% are cultural professionals (code 35); and 1% are health professionals and legal professionals (code 31).

man (mean 71%), is 42 years old (mean 42), and earns an annual wage of 43,000 euros (mean 53,000 euros), which corresponds to the 90th percentile of the wage distribution of full-time workers in France.[6] Finally, a $4/31^{\text{st}}$ subsample of the employer-employee panel data (individuals born in the first four days of October) can be linked to census data, which contain demographic 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. They also report the nationality of the ultimate owner, enabling 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 are 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 3.8% of total employment and 12% of skilled employment, reflecting that ICT is intensive in skilled labor. The ICT sector is particularly intensive in STEM skills: the fraction of skilled workers in STEM occupations is 71% in the ICT sector versus 23% in other sectors.

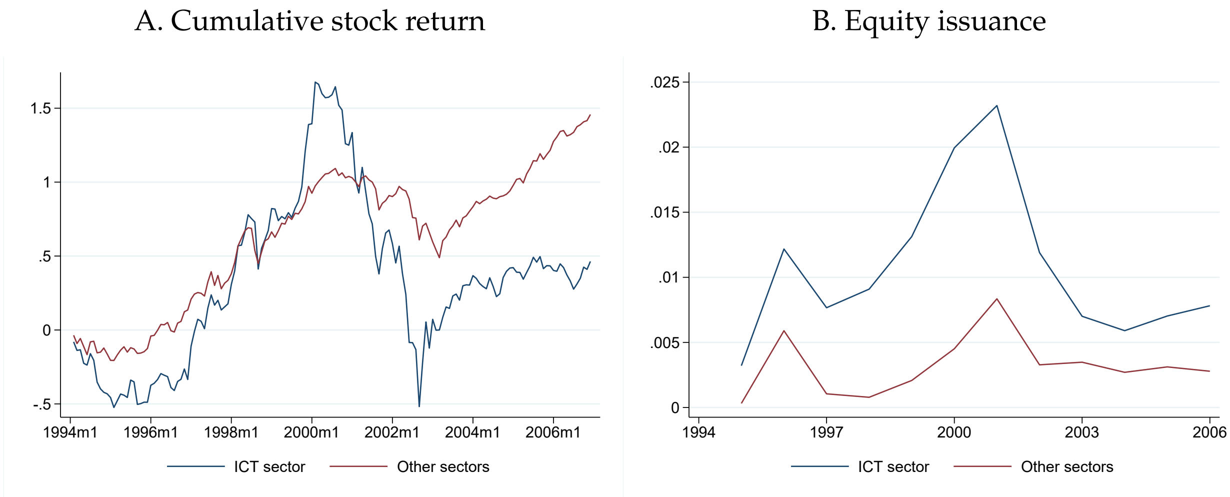
2.2 Capital Flow

Fast-paced technological change in the ICT sector in late-1990s France coincided with a run-up in equity valuations and an inflow of capital to the 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 into the ICT sector that benefited both listed and private firms. To measure capital flow

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.

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.

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 mirrors equity valuations, peaking in 2000–2001.

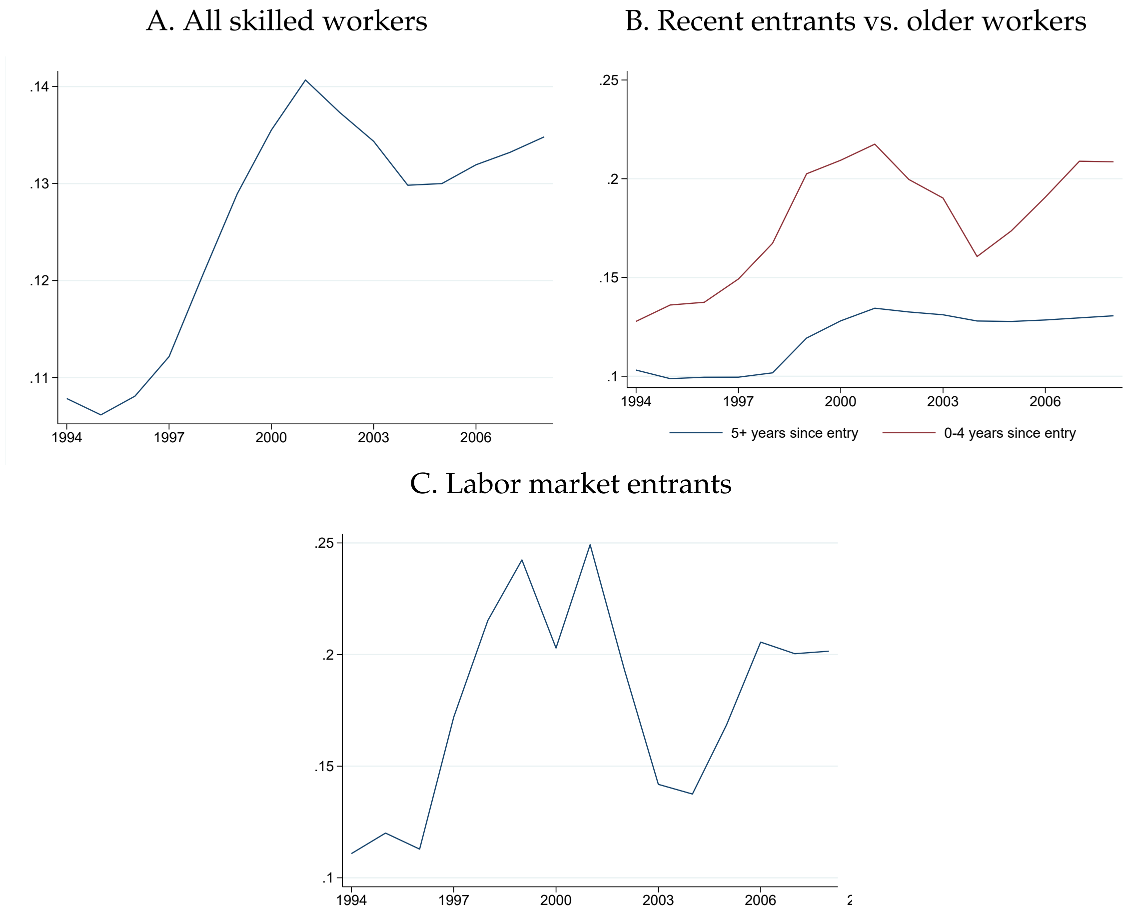
2.3 Labor Flow

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 rises sharply above its trend during the 1998–2001 period. The ICT share goes from 10.6% in 1996 up to 14.0% in 2001 and down to 12.9% in 2004. The coincidence of labor inflows with high wages (see Figure 3) supports interpreting the capital inflow as a labor demand shock.

Panel B breaks down this reallocation into young workers (workers in the labor market for four years or less) and seasoned workers (workers in the labor market for five years or more). The large inflow to the ICT sector is entirely driven by young workers: while the ICT share among seasoned workers exhibits only a slight upward trend, the share among young workers deviates sharply upward 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

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



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 share of the ICT sector among high-skill labor market entrants.

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-quarter of entering cohorts of skilled workers. The effect of this 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 boom to develop and diffuse these new technologies.

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.

3 Wage Dynamics

We now estimate the long-term value of the human capital accumulated 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 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:

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

$Wage_{i,t}$ 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.[8] 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 at entry, 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.

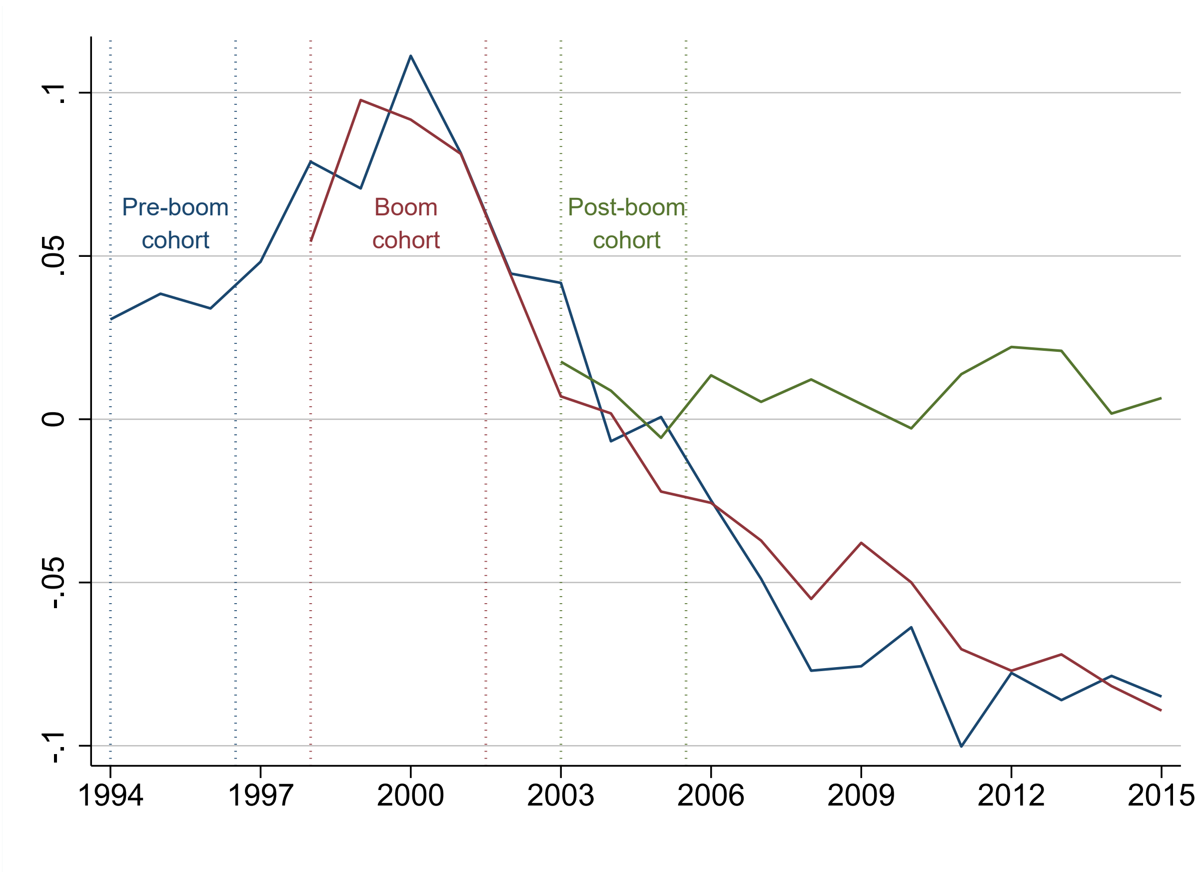
The coefficient β_t^{boom} estimates the average wage difference in year t between boom-cohort workers who start in the ICT sector and those who start elsewhere, conditional on having the same characteristics and occupation. This comparison isolates the effect of starting in the ICT sector during the 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 8% higher than individuals from the same cohort and with the same characteristics, starting outside the ICT sector. The initial 8% wage premium shrinks rapidly after the boom ends in 2001. Strikingly,

8. We define $ICT_{i,0}$ based on the sector in the year in which the individual enters the labor market rather than the sector in the current year because the latter is endogenous to job opportunities and wages.

the wage difference keeps falling and eventually turns negative. By 2015, workers who started in the booming ICT sector earn on average 9% less than workers from the same cohort, same demographics, and same occupation, who started outside the ICT sector.

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).

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 in Section 2.3 that sectoral reallocation occurs mostly through the sectoral choice of labor market entrants, we assume workers cannot switch sectors after 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 8% 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), stemming from a labor market imbalance due to a persistent decline in labor demand or excess entry of workers. Second, human capital accumulated by the boom cohort in the ICT sector may depreciate over time compared to that 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—i.e., 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 oversupply 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 since after the boom, technologies in the ICT sector have matured and are more stable.

We estimate equation (1) on the *post-boom cohort*, defined as skilled workers who enter the labor market between 2003 and 2005.[9] 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 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:

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

9. 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.

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 ($\gamma_t \times ICT_{i,0}$) to compare workers exposed to the same sectoral shocks, a starting-year×year fixed effect ($\delta_{c,t}$) to compare workers from the same cohort, and worker controls (sex, age at entry dummies, two-digit occupation at entry) interacted with year fixed effects.

Panel A of Figure 4 plots the regression coefficients. The downward trend indicates progressive depreciation of human capital accumulated by the boom cohort in ICT, relative to both non-ICT boom-cohort workers and post-boom cohort workers. These coefficients capture the difference in the estimated coefficients for the boom and post-boom cohorts from Figure 3.

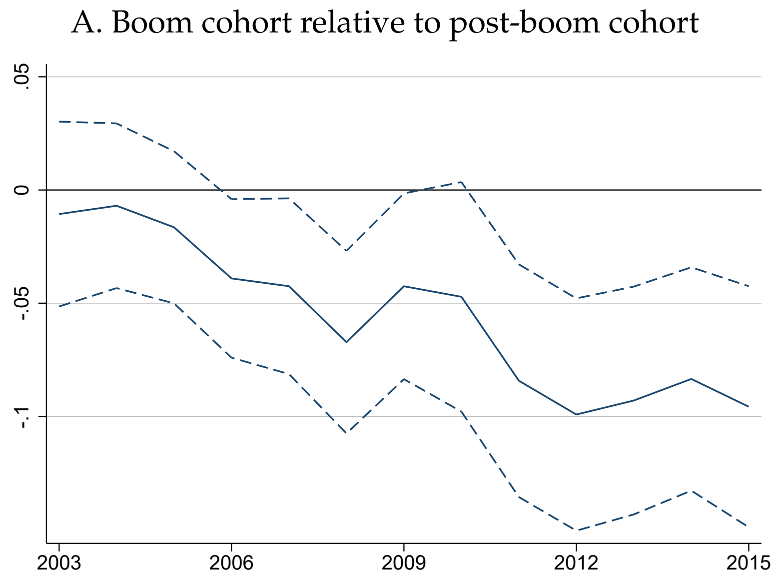
3.3.2 Selection

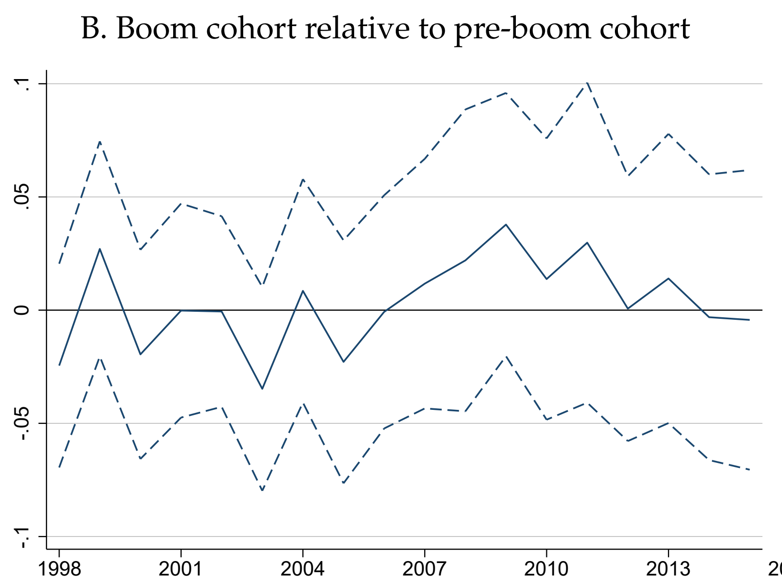
We now examine whether these estimates are explained by negative selection into ICT during the boom. This would happen if either (1) the booming ICT sector attracted a disproportionate share of low-productivity workers, or (2) the rapid expansion in ICT hiring increased worker-sector mismatches. Such a mismatch would happen either if skilled workers drawn to the ICT sector by the salience and pay of the boom were willing to forgo employment opportunities elsewhere with better long-run match, or if the tighter labor market produced by heightened demand leads to quicker job matches with lower quality (see, in a related search context, Acemoglu and Shimer, 2000).

Our baseline starting-sector×year fixed effect ($\gamma_t \times ICT_{i,0}$) controls for selection if unobserved heterogeneity shifts the wage levels by a time-invariant term, as $\theta_{i,k}$ does in the wage equation (2), effectively acting as a worker fixed effect (Abowd, Kramarz, and Margolis, 1999). However, if ICT during the boom drew workers who would have experienced lower wage growth regardless of sector, this more subtle form of negative selection could explain the downward trend. Such a bias would happen for instance if a reasonably skilled but mismatched worker successfully obtains a first STEM job but fails to climb the ladder of promotions as the mismatch slowly reveals itself.

To account for selection correlated with wage growth, we bring in the pre-boom cohort. Individuals entering the labor market before the ICT boom experience the same human capital shocks and sectoral productivity shocks as those 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

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 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).

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 the selection effect.

We start by returning to Figure 3, where we also plot the pre-boom cohort's wage dynamics (the blue line). The pre-boom cohort experiences the same downward trend after the boom as the boom cohort. This suggests that the long-term wage discount reflects human capital depreciation among workers exposed to the technologies developed by the booming ICT sector, rather than negative selection into the ICT sector during the boom ($\Delta\theta_c$ in equation (2)), since both cohorts embedded the same new technologies.

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.

Additional evidence on selection. We also implement a test of a search-friction mismatch channel in the spirit of Acemoglu and Shimer (2000). With search frictions, match quality depends on how long workers are willing to search for jobs that better match their skills. When the unemployment rate is low, workers tend to take a job "too quickly," rather than searching for a better match. We therefore re-estimate the boom-cohort ICT discount separately for workers starting in counties with above and below median unemployment rates. Table B.16 reports the results. We find that boom-cohort workers who started in the ICT sector face the same long-term wage discount, regardless of whether they started in a county with low or high unemployment, i.e., with high or low potential for initial mismatch.

While this test is specific to the search-friction version of mismatch, we note that even the broader notion of excitement-driven selection would not predict that the long-run wage discount should be concentrated in industries that subsequently became technologically obsolete and absent in industries that did not. Initial match quality has no reason to correlate with the speed of future technological churn in the worker's starting industry. The obsolescence story directly predicts this pattern. We discuss this point further in subsubsection 4.1.2 when we present the evidence on the role of technological obsolescence in driving the long-term wage discount.

3.3.3 Baseline Specification and Additional Controls

Our setting allows us to further control for 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 $ICT_{i,0}\times$cohort-dummy$\times$year-dummy with dummies for the three time periods 2003–2005, 2006–2010, and 2011–2015. The specification is otherwise identical to equation (4):

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

The baseline specification controls for worker demographic characteristics and experience (sex, age at entry dummies) gathered in vector $X_{i,0}$, interacted with year fixed effects (α_t) to account for changes in the returns to experience over time and evolving gender wage gaps. We also control for occupation-specific patterns in skill accumulation and depreciation (e.g., Kogan, Papanikolaou, Schmidt, and Seegmiller, 2023) 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 to 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 6.2% 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

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.

Table 1: Wage Regressions

	log(Wage)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{ICT}_0 \times \text{Boom} \times [03\text{–}05]$	0.014						
	(0.014)						
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.029*	-0.045***	-0.040***	-0.041**	-0.037**	-0.038**	
	(0.016)	(0.014)	(0.015)	(0.017)	(0.016)	(0.017)	
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.062***	-0.077***	-0.072***	-0.079***	-0.075***	-0.076***	
	(0.021)	(0.020)	(0.021)	(0.023)	(0.023)	(0.023)	
$\text{ICT}_0 \times \text{Time of exposure} \times [06\text{–}10]$							-0.014***
							(0.004)
$\text{ICT}_0 \times \text{Time of exposure} \times [11\text{–}15]$							-0.023***
							(0.006)
Fixed Effects							
Worker	—	✓	✓	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓	✓	✓	✓
$\text{Pseudo firm}_0 \times \text{Year}$	—	—	✓	—	—	—	—
Sales growth ($t \to t+5$) quintile × Year	—	—	—	✓	✓	✓	—
Entry wage quintile × Year	—	—	—	—	✓	✓	—
$\text{Commuting zone}_0 \times \text{Year}$	—	—	—	—	—	✓	—
Observations	122,722	122,722	122,722	122,722	122,722	122,722	122,722

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* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. 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. In column 7, *Time of exposure* is equal to 2002 minus the worker's starting year for boom-cohort workers (i.e., with starting year between 1998 and 2001), and zero for the post-boom cohort. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

discount. We provide additional evidence that attrition does not explain our results in Appendix B.8.

The 7.7% long-term wage discount is economically significant. It amounts to approximately two years of early career experience. We obtain this number by estimating the return to experience over the first ten years of workers' careers in our sample to be in the range of 3.0% 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.

In column 3, we include pseudo-firm fixed effects interacted with year to account for the relationship between employer characteristics and wage trajectories.[11] If firm characteristics in the ICT sector changed during the boom due to easy financing, the wage discount might partially reflect first employer's characteristics rather than human capital depreciation.

Ideally, we would include initial employer fixed effects $\times$ year fixed effects 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 hire multiple sampled high-skill workers across cohorts, such firm$\times$year fixed effects would absorb most identifying variation. Instead, we construct "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 that 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. To further ensure that we compare workers with the same initial productivity, in column 5 we include entry wage quintile$\times$cohort$\times$year fixed effects.[12]

In column 6, we include commuting zone$\times$cohort$\times$year fixed effects. This removes any correlation arising from spatial sorting of productive workers that would expose them to different local shocks such as local tax shocks that interact with technological change, local demand shocks, or local credit shocks. Across all specifications, the long-term wage discount from starting in the ICT sector during the boom is quantitatively robust.

Finally, in column 7, we show that the magnitude of the wage discount is increasing in the duration of exposure to the ICT boom. We replace the boom cohort dummy by the duration of exposure to the boom defined as 2002 minus the worker's starting year for

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), and firm productivity (Abowd, Kramarz, and Margolis, 1999).

12. For a similar strategy, see: Michelacci and Schivardi (2020), Kogan, Papanikolaou, Schmidt, and Seegmiller (2023), and Green, Kogan, Papanikolaou, and Schmidt (2025).

boom-cohort workers (i.e., with starting year between 1998 and 2001), and zero for the post-boom cohort. The negative coefficient on the duration of exposure interacted with ICT implies that, within the boom cohort, earlier cohorts that were exposed to the ICT boom suffer from a larger long-term depreciation of human capital. In Appendix B.2, we further estimate the ICT wage discount by worker's starting year. We find that, while the discount is not driven by any particular starting year, it decreases monotonically from early cohorts to late cohorts, consistent with the result that the discount increases with the duration of exposure.

We discuss in depth in Section 4.2 why the ICT bust cannot explain our results. As a simple first approach, we include in columns 2 and 3 of Table B.6 pseudo-firm fixed effects for the current employer in addition to the initial employer and find a similar wage discount. This implies that the result is not explained by boom-cohort ICT workers ending up in different or worse 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. 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 capital flows during the boom are directed towards firms whose workers experience the largest depreciation. In such a scenario, more workers would face long-term human capital losses.[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.

Empirical analysis. To examine how human capital depreciation correlates with capital availability during the boom, we extend our baseline specification (equation (5)) by in-

13. In Appendix B.3, we show that capital flows are indeed strongly correlated with labor flows in a panel regression at the industry×geography×year level with industry, geography, and year fixed effects.

corporating 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×commuting zone×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]

Results. Table 2 reports the results. We define $CapitalAvailability_i$ as a dummy variable indicating above-median values for each capital availability measure, and focus on the interaction term $ICT_{i,0} \times CapitalAvailability_i \times BoomCohort_i \times$ 2011-15. 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 across both proxies (columns 1 and 2). The magnitudes are large, with workers facing an additional 10 to 11 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 reducing 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, and 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.[16]

Why the abundance of finance would correlate with skills that depreciate faster over time was a priori not obvious. Indeed, an alternative possible view is that overvaluation in the innovative sector can enhance growth by promoting investments that increase

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".

16. This is a statement about the long-term (i.e., ex-post) effect of the capital allocation. Whether this effect was predictable at the time of the boom is a more challenging question, which our empirical design does not address.

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)
$ICT_0 \times$Boom$\times$[06–10]	-0.027	-0.011		-0.017
	(0.027)	(0.022)		(0.023)
$ICT_0 \times$Boom$\times$[11–15]	-0.025	-0.041		-0.053
	(0.043)	(0.031)		(0.033)
$ICT_0 \times$Capital availability$\times$Boom$\times$[06-10]	-0.052	-0.084***	-0.054	-0.064**
	(0.035)	(0.030)	(0.035)	(0.032)
$ICT_0 \times$Capital availability$\times$Boom$\times$[11-15]	-0.111**	-0.100**	-0.106**	-0.063
	(0.052)	(0.043)	(0.050)	(0.046)
Fixed Effects				
Worker	✓	✓	✓	✓
$ICT_0 \times$Year	✓	✓	✓	✓
Worker controls$\times$Year	✓	✓	✓	✓
$\text{Industry}_0 \times$Year	—	—	✓	—
Commuting $\text{zone}_0 \times$Year	—	—	—	✓
Observations	78,508	95,347	95,347	95,347

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* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. *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 second 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. *Worker demographics×year* are a set of worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry, ICT_0) all 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.

future productivity (Olivier, 2000; Caballero, Farhi, and Hammour, 2006). We examine two non-mutually exclusive reasons for the relation between capital flows and skill depreciation. First, capital may be drawn to sectors that will experience faster technological experimentation, and it is the latter that causes skill depreciation. We analyze this channel in Section 4.1.2. Second, easier financing may causally accelerate skill depreciation—a possibility we explore next.

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 that exposes workers to the risk of failure and loss of project-specific human capital. Alternatively, sectors receiving large capital inflows may simply be those experiencing fast-paced technological change, which itself drives depreciation.

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$\times$commuting zone$\times$year level) by adding four-digit industry$\times$cohort$\times$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 that of technological change, which could drive capital flows and thus confound the results.

Column 3 reports the results with four-digit industry$\times$cohort$\times$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 negative, although with weaker statistical significance when we include commuting zone$\times$cohort$\times$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, industry, or local labor market productivity lead to a larger depreciation of human capital for workers starting in the ICT sector. We investigate the mechanism behind this pattern in Section 4.

3.5 Robustness

Capital income. We may underestimate 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.6), we assume the CEO holds all cash flow rights. We add the firm's net income to the CEO's earnings.[17] 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.[18]

For both measures, we calculate workers' total earnings as wage plus capital income and use the 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.5 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 5.5% lower than those of similar workers starting in other sectors. A specification in levels instead of logs shows that the discounted cumulative earnings loss is 24,000 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.

Total earnings. Our baseline specification uses wages from full-time jobs that last for at least six months because we are interested in measuring the value of workers' skills, which might be less well reflected in temporary and part-time jobs. In Appendix B.6, we show that the long-term wage discount for ICT-boom cohort workers is quantitatively robust to using total earnings from all job spells, and to adding (imputed) unemployment benefits when individuals are unemployed.

17. 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.

18. 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.

Other robustness. We run two additional tests to confirm that selection is unlikely to explain our results. First, using workers that we can link to education outcomes, we show there is no evidence that the pool of workers going to the ICT sector during the boom is of lower quality based on their education achievements (see Appendix B.7). 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 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.8).

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.6, 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? Why does this depreciation increase with the duration of exposure to the ICT boom, and why is it stronger at firms that received larger capital inflows?

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 feature intense experimentation and rapid introduction of multiple versions of new technologies before they stabilize. Afterwards, the economy contains overlapping vintages of technology, with older ones rendered obsolete by newer ones, even as both co-exist (Chari and Hopenhayn, 1991). As a result, the human capital embedding 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 developed human capital specific to early technology versions. For example, while many developers specialized in building static websites using early versions of HTML during the late 1990s, technologies like CSS3 and database-driven frameworks became the norm by the mid-2000s. IT consultants faced similar challenges, with on-premise CRM systems being rendered obsolete by cloud-based solutions.

In all the tests in this section, the post-boom cohort serves as the control group, while the pre-boom and boom cohorts are pooled together as the treatment group. Both treatment groups were employed in the ICT sector during the boom and therefore embed the same vintage of technologies in their human capital, even though they entered the labor market at different times. Consistent with this, the pre-boom and boom cohorts exhibit indistinguishable long-run wage dynamics (Figure 3), while the post-boom cohort, who joined ICT after the technologies had stabilized, does not. Pooling the two treated cohorts also increases sample size and statistical power for the split-sample tests that follow.

4.1.1 STEM Occupations

Human capital depreciation should be stronger for workers who were more exposed to the technological change, either because their firms innovated more during that period, or because their skills are more tightly linked to specific technology implementations. We test this prediction by examining the differential impact of technological change on workers' wages. Our analysis focuses on two key dimensions of exposure: (i) industries categorized by their STEM workforce composition, and (ii) the technological specificity of workers' skills (STEM vs. non-STEM roles).[19]

In Table 3, we present wage discount analyses across different exposure levels. For each measure of exposure intensity to technological change, we report the wage discount for more exposed workers in panel A, and less exposed workers in panel B. Columns 1 and 2 contrast the effects when we split workers along the median of the industry STEM share and reveal a sharp pattern: the long-run wage discount is concentrated in ICT industries with high STEM representation (panel A), while the effect in ICT industries with

19. Kogan, Papanikolaou, Schmidt, and Seegmiller (2023) make a similar argument to estimate the existence of vintage-specific human capital, where they compare the effect of technological changes on workers' wages across occupation task types (cognitive/manual/interpersonal) and argue that cognitive workers accumulate more technology-specific skills that become obsolete.

Table 3: Wage Regression by STEM Intensity

Dependent variable:	log(Wage)			
Proxy level:	Industry		Worker	
	(1)	(2)	(3)	(4)
	Panel A: STEM intensive			
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.048**	-0.027	-0.045***	-0.032*
	(0.020)	(0.028)	(0.014)	(0.017)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.105***	-0.060	-0.097***	-0.098***
	(0.030)	(0.042)	(0.021)	(0.025)
Observations	59,264	59,264	101,413	101,413
	Panel B: Non-STEM intensive			
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	0.030	0.041	-0.055	-0.017
	(0.035)	(0.047)	(0.038)	(0.051)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	0.046	0.041	-0.059	-0.023
	(0.045)	(0.061)	(0.052)	(0.065)
Fixed Effects				
Worker	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓
Sales growth ($t \to t+5$) quintile × Year	—	✓	—	✓
Entry wage quintile × Year	—	✓	—	✓
$\text{Commuting zone}_0 \times \text{Year}$	—	✓	—	✓
Observations	73,952	73,952	60,152	60,152
p-value: (High STEM - Low STEM)	.0054	.17	.49	.27

Note. The table presents OLS estimates for labor market entrants of the pre-boom cohort (1994–1996), boom cohort (1998–2001) and post-boom cohort (2003–2005) over the period 2003–2015. 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* is a dummy equal to one if the worker belongs to the boom or the pre-boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. The table estimates specification (5) by STEM intensity. In columns 1–2, intensity is measured as the share of STEM workers among the workforce at the four-digit industry level and split industries at the median within ICT and non-ICT. In columns 3–4, STEM intensity is a STEM occupation dummy measured at the worker level. The last line reports the p-values of the difference for $ICT_0 \times Boom \times [11-15]$ between panel (A) and panel (B). Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

low STEM intensity is statistically and economically insignificant (panel B). This suggests that workers whose human capital is more technology-embedded face accelerated skill obsolescence.

In columns 3 and 4, we examine worker occupation as a proxy for technological exposure. We hypothesize that human capital depreciation will be more severe for technology-skilled workers (e.g., engineers) whose expertise is tied to specific technological implementations, compared to managers with more generalist skills (e.g., CFOs) whose expertise transcends technological vintages. 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 to non-STEM workers who started outside the ICT sector (panel B).[20]

4.1.2 Pace of Technological Obsolescence

Conditional on having embedded new vintages of technologies into their human capital, workers whose technology vintages become more rapidly obsolete should face a faster depreciation of their human capital.

Measuring technological experimentation and obsolescence. While it is well established that the late 1990s tech boom featured intense technological innovation and financial speculation, the pace at which technologies from that period become obsolete is less understood.

Measuring technological experimentation and obsolescence using patents raises the issue that innovation outcomes may capture confounding factors (financing constraints, competitive pressures, or inherent productivity differences (e.g., Hombert and Matray, 2018)) that independently affect firm performance and worker compensation. To mitigate these concerns, we use US patents to measure technological experimentation and obsolescence facing French workers. This approach minimizes the risk of omitted variables driving our results (Rajan and Zingales, 1998; Ellison, Glaeser, and Kerr, 2010).

The identifying assumption is that the cross-sectional ranking of industries by experimentation and obsolescence is similar in the US and in France. This assumption is plausible if technological change is correlated across both countries, or if frontier US technologies diffuse to France. Both conditions are natural: the US is at the technological frontier, and ICT technologies were rapidly adopted internationally during this period. Using US patent data also has two empirical advantages. First, the larger scale of US patenting

20. While the average ICT wage discount is driven by STEM workers, the point estimate for non-STEM ICT workers is near zero—statistically indistinguishable from non-STEM, non-ICT workers. However, due to the limited number of non-STEM workers in ICT in the data, we cannot conclusively determine the statistical significance of the difference between STEM and non-STEM workers at conventional levels.

reduces idiosyncratic measurement error in patent-based experimentation and obsolescence proxies. Second, because the measures are constructed outside France, they are less likely to mechanically reflect French-specific factors that may directly affect French wages.

We use USPTO data covering all US patents filed during 1990–2010 to construct, at the four-digit CPC technology class level, two measures of technological *obsolescence* and one measure of technological *experimentation*. The two obsolescence measures capture how quickly existing technology vintages are superseded. The first is the *average age of cited patents*: in rapidly evolving fields, new patents cite increasingly recent work, so a lower average age of cited patents indicates that older knowledge becomes obsolete faster. We date patents by application year, following standard practice in the innovation literature. The second is *RETech*, the text-based measure of Bowen, Frésard, and Hoberg (2023), which captures how rapidly the vocabulary describing inventions grows across recent patents; higher values reflect more novel language and breakthroughs that render existing vintages obsolete. The experimentation measure is the *standard deviation of citations received*, computed within each technology class by year: high dispersion reflects intensive experimentation, during which innovations show greater variance in quality and impact (Hombert and Matray, 2017; Balsmeier, Fleming, and Manso, 2017).

On average across the boom years, ICT patents (i) cited younger patents, (ii) exhibited greater cross-patent dispersion in citations received, and (iii) employed more novel terminology than non-ICT patents (Appendix B.9, Table B.11). The static contrast between ICT and non-ICT classes is significant at the 1% level for all three measures; the RETech measure yields the sharpest year-by-year dynamics in Figure B.3, while the age and dispersion series are noisier within the boom window. Moreover, these obsolescence patterns are most pronounced in the overvalued technology segments, potentially explaining why the ICT wage discount is stronger among firms that benefited from easy financing (Table 2).[21]

Obsolescence pace and wage discount. To investigate whether faster obsolescence leads to human capital depreciation, we employ a methodology similar to that in Table 3 and estimate the wage regression across two samples: workers who started in sectors with higher obsolescence pace and those who experienced slower technological obsolescence. To proxy for obsolescence acceleration, we compute the deviation from the technology trend around the boom period. To construct the deviation from trend, we regress the

21. The within-ICT contrast between high- and low-overvaluation classes is significant at the 1% level for age and RETech, and at a p-value of 0.12 for the standard deviation of citations (Table B.11).

variable on a technology class fixed effect, and compute the average of the residual over the period during which technological experimentation deviates from trend in Figure B.3. We map technology classes to the French industry classification and, for each obsolescence measure, we split the sample at the broad industry median.

Table 4: Wage Regression by Technological Obsolescence

Dependent variable:	log(Wage)				
Technological Obsolescence Proxy:	Patents			Δ Workforce age	
Measure:	Age cited patents	sd[citations]	RETech	Median age	Growth young workers
	(1)	(2)	(3)	(4)	(5)
			Panel A: High obsolescence		
$ICT_0 \times Boom \times [06–10]$	-0.118***	-0.092***	-0.115***	-0.045*	-0.064***
	(0.023)	(0.022)	(0.023)	(0.025)	(0.023)
$ICT_0 \times Boom \times [11–15]$	-0.148***	-0.119***	-0.144***	-0.119***	-0.126***
	(0.033)	(0.031)	(0.032)	(0.032)	(0.034)
Observations	50,592	53,197	50,234	58,076	57,886
			Panel B: Low obsolescence		
$ICT_0 \times Boom \times [06–10]$	-0.009	-0.010	-0.003	-0.054***	-0.047**
	(0.031)	(0.033)	(0.034)	(0.018)	(0.019)
$ICT_0 \times Boom \times [11–15]$	-0.024	-0.013	-0.014	-0.048*	-0.051**
	(0.050)	(0.054)	(0.055)	(0.026)	(0.026)
Fixed Effects					
Worker	✓	✓	✓	✓	✓
$ICT_0 \times Year$	✓	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓	✓
Observations	77,010	74,405	77,368	74,627	67,448
p-value: (High obsolescence - Low obsolescence)	.037	.088	.042	.085	.075

Note. The table presents OLS estimates for labor market entrants of the pre-boom cohort (1994–1996), boom cohort (1998–2001) and post-boom cohort (2003–2005) over the period 2003–2015. 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* is a dummy equal to one if the worker belongs to the boom or the pre-boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. In columns 1–3, technological obsolescence is measured using patent characteristics. In column 1, we use -1 the average age of cited patents, such that an increase in the measure indicates new patents cite younger patents. In column 2, we use the standard deviation of all future citations received by the patent. In column 3, RETech is the measure from Bowen, Frésard, and Hoberg (2023) based on the analysis of patent text and captures how rapidly the vocabulary used to describe the invention is growing in use across recent patents. In columns 4–5, the change in workforce age is computed over 2003–2008. The growth of young workers (column 5) is measured as the log growth of workers less than 30-years old. For each measure, we sort industries along the median within broad industries and flag "high obsolescence" if the measure is above the median. The last line reports the p-values of the difference for $ICT_0 \times Boom \times [11-15]$ between panel (A) and panel (B). Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 reports the results. In columns 1 to 3, we use the three different measures constructed using the patent data. In column 1, we use -1 the average age of cited patents, such that an increase in the measure indicates new patents cite younger patents. Across each measure, we consistently find that the wage discount is concentrated among workers who started in firms more likely to develop technologies that would become rapidly obsolete during the post-boom period. In contrast, workers in firms developing technologies with a slower obsolescence pace show essentially no wage effect. The difference between these two worker categories is statistically significant across our measures.

4.1.3 Workforce Age

In theories where technological change is embodied in firm-worker matches (e.g., Mortensen and Pissarides, 1998; Eyigungor, 2010; Kogan, Papanikolaou, Schmidt, and Seegmiller, 2023; Braxton and Taska, 2023), such change occurs through new matches (i.e., new cohorts of workers), while existing matches (older cohorts) continue using older technology vintages at a discount. Therefore, firms that hire new cohorts of workers during the post-boom period are more likely to introduce new vintages of the technologies, making the older workers obsolete even though they continue to work for their employer, albeit at a lower (relative) wage.

To operationalize this idea, we construct two firm-level measures of hiring intensity for new cohorts of skilled workers between 2003 and 2008: (i) negative change in the median age of the skilled workforce, which captures firms that rejuvenate their skill base by disproportionately hiring younger workers; (ii) growth rate in the number of skilled workers aged 30 or less, which directly measures cohort-specific hiring. Each measure captures a different dimension of firms' employment dynamics: the first reflects changes in the relative share of young workers, while the second captures their absolute growth. For each measure, we estimate the wage regression on two samples: workers who start in firms with above-median hiring of new cohorts and those who start in firms with below-median hiring of new cohorts.

We report the results in columns 4 and 5 of Table 4. Across both measures of new-cohort hiring, we find a larger wage discount among workers who start in firms with above-median hiring of new cohorts, that is, firms more likely to introduce newer technological vintages during the post-boom period. In contrast, workers who start in firms with below-median hiring—where technological upgrading is slower and existing vintages remain in use for longer—experience little to no wage effect. Notably, firms with above-median absolute growth in young workers show a larger wage discount for boom-cohort workers, indicating that poor firm growth does not drive the discount—a theme we revisit in Section 4.2.

4.1.4 Skill Obsolescence and Financing

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), and hence where the early technologies developed are likely to become obsolete faster.

Table 5: Skill Obsolescence and Financing

Dependent variable:	Capital flow:1998→2001			
Obsolescence proxy:	STEM intensity	Age cited patents	sd[citations]	RETech
	(1)	(2)	(3)	(4)
ICT	0.077***	0.026***	0.021**	0.028***
	(0.022)	(0.009)	(0.008)	(0.008)
Exposure	0.013*	0.002	-0.007	0.003
	(0.007)	(0.008)	(0.007)	(0.007)
ICT × Exposure	0.052*	0.111***	0.116***	0.106***
	(0.030)	(0.036)	(0.036)	(0.035)
Fixed Effects				
Year	✓	✓	✓	✓
Commuting zone	✓	✓	✓	✓
Observations	173,196	142,782	142,782	142,782

Note. The table presents OLS estimates for capital flows on different proxies of technological obsolescence over the period 1998–2001. Capital flow is constructed as net equity issuance at the four-digit industry×commuting zone×year level. *Exposure* is the proxy of technological obsolescence as indicated on top of the column. Standard errors are clustered by industry and commuting zones. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We provide evidence for this mechanism in Table 5. In the four-digit industry×commuting zone×year panel over the boom period 1998–2001, we regress capital flow on each of our measures of exposure to skill obsolescence interacted with the ICT sector dummy. In column 1, exposure to skill obsolescence is a dummy equal to one if the industry STEM share is above median and zero otherwise, as in Table 3. In columns 2 to 4, exposure is based on the proxies of technological obsolescence constructed using patents as in Table 4. The positive coefficients on the interaction terms between each measure of exposure and ICT imply that capital flows to ICT firms that are more exposed to the risk of skill and technological obsolescence. 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.[22]

Taking stock, capital flows to firms that experiment and innovate intensively. These firms produce more technology vintages, leading to faster skill obsolescence. This generates the positive covariance between capital flow during the boom and future human capital depreciation. Consequently, the financing boom amplified the aggregate human capital depreciation by directing more workers toward firms where skills would quickly become obsolete.

4.2 ICT Bust

The main alternative explanation that can rationalize our results is that the ICT bust scarred workers. Our previous results already suggest this channel is unlikely: (i) The post-boom cohort displays no ICT wage discount (Figure 3); (ii) the boom discount is similar when we control for firms' ex-ante characteristics and ex-post performance (column 4 of Table 1); and (iii) the discount is concentrated among STEM occupations (Table 3) and in firms most exposed to technological obsolescence (Table 4), whereas a sectoral bust should affect all occupations and firms.

4.2.1 Firm Performance

Firm-level analysis. First, we examine the performance of ICT firms after 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.

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

22. 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).

Table 6: Firm Performance

Dependent variable:	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)	(0.020)	(0.007)	(0.004)	(0.005)	(0.009)
Observations	291,944	291,944	291,944	291,944	291,944	291,944
Controls						
Initial 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. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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. To do so, we re-estimate our baseline wage regression conditioning on treated and control firms being in the top quartile of the sales growth distribution. We find that even within these top performing firms, workers who started in 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.12).

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.[23] Here again, we find the same ICT-boom discount as in the whole sample.

Overall, 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 distri-

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

bution 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 who 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 7.0% at the 90th percentile to 8.6% at the 10th percentile.

Table 7: Quantile Wage Regressions

Dependent variable:	log(Wage)				
Quantile:	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
$\text{ICT}_0 \times \text{Boom} \times [06\text{-}10]$	-0.039	-0.040**	-0.040***	-0.040**	-0.041*
	(0.024)	(0.017)	(0.013)	(0.016)	(0.022)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.086***	-0.082***	-0.078***	-0.074***	-0.070***
	(0.024)	(0.017)	(0.013)	(0.016)	(0.023)
Observations	122,722	122,722	122,722	122,722	122,722
Fixed effects					
Worker	✓	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓	✓
Worker Controls × Year	✓	✓	✓	✓	✓

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* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all 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.

4.2.2 Job Termination

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 termination (e.g., Huckfeldt, 2022).

We rule out this hypothesis in two ways. First, we estimate job termination likelihoods and find that scarring effects are an order of magnitude too small to explain the wage discount. Second, controlling for job termination in the wage regression does not affect the estimated ICT wage discount.

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

Table 8: Job Termination

Dependent variable:	$\mathbb{1}$ =[Job Termination]			
Job termination proxy:	Any transition	$\Delta Emp < -10\%$	$\text{Wage}_t < \text{Wage}_{t_0}$	Either (2) or (3)
	(1)	(2)	(3)	(4)
ICT_0 x Boom cohort	0.019	0.048***	0.052**	0.063***
	(0.022)	(0.015)	(0.021)	(0.022)
Fixed Effects				
ICT_0	✓	✓	✓	✓
Worker controls×Cohort	✓	✓	✓	✓
Observations	11,489	11,489	11,489	11,489

Note. The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. Data are collapsed at the worker level. The dependent variable is a dummy that takes the value one if the worker has experienced a job termination in the four years following entry, and columns 1 through 4 use different proxies of job termination. In column 1, we use the probability of any job transition. In column 2 we use transitions associated with employment at the worker's initial employer decreasing by 10% or more in the year of the transition. In column 3 we use transitions that lead to a wage cut for the worker. In column 4 we use transitions where either condition happens. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In Table 8, we study 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. For each of the proxies of job transition, we regress a dummy equal to one if the worker experiences a job transition within four years of entry, on the dummy for starting in the ICT sector and the dummy for the boom cohort. We find that while boom-cohort ICT workers are not more likely to change jobs than same-cohort non-ICT workers (column 1), they are more likely to lose their job by 4.8 to 6.3 percentage points (columns 2–4).[24]

24. In Table B.13, we show that the increase in job termination is, if anything, larger for non-STEM workers than for STEM workers. Therefore, the larger wage discount for STEM workers than for non-STEM workers (see Table 3) is not driven by job termination.

Table 9: Wage Discount Controlling for Job Termination

Dependent variable:	log(Wage)			
job termination proxy:	Baseline	$\Delta Emp < -10\%$	$\text{Wage}_t < \text{Wage}_{t_0}$	Either (2) or (3)
	(1)	(2)	(3)	(4)
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.045***	-0.044***	-0.044***	-0.043***
	(0.014)	(0.014)	(0.014)	(0.014)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.077***	-0.075***	-0.075***	-0.075***
	(0.020)	(0.020)	(0.020)	(0.020)
Job termination × [06–10]		-0.028***	-0.061***	-0.053***
		(0.011)	(0.007)	(0.007)
Job termination × [11–15]		-0.046***	-0.071***	-0.064***
		(0.014)	(0.010)	(0.009)
Fixed Effects				
Worker	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓
Observations	122,722	122,722	122,722	122,722

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. ICT_0 is a dummy equal to one if the worker started in the ICT sector. *Boom* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. *Job termination* 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) employment at the worker's initial employer decreases by 10% or more in the year of the job transition (column 2); (ii) the transition leads to a wage cut for the worker (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.

Moreover, Table 9 shows that job termination is associated with a long-term wage decline of 4.6 to 7.1 percentage points on average, depending on the proxy of job termination. These wage effects are in line with previous estimates.[25] Therefore, heightened job termination can explain at best $0.063 \times 7.1 = 0.4$ percentage points of the overall 7.7 percentage points wage discount.

Controlling for scarring effects. In Table 9, we re-estimate the baseline wage regression controlling for job termination using the three proxies defined above. This barely changes the long-term wage discount, which decreases from 7.7% to 7.5%.

25. 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%.

Job termination might have a disproportionate impact on boom-cohort ICT workers, for instance because conditional on losing their jobs, the scarring effect would be particularly large as their skills face accelerated obsolescence (Braxton and Taska, 2023). To test this possibility, in Table B.14, 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. The long-term discount remains large and significant for boom-cohort ICT workers experiencing no job termination. The effect is, if anything, larger for those workers who experience job termination, consistent with Braxton and Taska (2023), although the difference is not statistically significant.

Workers who are not laid off might still experience lower wage growth when job terminations 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$\times$occupation level over the post-boom period 2002–2005. In Table B.15, 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 termination explaining the discount.

5 Concluding Remarks

Growth theories highlight that reallocating capital and talent to innovative sectors can enhance productivity, even when fueled by speculative financing in which investors over-invest. The impact on the human capital of workers drawn to these sectors during periods of intense technological change and easy financing, however, remains understudied.

Using the late 1990s ICT boom as a laboratory—when one-quarter 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 associated financing cycles can affect long-run productivity growth—their impact on the human capital of cohorts of skilled workers drawn to these sectors. Our results, however, 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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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:* 4/31st 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. *PatentsView:* USPTO patents data.

   See https://patentsview.org/home

10. *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	1,920,607	52,985	32,799	42,625	58,555
Male	1,920,607	.71	0	1	1
Age	1,920,607	42	34	42	50
	Panel B: Skilled workers entering the labor force over 1994–2005				
Annual wage	256,443	47,566	30,647	39,971	53,714
Male	256,443	.69	0	1	1
Age at entry	256,443	26	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.

[Back to Section 2.1]

Table B.2: ICT Industries

ICT industries	ISIC rev 3.1 codes	Share of total employment (%)	Share of skilled employment (%)
ICT: Services		1.4	6.4
IT consultancy	*7210*	0.5	2.9
Software	*7220*	0.5	2.6
Data processing	*7230*	0.2	0.7
Maintenance computers	*7250*	0.1	0.1
Other computer-related services	*7123,7240,7290*	0.0	0.1
ICT: Telecommunications		0.9	1.5
Telecommunications	*6420*	0.9	1.5
ICT: Manufacturing		1.2	2.9
Electronic/communication equipment	*3210,3220,3230*	0.6	1.3
Measurement/navigation/process control equipment	*3312,3313*	0.4	1.0
Computing machinery	*3000*	0.1	0.6
Insulated wire and cable	*3130*	0.1	0.1
ICT: Wholesale		0.3	1.0
Computers, electronics, telecoms	*5151,5152*	0.3	1.0
ICT: Total		**3.8**	**11.9**

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.

[Back to Section 2.1]

B.1 Return to Experience

To estimate the return to early career experience, 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, since age, cohort, and time are linearly dependent, 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 accounts 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). In both cases, we use data for the first ten years after entry to estimate early career experience.

The point estimates imply that one additional year of experience leads to a 3.0% to 4.4% wage increase.

Table B.3: Return to Experience

Dependent variable:	log(Wage)	
	(1)	(2)
Age	0.044***	0.030***
	(0.001)	(0.001)
Fixed Effects		
Worker	✓	—
Year	—	✓
Sex	—	✓
Industry_0	—	✓
Occupation_0	—	✓
Observations	113,246	113,246

Note. The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over each worker's first ten years after entry. 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.

[Back to Section 3.3.3]

B.2 Vintage Effects

We check whether the wage discount is driven by specific vintages of starting year. To do so, we re-estimate equation (5) using workers starting in years from 1997 to 2005, and replacing the boom cohort dummy by a set of dummy variables for each starting year.

The result is reported in Table B.4. We find that the wage discount is not driven by any particular starting year. Moreover, the wage discount is larger for earlier cohorts, consistent with our analysis of the duration of exposure (see column 7 of Table 1).

Table B.4: Vintage Effects

Dependent variable:	log(Wage)
	(1)
$\text{ICT}_0 \times$1997 cohort$\times$[11–15]	-0.085**
	(0.039)
$\text{ICT}_0 \times$1998 cohort$\times$[11–15]	-0.123***
	(0.037)
$\text{ICT}_0 \times$1999 cohort$\times$[11–15]	-0.123***
	(0.037)
$\text{ICT}_0 \times$2000 cohort$\times$[11–15]	-0.123***
	(0.036)
$\text{ICT}_0 \times$2001 cohort$\times$[11–15]	-0.089**
	(0.036)
$\text{ICT}_0 \times$2002 cohort$\times$[11–15]	-0.083**
	(0.036)
$\text{ICT}_0 \times$2003 cohort$\times$[11–15]	-0.058
	(0.042)
$\text{ICT}_0 \times$2004 cohort$\times$[11–15]	-0.044
	(0.038)
Fixed Effects	
Worker	✓
Sex$\times$Year	✓
$\text{Age}_0 \times$Year	✓
$\text{Year}_0 \times$Year	✓
$\text{ICT}_0 \times$Year	✓
$\text{Occupation}_0 \times$Year	✓
Observations	155,041

Note. The table presents OLS estimates for labor market entrants of cohorts from 1997 to 2005. 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. *yyyy cohort* is a dummy equal to one if the worker belongs to the *yyyy* cohort. *[11–15]* is a dummy equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all 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.

[Back to Section 3.3.3]

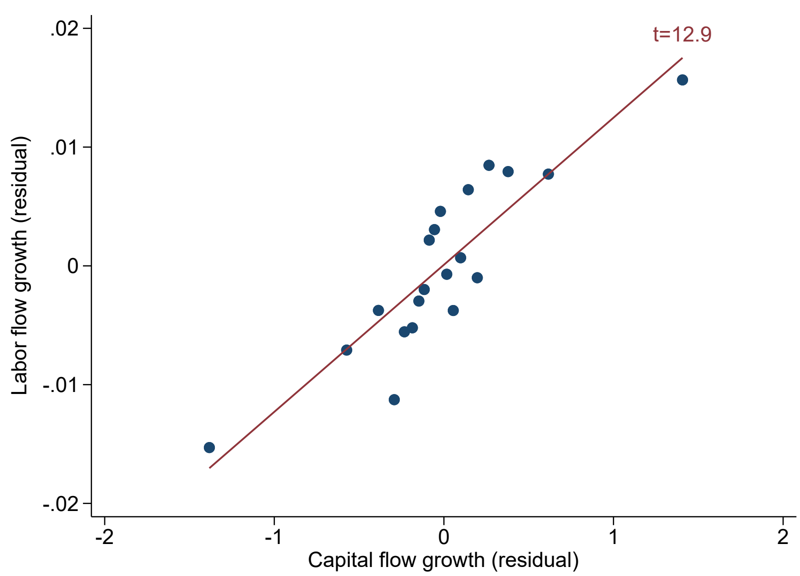
B.3 Correlation between Capital Flows and Labor Flows

In this appendix, we show that capital flows correlate with labor flows. We construct both measures at the four-digit industry×commuting zone×year level: capital flow as the mid-point growth rate of total paid-in equity, and labor flow as the mid-point growth rate of total employment. We regress labor flow on capital flow at the four-digit industry×commuting zone×year level for the years 1998 to 2001, controlling for four-digit industry fixed effects, commuting zone fixed effects, and year fixed effects.

To visualize the results, in Figure B.1, we partial 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 12.9). 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.5 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, if anything, 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 total paid-in equity. Labor growth is defined as the mid-point growth rate of total employment. 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.5: Capital Flows and Labor Flows

Dependent variable:	Labor flow	
	(1)	(2)
Capital flow	0.035***	0.035***
	(0.003)	(0.003)
Capital flow × ICT		0.013
		(0.013)
Fixed Effects		
Year	✓	✓
Industry	✓	✓
Communiting zone	✓	✓
Observations	113,467	113,467

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 the mid-point growth rate of total paid-in equity. Labor growth is defined as the mid-point growth rate of total employment. 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.

[Back to Section 3.4]

B.4 Additional Robustness

Table B.6: Robustness

Dependent variable:	log(Wage)				log(Wage+Cap.income)	
	Baseline			Excl. finance	Capital income assigned to CEOs	Capital income assigned to Skilled workers
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.045***	-0.038***	-0.042***	-0.045***	-0.048***	-0.046***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.077***	-0.063***	-0.067***	-0.082***	-0.084***	-0.079***
	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)	(0.020)
Fixed Effects						
Worker	✓	✓	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓	✓	✓
Pseudo $\text{firm}_0 \times \text{Year}$	—	—	✓	—	—	—
Pseudo $\text{firm}_t \times \text{Year}$	—	✓	✓	—	—	—
Observations	122,722	122,722	122,722	115,639	122,722	122,722

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* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. Column 1 is the baseline regression (column 2 of Table 1). In column 2 and 3, we add pseudo-firm fixed effects 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×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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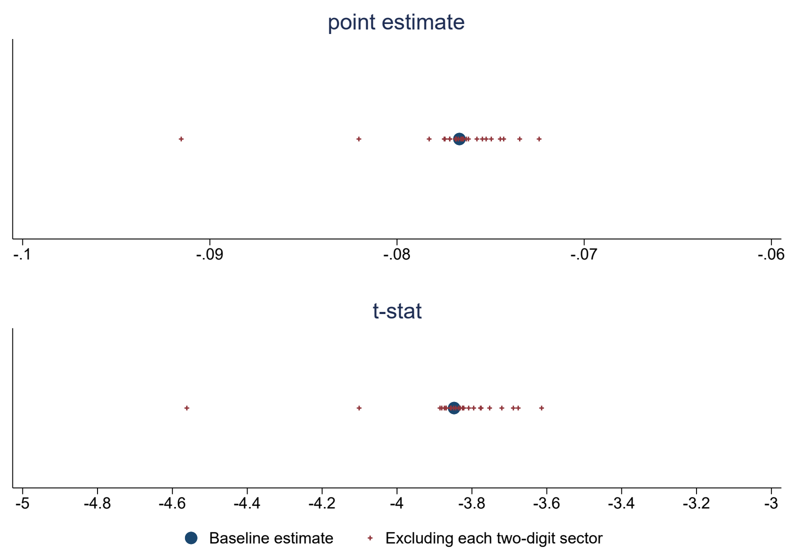
To check that the results are not driven by the wage dynamics in any of the non-ICT sectors in the control group, we re-run the baseline regression in column 2 of Table B.6 excluding workers starting in each of the two-digit non-ICT sectors, resulting in 26 different regressions. Figure B.2 plots the 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 figure 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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B.5 Cumulative Earnings

We estimate equation (1) using cumulative earnings as the dependent variable. Cumulative earnings include part-time and short job spells (excluded from previous regressions) from labor market entry to year t, discounted to the entry year at 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.7. High-skill workers starting in the ICT sector during the boom earn cumulative earnings from entry to 2015 that are 5.5% lower than those 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 24,000 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, for a duration roughly equal to that of their pre-unemployment job spell capped at two years. Since the data do not report termination motives, we assume in the baseline scenario that all job terminations yield one year of UB at a 60% replacement rate.[26] If anything, accounting for unemployment benefits increases slightly the cumulative earnings loss.

26. 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 (column 4), and when we use a more aggressive UB length of two years if the pre-unemployment job spell lasts for at least two years (column 5).

Table B.7: Cumulative Earnings

	Cumulative Earnings				
	Log	Level (in Euro)	Level incl. UB (in Euro)	(in Euro)	(in Euro)
UB replacement rate:			60%	30%	100%
	(1)	(2)	(3)	(4)	(5)
$ICT_0 \times 2001$	.05***	2,344***	2,670***	2,507***	2,759***
	(.0099)	(740)	(712)	(724)	(711)
$ICT_0 \times 2005$	.013	263	79	171	91
	(.014)	(1,928)	(1,896)	(1,909)	(1,875)
$ICT_0 \times 2010$	-.029*	-10,280***	-10,807***	-10,544***	-10,970***
	(.017)	(3,855)	(3,821)	(3,835)	(3,804)
$ICT_0 \times 2015$	-.055***	-23,812***	-24,800***	-24,306***	-25,186***
	(.02)	(6,225)	(6,219)	(6,219)	(6,216)
Fixed Effects					
Worker controls×Year	✓	✓	✓	✓	✓
Observations	127,747	127,747	127,747	127,747	127,747

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 specifications include worker demographic 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.6 Total Earnings

Our baseline regression uses earnings from full-time jobs that last for at least six months because we are interested in measuring the value of workers' skills, which might be less well captured by temporary and part-time jobs. In this appendix, we show that the long-term wage discount for ICT boom-cohort workers is quantitatively robust to using total earnings from all job spells, and to adding imputed unemployment benefits when individuals are unemployed.

The results are reported in Table B.8. In column 1, the dependent variable is the log of total earnings in the current year, including from short and part-time job spells. If the individual earns zero earnings the observation is dropped. In columns 2 to 4, we replace zero earnings with imputed unemployment benefits. We consider three different assumptions to impute unemployment benefits, as described in Appendix B.5. We find that our main result is quantitatively robust across specifications. The long-term wage discount lies between 10% and 11% and, if anything, is slightly larger than in the baseline.

Table B.8: Total Earnings

Dependent variable	Total Earnings			
UB replacement rate:	0%	60%	30%	100%
	(1)	(2)	(3)	(4)
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.070***	-0.074***	-0.078***	-0.059**
	(0.022)	(0.025)	(0.028)	(0.027)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.111***	-0.114***	-0.114***	-0.102***
	(0.029)	(0.033)	(0.035)	(0.035)
Fixed Effects				
Worker	✓	✓	✓	✓
$\text{Year}_0 \times \text{Year}$	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓
Observations	146,348	153,129	153,129	156,578

Note. ICT_0 is a dummy equal to one if the worker started in the ICT sector. *Boom* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all 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.7 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 into the ICT sector during the boom has lower educational achievement.

Table B.9: Education

Dependent variable	=1 if Master's degree		
	(1)	(2)	(3)
ICT_0	0.012	-0.006	-0.051
	(0.030)	(0.032)	(0.032)
$\text{ICT}_0 \times$Boom cohort	0.017	0.011	0.040
	(0.036)	(0.038)	(0.038)
Fixed Effects			
Sex	✓	✓	✓
Age_0	✓	✓	✓
Year_0	✓	✓	✓
Commuting zone_0	—	—	✓
Occupation_0	—	✓	✓
Observations	1,273	1,273	1,273

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. Column 2 adds occupation at entry fixed effects. Column 3 adds 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.8 Attrition

Our main specification in Table 1 already controls for composition effects by including individual fixed effects, which ensure that we identify wage changes from individual wage trajectories and not from changes in the pool of workers induced by attrition. Differential attrition across cohorts could still bias the results if attrition correlates with wage growth, not just wage levels. In this case, the counterfactual wage of individuals who drop out differs on average from that of individuals who remain, 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.10. 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 insignificant coefficient on wage growth interacted with $ICT_{i,0}$ implies that workers who started in ICT are not 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, workers who started outside ICT, and 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.10: Attrition

Dependent variable	=1 if exits in $t+1$		
	(1)	(2)	(3)
Wage growth$_{i,t-2\to t}$	-0.006**	-0.007*	-0.011**
	(0.003)	(0.004)	(0.005)
Wage growth$_{i,t-2\to t}\times$ICT$_0$		0.002	0.015
		(0.007)	(0.013)
Wage growth$_{i,t-2\to t}\times$Boom cohort			0.006
			(0.007)
Wage growth$_{i,t-2\to t}\times$ICT$_0\times$Boom cohort			-0.018
			(0.015)
Industry$_0\times$Year	✓	✓	✓
Worker controls$\times$Year	✓	✓	✓
Observations	53,403	53,403	53,403

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$_{i,t-2\to t}$ is the worker's wage growth from year $t-2$ to year t. ICT_0 is a dummy equal to one if the worker started in the ICT sector. *Boom cohort* is a dummy equal to one if the worker belongs to the boom cohort. All the specifications include starting industry fixed effects, and worker demographic 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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B.9 Technological Obsolescence

Evidence of heightened obsolescence. To study whether ICT technologies produced during the boom displayed higher levels of obsolescence, we estimate a standard difference-in-differences at the technological class-year level of the form:

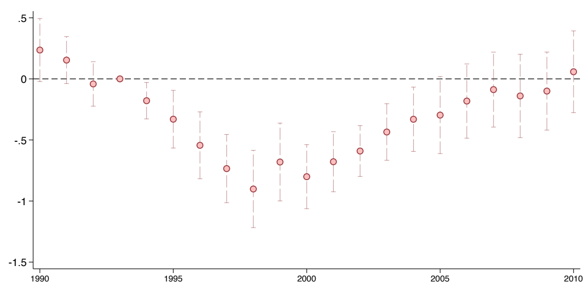
$$Y_{c,t} = \sum_{k=1990,k\neq 2000}^{2010} \beta_k \Big[ICT_c \times \mathbb{I}(t=k) \Big] + \gamma_c + \delta_t + \varepsilon_{c,t} \tag{B.6}$$

where $Y_{c,t}$ are the different measures of obsolescence at the technology-year level, and ICT_c is a dummy that takes the value one if the technology belongs to the ICT sector.[27]

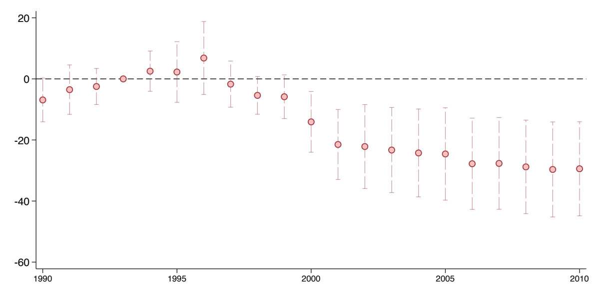
Figure B.3 presents our results, revealing substantial differences between the second half of the 1990s and the 2000s. During the boom, ICT patents (i) cited significantly younger patents, consistent with an acceleration of the innovation process and thus of the pace of obsolescence of older vintages of technologies; (ii) showed greater variance in citation impact, consistent with a higher rate of experimentation; and (iii) employed more novel terminology compared to established patent language, again consistent with accelerated innovation and obsolescence.

Figure B.3: Technological Experimentation Around ICT Boom Period

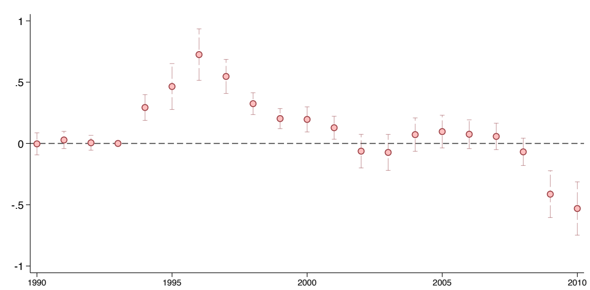
A. Age of cited patents



B. Standard deviation of received citations



C. RETech



This figure shows the evolution of different proxies of technological experimentation around the ICT boom period, across technological classes, for ICT technologies relative to non-ICT technologies. *Age of cited patents* (panel A) is constructed as the average age of patents cited by the focal patents filed each year in a given technological class. *Standard deviation of received citations* (panel B) is the standard deviation of all the citations received by the focal patents filed each year in a given technological class. *RETech* (Panel C) is the measure of Bowen, Frésard, and Hoberg (2023) that uses patent text to identify patents whose text differs from that of all patents filed previously. Standard errors are clustered at the technology level and we report the 95% confidence interval.

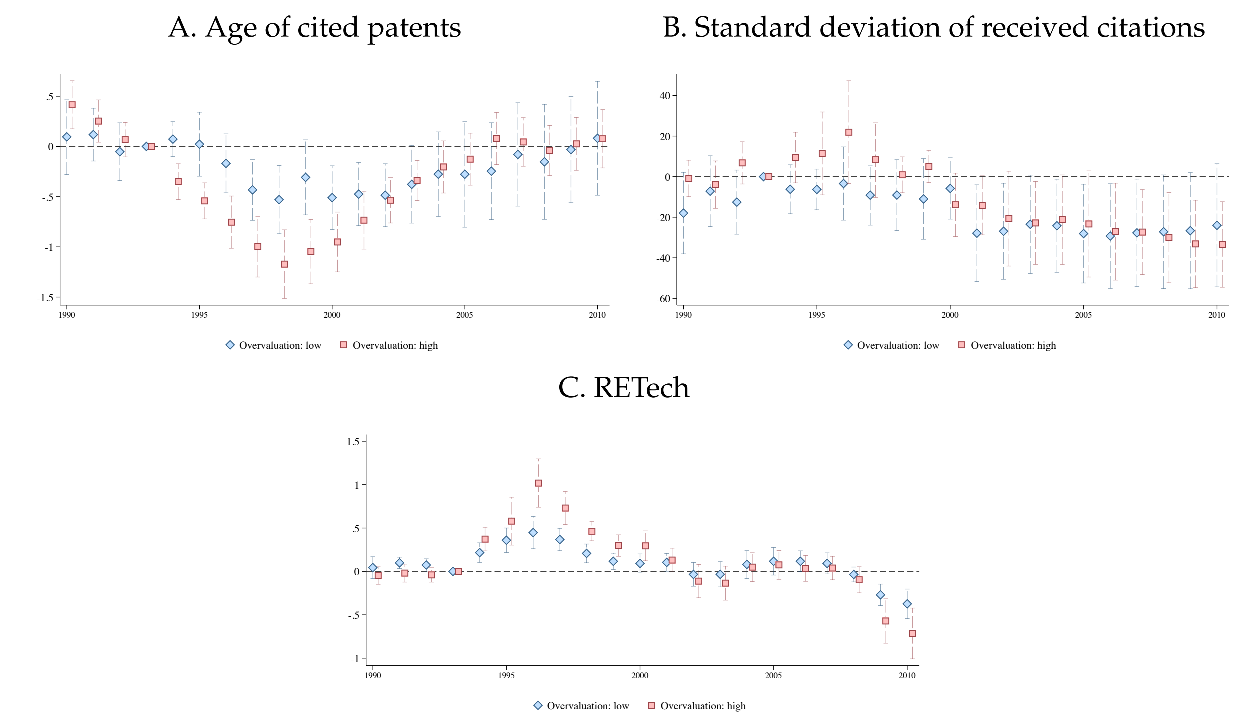
Technological obsolescence and overvaluation. We further demonstrate that these innovation patterns were most pronounced in the technology segments experiencing the

27. We construct this dummy by using a mapping between the USPTO CPC class and the industrial classification ISIC rev 3.1 that we use to identify ICT sectors according to the list from OECD (2002).

greatest overvaluation, particularly within ICT. We construct measures of overvaluation using Compustat data by calculating the average market-capitalization-to-revenue ratio during 1999–2000 (as in, e.g., Lewellen, 2003; Greenwood and Nagel, 2009). We then map these firm-level measures to technology classes based on firms' patent portfolios. Technologies are classified as overvalued if their associated market-capitalization-to-revenue ratio exceeds the sample median, with this classification performed separately for ICT and non-ICT technologies.

We replicate the analysis from Figure B.3, disaggregating technologies by overvaluation status, and present the results in Figure B.4. Consistent with the hypothesis that financial speculation accelerates technological experimentation and obsolescence, we find that all patterns documented in Figure B.3 are amplified among overvalued technologies.

Figure B.4: Technological Experimentation and Overvaluation: ICT vs. Non-ICT



This figure shows the evolution of different proxies of technological experimentation of technological classes around the ICT boom period, for ICT technologies relative to non-ICT technologies, when we split technologies between overvalued and non-overvalued technologies. Overvaluation is defined as technologies with an average market-capitalization-to-revenue ratio during 1999–2000 that is above the sample median within ICT and non-ICT. *Age of cited patents* (panel A) is constructed as the average age of patents cited by the focal patents filed each year in a given technological class. *Standard deviation of received citations* (panel B) is the standard deviation of all the citations received by the focal patents filed each year in a given technological class. *RETech* (Panel C) is the measure of Bowen, Frésard, and Hoberg (2023) that uses patent text to identify patents whose text differs from that of all patents filed previously. Standard errors are clustered at the technology level and we report the 95% confidence interval.

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Table B.11: Technological Obsolescence Proxies

	Age cited patents		RETech		sd[citations]	
	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
ICT×Boom	-0.471***		0.422***		16.454***	
	(0.161)		(0.086)		(5.377)	
ICT×Boom×Overvaluation		-0.851***		0.512***		16.025
		(0.242)		(0.128)		(10.360)
Fixed Effects						
Technology	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
ICT×Boom	—	✓	—	✓	—	✓
Observations						

Note. The table reports OLS estimates from a CPC technology-class × year panel covering 1990–2010. The dependent variables are three measures of technological obsolescence at the CPC-year level: the average age of cited patents (columns 1–2), the 5-year RETech stock of text-based novelty (columns 3–4), and the standard deviation of citations received (columns 5–6). *ICT×Boom* is a difference-in-differences term equal to one for ICT CPC classes during the boom years 1994–2001 (and zero otherwise). *ICT×Boom×Bubble* is a triple-difference term that interacts *ICT×Boom* with an indicator equal to one for CPC classes with above-median stock-market overvaluation during 1999–2000, where the median is taken separately within ICT and non-ICT classes. Odd-numbered columns report the DiD; even-numbered columns add the triple difference and control for *ICT×Boom* as a main effect. All specifications include CPC and year fixed effects. Standard errors clustered at the CPC level are in parentheses.

Table B.12: Subsample Analysis: High Growth Firms and US Firms

Dependent variable	log(Wage)	
Sample	Firm growth top 75^{th}	US subsidiaries
	(1)	(2)
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.061**	-0.043
	(0.026)	(0.056)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.095**	-0.144**
	(0.038)	(0.073)
Fixed Effects		
Worker	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓
Worker controls × Year	✓	✓
Observations	28,745	8,928

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 company, defined as firms 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×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.13: Job Termination in STEM vs. Non-STEM Occupations

Dependent variable:	$\mathbb{1}$ =[Job Termination]			
Job termination proxy:	Any transition	$\Delta Emp < -10\%$	$\text{Wage}_t < \text{Wage}_{t_0}$	Either (2) or (3)
	(1)	(2)	(3)	-4)
		Panel A: STEM workers		
ICT_0 x Boom cohort	0.005	0.052***	0.036	0.055**
	(0.024)	(0.017)	(0.024)	(0.025)
Observations	7,241	7,241	7,241	7,241
		Panel B: Non-STEM workers		
ICT_0 x Boom cohort	0.075	0.029	0.116**	0.099*
	(0.050)	(0.037)	(0.050)	(0.051)
Observations	4,248	4,248	4,248	4,248
Fixed effects				
ICT_0	✓	✓	✓	✓
Worker controls×Cohort	✓	✓	✓	✓

Note. The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. Data are collapsed at the worker level. The dependent variable is a dummy that takes the value one if the worker has experienced a job termination in the four years following entry, and columns 1 through 4 use different proxies of job termination. In column 1, we use the probability of any job transition. In column 2 we use transitions associated with employment at the worker's initial employer decreasing by 10% or more in the year of the transition. In column 3 we use transitions that lead to a wage cut for the worker. In column 4 we use transitions where either condition happens. In Panel A, we estimate the regression using only workers who started in a STEM occupation. In Panel B we restrict the regression to workers who started in a non-STEM occupation. 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.14: Controlling for Job Termination

Dependent variable:	log(Wage)			
job termination proxy:	Baseline	$\Delta Emp < -10\%$	$\text{Wage}_t < \text{Wage}_{t_0}$	Either (2) or (3)
	(1)	(2)	(3)	(4)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.077***	-0.067***	-0.079***	-0.072***
	(0.020)	(0.021)	(0.023)	(0.024)
Job termination × [11–15]		-0.048*	-0.173***	-0.138***
		(0.026)	(0.018)	(0.017)
$\text{Job termination} \times \text{ICT}_0 \times [11\text{–}15]$		0.037	0.011	0.029
		(0.058)	(0.035)	(0.034)
Job termination × Boom × [11–15]		0.007	0.141***	0.099***
		(0.035)	(0.024)	(0.023)
$\text{Job termination} \times \text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$		-0.058	0.001	-0.018
		(0.068)	(0.043)	(0.041)
Fixed Effects				
Worker	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓
Observations	122,722	122,722	122,722	122,722

Note. The table presents OLS estimates for labor market entrants of the pre-boom cohort (1994–1996), boom cohort (1998–2001) and post-boom cohort (2003–2005) over the period 2003–2015. 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* is a dummy equal to one if the worker belongs to the boom or the pre-boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. *Job termination* 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) employment at the worker's initial employer decreases by 10% or more in the year of the job transition (column 2); (ii) the transition leads to a wage cut for the worker (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.15: Wage Discount in Local Labor Markets with High vs. Low Job Termination

Dependent variable:	log(Wage)			
job termination proxy:	Baseline	$\Delta Emp < -10\%$	$\text{Wage}_t < \text{Wage}_{t_0}$	Either (2) or (3)
	(1)	(2)	(3)	(4)
	Panel A: Labor markets with high job termination			
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.020	-0.020	-0.018	-0.018
	(0.019)	(0.019)	(0.019)	(0.019)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.052*	-0.051*	-0.049*	-0.050*
	(0.027)	(0.027)	(0.027)	(0.027)
Job termination × [06–10]		-0.014	-0.066***	-0.055***
		(0.013)	(0.010)	(0.010)
Job termination × [11–15]		-0.036*	-0.080***	-0.069***
		(0.019)	(0.014)	(0.013)
Observations	61,749	61,749	61,749	61,749
	Panel B: Labor markets with low job termination			
$\text{ICT}_0 \times \text{Boom} \times [06\text{–}10]$	-0.068***	-0.066***	-0.068***	-0.067***
	(0.021)	(0.021)	(0.021)	(0.021)
$\text{ICT}_0 \times \text{Boom} \times [11\text{–}15]$	-0.093***	-0.090***	-0.093***	-0.092***
	(0.031)	(0.031)	(0.031)	(0.031)
Job termination × [06–10]		-0.049***	-0.060***	-0.057***
		(0.018)	(0.011)	(0.010)
Job termination × [11–15]		-0.063***	-0.070***	-0.068***
		(0.022)	(0.014)	(0.013)
Observations	60,114	60,114	60,114	60,114
Fixed effects				
Worker	✓	✓	✓	✓
$\text{ICT}_0 \times \text{Year}$	✓	✓	✓	✓
Worker controls × Year	✓	✓	✓	✓

Note. The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. Data are collapsed at the worker level. The dependent variable is a dummy that takes the value one if the worker has experienced a job termination in the four years following entry, and columns 1 through 4 use different proxies of job termination. In column 1, we use the probability of any job transition. In column 2 we use transitions associated with employment at the worker's initial employer decreasing by 10% or more in the year of the transition. In column 3 we use transitions that lead to a wage cut for the worker. In column 4 we use transitions where either condition happens. We compute local market job termination as the average yearly termination rate at the commuting zone × occupation level over 2002–2005. In Panel A, we estimate the regression using only workers who started in commuting zones with above-median termination rate. In Panel B, we estimate the regression using only workers who started in commuting zones with below-median termination rate. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

[Back to Section 4.2.2]

Table B.16: ICT Wage Discount Across County Unemployment Rate

	log(Wage)	
sample:		
	(1)	(2)
$ICT_0 \times Boom \times [06–10]$	-0.046**	-0.040**
	(0.022)	(0.019)
$ICT_0 \times Boom \times [11–15]$	-0.072**	-0.077***
	(0.028)	(0.029)
Fixed Effects		
Worker	✓	✓
$ICT_0 \times$Year	✓	✓
Worker controls$\times$Year	✓	✓
Observations	59,543	62,477

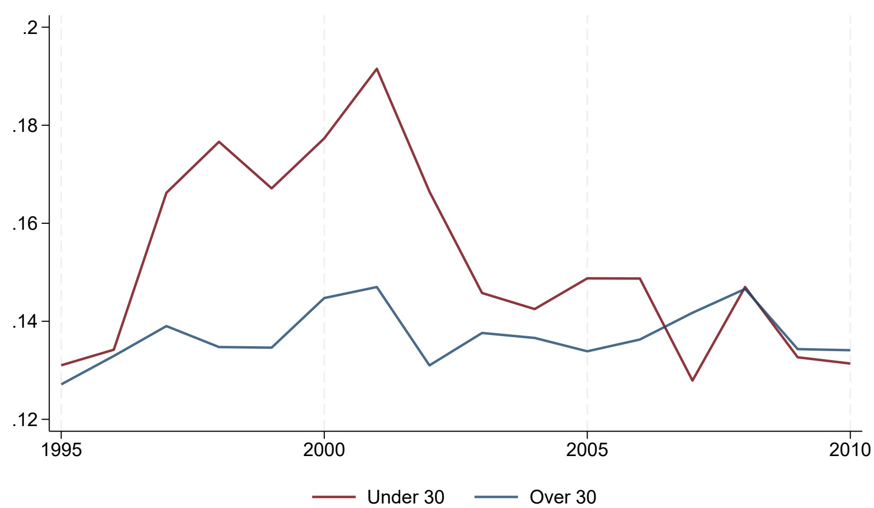
Note. The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if the worker started in the ICT sector. *Boom* is a dummy equal to one if the worker belongs to the boom cohort. *[06–10]*, and *[11–15]* are dummies equal to one if year t belongs to the corresponding time period. All specifications include ICT_0, as well as worker demographic controls (sex, age dummies, entry year dummies, two-digit occupation at entry) all interacted with year fixed effects. In column 1 (resp. 2), we estimate the regression using only workers who started in counties with above-median (resp. below-median) unemployment rate over 1998–2001. Standard errors are clustered at the individual level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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 years old and who are in the labor force. We define skilled workers as individuals with some college education. We flag ICT sectors using the variable *ind*1990 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). As 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 incumbent 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.

[Back to Section 1]

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.[28] 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.[29] $H_{i,c,k,t}$ 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:

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

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.

28. 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.

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

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.[30]

Workers' sectoral choices depend on expectations of future wages. The equilibrium outcomes do not require rational expectations; the only difference is that with non-rational expectations, workers are systematically surprised by realized wages. Assessing whether workers' expectations are rational is outside the scope of this paper.

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

Corporate sector. We model the corporate sector with a final good sector that purchases inputs from intermediate goods sectors, which in turn produce 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 $c = -\infty, \dots, t$. 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 is determined by the marginal productivity of labor:[31]

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

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.

31. 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.

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:

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

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

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

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:*

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

$$\text{(D.13)} \qquad \Delta E_t \simeq \Delta E^* + E_z \,.\, \Delta z_t + E_\ell \,.\, \left(\Delta \ell_t - \Delta \ell^*\right) + E_h \,.\, \Delta \overline{dh}_t,$$

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:

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

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

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

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:

(D.18)

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

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:

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

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:

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

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:

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

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 $\log\left(L_{k,t} + L_{k,t}^{new}\right)$. We obtain:

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

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:

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

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

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

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

$$\text{(D.27)} \qquad \mathbb{E}_t\left[\Delta w_{t+\tau} - \Delta w^*\right] \simeq w_z \mathbb{E}_t\left[\Delta z_{t+\tau}\right] + w_\ell \mathbb{E}_t\left[\Delta \ell_{t+\tau} - \Delta \ell^*\right] + w_h \mathbb{E}_t\left[\Delta \overline{dh}_t\right].$$

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

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

where

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

A first-order approximation of the weights is:

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

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

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

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

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

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

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

Therefore:

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

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:

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

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:

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

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:

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

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

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

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

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

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:

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

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).