

Innovation Booms, Easy Financing, and Human Capital Accumulation ^{*}

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Abstract

Innovation booms occur frequently and are often fueled by easy financing that allows new technology firms to pay high wages that attracts skilled labor. Using the late 1990s Information and Communication Technology (ICT) boom as a laboratory, we show that skilled labor joining this new sector experienced sizeable long-term earnings losses. We trace these losses to skill obsolescence, that cannot be explained by either selection or the subsequent ICT sector bust. During the boom, capital flowed more to firms whose workers would ultimately experience a larger productivity decline. This suggests that financial capital can amplify the negative effects of labor reallocation into booming sectors on aggregate labor productivity.

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1 Introduction

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

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

The answers are not obvious. For the first question, a worker joining a booming innovative sector could perform tasks that embed the new, superior technologies and as a result, accumulate useful human capital. In that case, even if capital markets overvalue the industry during the boom and investors lose money during a market correction, workers reallocated to the booming sector have gained valuable and portable skills that make them more productive in the long run. This argument echoes the assumption in speculative growth models that technology bubbles can be growth-enhancing because

1. See for instance “Amazon’s shopping spree at business schools,” *Financial Times*, March 2017.

they promote investments that increase future productivity (Olivier 2000; Caballero, Farhi, and Hammour 2006).

However, the skills acquired by workers during innovation booms may also rapidly lose value, leaving these workers with lower human capital in the long run. This could happen because innovation booms coincide with periods of intense experimentation and fast-paced technological change that may accelerate the obsolescence of vintage-specific skills. In addition, if innovation booms lead to firm overvaluation and lax financing conditions such that low quality projects are funded, workers will be more likely to acquire skills that quickly depreciate.

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

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

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

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

paths and on firms' financial statements.

We have four sets of findings. Our first set of results documents the large reallocation of both capital and high-skill labor toward the ICT sector during the boom. The labor reallocation takes place almost exclusively at the extensive margin of the labor market, i.e., when workers take their first job. The share of high-skill labor market entrants starting in the ICT sector almost doubles during the boom, from 17% beforehand to 31% at the peak, and back down to 19% when the boom ends. By contrast, the flow of seasoned skilled workers from other sectors does not change significantly. This implies that existing workers outside the booming tech sector are poor substitutes for new workers and therefore that there are multiple vintages of human capital within existing occupations.³

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

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

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

stabilized technologies for the post-boom cohort.

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

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

Workers from the post-boom cohort who start in ICT on the other hand exhibit a wage dynamics that is very similar to similar workers from the same cohort who started in other sectors. Therefore, the long-term wage discount of the boom cohort cannot be explained by a sector-level shift in productivity or labor demand, since post-boom cohort workers in the ICT sector face similar sector-level shocks. Instead, low long-term earnings concentrated on the boom cohort of ICT workers is consistent with steady depreciation of human capital accumulated in the ICT sector during the boom.⁴

The granularity and richness of the data allow us to include a battery of additional fixed effects to control for other unobserved shocks that might correlate with the decision to start in the ICT sector during the boom. Our results are quantitatively unchanged when we saturate the regression with controls that allow for time-varying shocks along local labor market, worker demographics and experience, entry wage bin, and sector. Our results are also robust to controlling for a host of firm-level characteristics, implying that human capital depreciation is not driven by a shift in the firm characteristics distribution, but is instead a within-firm phenomenon. We perform numerous additional robustness checks, showing that the wage discount is similar if we remove the financial sector from the control group, if we include capital income in the total compensation of workers to account for stock grants and stock options, and if we focus on US companies operating in France.

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

We rule out the remaining source of potential bias coming from changes in workers' self-selection by using the pre-boom cohort. We show that the workers starting in the ICT sector during the pre-boom period experience a quantitatively similar long-run wage discount as workers from the boom cohort. Since this cohort of workers sorted into jobs before the ICT boom starts, pre-boom cohort workers constitute a group of workers whose human capital will be affected by the boom, but whose sorting decision is not. The fact that the wage dynamics of the pre-boom cohort cannot be explained by selection into the booming sector (by construction) reinforces the interpretation that the long-run wage discount is due to human capital depreciation.

Our third set of results examines the role of financial capital flows that allow firms to compete for the scarce supply of talent. We find that higher capital availability for firms is associated with higher human capital depreciation for these firms' workers, indicating that capital flows can worsen long-term aggregate human capital during episodes of intense technological change, since it increases the number of workers exposed to a depreciation of their human capital and amplifies the depreciation each worker experiences.

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

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

workers who start in capital-flushed firms to lower quality technologies that have a strong vintage component.

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

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

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

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

We therefore also contribute to the literature that studies how financing booms and

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

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.⁵

Our evidence of human capital depreciation connects our paper to the large literature on technological displacement, which studies how technological change affects the usage of tasks (Autor, Levy, and Murnane, 2003; Goos, Manning, and Salomons, 2014; Ma, Ouimet, and Simintzi, 2022) and the value of human capital (Beaudry, Doms, and Lewis, 2010; Beaudry, Green, and Sand, 2016; Kogan, Schmidt, and Seegmiller, 2022), and the implications of the induced income risk for asset prices (Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, Schmidt, and Song, 2019). We add to this literature by showing that a wave of innovation has a negative impact on the earnings of skilled workers who contribute to its development and diffusion because their vintage of human capital becomes obsolete. Thus, we also contribute to the literature on vintage human capital,

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

which proposes that several vintages of knowledge can co-exist, and that technological change makes old vintages obsolete (Chari and Hopenhayn, 1991; Violante, 2002; Deming and Noray, 2020; Kogan, Schmidt, and Seegmiller, 2022; Ma, 2022).

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

2 Sectoral Reallocation during the ICT Boom

2.1 Data

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

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

For a 1/24th subsample of the full employer-employee data (individuals born in October of even-numbered years), individuals are assigned a unique identifier that enables us to reconstruct their entire employment history.⁶ Individuals are not present in this panel data during periods when they earn no wage, they exit the labor force, become unemployed, switch to self-employment and pay themselves only dividends, or move abroad.

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

We focus on the employer-employee panel from 1994 to 2015. Each observation corresponds to a unique firm-worker-year combination. We focus on job spells that are full time and last for at least six months in a given year. After we apply this filter, each individual has at most one job per year.⁷ We obtain a panel at the worker-year level. Workers can have gap years in this panel when they earn no wage in the private sector, work part time or had jobs for periods of less than six months.

The employer-employee data include a two-digit classification of job occupations that maps into the skill content of the job. High-skill workers represent 16% of the labor force over 1994–2015. Among them, 42% hold a sales and administration occupation (two-digit code 37), 33% hold a STEM occupation (code 38), and 4% are heads of company with at least ten employees (code 23).⁸ Appendix Table B.1 reports summary statistics for the sample of skilled workers. The median skilled worker is a man (mean 69%), is 43 years old (mean 43), and earns an annual wage of 41,000 euros (mean 50,000 euros), which corresponds to the 90th percentile of the wage distribution of full-time workers in France.⁹ Finally, a 4/31 subsample of the employer-employee panel data (individuals born in the first four days of October) can be linked to census data, which contain demographics information. We use this smaller sample when we also retrieve information on education.

Firms. We retrieve information on firms from four sources. Firm accounting information is from tax-files, which cover all firms subject to the regular or simplified corporate tax regime. Information on firm ownership structure is from a yearly survey of business groups run by the statistical office and crossed with information from Bureau Van Dijk. The data include information on both direct and indirect stakes and cross-ownership, which allow us to reconstruct group structures even in the presence of pyramids. The data

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

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

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

include information on the nationality of the ultimate owner, which allows us to identify subsidiaries of foreign companies. We retrieve the list of all new business registrations with the event date from the firm register, and use this information to measure firm age. Stock prices come from Eurofidai.

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

2.2 Capital Reallocation

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

Figure 1 shows the stock price run-up in the ICT sector, using two different measures of equity valuation: the value-weighted cumulative stock return (Panel 1a) and the ratio of the stock price over sales per share (Panel 1b).¹⁰ Both measures of equity valuation display a sharp increase in the ICT sector during the period 1997–2000, followed by an abrupt reversal.

Figure 2 shows that the run-up in equity valuations translates into an inflow of capital in the ICT sector that benefited both listed and private firms. We construct two measures of capital inflow using the administrative tax-files, which cover the universe of French

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

firms. Panel 2a uses equity issuance, defined as firm-level equity issuance scaled by lagged total assets averaged at the sector level. Panel 2b uses firm entry rate, defined as the number of new registered firms scaled by the stock of firms. For both measures, we observe the same boom-bust pattern as for equity valuation where capital reallocation peaks in 2000–2001, then sharply drops and returns to its pre-boom level around 2003.

2.3 Labor Reallocation

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

Figure 3b unpacks this reallocation of human capital between individuals who recently entered the labor market (four years prior or fewer) and individuals who have been in the labor market for longer (for five years or more). It shows that the deviation from trend in the share of skilled workers in the ICT sector is entirely driven by labor market entrants. The ICT sector share among workers who have been in the labor force for five years or more exhibits a slight upward trend but no significant deviation from trend. By contrast, the ICT sector share among new workers exhibits a sharp upward deviation from trend during the boom. This sharp difference in labor reallocation between cohorts points to the existence of different vintages of human capital within occupations. Workers with older vintages of human capital outside the ICT sector appear to be poor substitutes for new workers in the ICT sector during the development phase of new technologies.

Since sectoral reallocation of skilled labor induced by the boom mostly happens at the time of labor market entry, we focus on skilled workers who enter the labor market around the boom period in the rest of the paper. For our relevant sample, we define the entry year in the labor market as the year in which individuals take their first full-time

job, conditional on not being older than 30 at that time.¹¹

2.4 Taking Stock

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

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

Third, the boom is sharply delimited over time, from 1997/98 to 2001, which allows us to define the *boom cohort* of workers, that enters the labor market during the ICT boom, alongside with the *pre-boom cohort* and the *post-boom cohort* of workers, that enter the labor market in the period right before and right after the boom, respectively.

3 Human Capital Depreciation

We now estimate the long-term value of human capital accumulated during the ICT boom by skilled workers who start in the booming ICT sector. We start by outlining a simple

11. 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.

model showing how this value can be inferred from the long-run wage dynamics of the different cohorts by comparing wages across sectors and cohorts.

3.1 Model

Human capital. Time is discrete and the horizon is infinite. At the beginning of each period, a mass one cohort of workers enters the labor market and chooses in which sector $k = 1, 2$ to work. In line with the evidence presented in Section 2.3 that sectoral reallocation occurs mostly through the sectoral choice of labor market entrants, we assume workers cannot switch sector after the initial sectoral choice made at the time of entry.¹² 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 .¹³ $H_{i,c,k,t}$ represents the number of efficiency units of labor supplied by the worker. A worker's human capital has two components:

$$h_{i,c,k,t} = \theta_{i,k} + h_{c,k,t}. \quad (1)$$

$\theta_{i,k}$ 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:

$$h_{c,k,c} = 0, \quad (2)$$

$$h_{c,k,t} = h_{c,k,t-1} + dh_{c,k,t}, \quad t > c, \quad (3)$$

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:

$$dh_{c,k,t} = \mu_h + \rho_h(dh_{c,k,t-1} - \mu_h) + \varepsilon_{k,t}^h, \quad t > c, \quad (4)$$

12. The assumption of no sectoral mobility can be derived as a result if human capital accumulated on-the-job is sector specific (Rogerson, 2005).

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

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

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

$$w_{i,c,k,t} = w_{k,t} + \theta_{i,k} + h_{c,k,t}, \quad (5)$$

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

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

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

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

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 .¹⁴

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

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

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

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

$Z_{k,t}$ is sectoral productivity and follows the autoregressive process $z_{k,t} = \rho_z z_{k,t} + \varepsilon_{k,t}^z$, where $\rho_z \in [0, 1]$ and $\varepsilon_{k,t}^z$ is a productivity shock with mean zero. The infinite sum in (7) is the efficient quantity of labor supplied in sector k in period t by all cohorts of workers $c = -\infty, \dots, t$. 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:

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

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:¹⁵

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

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

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

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

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

3.2 Baseline Results

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

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

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

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

3.2.1 Simple Difference: Across Sectors (Within Cohorts)

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

2005, respectively.¹⁶

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

$Wage_{i,t}$ is the annualized wage of individual i in year t . $ICT_{i,0}$ is a dummy equal to one if individual i starts in the ICT sector. It is interacted with year dummies. The baseline specification includes year fixed effects α_t , interacted with the vector $X_{i,0}$ of worker characteristics, which includes sex, age, entry year, and two-digit occupation at entry. We superscript the regression coefficient β_t^c with c to emphasize that we estimate (10) separately for each cohort $c \in \{Pre, Boom, Post\}$. $e_{i,t}$ is an error term clustered at the individual level.¹⁷

The regression coefficient β_t^c captures the average wage difference in year t between workers from cohort c who start in the ICT sector and workers from the same cohort and with the same characteristics in the same occupation, who start outside the ICT sector.

Figure 4 presents the estimated β_t^c for each cohort. Focusing first on the boom cohort, the figure shows that workers who start in the ICT sector during the boom earn an entry wage on average 5% higher than individuals from the same cohort and with the same characteristics, starting outside the ICT sector. Strikingly, the wage difference vanishes rapidly once the boom ends in 2001, and keeps falling after the bust so that the wage difference becomes negative after 2004. By 2015, workers who started in the booming ICT sector earn on average 6% less than workers from the same cohort and same occupation, who started outside the ICT sector.

The wage decomposition (5) implied by the model shows that the 6% difference encompasses three economic forces. In the model, the regression coefficient β_t^c is equal to the difference in average wage between workers who started in ICT and workers who started in other sectors. Therefore, β_t^c can be calculated by averaging (5) over i at the

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

17. We refer to this specification as a simple difference although it is formally a difference-in-differences because of the time dimension (i.e., we compare the wage *dynamics* of two groups of individuals).

cohort-year level and differencing by k between the ICT sector and other sectors:

$$\beta_t^c = \Delta w_t + \Delta \bar{\theta}_c + \Delta h_{c,t} \quad (11)$$

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

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

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

3.2.2 Difference-in-Differences: Across Sectors and Across Cohorts

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

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

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

Figure 4 shows that, in sharp contrast with the boom cohort, the post-boom cohort shows no downward trend in the wage dynamics of workers who start in ICT. Therefore, the long-run wage discount of boom-cohort workers joining the ICT sector is not explained by a secular decline in labor demand or over-supply of skilled workers in the wake of the ICT bust (because if it were, the post-boom cohort would also experience the long-term wage decline). The wage dynamics are instead consistent with human capital accumulated during the boom depreciating over time.

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

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

We now include a starting-sector \times year fixed effect ($\delta_t \times ICT_{i,0}$) to ensure that the cross-cohort comparison is done within a starting sector. Figure 5 Panel A plots the regression coefficients. The downward trend indicates that there is a progressive depreciation of human capital accumulated by the boom cohort in the ICT sector during the boom relative to similar boom cohort-workers starting in other sectors, relative to the same comparison for the post-boom cohort. These coefficients capture the difference in the estimated coefficients for the boom and post-boom cohorts from Figure 4.

3.2.3 Selection

We now examine whether these estimates are explained by negative selection into ICT during the boom. This would happen if the booming ICT sector attracts a disproportionate share of low productivity workers or if large expansion in the share of new workers joining the sector increases the risk of mismatch between workers and sectors.¹⁸

Our baseline starting-sector \times year fixed effect ($\delta_t \times ICT_{i,0}$) adequately controls for selection if unobserved heterogeneity shifts the wage profile by a time-invariant term, as $\theta_{i,k}$ does in the wage equation (5), effectively acting as a worker fixed effect (Abowd, Kramarz, and Margolis, 1999; Babina, Ma, Moser, Ouimet, and Zarutskie, 2022). However, the starting-sector \times year fixed effect fails to control for selection if unobserved heterogeneity is correlated with wage *growth* and not just with the wage level. In this case, the downward trend in the boom cohort's wage dynamics could be explained by a more subtle form of negative selection: the booming ICT sector might draw workers who would experience lower wage growth even if they had started in another sector.

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

Figure 4 shows that the pre-boom cohort's wage dynamics has a downward trend very similar to that of the boom cohort. The difference-in-differences regression (13) estimated using the pre-boom cohort and the boom cohort shows that the difference in

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

wage dynamics between the two cohorts is statistically insignificant (Panel B of Figure 5), consistent with human capital depreciation but not with negative selection during the boom.

3.3 Ruling out Additional Confounders

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

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

The baseline specification controls for worker demographic characteristics and experience (sex, age dummies, entry year dummies) gathered in vector $X_{i,0}$, interacted with cohort \times year fixed effects (α_{ct}) to account for potential changes in return to experience (e.g., Buchinsky, Fougère, Kramarz, and Tchernis, 2010) and in the gender gap (e.g., Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon, 2022). We also control for potential differences in on-the-job learning and human capital depreciation across occupations (e.g., Kogan, Schmidt, and Seegmiller, 2022) by including two-digit occupation at entry in the vector of worker characteristics $X_{i,0}$.¹⁹

Column 1 of Table 1 reports the result of the baseline specification. The result is in line with Panel A of Figure 5. During the 2003–2005 period, individuals from the

19. 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.

boom cohort who started in the ICT sector have similar wages as individuals from the post-boom cohort who also started in the ICT sector (relative to the same comparison for individuals who started in other sectors.) However, as time passes, individuals who started in ICT during the boom experience slower wage growth such that their wage is 7.3% lower over the 2011–2015 period.

In column 2, we add individual fixed effects, which ensure that we identify wage changes off individual wage trajectories and not off changes in the pool of workers induced by attrition. The inclusion of individual fixed effects implies that the β coefficients are identified relative to a reference time period that we fix to 2003–2005. The coefficients for the period 2006–2015 relative to the reference period are very similar to those in column 1, implying that non-random attrition does not explain the wage discount.²⁰ We provide additional evidence that attrition does not explain our results in Section 3.4.

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

In column 4, we add entry wage quintile \times cohort \times year fixed effects. This ensures that we compare workers with the same entry wage and therefore accommodates the possibility that workers with different ex-ante productivity are on different wage trends. In column 5, we include four-digit sector \times year fixed effects to control for worker sorting that might correlate with sector-level differences in wage trajectories such as differences in return to talent and rent sharing (Philippon and Reshef, 2012; Célérier and Vallée, 2019) and

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

differences in unionization and collective bargaining rules that affect innovation and wage dynamics (e.g., Bena, Ortiz-Molina, and Simintzi, 2021). In this case, the coefficient on $ICT_{i,0} \times BoomCohort_i \times 2011-15$ remains identified off variation across workers starting in the same four-digit sector from the boom cohort relative to those from the post-boom cohort. In all cases, we find quantitatively similar effects.

Despite the tight identification strategy, it could still be the case that within occupations, narrowly defined sectors, and local labor markets, the composition of firm characteristics in the ICT sector changes during the boom. This could pose a problem for identification since workers’ long-term outcomes have been shown to be associated with firm characteristics.²¹ Ideally, we would like to add fixed effects for the worker’s initial employer interacted with year fixed effects and compare workers from different cohorts starting in the same firm. Because of the way the data are sampled, whereby individuals are randomly selected to be part of the panel irrespective of their employer, we cannot implement this strategy as few firms beyond the large ones hire sampled high-skill workers from several cohorts. However, it is still possible to absorb much of the potential endogeneity coming from the correlation between firm characteristics and worker productivity by creating “pseudo firms” based on firm characteristics.

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

While these fixed effects hold constant the distribution of firms’ ex-ante characteristics, variation in firms’ future performance may remain and explain wage dynamics.

21. For instance: size and differences in rent sharing and ability to insure workers (Bloom, Guvenen, Smith, Song, and Wachter, 2018; Hartman-Glaser, Lustig, and Xiaolan, 2019), connection to a business group (Tate and Yang, 2015; Cestone, Kramarz, and Fumagalli, 2018), firm age (Ouimet and Zarutskie, 2014; Babina, Ma, Moser, Ouimet, and Zarutskie, 2022), productivity (Abowd, Kramarz, and Margolis, 1999), and workforce composition (D’Acunto, Tate, and Yang, 2020).

In column 7, we address this possibility by adding the quintiles of five-year future sales growth in the set of variables used to construct pseudo firms.²² Finally, we include in column 8 all the high-dimensional fixed effects used in columns 3 to 5 and the pseudo-firm fixed effects used in column 7. The result is quantitatively robust across specifications.

3.4 Robustness

Excluding the financial sector. Compensation of high-skill workers in the financial sector grew faster than in other sectors during the 2000s (see Philippon and Reshef, 2012 for the US; Célérier and Vallée, 2019 for France), which could partially drive the wage discount in the ICT sector relative to the other sectors that include the financial sector. In column 1 of Table 2, we show that our results are robust to excluding workers starting in the financial sector.

Excluding French firms. While France fully embraced the ICT revolution and produced successful ICT firms, the country has not become the worldwide leader in that sector. As such, the wage discount might be specific to employees of French firms. To test this possibility, we leverage the fact that many large US firms have offices across the world, including in France, so their employees located in France appear in our data. We use ownership data to identify subsidiaries of US companies defined as firms that are 100% owned by a US company.²³ In column 2 of Table 2, we re-estimate the baseline regression for this subset of firms and find a similar effect as on the entire sample of firms. Therefore, the long-term wage decline is not a French firm phenomenon and extends to US firms—at least to their high-skill workers in France.

Capital income. We may under-estimate workers’ earnings because the matched employer-employee data report labor income but not capital income. Capital income can be significant for entrepreneurs and high-skill employees when they are granted shares or options in their employer’s stock (e.g., Kim and Ouimet, 2014; Eisfeldt, Falato, and Xiaolan,

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

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

2022). To account for capital income, we link the employer-employee data with employers' financial statements from tax filings. Since we do not have information on stock grants and stock options, we calculate capital income under two scenarios.

In the first scenario (column 3 of Table 2), we assume the CEO holds all cash flow rights. We add the firm's net income to the CEO's earnings.²⁴ In the second scenario (column 4), we assume employees receive ownership stakes when they join startup companies. We allocate during the first eight years of a firm's life one-third of its net income to the skilled employees who joined the firm within three years of firm creation.²⁵

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

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

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

24. 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.

25. 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 (e.g., Eisefeldt, 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.

in the ICT sector during the technology boom are worse-off in the long-run.

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

3.5 Taking Stock

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

4 Financial Capital Flows and Human Capital Depreciation

The finding that workers who started in the ICT sector during the boom experience sizable long-run human capital depreciation could imply that financing booms that accompany periods of rapid technological change weigh on aggregate human capital and ultimately on economic growth. This occurs if the capital flows during the boom are directed towards firms whose workers will experience larger depreciation of their human capital,

as more workers would lose human capital in the long term.²⁶ Conversely, if the capital flows during the boom and directed towards firms whose workers will experience smaller depreciation of their human capital, capital flows tend to mitigate aggregate human capital depreciation. Therefore, which case prevails depends on the *correlation* between human capital depreciation and capital flow during the boom. We study this correlation in Section 4.1.

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

4.1 Correlation Between Capital Availability and Human Capital Depreciation

To understand how human capital depreciation correlates with capital availability during the innovation boom, we augment equation (14) with interactions with the three proxies of capital availability that we introduced in Section 2.2.²⁷ The first two proxies measure overvaluation at the four-digit industry level using stock prices: value-weighted stock return during the year 1999 (ICT stocks peak in March 2000); and the median ratio of stock price over company sales per share (P/S) at the end of 1999.

The third proxy measures capital inflow using all public and private firms. We take net equity issuance normalized by lagged total assets at the firm level from the tax filings, and calculate the leave-one-out mean at the four-digit industry \times commuting zone \times year level. The leave-one-out mean ensures that capital availability is not endogenous to the firm’s intrinsic productivity. An advantage of this proxy is that it varies across industries and geographies, which allows us to augment the specification with a rich set of fixed effects.

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

27. 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.

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

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

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

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

4.2 Does Capital Availability Cause Human Capital Depreciation?

If the relationship between capital availability and human capital depreciation is causal, capital inflows have an additional impact on aggregate human capital by accelerating the human capital depreciation that the average worker experiences. This may occur if greater capital availability lowers the hurdle for innovative projects to be financed and if, in turn, workers exposed to lower quality projects develop skills more prone to obsolescence. Alternatively, the relationship may not be causal. For instance, sectors

receiving large capital inflows during the boom may be sectors experiencing fast-paced technological change, which is the true driver of the depreciation of human capital exposed to technological change.

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

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

5 Mechanisms for Human Capital Depreciation

We now examine what drives the human capital depreciation of high-skill workers starting in ICT during the boom and why this depreciation is amplified by capital availability

during the boom. We study three potential mechanisms: (i) obsolescence of technology vintage-specific skills; (ii) heightened risk of job termination; (iii) winner-take-all effect.

5.1 Skill Obsolescence

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

We test the skill obsolescence mechanism by studying whether the wage discount is larger for jobs with higher technological content in which human capital accumulation is more likely to be tied to those technologies. We proxy for the degree of technological content of a job by leveraging the fact that the occupation classification in the data maps directly into three broad levels of skill: high-skill, middle-skill, and low-skill.²⁸ This allows us to compare the obsolescence of human capital when new technologies appear between the three groups of workers classified according to the skill level corresponding to their first job. To do so, we re-run the baseline regression (14) separately for each group of workers, as well as the specification augmented with interactions with capital flow to the worker's four-digit sector \times commuting zone in the year in which she starts.

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

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

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

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

5.2 Job Termination

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

We examine this hypothesis by controlling directly for job termination in the wage regression (14). Job termination is a dummy equal to one if the worker experiences a forced job change within the first four years after entry. We proxy for a forced job change as a change in employer such that either (i) employment at the worker’s initial employer decreases by 10% or more in the year of the job change or (ii) the transition to the next job leads to a wage cut for the worker.²⁹

Column 1 of Table 5 reproduces the baseline wage discount without controlling for job termination. Column 2 controls for job termination interacted with the five-year period dummies.³⁰ This barely changes the long-term wage discount, which decreases from 7.7% to 7.6%.

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

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

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

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

The muted role of job termination in explaining the wage discount is not due to bad measurement of job termination. In Appendix B.5, we estimate the effect of starting in the ICT sector during the boom on the likelihood of subsequent job termination and we do find a significant increase in job termination of 7 percentage points. Instead, our results show that the phenomenon of accelerated obsolescence of technology-related skills is not explained by, nor correlated with, changing risk in job termination.

5.3 Winner-Take-All

The average long-term wage discount may mask a winner-take-all effect due to right-skewed returns to starting in technology sectors flushed with capital during periods of rapid technological change. Indeed, fast-paced technological change creates uncertainty regarding which firms and technologies will prevail in the long run (e.g., Kerr, Nanda, and Rhodes-Kropf, 2014). High inflow of capital can further amplify this risk, if capital is

provided by investors whose business model is to finance projects with a small probability of a large success, such as venture capitalists and angel investors.³¹ In this case, akin to patterns documented in the literature on the return to entrepreneurship (e.g., Hamilton, 2000; Kerr, Nanda, and Rhodes-Kropf, 2014; Kisseleva, Mjøs, and Robinson, 2022), low average earnings may conceal positive skewness and high earnings in the right tail of the distribution.

To test for this possibility, we estimate quantile regressions for the baseline specification (14) as well as for the specification augmented with interactions with capital flow. This allows us to examine the distribution of the long-term wage discount and determine if the discount turns into a premium in the right tail of the distribution.

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

6 Concluding Remarks

Bubbles in new technology sectors foster the reallocation of skilled labor from other sectors, at the expense of investors who finance negative NPV projects in the bubbly technology sector. Theories of endogenous growth (ref) and speculative growth (ref) posit that such reallocation can be socially beneficial as it enhances future productivity

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

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

References

- Abowd, John M, Francis Kramarz, and David N Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67 (2): 251–333.
- Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr. 2018. "Innovation, Reallocation, and Growth." *American Economic Review* 108 (11): 3450–3491.
- Adelino, Manuel, Song Ma, and David Robinson. 2017. "Firm Age, Investment Opportunities, and Job Creation." *Journal of Finance* 72 (3): 999–1038.
- Altonji, Joseph G, Lisa B Kahn, and Jamin D Speer. 2016. "Cashier or consultant? Entry labor market conditions, field of study, and career success." *Journal of Labor Economics* 34 (S1): S361–S401.
- Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.
- Babina, Tania, and Sabrina Howell. 2022. "Entrepreneurial Spillovers from Corporate R&D." *Working Paper*.
- Babina, Tania, Wenting Ma, Christian Moser, Paige Ouimet, and Rebecca Zarutskie. 2022. "Pay, Employment, and Dynamics of Young Firms." *Working Paper*, 1–56.
- Barrot, Jean-Noel, Thorsten Martin, Julien Sauvagnat, and Boris Vallée. 2019. "Employment Effects of Alleviating Financing Frictions: Worker-Level Evidence from a Loan Guarantee Program." *Working Paper*.
- Baumol, William. 1990. "Entrepreneurship: Productive, Unproductive, and Destructive." *Journal of Political Economy* 98 (5): 893–921.
- Beaudry, Paul, Mark Doms, and Ethan Lewis. 2010. "Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas." *Journal of Political Economy* 118 (5): 988–1036.
- Beaudry, Paul, David A Green, and Benjamin M Sand. 2016. "The great reversal in the demand for skill and cognitive tasks." *Journal of Labor Economics* 34 (S1): S199–S247.
- Bena, Jan, Hernán Ortiz-Molina, and Elena Simintzi. 2021. "Shielding firm value: Employment protection and process innovation." *Journal of Financial Economics*.
- Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2022. "Do Firms Respond to Gender Pay Gap Transparency?" *Journal of Finance* 77 (4): 2051–2091.
- Bernstein, Shai. 2015. "Does Going Public Affect Innovation?" *Journal of Finance* 70 (4): 1365–1403.
- Bernstein, Shai, Tim McQuade, Ramana Nanda, and Benjamin Roth. 2019. "More Capital , Less Innovation ? The Implications of Large Capital Inflows to the Venture Capital Industry." *Working Paper*, 1–48.
- Bloom, Nicholas, Fatih Guvenen, Benjamin S Smith, Jae Song, and Till von Wachter. 2018. "The Disappearing Large-Firm Wage Premium." *AEA Papers and Proceedings* 108:317–22.
- Brown, James, Steven Fazzari, and Bruce Petersen. 2009. "Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s RD Boom." *Journal of Finance* 64 (1): 151–185.

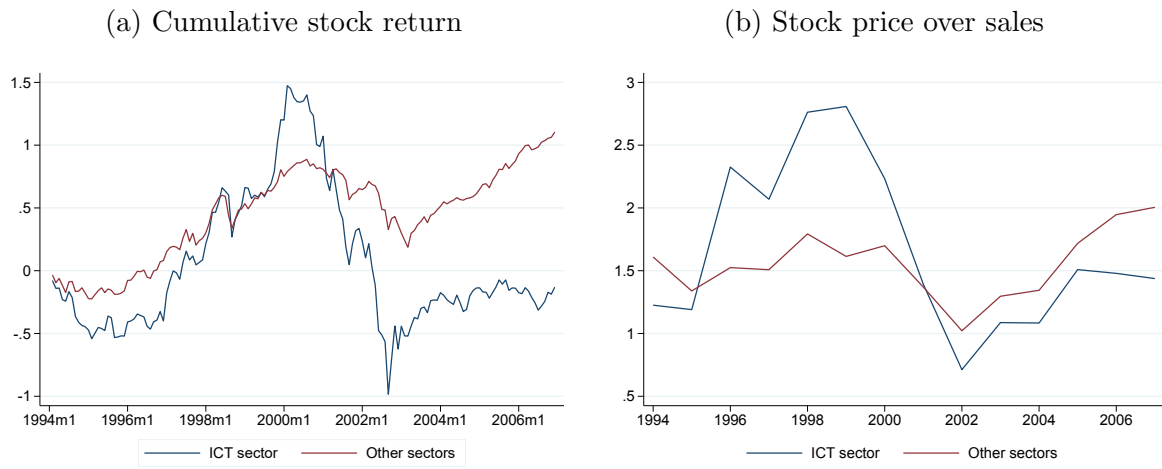
- Brunnermeier, Markus K, and Stefan Nagel. 2004. "Hedge Funds and the Technology Bubble." *Journal of Finance* 59 (5): pp. 2013–2040.
- Buchinsky, Moshe, Denis Fougère, Francis Kramarz, and Rusty Tchernis. 2010. "Interfirm Mobility, Wages and the Returns to Seniority and Experience in the United States." *Review of Economic Studies* 77 (3): 972–1001.
- Caballero, Ricardo J, Emmanuel Farhi, and Mohamad L Hammour. 2006. "Speculative growth: hints from the US economy." *American Economic Review* 96 (4): 1159–1192.
- Cahuc, Pierre, and Corinne Prost. 2015. "Améliorer l'assurance chômage pour limiter l'instabilité de l'emploi." *Notes du Conseil d'Analyse Economique* 24:1–12.
- Campello, Murillo, and John Graham. 2013. "Do stock prices influence corporate decisions? Evidence from the technology bubble." *Journal of Financial Economics* 107 (1): 89–110.
- Carrillo, Bladimir. 2020. "Present bias and underinvestment in education? long-run effects of childhood exposure to booms in colombia." *Journal of Labor Economics* 38 (4): 1127–1265.
- Célérier, Claire, and Boris Vallée. 2019. "Returns to talent and the finance wage premium." *The Review of Financial Studies* 32 (10): 4005–4040.
- Cestone, Giacinta, Francis Kramarz, and Chiara Fumagalli. 2018. "Insurance Between Firms : The Role of Internal Labor Markets." *Working Paper*, no. April.
- Chari, V V, and Hugo Hopenhayn. 1991. "Vintage Human Capital, Growth, and the Diffusion of New Technology." *Journal of Political Economy* 99 (6): 1142–1165.
- Charles, Kerwin Kofi, Erik Hurst, and Matthew J Notowidigdo. 2018. "Housing Booms and Busts, Labor Market Opportunities, and College Attendance." *American Economic Review* 108 (10): 2947–94.
- Choi, Darwin, Dong Lou, and Abhiroop Mukherjee. 2022. "Superstar Firms and College Major Choice." *Working Paper*.
- D'Acunto, Francesco, Geoffrey Tate, and Liu Yang. 2020. "Entrepreneurial Teams: Diversity of Skills and Early-Stage Growth." *Working Paper*.
- Deming, David J, and Kadeem Noray. 2020. "Earnings dynamics, changing job skills, and STEM careers." *The Quarterly Journal of Economics* 135 (4): 1965–2005.
- Dustmann, Christian, and Costas Meghir. 2005. "Wages, Experience and Seniority." *Review of Economic Studies* 72 (1): 77–108.
- Eisfeldt, Andrea L., Antonio Falato, and Mindy Z. Xiaolan. 2022. "Human Capitalists." *NBER Macro Annual*.
- Ewens, Michael, and Joan Farre-Mensa. 2020. "The Deregulation of the Private Equity Markets and the Decline in IPOs." *Review of Financial Studies* 33 (12): 5463–5509.
- Fedyk, Anastassia, and James Hodson. 2022. "Trading on Talent: Human Capital and Firm Performance." *Review of Finance*.
- Gârleanu, Nicolae, Leonid Kogan, and Stavros Panageas. 2012. "Displacement risk and asset returns." *Journal of Financial Economics* 105 (3): 491–510.

- Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routinization and Offshoring." *American Economic Review* 104 (8): 1–20.
- Griffin, John M, Jeffrey H Harris, Tao Shu, and Selim Topaloglu. 2011. "Who Drove and Burst the Tech Bubble?" *Journal of Finance* 66 (4): 1251–1290.
- Guiso, Luigi, Luigi Pistaferri, and Fabiano Schivardi. 2012. "Credit within the Firm." *Review of Economic Studies* 80 (1): 211–247.
- Gupta, Nandini, and Isaac Hacamo. 2022. "The Finance Wage Premium and Entrepreneurship." *Working Paper*.
- Haddad, Valentin, Paul Ho, and Erik Loualiche. 2022. "Bubbles and the value of innovation." *Journal of Financial Economics* 145 (1): 69–84.
- Hamilton, Barton H. 2000. "Does entrepreneurship pay? An empirical analysis of the returns to self-employment." *Journal of Political economy* 108 (3): 604–631.
- Hartman-Glaser, Barney, Hanno Lustig, and Mindy Xiaolan. 2019. "Capital Share Dynamics When Firms Insure Workers." *Journal of Finance* 74 (4): 1707–1751.
- Hombert, Johan, and Adrien Matray. 2018. "Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China?" *Journal of Finance* 73 (5): 2003–2039.
- Howell, Sabrina T, Josh Lerner, Ramana Nanda, and Richard R Townsend. 2021. "How Resilient is Venture-Backed Innovation? Evidence from Four Decades of U.S. Patenting," Working Paper Series.
- Hsieh, Chang-Tai, and Peter J Klenow. 2009. "Misallocation and manufacturing TFP in China and India." *The Quarterly journal of economics* 124 (4): 1403–1448.
- Janeway, William, Ramana Nanda, and Matthew Rhodes-Kropf. 2021. "Venture Capital Booms and Start-Up Financing." *Annual Review of Financial Economics* 13 (1): 111–127.
- Kahn, Lisa B. 2010. "The long-term labor market consequences of graduating from college in a bad economy." *Labour Economics* 17 (2): 303–316.
- Kerr, William, and Ramana Nanda. 2015. "Financing Innovation." *Annual Review of Financial Economics* 7 (1): 445–462.
- Kerr, William R, Ramana Nanda, and Matthew Rhodes-Kropf. 2014. "Entrepreneurship as experimentation." *Journal of Economic Perspectives* 28 (3): 25–48.
- Kim, Ehan, and Paige Ouimet. 2014. "Broad-Based Employee Stock Ownership: Motives and Outcomes." *Journal of Finance* 69 (3): 1273–1319.
- Kisseleva, Katja, Aksel Mjøs, and David Robinson. 2022. "Firm Dynamics and the Returns to Early-Stage Investment." *Working Paper*.
- Kogan, Leonid, Dimitris Papanikolaou, Lawrence D. W. Schmidt, and Jae Song. 2019. "Technological Innovation and Labor Income Risk." *Working Paper*.
- Kogan, Leonid, Lawrence Schmidt, and Bryan Seegmiller. 2022. "Technology , Vintage-Specific Human Capital , and Labor Displacement: Evidence from Linking Patents with Occupations." *Working Paper*.

- Kortum, Samuel, and Josh Lerner. 2000. "Assessing the Contribution of Venture Capital to Innovation." *RAND Journal of Economics* 31 (4): 674–692.
- Lazear, Edward P. 1981. "Agency, Earnings Profiles, Productivity, and Hours Restrictions." *American Economic Review* 71 (4): 606–620.
- Lewellen, Jonathan. 2003. "Discussion of "The Internet downturn: Finding valuation factors in Spring 2000"." *Journal of Accounting and Economics* 34 (1-3): 237–247.
- Ma, Song. 2022. "Technological Obsolescence." *Working Paper*.
- Ma, Wenting, Paige Ouimet, and Elena Simintzi. 2022. "Mergers and Acquisitions , Technological Change and Inequality." *Working Paper*, no. June.
- Murphy, Kevin, Andrei Shleifer, and Robert Vishny. 1991. "The Allocation of Talent: Implications for Growth." *Quarterly Journal of Economics* 106 (2): 503–530.
- Nagler, Markus, Marc Piopiunik, and Martin R West. 2020. "Weak Markets, Strong Teachers: Recession at Career Start and Teacher Effectiveness." *Journal of Labor Economics* 38 (2): 453–500.
- Nanda, Ramana, and Matthew Rhodes-Kropf. 2013. "Investment cycles and startup innovation." *Journal of Financial Economics* 110 (2): 403–418.
- . 2017. "Financing Risk and Innovation." *Management Science* 63 (4): 901–918.
- OECD. 2002. *Measuring the Information Economy*. OECD Publications.
- Ofek, Eli, and Matthew Richardson. 2003. "DotCom Mania: The Rise and Fall of Internet Stock Prices." *Journal of Finance* 58 (3): 1113–1137.
- Olivier, Jacques. 2000. "Growth-enhancing bubbles." *International Economic Review* 41 (1): 133–152.
- Oreopoulos, Philip, Till von Wachter, and Andrew Heisz. 2012. "Short and long-term career effects of graduating in a recession." *American Economic Journal: Applied Economics* 4 (1): 1–29.
- Ouimet, Paige, and Rebecca Zarutskie. 2014. "Who works for startups? The relation between firm age, employee age, and growth." *Journal of financial Economics* 112 (3): 386–407.
- Oyer, Paul. 2006. "Initial Labor Market Conditions and Long-Term Outcomes for Economists." *Journal of Economic Perspectives* 20 (3): 143–160.
- Pástor, Ľuboš, and Pietro Veronesi. 2006. "Was there a Nasdaq bubble in the late 1990s?" *Journal of Financial Economics* 81 (1): 61–100.
- Philippon, Thomas. 2010. "Financiers versus Engineers: Should the Financial Sector be Taxed or Subsidized?" *American Economic Journal: Macroeconomics* 2 (3): 158–182.
- Philippon, Thomas, and Ariell Reshef. 2012. "Wages and human capital in the US finance industry: 1909–2006." *The Quarterly Journal of Economics* 127 (4): 1551–1609.
- Reshef, Ariell, and Thomas Philippon. 2012. "Wages and Human Capital in the U.S. Financial Industry: 1909–2006." *Quarterly Journal of Economics* (Cambridge, Mass.): 127 (4): 1551–1609.
- Rogerson, Richard. 2005. "Sectoral shocks, human capital, and displaced workers." *Review of Economic Dynamics* 8 (1): 89–105.

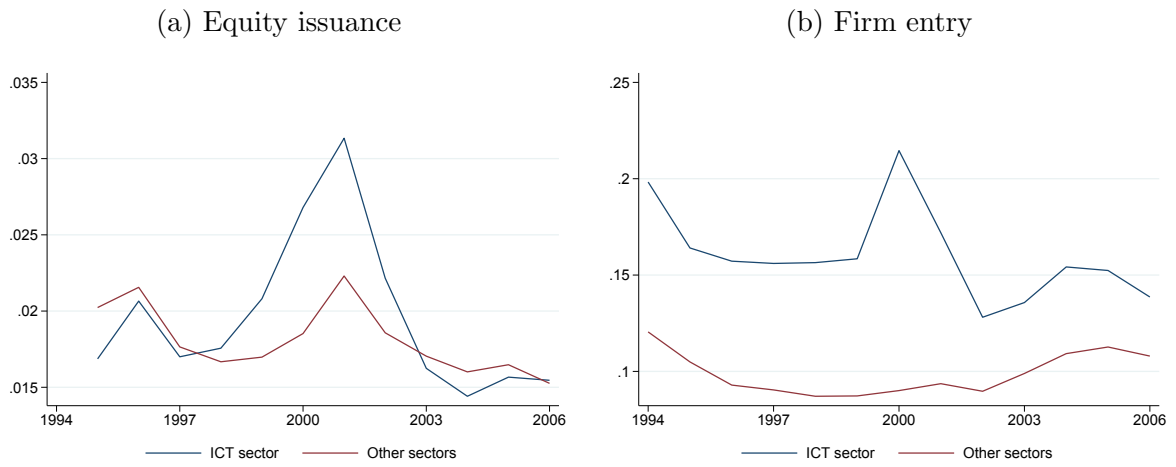
- Scheinkman, Jose. 2014. *Speculation, Trading, and Bubbles*. Edited by Kenneth J. Arrow Lecture Series. Columbia University Press.
- Schoar, Antoinette, and Luo Zuo. 2017. “Shaped by Booms and Busts: How the Economy Impacts CEO Careers and Management Styles.” *Review of Financial Studies* 30 (5): 1425–1456.
- Shu, Pian. 2016. “Innovating in Science and Engineering or ‘Cashing In’ on Wall Street? Evidence on Elite STEM Talent.” *Working Paper*.
- Tate, Geoffrey, and Liu Yang. 2015. “The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets.” *Review of Financial Studies* 28 (8): 2203–2249.
- Townsend, Richard. 2015. “Propagation of Financial Shocks: The Case of Venture Capital.” *Management Science* 61 (11): 2782–2802.
- Violante, Giovanni L. 2002. “Technological acceleration, skill transferability, and the rise in residual inequality.” *The Quarterly Journal of Economics* 117 (1): 297–338.

Figure 1: Equity Valuation



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

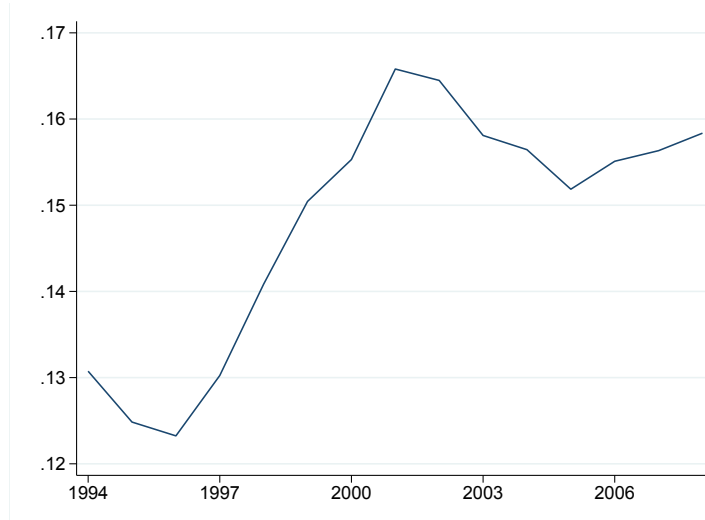
Figure 2: Capital Reallocation



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

Figure 3: Labor Reallocation

(a) ICT sector share among all skilled workers

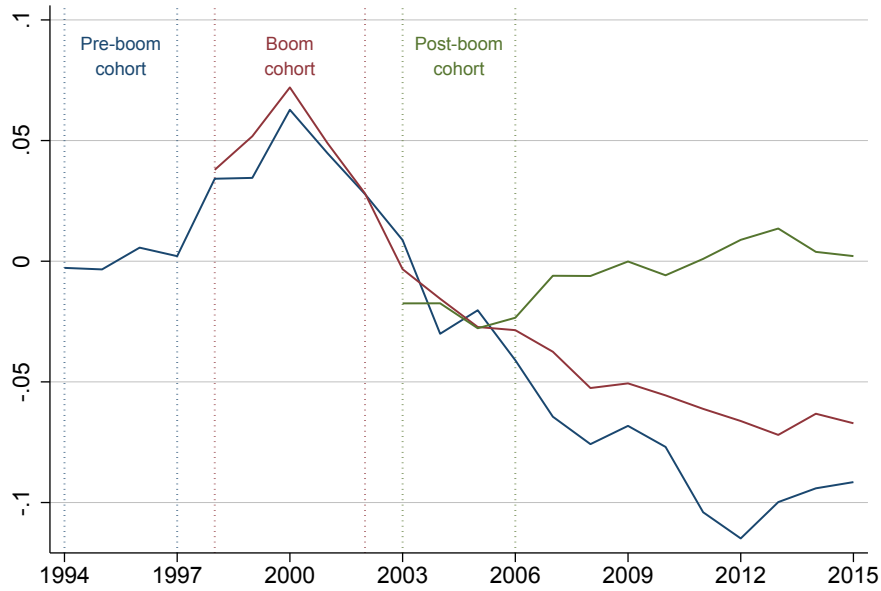


(b) ICT sector share among skilled workers: recent entrants vs. older workers



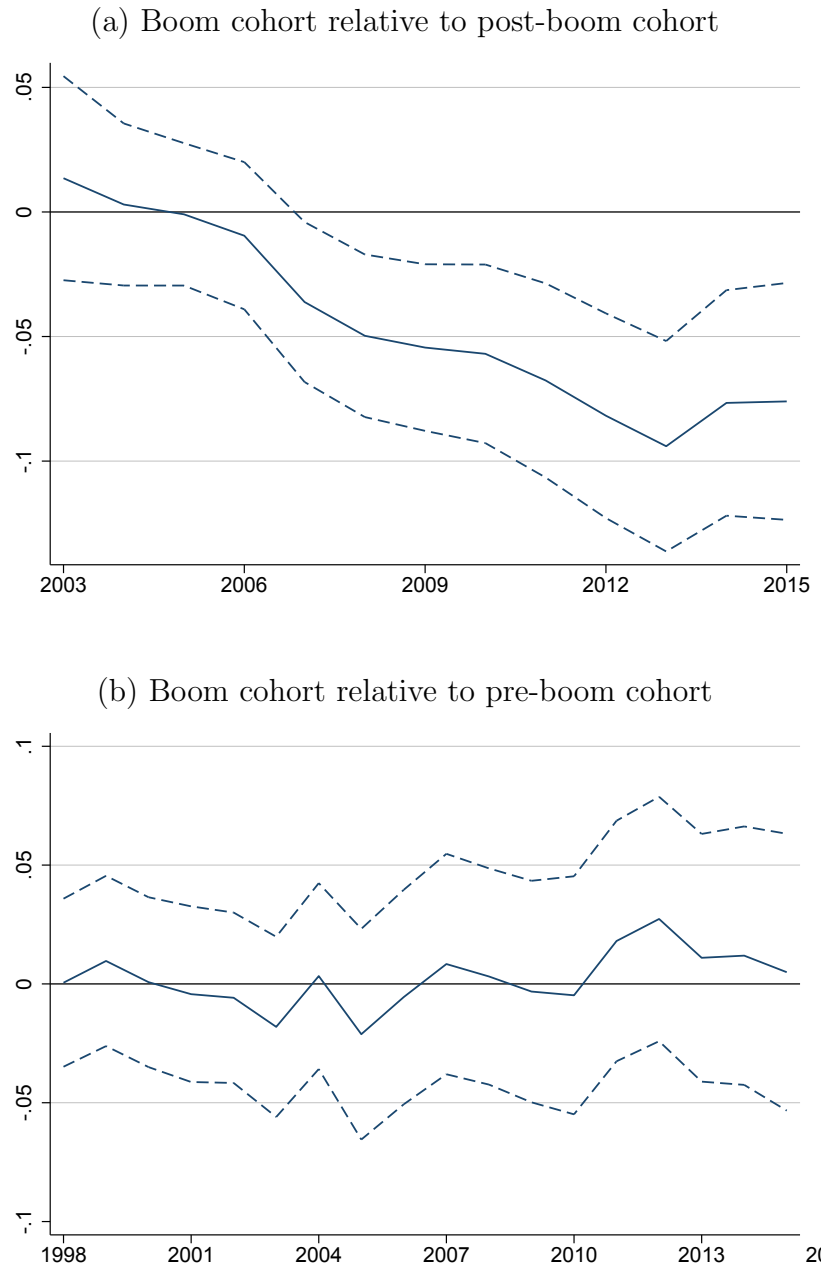
Panel (a) plots the share of the ICT sector in high-skill employment. Panel (b) shows the share of the ICT sector in high-skill employment separately for workers who entered the labor market five years ago or more (blue line) and for workers who entered four years ago or less (red line).

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



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

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



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

Table 1: Wage Regressions

	log(Wage)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT ₀ × Boom cohort × 2003-05	0.001 (0.013)							
ICT ₀ × Boom cohort × 2006-10	-0.035** (0.014)	-0.048*** (0.010)	-0.041*** (0.011)	-0.043*** (0.010)	-0.045*** (0.013)	-0.037*** (0.011)	-0.039*** (0.012)	-0.034** (0.016)
ICT ₀ × Boom cohort × 2011-15	-0.073*** (0.019)	-0.077*** (0.015)	-0.067*** (0.016)	-0.075*** (0.015)	-0.078*** (0.019)	-0.065*** (0.016)	-0.070*** (0.018)	-0.074*** (0.024)
Adjusted-R2	.3	.84	.84	.84	.84	.84	.84	.84
Observations	93,304	92,901	92,719	92,901	91,343	92,714	90,473	88,586
ICT ₀ × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Worker FE	—	✓	✓	✓	✓	✓	✓	✓
Commuting zone × Cohort × Year FE	—	—	✓	—	—	—	—	✓
Entry wage quintile × Cohort × Year FE	—	—	—	✓	—	—	—	✓
Four-digit sector × Year FE	—	—	—	—	✓	—	—	✓
Pseudo firm FE × Year FE	—	—	—	—	—	✓	✓	✓
Sales growth ($t \rightarrow t + 5$) Quintile FE × Year FE	—	—	—	—	—	—	✓	✓

The table presents the OLS estimates of equation (14) for high-skill entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t . ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2002–05, 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Column 2 adds two-digit occupation at entry × cohort × year fixed effects. Column 3 includes commuting zone at entry × cohort × year fixed effects. Column 4 includes initial wage quintile at entry × cohort × year fixed effects. Column 5 includes four-digit sector at entry × year fixed effects. Column 6 includes initial employer’s pseudo firm (based on employment, firm age, labor productivity, affiliation with a conglomerate) × year fixed effects. Column 7 adds five-year futures sales growth in the set of variables used to construct pseudo firms. Column 8 includes all the controls and fixed effects together, using the same definition of pseudo firms as in column 7. All specifications include ICT₀ 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.

Table 2: Robustness

	log(Wage)		log(Wage+Cap.income)	
	Excl. finance	US firms	Capital income assigned to CEOs	Skilled workers
	(1)	(2)	(3)	(4)
ICT ₀ × Boom cohort × 2006-10	-0.049*** (0.010)	-0.033 (0.032)	-0.051*** (0.011)	-0.052*** (0.011)
ICT ₀ × Boom cohort × 2011-15	-0.079*** (0.015)	-0.074* (0.044)	-0.076*** (0.015)	-0.081*** (0.016)
Adjusted-R2	.83	.83	.82	.82
Observations	87,522	11,359	92,901	92,901
ICT ₀ ×Year FE	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓

The table presents the OLS estimates of equation (14) for skilled entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. In columns 1 and 2, the dependent variable is log wage of worker i in year t . In column 1, we exclude workers who started in the financial sector. In column 2, the sample is restricted to workers who started in the subsidiary of a US firm. In columns 3 and 4, the dependent variable is log wage plus capital income. In column 3, capital income is equal to the employer’s profits if the worker is the CEO of the firm. In column 4, capital income is equal to one-third of the employer’s profits times the share of the worker’s wage in the firm’s total high-skill wage bill, if the firm is eight year old or less. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT₀ 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.

Table 3: Capital Availability and Human Capital Depreciation

Proxy of capital availability:	log(Wage)				
	1999 return (sector level)	1999 P/S (sector level)	Equity issuance (sector×geo×entry year level)		
	(1)	(2)	(3)	(4)	(5)
ICT ₀ × Boom cohort × 2006-10	0.011 (0.030)	0.008 (0.030)	-0.024 (0.017)		-0.027 (0.018)
ICT ₀ × Boom cohort × 2011-15	0.022 (0.044)	0.007 (0.042)	-0.029 (0.025)		-0.033 (0.027)
ICT ₀ × Capital availability × Boom cohort × 2006-10	-0.062* (0.033)	-0.063* (0.033)	-0.033 (0.021)	-0.030 (0.024)	-0.022 (0.022)
ICT ₀ × Capital availability × Boom cohort × 2011-15	-0.129*** (0.049)	-0.113** (0.047)	-0.081*** (0.031)	-0.083** (0.035)	-0.067** (0.033)
Adjusted-R2	.84	.84	.84	.84	.84
Observations	60,420	60,420	85,128	77,556	83,366
ICT ₀ ×Year FE	✓	✓	✓	✓	✓
Worker controls×Cohort×Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t . ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Each variable is interacted with a proxy of capital availability in the sector (and geography and time for the third proxy) at which the worker takes her first job. In column 1, the proxy of capital availability is the value-weighted stock return in 1999 at the four-digit sector level. In column 2, it is the median ratio of stock price over company sales at the end of 1999 at the four-digit sector level. In columns 3 to 5, it is net equity issuance at the four-digit sector×commuting zone×year level. All specifications include worker fixed effects, ICT₀ 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.

Table 4: Heterogeneity Across Skill Levels and Capital Availability

	log(Wage)					
	High-skill		Middle-skill		Low-skill	
	(1)	(2)	(3)	(4)	(5)	(6)
ICT ₀ × Boom cohort × 2006-10	-0.048*** (0.010)	-0.024 (0.017)	-0.048*** (0.011)	-0.024 (0.017)	-0.028* (0.015)	-0.025 (0.027)
ICT ₀ × Boom cohort × 2011-15	-0.077*** (0.015)	-0.029 (0.025)	-0.068*** (0.014)	-0.039* (0.023)	-0.022 (0.020)	-0.027 (0.040)
ICT ₀ × Capital availability × Boom cohort × 2006-10		-0.033 (0.021)		-0.025 (0.022)		-0.012 (0.030)
ICT ₀ × Capital availability × Boom cohort × 2011-15		-0.081*** (0.031)		-0.033 (0.029)		-0.004 (0.041)
Adjusted-R2	.84	.84	.83	.83	.8	.81
Observations	92,901	85,128	206,918	186,477	250,620	218,927
ICT ₀ × Year FE	✓	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t . In columns 1 and 2, the sample is workers with a high-skill occupation at entry. In columns 3 and 4, the sample is workers with an intermediate-skill occupation at entry. In columns 5 and 6, the sample is workers with a low-skill occupation at entry. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. Capital availability is net equity issuance in the four-digit sector × commuting zone × year at which the worker takes her first job. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT₀ 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.

Table 5: Controlling for Job Termination

Control for:	log(Wage)					
	—	Job loss	Job termination × ICT ₀ × BoomCoh.	—	Job termination	Job termination × ICT ₀ × BoomCoh.
	(1)	(2)	(3)	(4)	(5)	(6)
ICT ₀ × Boom cohort × 2006-10	-0.048*** (0.010)	-0.046*** (0.010)	-0.042*** (0.012)	-0.024 (0.017)	-0.021 (0.017)	-0.022 (0.020)
ICT ₀ × Boom cohort × 2011-15	-0.077*** (0.015)	-0.076*** (0.015)	-0.069*** (0.017)	-0.029 (0.025)	-0.026 (0.025)	-0.019 (0.028)
ICT ₀ × Capital availability × Boom cohort × 2006-10				-0.033 (0.021)	-0.035* (0.021)	-0.028 (0.025)
ICT ₀ × Capital availability × Boom cohort × 2011-15				-0.081*** (0.031)	-0.082*** (0.031)	-0.083** (0.035)
Adjusted-R2	.84	.84	.84	.84	.84	.84
Observations	92,901	92,901	92,901	85,128	85,128	85,128
ICT ₀ × Year FE	✓	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

The table presents OLS estimates for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variable is log wage of worker i in year t . ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. Capital availability is net equity issuance in the four-digit sector × commuting zone × year at which the worker takes her first job. Column 1 reproduces the specification in column 2 of Table 1. In column 2, we control for a job termination dummy equal interacted with the five-year period dummies. Job termination equals one if the worker experiences forced job change within the first four years after entry, where forced job change is defined as a change in employer such that either (i) employment at the worker’s initial employer decreases by 10% or more in the year of the job change or (ii) the transition to the next job leads to a wage cut for the worker. In column 3, we include the interaction term between job termination and all the interactions between ICT₀, BoomCohort, and the five-year period dummies. Column 4 reproduces the specification in column 3 of Table 3. In column 5, we control for job termination and its interaction with capital availability and with the five-year period dummies. In column 6, we include the interaction term between job termination and all the interactions between ICT₀, BoomCohort, capital availability, and the five-year period dummies. All specifications include worker fixed effects, ICT₀ 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.

Table 6: Quantile Regressions

<i>Panel A: Unconditional Wage Discount</i>		log(Wage)			
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT ₀ × Boom cohort × 2006-10	-0.053*** (0.016)	-0.053*** (0.011)	-0.053*** (0.009)	-0.053*** (0.012)	-0.053*** (0.016)
ICT ₀ × Boom cohort × 2011-15	-0.090*** (0.017)	-0.086*** (0.012)	-0.080*** (0.009)	-0.075*** (0.012)	-0.071*** (0.017)
Observations	93,306	93,306	93,306	93,306	93,306
ICT ₀ × Year FE	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓
<i>Panel B: Conditional on Capital Availability</i>		log(Wage)			
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT ₀ × Boom cohort × 2006-10	-0.033 (0.025)	-0.030* (0.018)	-0.026** (0.013)	-0.023 (0.016)	-0.020 (0.022)
ICT ₀ × Boom cohort × 2011-15	-0.053** (0.027)	-0.045** (0.019)	-0.033** (0.014)	-0.022 (0.017)	-0.014 (0.024)
ICT ₀ × Capital availability × Boom cohort × 2006-10	-0.028 (0.034)	-0.034 (0.024)	-0.042** (0.017)	-0.050** (0.022)	-0.056* (0.030)
ICT ₀ × Capital availability × Boom cohort × 2011-15	-0.056 (0.036)	-0.065** (0.026)	-0.077*** (0.018)	-0.089*** (0.023)	-0.098*** (0.032)
Observations	87,114	87,114	87,114	87,114	87,114
ICT ₀ × Year FE	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓

The table presents quantile regressions of equation (14) for skilled entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005 over the period 1998–2015. The dependent variables in columns 1 through 5 are the 10th, 25th, 50th, 75th and 90th percentiles of the log wage. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. Capital availability is net equity issuance in the four-digit sector × commuting zone × year at which the worker takes her first job. 2006–10 and 2011–15 are dummies equal to one if year t belongs to the corresponding time period. All specifications include worker fixed effects, ICT₀ 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.

ONLINE APPENDIX

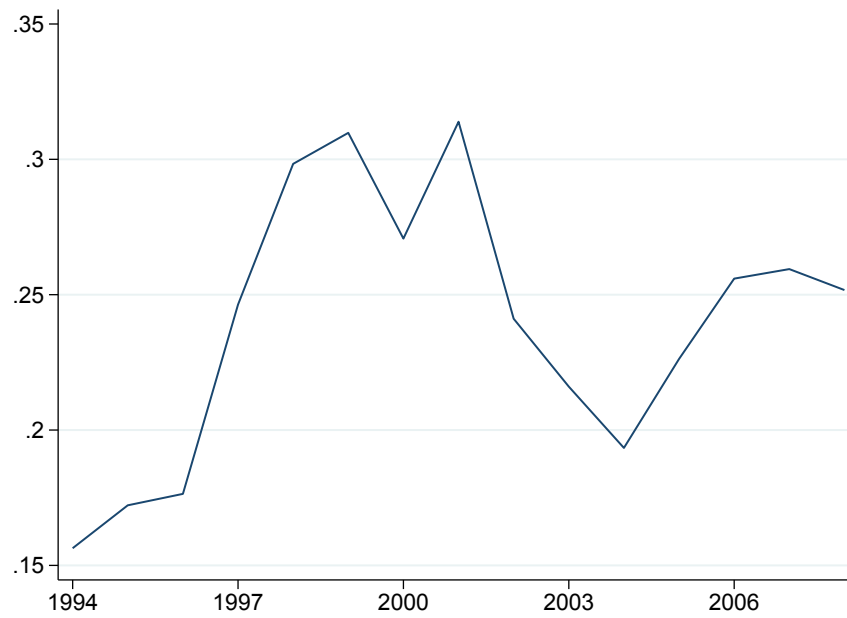
A Data Sources

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 data sources used in the paper are:

1. *Déclaration Annuelle des Données Sociales (DADS)*: Exhaustive employer-employee cross-sectional data, from social security filings.
2. *DADS Panel Tous Salariés*: 1/24th employer-employee panel data (individuals born in October of even-numbered years), from social security filings.
3. *DADS Echantillon Démographique Permanent*: 4/30th subsample of the employer-panel data (individuals born in the first four days of October), which is linked with census data.
4. *FICUS-FARE*: Firm financial statement, from tax filings.
5. *Enquête LIaisons FInancières (LIFI)*: Firm ownership structure, from Bureau van Dijk and survey run by the statistical office.
6. *Répertoire des Entreprises et des Etablissement (SIRENE)*: New business creation, from firm register.

B Additional Figures and Tables

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



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

Table B.1: Summary Statistics

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

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

Table B.2: ICT Industries

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

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

B.1 Cumulative Earnings

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

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

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

In column 3, we account for unemployment benefits in the calculation of cumulative earnings. Since unemployment benefits (UB) are only reported starting in 2008, we assign estimated UB when an individual has no earnings reported in the data in a given year. In France, individuals are entitled to UB if the job is terminated or not renewed by the employer, but not if they resign, and UB are paid for a period of time roughly equal to that of their pre-unemployment job spell and no longer than two years (Cahuc and Prost, 2015). Since the data do not report the motive for job termination, we assume in the baseline scenario that all job terminations give rise to one year of UB equal to the average replacement rate in France of 60% of the total wage earned in the previous year.³² If anything, accounting for unemployment benefits increases slightly the

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

cumulative earnings loss.

Table B.3: Cumulative Earnings

	Cumulative Earnings		
	Log	Level	Level incl. UB
	(1)	(in Euro) (2)	(in Euro) (3)
ICT ₀ × 2001	.041*** (.01)	2093*** (660)	2244*** (641)
ICT ₀ × 2005	.0086 (.014)	74 (1874)	-288 (1854)
ICT ₀ × 2010	-.021 (.018)	-8924** (3749)	-9558** (3713)
ICT ₀ × 2015	-.041** (.02)	-19596*** (6049)	-20650*** (6029)
Adjusted-R2	.56	.41	.43
Observations	120,457	120,457	120,457
ICT ₀ × Year FE	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓

The table presents OLS estimates for high-skill entrants of the boom cohort 1998–2001 over the period 1998–2015. In column 1, the dependent variable is the log of cumulative wage of worker i from entry up to year t . In column 2, the dependent variable is the level of cumulative wage of worker i from entry up to year t . In column 3, the dependent variable is the level of cumulative wage plus unemployment benefits of worker i from entry up to year t . The sample is restricted to the worker's entry year and the years 1998–2001, 2005, 2010, and 2015. ICT₀ is a dummy equal to one if the worker started in the ICT sector. All specification include ICT₀ 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.

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

B.2 Education

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

Table B.4: Education

	=1 if Master's degree				
	(1)	(2)	(3)	(4)	(5)
ICT ₀	-0.004 (0.034)	-0.023 (0.034)		-0.011 (0.032)	
ICT ₀ × BoomCohort	-0.016 (0.041)	-0.020 (0.043)	-0.019 (0.053)	-0.014 (0.040)	0.018 (0.063)
Constant	0.902*** (0.011)	0.915*** (0.011)	0.912*** (0.018)	0.797*** (0.030)	0.846*** (0.045)
Adjusted-R2	.02	.029	.055	.041	.032
Observations	1,138	1,097	1,009	1,083	902
Commuting zone×Cohort FE		✓			✓
Four-digit sector FE			✓		✓
Pseudo-firm FE				✓	✓

The table presents OLS estimates of cross-sectional regressions for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. The dependent variable is a dummy equal to one if the worker holds a Master's degree. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B.3 Attrition

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

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

Table B.5: Attrition

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

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

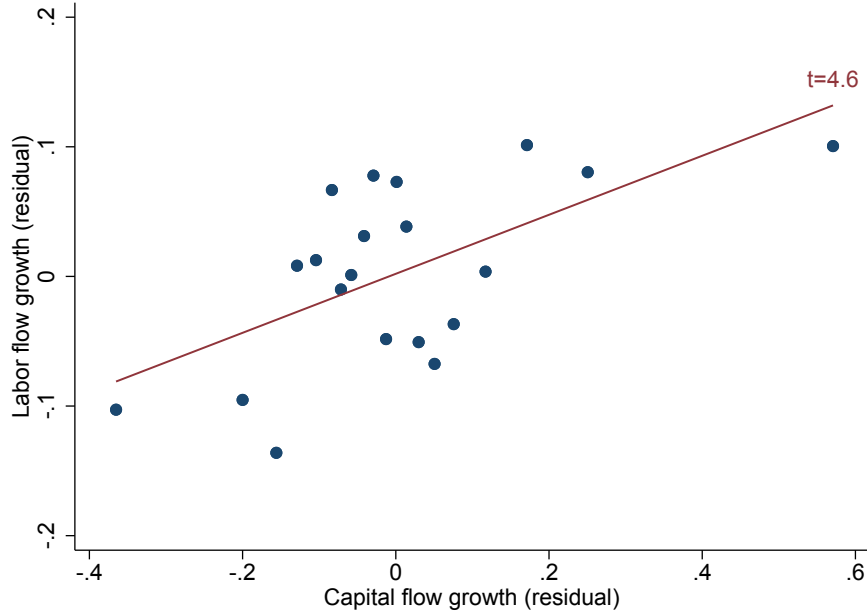
B.4 Correlation between Capital Flows and Labor Flows

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

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

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

Figure B.2: Capital Flows and Labor Flows



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

Table B.6: Capital Flows and Labor Flows

	Labor flow	
	(1)	(2)
Capital flow	0.26** (0.08)	0.13** (0.05)
Capital flow × ICT ₀		0.34*** (0.08)
Adjusted-R ²	.57	.57
Observations	5,464	5,464
Year FE	✓	✓
Sector FE	✓	✓
Commuting zone FE	✓	✓

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

B.5 Job Loss

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

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

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

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

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

A back-of-the-envelope calculation helps understand why heightened risk of job termination explains only a negligible part of the wage discount. The probability of job termination increases by 6.6 percentage points for high-skill workers starting in ICT during the boom (column 4 of Table B.8). Job termination is associated with a long-term wage decline of 3.3 percentage points on average (column 2 of Table B.7).³³ Put together, these estimates imply that heightened job termination explains $0.066 \times 0.033 = 0.2$ percentage points of the 7.7 percentage points wage discount. This is consistent with the magnitude of the reduction in the estimated wage discount from 7.7 percentage points when we do not control for job termination (column 1 of Table B.7) to 7.6 percentage points when we control for job termination (column 2).

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

Table B.7: Controlling for Job Losses

Control for:	log(Wage)					
	Job loss		Job loss ×ICT ₀ ×BoomCoh.		Job loss ×ICT ₀ ×BoomCoh.	
	(1)	(2)	(3)	(4)	(5)	(6)
ICT ₀ × Boom cohort × 2011-15	-0.077*** (0.015)	-0.076*** (0.015)	-0.069*** (0.017)	-0.029 (0.025)	-0.026 (0.025)	-0.019 (0.028)
Job loss × 2011-15		-0.033*** (0.007)	-0.064*** (0.015)		-0.046*** (0.011)	-0.070*** (0.023)
Job loss × ICT ₀ × 2011-15			0.045 (0.028)			0.055 (0.042)
Job loss × Boom cohort × 2011-15			0.034* (0.019)			0.013 (0.029)
ICT ₀ × Job loss × Boom cohort × 2011-15			-0.027 (0.033)			-0.028 (0.050)
ICT ₀ × Capital availability × Boom cohort × 2011-15				-0.081*** (0.031)	-0.082*** (0.031)	-0.083*** (0.035)
ICT ₀ × Capital availability × 2011-15				0.065** (0.025)	0.064** (0.025)	0.070** (0.029)
Capital availability × 2011-15				-0.014 (0.014)	-0.015 (0.014)	-0.011 (0.016)
Capital availability × Boom cohort × 2011-15				0.010 (0.018)	0.010 (0.018)	0.001 (0.020)
Capital availability × Job loss × 2011-15					0.010 (0.016)	-0.004 (0.033)
ICT ₀ × Capital availability × Job loss × 2011-15						-0.024 (0.058)
Capital availability × Job loss × Boom cohort × 2011-15						0.034 (0.042)
ICT ₀ × JCapital availability × ob loss × Boom cohort × 2011-15						0.004 (0.070)
Adjusted-R2	.84	.84	.84	.84	.84	.84
Observations	92,901	92,901	92,901	85,128	85,128	85,128
ICT ₀ × Year FE	✓	✓	✓	✓	✓	✓
Worker controls × Cohort × Year FE	✓	✓	✓	✓	✓	✓
Worker FE	✓	✓	✓	✓	✓	✓

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

Table B.8: Early Career Job Losses

	=1 if Job termination			
	All	Employment decline	Wage cut	Both
	(1)	(2)	(3)	(4)
ICT ₀ × Boom cohort	.0072 (.022)	.04*** (.015)	.04** (.017)	.066*** (.02)
ICT ₀	.065*** (.018)	-.0023 (.012)	-.012 (.014)	-.0069 (.016)
Adjusted-R2	.008	.0021	.001	.0022
Observations	11,312	11,312	11,312	11,312
Worker controls×Cohort FE	✓	✓	✓	✓

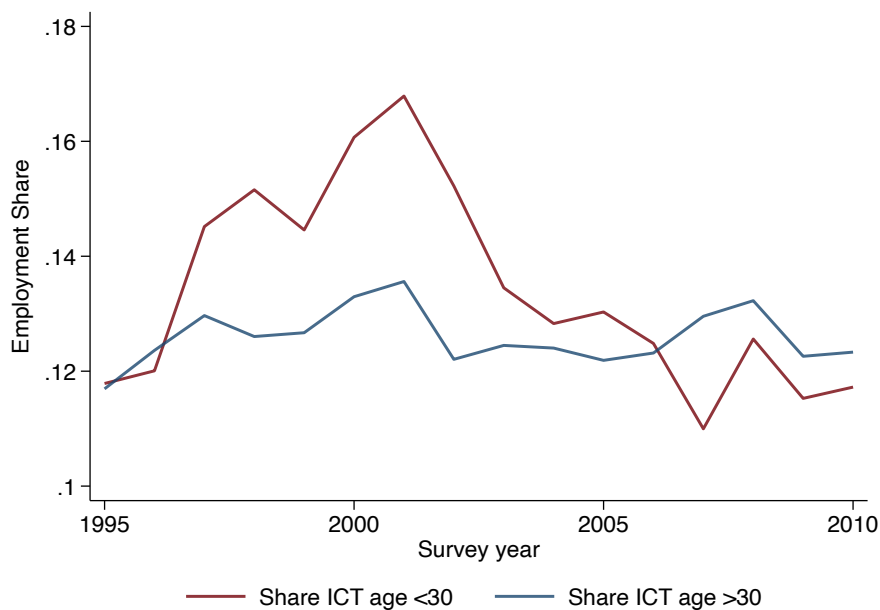
The table presents OLS estimates of cross-sectional regressions for labor market entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. The dependent variable is a dummy equal to one if the worker experiences job termination in the first four years of her career. In column 1, job termination is defined as any change in employer. In column 2, job termination is defined as a change in employer while employment at the initial employer declines by more than 10% in the year of the transition. In column 3, job termination is defined as a change in employer such that the transition to the next job leads to a wage cut for the worker. In column 4, job termination is defined as a change in employer such that either employment at the initial employer declines by more than 10% in the year of the transition or the transition to the next job leads to a wage cut for the worker. ICT₀ is a dummy equal to one if the worker started in the ICT sector. BoomCohort is a dummy equal to one if the worker belongs to the boom cohort. All the specifications include worker controls (sex, age dummies, entry year dummies, two-digit occupation at entry) interacted with cohort fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

C Employment Share of ICT in the US

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

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

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



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

D Equilibrium of the Model

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

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

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

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

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

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

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

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

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

We can now solve for a stationary equilibrium using a first-order approximation when productivity shocks and human capital shocks are small. Proposition 1 states that the equilibrium can be characterized in difference between sector $k = 1$ and sector $k = 2$,

which we denote using the operator Δ , e.g., $\Delta w_t = w_{1,t} - w_{2,t}$. The state of the economy can be summarized by three variables: the (exogenous) sectoral difference in productivity, Δz_t , the (exogenous) sectoral difference in average human capital shock, $\Delta \bar{d}h_t$, 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 $L_{k,t} = \sum_{c=-\infty}^{t-1} (1-\delta)^{t-c} \int_{i \in \mathcal{I}_{k,c,t}} H_{i,c,k,t} di$. We denote steady state values with $*$.

Proposition 1 *At the stationary equilibrium:*

$$\Delta w_t \simeq \Delta w^* + w_z \cdot \Delta z_t + w_\ell \cdot (\Delta \ell_t - \Delta \ell^*) + w_h \cdot \Delta \bar{d}h_t, \quad (\text{D.3})$$

$$\Delta E_t \simeq \Delta E^* + E_z \cdot \Delta z_t + E_\ell \cdot (\Delta \ell_t - \Delta \ell^*) + E_h \cdot \Delta \bar{d}h_t, \quad (\text{D.4})$$

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

$$\Delta \ell_{t+1} - \Delta \ell^* \simeq (1-\delta)e^{\mu_h} \cdot (\Delta \ell_t - \Delta \ell^*) + \ell_E \cdot (\Delta E_t - \Delta E^*) + \Delta \bar{d}h_{t+1}, \quad (\text{D.5})$$

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

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

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

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

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

D.1 Proof of Proposition 1

Law of motion of old labor. Let

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

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

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

where

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

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

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

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

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

(D.9) at steady state implies:

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

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

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

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

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

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

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

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

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

We linearize the log efficient quantity of labor:

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

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

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

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

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

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

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

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

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

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

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

where

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

A first-order approximation of the weights is:

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

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

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

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

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

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

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

Therefore:

$$\Delta\ell_{t+\tau} - \Delta\ell^* \simeq (-\sigma w_\ell)^\tau (\Delta\ell_t - \Delta\ell^*) + \sum_{s=0}^{\tau-1} (-\sigma w_\ell)^{\tau-1-s} \left[(\sigma - 1 - \sigma w_z) \Delta z_{t+s} + \Delta \bar{d}h_{t+s+1} \right]. \quad (\text{D.25})$$

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

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

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

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

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

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

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

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

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

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

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

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

where

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

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

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

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

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

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

Equalizing the term in front of $\Delta \bar{d} \bar{h}_t$, we obtain that:

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

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

Solving for (E_z, E_{ℓ}, E_h) . Combining (D.28) and (D.30), we obtain:

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

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

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

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

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

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

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

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

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

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

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