Technology Boom, Labor Reallocation, and Human Capital Depreciation*

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Abstract

Using matched employer-employee data from France, we uncover an *ICT boom-cohort discount* on the long-term wage of the large cohort of skilled workers entering in the Information and Communication Technology (ICT) sector during the late 1990s technology boom. Despite starting with 5% higher wages, these workers experience lower wage growth and end up with 6% lower wages fifteen years out, relative to similar workers who started outside the ICT sector. Other moments of the wage distribution are inconsistent with selection effects. These workers accumulate human capital early in their career that rapidly depreciates, implying that labor reallocation during technology booms can have long-lasting effects.

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1 Introduction

Radical technological change often comes with episodes of boom and bust in the technology sector, during which high firm valuations, easy financing, and reallocation of labor and capital from the rest of the economy to the tech sector, are followed by sharp reversals (Schumpeter (1942)). During the boom, the tech sector attracts talents and especially, as we document in this paper, young talents who enter the labor market.

These early career choices are determinant for post-schooling human capital accumulation of skilled workers.[1] Therefore, the large flow of young talents in and out of the tech sector during a boom can have long-lasting consequences for productivity through its effect on skilled workers' human capital. These consequences are beyond the direct effect of developing new technologies: They determine the different implications for long-run productivity between smooth sectoral reallocation, and the more bubbly process of sectoral reallocation induced by technological change that we observe in the data.

One view is that workers starting in the booming tech sector are exposed to new technologies, which enables them to acquire valuable skills and enhances their long-run productivity. Even if, as is sometimes argued, investment during technology booms is excessive from the point of view of firm value maximization, skilled workers may still benefit from over-investment in new technologies, by acquiring new skills that can be redeployed in other firms or other sectors. In this view, the large reallocation of labor to the booming tech sector can be beneficial for aggregate productivity through its effect on workers' human capital. This would stand in contrast to the negative effect on human capital of labor reallocation induced by booms in low-tech sectors, such as housing (Charles, Hurst, and Notowidigdo (2018)).

The opposite view is that human capital accumulated in a booming tech sector has low value in the long run. This may happen if: skilled workers acquire skills that quickly depreciate due to technological acceleration; workers are more likely to lose their job in the bust, thus losing firm-specific human capital and facing the risk of future mismatch in the labor market; or the boom creates a demographic imbalance in tech firms that reduces future opportunities to move up the hierarchy.

To shed light on these issues, we study the long-run wage dynamics of skilled workers allocated to a booming technology sector, using the late 1990s Tech Bubble as a laboratory. This boom has several advantages for our research design. First, it is large. The fraction of skill workers starting in the Information and Communication Technology (ICT) sector increases from about one-sixth to one-third during the boom. Second, we (or any researcher[2]) can have access to administrative matched employer-employee data from France for the period 1994–2015, providing us with high quality, longitudinal infor-

[1] See Gibbons and Waldman (2006) for a model and Altonji, Kahn, and Speer (2016) for empirical evidence and additional references.

[2] See Appendix A for information about data access.

mation on skilled workers who enter the labor market during the boom. Third, we have over fifteen years of hindsight to study the impact of workers' initial sectoral allocation on their long-term productivity.

We start by documenting the impact of the ICT boom on labor market allocation. The share of skilled workers in the ICT sector sharply deviates from trend between 1998 and 2001. The deviation comes almost entirely from individuals who recently entered the labor market, consistent with sectoral choices being made early in one's career. The share of skilled labor market entrants starting in the ICT sector almost doubles during the boom, from 17% to 31%, before dropping back to 19% when the boom ends. The sharp delimitation in time of the boom enables us to define a "boom cohort" of skilled workers who enter the labor market during 1998–2001.

We analyze the data through the lenses of a simple two-sector model with worker sectoral choice and on-the-job human capital accumulation. Worker human capital depends on two components: a pre-working experience component, which reflects innate ability and education; and on-the-job human capital accumulation or depreciation, which depends on the sector in which the individual works. The model provides an intuitive decomposition of the average wage in a sector-cohort into three components: human capital accumulated since labor market entry, a selection term that depends on the endogenous composition of workers in the sector, and a sectoral labor demand shock. The model highlights how the human capital accumulation component can be backed out by comparing the wage dynamics of different cohorts of workers.

We have three sets of findings. The first main finding is the existence of an *ICT boom-cohort discount.* Exploiting the panel dimension of the data, we compare the wage dynamics of skilled workers starting in the ICT sector to that of otherwise similar individuals, but starting in a different sector. We find that skilled workers starting in the booming ICT sector earn on average 5% higher entry wages than same-cohort workers starting in other sectors. This wage advantage disappears when the boom ends in the early 2000s. Remarkably, even after the bust, the wage of workers who started in the booming ICT sector keeps on growing more slowly than wages of same-cohort workers who started in other sectors. By 2015, a career start in the booming ICT sector is associated with a 6% wage discount, or 11 percentage points lower wage growth over the first fifteen years of a worker's career.

The ICT boom-cohort discount is quantitatively robust to controlling for sex, education, broad occupation at entry, regional trends, and to excluding workers starting in the financial sector from the comparison group. It is also robust to controlling for observable characteristics of workers' initial employer that may affect workers' earnings such as firm size, productivity, or age. The ICT boom-cohort discount does not vanish when we zoom in on workers starting in high-growth firms, or in subsidiaries of US companies, ruling out that it is a low-quality firm or a French firm phenomenon.

Quantile regressions further show that the entire wage growth distribution of skilled workers starting in the booming ICT sector is shifted to the left. The evidence is thus inconsistent with the boom creating winners and losers among talents who go into the booming ICT sector. In particular, starting in the booming tech sector does not generate the same right-skewed distribution of earnings as becoming entrepreneur (e.g. Hamilton (2000), Kerr, Nanda, and Rhodes-Kropf (2014), Hurst and Pugsley (2015), Manso (2016)). A present value calculation shows that a career start in the booming ICT sector is associated with 4% lower cumulative earnings on average, or 18,000 euros over the first fifteen years of a worker's career.

Our second set of findings is that the ICT boom-cohort discount is consistent with the depreciation of human capital acquired during the boom in the ICT sector, but not with negative selection or with persistently low labor demand in the ICT sector. We provide several pieces of evidence inconsistent with a selection effect by which workers attracted to the booming ICT sector would have low intrinsic productivity. First, such a selection effect would induce a worsening of the quality of workers at the low end of the distribution, generating a larger drop in the bottom quantiles of wage growth than in the top quantiles. The quantile regressions reject this prediction of the selection hypothesis.

Second, we exploit the cohort of workers who started in the ICT sector just before the boom (between 1994 and 1996). To the extent that the boom was not anticipated in the mid-1990s, these slightly older workers were treated, but not selected by the boom. Thus, the difference in outcomes between the boom cohort and the pre-boom cohort can be interpreted as the selection effect of the boom, whereas the commonalities in outcomes can be interpreted as the treatment effect on skilled workers exposed to the boom. Consistent with the absence of negative selection for the pre-boom cohort, we find that pre-boom entrants in the ICT sector have similar or slightly higher entry wages compared to entrants in other sectors. While those workers experience a relative wage increase during the boom, their wage dynamics after the boom follows the same pattern as the boom cohort, ending up 6% below that of entrants in other sectors. The similar long-run wage dynamics of the pre-boom cohort and the boom cohort of workers starting in the ICT sector is consistent with a treatment effect of the boom, but not with a selection effect by which low quality workers would select into the booming sector.

An alternative explanation is that demand for skilled labor in the ICT sector is persistently low after the bust. We rule out this hypothesis by focusing on the cohort of workers who start in the ICT sector after the bust (between 2003 and 2005). We find that these workers earn slightly lower entry wages than entrants in other sectors, but they catch up over time. Therefore, whereas both the pre-boom and boom cohorts of ICT sector entrants have low wage growth after the boom, the pattern is reversed for ICT entrants who did not experience the boom. Overall, the evidence is consistent with the depreciation of human capital acquired by skilled workers in the ICT sector during

the boom.

In our third set of tests, we explore three potential mechanisms to explain why human capital accumulated during the boom has low long-term value. First, skills acquired during a technology boom may become rapidly obsolete as a result of technological acceleration (e.g. Chari and Hopenhayn (1991), Deming and Noray (2018)). Second, workers losing their jobs in the bust may lose firm-specific human capital or be poorly matched later on and end up on a different career path associated with long-term earnings losses (e.g. Gibbons and Katz (1991), Jacobson, LaLonde, and Sullivan (1993), von Wachter and Bender (2006), Jarosch (2015) Kogan, Papanikolaou, Schmidt, and Song (2019)). Third, the large flow of boom-cohort workers into ICT may create a demographic imbalance that reduces the scope for promotions to management positions.

We find some support for the skill obsolescence mechanism. We hypothesize that if human capital acquired by young workers during the boom depreciates rapidly because of fast technological change, then skill obsolescence should be an increasing function of the intensity of workers' job technological content. We construct three measures of job technological intensity. First, we distinguish among skilled workers between those holding a STEM occupation and those holding a management/business occupation. Consistent with technical skills being more subject to obsolescence, we find that workers starting in STEM occupations in the booming ICT sector experience low long-run wage growth, but not those starting in non-STEM occupations. The second proxy for job technological content is firm specific and is equal to the share of STEM workers in the skilled workforce of the worker's initial employer. The third proxy is four-digit-industry specific and is equal to the share of STEM workers in the industry in which the workers takes her first job. In both cases, the ICT boom-cohort discount is larger for workers who started in more tech-intensive firms or sectors. The swift obsolescence of human capital in STEM jobs is consistent with contemporaneous findings by Deming and Noray (2018), who show using job vacancy data that skill requirements of STEM occupations can change in a short period of time.

By contrast, we find no support for the job termination mechanism and the demographic imbalance mechanism. Regarding the former, we decompose total wage growth from entry to 2015 into a within-jobs and a between-jobs component, and find that almost all of the relative wage decline takes place within jobs. We also show that controlling directly for job termination explains a negligible part of the lower wage growth. Regarding the demographic imbalance mechanism, we do not find that skilled workers from the boom cohort are less likely to be promoted.

We contribute to several strands of literature. The literature on vintage human capital (Chari and Hopenhayn (1991), MacDonald and Weisbach (2004)) emphasizes that several vintages of knowledge can co-exist, and that technological tends to make old vintages obsolete. Deming and Noray (2018) provide evidence that required skills in STEM

occupations change rapidly, making incumbent workers' skills obsolete. We show that skill obsolescence is particularly acute for the large cohort of workers allocated to the booming tech sector. Skill obsolescence is not caused by there being a boom-bust cycle in the tech sector. Instead, technological change (regardless of what causes it) drives both, firms' investment decisions and thus sectoral labor reallocation on the one hand, and accelerating skill obsolescence on the other hand. The patterns of labor reallocation during the boom matter however, because workers allocated to the booming tech sector are exposed to human capital depreciation. Therefore, the quantity of labor allocated to the booming tech sector can affect long-term aggregate productivity, implying that short-term fluctuations can have long-lasting consequences.

The implications of sectoral booms on workers' choices and outcomes have been studied in other contexts. Oyer (2008) shows that MBAs are more likely to become investment bankers if the financial sector is expanding while they are in school. He further shows that earnings in investment banking are unconditionally higher than in other sectors, but he does not study how these earnings depend on market conditions when individuals start their career. Gupta and Hacamo (2018) focus on the 2000s finance boom and show that it led to a reallocation of engineers to the financial sector that made them less likely to subsequently become entrepreneurs. Charles, Hurst, and Notowidigdo (2018) analyze the 2000s housing boom and show that it reduces educational attainment, because individuals drop out of school to work in the housing sector. Choi, Lou, and Mukherjee (2017) show that the presence of salient successful firms in a sector affects college major choices and is associated with lower future wages in that sector. Our paper differs from these papers in at least two important dimensions. First, we focus on a large, well-identified technology boom. Second, we relate workers' long-term wage dynamics to their initial sectoral choice using individual panel data.

A different literature analyzes how the aggregate state of the economy affects labor market entrants' long-run outcomes. This literature finds that workers starting in a recession have persistently lower earnings (e.g. Kahn (2010), Oreopoulos, von Wachter, and Heisz (2012), Altonji, Kahn, and Speer (2016), Speer (2016), Schwandt and von Wachter (2019)) and are less likely to reach high-end positions (e.g. Oyer (2006) for academics, Schoar and Zuo (2017) for CEOs). Our focus is different: We are interested in how sector-specific booms affect the long-run outcomes of workers allocated to the booming sector relative to same-cohort workers allocated to other sectors.

A strand of literature focuses more specifically on the late 1990s ICT boom. Beaudry, Green, and Sand (2016) argues that the overall demand for cognitive tasks declined after the tech boom. Among other differences with our paper, they do not distinguish between ICT-related tasks and other tasks, and they do not distinguish between different cohorts of workers. A strand of papers argue that the high stock prices in the tech sector were a bubble (e.g. Ofek and Richardson (2003)) and facilitated investment by young tech firms

(Brown, Fazzari, and Petersen (2009)) and by non-tech firms (Campello and Graham (2013)).[3]

2 The ICT Boom

2.1 Data

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

Matched 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 includes all employed individuals in the private sector, with information about the gross and net wage, dated employment periods, number of hours worked, job occupation, and the individual's birth year and sex. The data also includes unique firm and establishment identifiers that can be linked with other administrative data. The exhaustive employer-employee data does not include unique individual identifiers.

For a 1/24th subsample of the exhaustive 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 (see Abowd, Kramarz, and Margolis (1999) for a detail description). An individual exits the panel only if she earns no wage in the private sector, because she drops out of the labor force, becomes unemployed, switches to self-employment and pays herself only dividends, or moves abroad.

We focus on the employer-employee panel over the years 1994–2015. Each observation corresponds to a unique firm-worker-year combination. In most of the analysis, 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.[4] We obtain a panel at the worker-year level. Workers can have gap years in this panel when they earn no wage in the private sector, work part time, or over periods of less than six months.

The employer-employee data includes a two-digit classification of job occupations that maps the skill content of the job. We identify skilled workers as those holding higher-level occupations, which are comprised of "managers and professionals" (one-digit code 3) and "heads of company with at least ten employees" (two-digit code 23). They represent 16% of the labor force over 1994–2015. Within managers and professionals, the two-digit classification distinguishes between occupations with a STEM (Science, Technology,

[3]While not focused specifically on the 1990s boom, Dong, Hirshleifer, and Teoh (2017) show that stock market overvaluation induces firms to invest more in innovation. A different strand of literature analyzes how the composition of innovation activity varies over the business cycle (Nanda and Rhodes-Kropf (2013), Manso, Balsmeier, and Fleming (2017)).

[4]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.

Engineering, Mathematics) skill content (two-digit code 38) and those with a management/business content (two-digit code 37), which represent 33% and 42%, respectively, of skilled jobs over 1994–2015, and heads of company with at least ten employees (code 23) represent another 4%.[5] Appendix Table B.1 reports summary statistics for the sample of skilled workers over the period 1994–2015. The median skilled worker is a man (fraction 69%), is 43 year old (mean 43), and earns an annual gross salary of 41,000 euros (mean 50,000 euros). Unless otherwise stated, all amounts in the paper are in constant 2000 euros. Finally, a 4/30th subsample of the employer-employee panel data (individuals born in the first four days of October) can be linked with census data, which contains demographics information. We use this smaller sample to retrieve information on education.

We retrieve information on firms from three 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 provides information both about direct and indirect stakes and cross-ownerships, which allows us to reconstruct group structures even in the presence of pyramids. The data includes information on the nationality of the ultimate owner, which allows us to identify subsidiaries of foreign companies. Finally, we retrieve the list of all business creation with the date of registration from the firm register, and use this data to identify startups.

2.2 The ICT Boom and Bust

We analyze the late 1990s boom in the Information and Communications Technology (ICT) sector using the OECD (2002) definition of ICT industries. Appendix Table B.2 reports the list of four-digit ICT industries and their shares 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 five-year college 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 occupation is 35% across all sectors and 70% in the ICT sector.

Figure 1 illustrates the boom and bust cycle in the ICT sector in the late 1990s. While modest for total employment (Panel A), the ICT boom is evident for skilled workers. The share of this sector in skilled employment displays a sharp deviation from an increasing

[5]The other two-digit occupations within managers and professionals are mostly for occupations held by self-employed or public sector workers: health professionals and legal professionals (code 31); public sector managers and professionals (33); teaching professionals (34); cultural professionals (35), which represent less than 1%, 8%, 9%, and 3%, respectively, of skilled jobs.

trend during the 1998–2001 period, with the share going from 12.5% in 1996 up to 16.5% in 2001 and down to 15% in 2005.

Panel C shows that the deviation from the trend is driven by labor market entrants. The figure decomposes the ICT sector's share of skilled employment (plotted in Panel B) into the part made of workers who entered the labor force four years ago or less, and the part made of workers who have been in the labor force for five years or more. The latter exhibits an upward trend but shows no significant deviation. By contrast, the component representing young workers exhibits a sharp upward deviation from the trend during the ICT boom.

Since sectoral reallocation induced by the boom mostly happens at labor market entry, we focus on skilled labor market entrants in the rest of the paper. We define the entry year in the labor market as the year in which the individual takes her first full-time job, subject to the condition that she is no more than 30 year old at that time.[6] Appendix Table B.1 reports summary statistics for skilled individuals entering the labor market over 1994–2005. The median skilled entrant takes her first job at the age of 26 (mean 26) and has an annual gross salary of 38,000 euros (mean 45,000 euros).

Panel D shows that the share of skilled labor market entrants starting in the ICT sector exhibits a sharp deviation from the trend during the 1998–2001 period. The ICT sector share of skilled entrants almost doubles from 17.5% in 1996 to 31% in 1999, before dropping down to 19% in 2004.

Two main facts emerge from these patterns. First the ICT boom induces a large reallocation of labor, which happens almost exclusively through the sectoral choice of labor market entrants. During the boom, the ICT sector absorbs one-third of skilled labor market entrants. Therefore, the boom may have significant aggregate effects depending on how it impacts the human capital accumulation of this cohort of workers. Second, the boom is sharply delimited over time, from 1997/8 to 2001, which allows us to define the "ICT boom cohort" of workers, who enter the labor market during the ICT boom, and the "pre-boom cohort" and "post-boom cohort", who enter the labor market in the period right before and right after the boom, respectively.

The objective of the paper is to determine the effect of the initial sectoral choice of the ICT boom cohort of workers on their human capital accumulation. In the next section, we lay out a simple model to determine how this effect can be inferred from the long-run wage dynamics of the different cohorts.

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

3 Model

3.1 Setup

Time is discrete and horizon is infinite. At the beginning of each period, a mass one cohort of workers enter the labor market and choose in which sector $k = 1, 2$ to work. With a slight abuse of notation, let $E_{k,t}$ denote both the mass and the set of labor market entrants going to sector k in period t. In line with the evidence presented in Section 2 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. Worker i in sector k from cohort c supplies $H_{k,c,i,t}$ efficiency units of labor in period t. At the end of each period, a fraction δ of workers of every cohort exit the labor market.

Human capital $H_{k,c,i,t}$ has two components. First, a worker fixed effect, θ_i, which may reflect innate ability and education. Second, a process $\{dh_{k,c,t}\}_{t \geq c}$, which drives post-entry human capital accumulation or depreciation:[7]

$$h_{k,c,i,c} = \theta_i, \tag{1}$$

$$h_{k,c,i,t} = h_{k,c,i,t-1} + dh_{k,c,t}, \qquad t > c. \tag{2}$$

Human capital at entry is given by θ_i. The distribution of θ_i across workers is the same in every cohort, with mean zero. $dh_{k,c,t}$ is a shock to the human capital of individuals who worked in sector k during period $t-1$, which is effective from period t on. Human capital shocks follow the autoregressive process:

$$dh_{k,c,t} = dh + \varepsilon^h_{k,t} + \rho_h(dh_{k,c,t-1} - dh), \quad t > c, \tag{3}$$

where $\rho_h \in [0, 1)$, $dh_{k,c,c} - dh \equiv 0$, and $\varepsilon^h_{k,t}$ has zero mean. $dh_{k,c,t}$ has unconditional mean dh.[8] $\varepsilon^h_{k,t}$ is a human capital shock affecting all cohorts of workers in sector k in period $t-1$. It may reflect on-the-job learning, or the change in firm-specific human capital upon (unmodelled) job termination and within-sector job mobility. When $\rho_h > 0$, shocks experienced by a given cohort are serially correlated, implying that productivity shocks diffuses progressively in the sector over time.

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

$$X_{k,t} = Z_{k,t} \sum_{c=-\infty}^{t} (1-\delta)^{t-c} \int_{i \in E_{k,c}} H_{k,c,i,t} di. \tag{4}$$

[7] Throughout the paper, we denote logs of uppercase variables using lowercase letters.

[8] dh is possibly non-zero to allow human capital to drift over the lifetime of workers, and $dh < -\log(1-\delta)$ such that the aggregate supply of efficient labor in Equation (4) remains bounded almost surely.

$Z_{k,t}$ is sectoral productivity and follows the autoregressive process $z_{k,t} = \rho_z z_{k,t} + \varepsilon^z_{k,t}$, where $\rho_z \in [0,1]$ and $\varepsilon^z_{k,t}$ is a productivity shock with mean zero. The infinite sum in (4) is the efficient quantity of labor supplied in sector k in period t by all cohorts of workers $c = -\infty, \ldots, t$. The efficient quantity of labor supplied by cohort c is equal to the fraction of workers from cohort c who are still active, $(1-\delta)^{t-c}$, times the efficient quantity of labor supplied by workers from cohort c who started in sector k, $i \in E_{k,c}$.

The model allows for two types shocks: sectoral shocks that affect all workers in the sector, as well as sectoral shocks that affect different cohorts of workers differently. As an example of the former, consider a positive sectoral productivity shock, $\varepsilon^z_{k,t} > 0$. It raises the productivity of all workers in sector k. As an example of a shock that affects different cohorts differently, consider again $\varepsilon^z_{k,t} > 0$, but accompanied by a negative human capital shock to workers already in sector k, $\varepsilon^h_{k,t} < 0$. In this case, new workers benefit from the sectoral productivity shock and are not affected by the negative human capital shock, because $dh_{k,t,t}$ does not depend on $\varepsilon^h_{k,t}$. By contrast, for old workers, the sectoral productivity gain is offset by the loss of human capital, because $dh_{k,c,t}$ depends on $\varepsilon^h_{k,t}$ for $c < t$ (see Equation (3)). In practice, a shock that affects different cohort differently can occur when new workers enter with knowledge of up-to-date technologies, whereas old workers remain with older vintages of knowledge.

The final good is produced using the intermediate goods with CES:

$$Y_t = \Big(\sum_{k=1,2} A_k X_{k,t}^{\frac{\sigma-1}{\sigma}} \Big)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where $\sigma > 1$, and $A_1^\sigma + A_2^\sigma$ is normalized to 1. The wage rate per efficiency unit of labor is determined by the marginal productivity of labor:

$$w_{k,t} = a_k + z_{k,t} - \frac{1}{\sigma}(x_{k,t} - y_t). \tag{6}$$

The wage of worker i is equal to her human capital times the wage rate in her sector in the current period. In log terms:

$$w_{k,c,i,t} = h_{k,c,i,t} + w_{k,t}. \tag{7}$$

Workers derive log utility over per-period consumption with discount factor $\beta < 1$, and consumption is equal to the current wage.

Workers have idiosyncratic preferences over their career choice. Worker i incurs a non-pecuniary cost γ_i if she chooses sector $k = 1$. The distribution of γ_i across workers is the same in every cohort. Worker i from cohort c going to sector k obtains expected

utility[9]

$$U_{k,c,i} = \sum_{t=c}^{\infty} \beta^{t-c}\, \mathbb{E}_c[w_{k,c,i,t}] - 1_{\{k=1\}}\gamma_i, \tag{8}$$

where $\mathbb{E}_c[.]$ denotes expectation conditional on beginning-of-period c information. Worker i chooses sector $k = 1$ if and only if $U_{1,c,i} > U_{2,c,i}$. Since expected learning is the same in both sectors, the expected wage differential between the two sectors for any worker is equal to the expected wage rate differential: $\mathbb{E}_c[w_{1,c,i,t} - w_{2,c,i,t}] = \mathbb{E}_c[w_{1,t} - w_{2,t}]$. Therefore, the set of entrants in sector $k = 1$ in period c is:

$$E_{1,c} = \left\{ i : \gamma_i < \sum_{t=c}^{\infty} \beta^{t-c}\, \mathbb{E}_c[w_{1,t} - w_{2,t}] \right\}. \tag{9}$$

We assume that, when expected wages are equalized across sectors, the sectoral allocation of new workers is proportional to the sector weights in the production function, that is, the mass of $\{i : \gamma_i < 0\}$ is equal to A_1^{σ}.

3.2 Equilibrium

We solve for a stationary equilibrium using a first-order approximation when productivity shocks and human capital shocks are small. The following proposition shows 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., $\Delta w_t \equiv w_{1,t} - w_{2,t}$. The relevant state variables are the (exogenous) sectoral difference in productivity, Δz_t, the (exogenous) sectoral difference in average human capital shock, $\Delta\overline{dh}_t$, and the (endogenous) sectoral difference in the efficient quantity of labor supplied by old workers, $\Delta\ell_t$, defined as $L_{k,t} = \sum_{c=-\infty}^{t-1}(1-\delta)^{t-c}\int_{i\in E_{k,c}} H_{k,c,i,t}di$. We denote steady state values with *.

Proposition 1 *At the stationary equilibrium:*

$$\Delta w_t \simeq \Delta w^* + w_z \,.\, \Delta z_t + w_\ell \,.\, \left(\Delta\ell_t - \Delta\ell^*\right) + w_h \,.\, \Delta\overline{dh}_t, \tag{10}$$

$$\Delta E_t \simeq \Delta E^* + E_z \,.\, \Delta z_t + E_\ell \,.\, \left(\Delta\ell_t - \Delta\ell^*\right) + E_h \,.\, \Delta\overline{dh}_t, \tag{11}$$

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:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq (1-\delta)dH \,.\, \left(\Delta\ell_t - \Delta\ell^*\right) + \ell_E \,.\, \left(\Delta E_t - \Delta E^*\right) + \Delta\overline{dh}_{t+1}, \tag{12}$$

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

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

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. Workers' idiosyncratic sectoral preferences imply that the wage rate must increase in sector 1 relative to sector 2 ($w_z > 0$ in (10)) in order to induce more entry in sector 1 ($E_z > 0$ in (11)).

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 (10)), which reduces entry in sector 1 ($E_\ell < 0$ in (11)). 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 (12) 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 by dH. Thus, the efficient quantity of labor by old workers mechanically reverts at rate $(1-\delta)dH$. 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.

3.3 Wage Dynamics

Combining (1), (2), (6) and (7), the average wage difference between the two sectors for cohort c in period t is:

$$\Delta\overline{w}_{c,t} = \underbrace{\sum_{\tau=c+1}^{t} \Delta dh_{c,\tau}}_{\substack{\text{accumulated} \\ \text{human capital}}} + \underbrace{\Delta\overline{\theta}_c}_{\text{selection}} + \underbrace{\Delta w_t}_{\text{unit wage}} \tag{13}$$

where upper bars denote the cross-sectional average across workers of a given sector k cohort c, that is, $\overline{w}_{k,c,t} = \sum_{i \in E_{k,c}} w_{k,c,i,t}$ and $\overline{\theta}_{k,c} = \sum_{i \in E_{k,c}} \theta_i$.

Equation (13) shows that the average wage (in sector 1 relative to sector 2) in a cohort, $\Delta\overline{w}_{c,t}$, has three components. The first component is the quantity of human capital accumulated by this cohort of workers since entry, $\sum_{\tau=c+1}^{t} \Delta dh_{c,\tau}$. It varies across cohorts because different cohorts have different experiences, and thus have accumulated different amounts of human capital.

The second component reflects selection and is equal to the average worker innate skill in the cohort, $\Delta\overline{\theta}_c$. It is determined by worker selection into sectors and thus depends on the joint distribution of worker skill, θ_i, and worker sectoral preference, γ_i. $\Delta\overline{\theta}_c$ may vary across cohorts, because labor demand shocks affect the size, and thus the composition, of the pool of each cohort of entrants in each sector.[10]

The third component is the wage rate per efficiency unit of human capital, Δw_t. It is common to all cohorts in a given year and reflects time-varying labor demand shocks.

Our empirical strategy to disentangle the different components of the average wage will rely on comparing the wage dynamics across cohorts.

4 The ICT Boom-Cohort Discount

4.1 Wage Dynamics

To study the wage dynamics of skilled workers who enter the labor market during the ICT boom, we estimate the following wage equation:

$$\log(w_{i,t}) = \alpha_t + \beta_t ICT_{i,0} + \gamma_t X_i + \epsilon_{i,t}, \tag{14}$$

where $w_{i,t}$ is the annualized wage of worker i in year t, $ICT_{i,0}$ is a dummy variable equal to one if worker i's first job is in the ICT sector, and X_i is a vector of worker characteristics including sex, age and age squared at entry, entry year, and two-digit occupation at entry. β_t measures the wage differential in year t for an individual who started in the ICT sector relative to an individual of the same cohort and with the same observable characteristics who started outside the ICT sector. β_t is the empirical counterpart to $\Delta\overline{w}_{c,t}$ for the boom cohort in the model.

Figure 2 plots the time-series of β_t for the boom cohort and 95% confidence interval. Workers starting in the booming ICT sector earn an entry wage on average 5% higher than workers of the same cohort and with the same observable characteristics, starting outside the ICT sector. This wage difference vanishes rapidly after the boom ends in 2001. More surprisingly, the wage difference keeps falling after the bust such that by 2015, workers who started in ICT earn on average 6% less than same-cohort workers who started outside the ICT sector.

Table 1 reports the regression results. We estimate Equation (14) using for each worker, the year of entry and the years 2002, 2006, 2010, and 2015. Column 1 shows that during the boom, entrants in the ICT sector start with a wage higher by 4.6% (significant at 1%) relative to entrants in other sectors. This wage premium decreases over time and

[10] In Appendix C.2, we analyze how the joint distribution of (θ_i, γ_i) determines the effect of labor demand shocks on the average skill in each sector-cohort.

eventually becomes negative. In 2015, these workers earn on average 6.2% (significant at 1%) less than workers who started outside the ICT sector.

We include worker fixed effects in column 2 to ensure that time variation in β_t is identified on a constant set of workers, purging potential composition effects driven by differences in propensity to exit the sample. When worker fixed effects are included, the β_t time-series is identified up to an additive constant and use the entry year as the reference year. The pattern is similar to that without worker fixed effects: The wage difference decreases over time and reaches -10.9% (significant at 1%) in 2015. Therefore, composition effects due to attrition do not seem to be important as the relative wage discount in 2015 estimated with worker fixed effects is close to the wage discount in 2015 minus that at entry estimated without worker fixed effects.

Given that the ICT boom-cohort discount is the result of a steady wage decline after the bust, we can estimate that discount using the long difference in the log wage from the entry year to 2015 by running the cross-sectional regression:

$$\log(w_{i,2015}) - \log(w_{i,0}) = \beta\, ICT_{i,0} + \gamma\, X_i + \epsilon_i, \tag{15}$$

The identification of β in (15) comes from the same variation in the data as the identification of β_{2015} in the panel regression equation (14) with worker fixed effects, and taking the year of entry as the reference year. The coefficient on ICT_0 in column 1 of Table 2 implies that entrants in the booming ICT sector experience 10.5 percentage points (significant at 1%) lower wage growth from entry to 2015.[11]

Up to now, our results could be explained by differences in workers characteristics (location, education) or differences in their first employer characteristics. We explore these possibilities in the next section.

4.2 Robustness

Worker heterogeneity. We rule out several basic explanations for the ICT boom-cohort discount. First, we control for geographical disparities in wage dynamics by adding commuting zone fixed effects in column 2 of Table 2.[12] The ICT boom-cohort discount remains and is even slightly stronger, reflecting the facts that the ICT sector is over-represented in urban areas and that wage growth has been stronger in these areas during the sample period.

Second, we check whether the discount is driven by exceptionally high wage growth in

[11] The coefficient is not exactly equal to the one on $ICT_0 \times (t = 2015)$ in column 2 of Table 1 because the latter depends on worker fixed effects that are estimated using the year of entry, 2002, 2006, 2010 and 2015, whereas the coefficient in column 1 of Table 2 is estimated only using the year of entry and 2015.

[12] We define commuting zones as *départements*, which partition France into 99 areas. We obtain similar results when we use *bassins d'emploi*, which partition France into 380 areas.

a few other sectors, such as the financial sector as pointed out by Philippon and Reshef (2012) for the US and Célérier and Vallée (2017) for France. In column 3, we exclude entrants starting in the financial sector, who represent 5% of skilled entrants during the ICT boom. The discount is slightly reduced, reflecting high wage growth in finance during the 2000s, but it remains large and significant.

Third, we test whether the ICT boom-cohort discount is explained by observable worker characteristics. The baseline specification already controls for sex, age and occupation at entry. In columns 4 and 5, we use the subset of the data that can be linked with census data, which provides information on education. We construct two variables of educational attainment: a dummy equal to one if the individual holds at least a three-year college degree (*Licence* or equivalent) and a dummy equal to one if the individual holds at least a five-year college degree (*Master* or equivalent). 91% of skilled entrants hold at least a three-year college degree and 83% hold at least a five-year college degree. Column 4 shows the baseline specification on the subsample linked with census data. The discount is slightly larger than that on the main sample due to sampling noise, but the difference is not statistically significant. In column 5, we control for the level of education and this does not affect the magnitude of the discount.

Fourth, workers' earnings may be under-estimated because employer-employee data reports wages but not capital income. Capital income can be significant for entrepreneurs. It may also be relevant for employees receiving stocks or options in the firm. To account for capital income, we merge the data with firm balance sheet information and retrieve the net income of the firm. Since we do not have information on stock grants or stock options, we calculate capital income under two different assumptions. First, assuming that the CEO holds all cash flow rights, we identify the CEO using the information on occupation and we allocate the firm's net income to her.[13] Alternatively, assuming that employees have ownership stakes in the company, we allocate the firm's net income to all skilled employees according their share in total skilled-worker wage bill. We calculate total earnings as wage plus capital income and use log of total earnings as the dependent variable. Column 6 reports the results when firm profits are allocated to the CEO only and column 7 when firm profits are shared among all skilled workers. In both cases, accounting for capital income has little effect on the magnitude of the discount.

Firm heterogeneity. We test whether the ICT boom-cohort discount is explained by ICT employers during the boom having specific characteristics that might affect workers' long-run wage.[14] We compare characteristics of ICT employers to that of non-ICT

[13]Results are similar when we use dividends instead of net income. We prefer net income because it includes capital gains coming from undistributed profits. When the firm reports several owner-managers (one-digit occupation code 2), we split the net income equally among them.

[14]Evidence that firm characteristics have long lasting consequences on workers' earnings can be found in Garicano, Lelarge, and Van Reenen (2016) and Bloom, Fatih, Brian, Ben, Jae, and Til (2019) for firm

employers in Appendix Table B.3. Panel A shows that ICT employers during the boom have on average fewer employees, are more likely to be two year old or less, and have lower value added per worker than non-ICT employers. However, these differences are not specific to the boom period. Panel B shows that ICT employers in the post-boom period (2003–2005) feature similarly different characteristics from non-ICT employers as in the boom period. In particular, differences between ICT employers and non-ICT employers during the boom are not statistically different from that after the boom, except for the probability that the employer is a startup (significant at 10%). To further check whether these differences explain the ICT boom-cohort discount, we directly control for employer characteristics in the wage growth regression. Column 1 of Table 3 shows that the wage discount is not driven away by controlling for the initial employer's characteristics.

Second, while France fully embraced the ICT revolution and produced successful ICT firms, it has not become the worldwide leader in that sector. As such, one may wonder whether the ICT boom-cohort discount is specific to workers employed by French firms or whether it also exists for US employers. The scope of this paper is limited to France, yet many large US firms have offices across the world, France included, so their workers located in France appear in our data. We use ownership data to identify subsidiaries of US companies as firms that are 100% owned by a US company. In column 2 of Table 3, we restrict the sample to workers taking their first job in the subsidiary of a US firm. If anything, the effect is slightly larger in this subsample than in the entire sample, i.e., the ICT boom-cohort discount is not a French firm phenomenon. In a similar spirit, one may wonder whether that phenomenon originates from ICT employers with little or mild commercial success or whether it also affects individuals employed by successful firms. In column 3, we restrict the sample to workers taking their first job in a firm that with sales growth over the next five years above 40% (the top quartile of the distribution). The ICT boom-cohort discount in this subsample of successful employers is as large as in the entire sample.

4.3 Quantile Regressions

A career start in the booming ICT sector is associated with low average long-term wage growth. One possible interpretation is that such a career start exposed workers to high idiosyncratic risk because of the uncertainty regarding which firms and technologies would prevail in the long run (Kogan, Papanikolaou, Schmidt, and Song (2019)). In this case, akin to patterns documented in the literature on the returns to entrepreneurship (e.g.

size, in Ouimet and Zarutskie (2014), Burton, Dahl, and Sorenson (2017) and Babina, Wenting, Paige, and Rebecca (2018) for firm age, in Abowd, Kramarz, and Margolis (1999) and Card, Heining, and Kline (2013) for firm productivity, in Tate and Yang (2015) and Cestone, Fumagalli, Kramarz, and Pica (2017) for firms' internal labor market, in Benmelech, Bergman, and Seru (2011), Hombert and Matray (2016) and Fonseca and Doornik (2019) for credit constraints.

Hamilton (2000), Hurst and Pugsley (2015)), the low average wage growth may conceal a small probability of success, positive skewness, and high wage growth in the right tail of the distribution.

Table 4 reports estimates of quantile regressions for the 10th, 25th, 50th, 75th, and 90th percentiles of wage growth, including the same set of control variables as in the linear regression equation (15). Workers starting in ICT during the boom face a wage growth discount that is fairly uniform across the entire wage growth distribution, with long-run discounts ranging from 10.5% (at the 10th and 25th percentiles) to 12.1% (at the 75th percentile). If anything, the discount is larger at the top of the wage growth distribution, rejecting the hypothesis that the average discount is associated with a small probability of very positive outcomes. Thus, the boom in ICT does not appear to create winners and losers, but instead shifts the entire wage growth distribution to the left for talents who started in the booming ICT sector.

4.4 Cumulative Earnings

A career start in the booming ICT sector is associated with a higher wage during the boom and a lower wage after the boom. We now assess whether this leads to a higher or a lower present value of cumulative earnings from entry to 2015. For each worker, we compute cumulative earnings up to every year t post-entry by summing all the worker's earnings from the entry year to year t discounted back to the entry year at a rate of 5% per year. We estimate the panel regression equation (14) using cumulative earnings, in log or in level, as the dependent variable.

Using the specification in log (column 1 of Table 5), we find that skilled workers starting in ICT during the boom earn cumulative earnings from entry to 2015 that are 4.3% (significant at 1%) lower than similar workers starting in other sectors. Using the specification in level (column 2), we find that the discounted cumulative earnings loss is about 18,400 euros (significant at 1%). Column 3 shows that this estimate is robust to accounting for unemployment benefits.[15]

[15]Since unemployment benefits (UB) are only reported starting in 2008, we assign an estimated UB when a worker 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 (see Cahuc and Prost (2015)). Since the data does 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. We obtain an UB-adjusted cumulative earnings loss that varies within a range of 500 euro of that of the baseline scenario when we use a more conservative replacement rate of 30% to account for the fact that not all job terminations give rise to UB, or when we use a more aggressive UB length of two years if the pre-unemployment job spell lasts for at least two years.

5 Disentangling the ICT Boom-Cohort Discount

The stylized model highlights three mechanisms that can explain the ICT boom-cohort discount (see Equation (13)). First, human capital accumulated by the ICT boom cohort may depreciate quickly after the boom. Second, the booming ICT sector may have attracted workers with low intrinsic productivity. Third, labor demand in the ICT sector may remain persistently low after the boom. In this section, we analyze further whether each of these mechanisms is consistent with the data.

Throughout this section, we denote the ICT sector by $k = 1$ and other sectors by $k = 2$, so that variables preceded by the operator Δ refer to the value of the variable in the ICT sector relative to other sectors. We denote the boom cohort by $c = B$. Therefore, the average wage difference in year $t \geq B$ between workers from the boom cohort who started in ICT and those who started outside of ICT is equal to $\Delta\overline{w}_{B,t}$ given by Equation (13).

5.1 Human Capital Depreciation

We study whether the ICT boom-cohort discount is consistent with human capital depreciation. Consider a negative shock to the human capital of skilled individuals working in the ICT sector during the boom, that is, $\Delta\varepsilon^h_{B+1} < 0$, and suppose all other innovations to the human capital shock are set to zero, i.e, $\Delta\varepsilon^h_t < 0$ for all $t \neq B+1$. Human capital of the ICT boom cohort experiences a post-boom declining trend given by

$$\sum_{\tau=B+1}^{t} \Delta dh_{B,\tau} = \sum_{\tau=B+1}^{t} (\rho_h)^{\tau-B-1}\Delta\varepsilon_{B+1} = \frac{1-(\rho_h)^{t-B}}{1-\rho_h}\Delta\varepsilon^h_{B+1}. \tag{16}$$

The trend arises when human capital shocks are positively autocorrelated, i.e., if $\rho_h > 0$. Positive autocorrelation, in turn, arises if technological change that affects the human capital of existing workers is persistent. For instance, if the ICT boom sparks a series of changes to the skills required in the ICT sector, which workers of the boom cohort do not possess, then the shock realized during the boom ($\Delta\varepsilon^h_{B+1} < 0$) will trigger a series of negative changes to the human capital of the boom cohort ($\Delta dh_{B,\tau} < 0$ for $\tau \geq B+1$).

Therefore, the wage dynamics of boom cohort displayed in Figure 2 and Table 1 is consistent with a positive shock to labor demand during the boom (high Δw_B) followed by a negative shock to human capital (low $\Delta\varepsilon^h_{B+1}$) that triggers a progressive productivity decline as shown by Equation (16).

5.2 Ruling Out Selection

We analyze whether the ICT boom-cohort discount can be explained by selection. The selection hypothesis is that the marginal worker attracted by the booming ICT sector

has low intrinsic productivity. This low productivity would not be reflected in low wages during the boom, because high labor demand drives wages up, and would only become apparent over time as labor demand in the ICT sector reverts to normal. In the model, $\Delta\overline{\theta}_B < 0$, and assuming no shock to human capital, the sectoral difference in average wage of the boom cohort, $\Delta\overline{w}_{B,t} = \Delta\overline{\theta}_B + \Delta w_t$, is positive during the boom because $\Delta w_t > 0$, and turns negative over time as Δw_t reverts to zero.

A first piece of evidence going against the selection hypothesis is the result of quantile regressions in Section 4.3. Quantile regression results are not consistent with a selection mechanism by which the booming ICT sector would disproportionately attract workers from the left tail of the (unobserved) productivity distribution. Suppose it was the case, such that the pool of workers who select into ICT during the boom consists of the set of workers who would have gone into ICT no matter what and a set of low-quality workers who select into ICT because of the boom. Such a shift in the worker quality distribution would add a mass to the left of the wage growth distribution, shifting the bottom quantiles to the left by more than the top quantiles, which is rejected by the quantile regressions.

To test more systematically for selection, we compare the wage dynamics of the boom cohort to that of the pre-boom cohort. The intuition for this test is that individuals entering the labor market before the boom experience the boom, but are not selected by the boom. If the ICT boom-cohort discount is explained by negative selection during the boom, the pre-boom cohort should not experience a similar long-term wage discount. By contrast, if the ICT boom-cohort discount is explained by the depreciation of human capital of workers experiencing the boom, or by persistently low labor demand in the ICT sector, then the pre-boom cohort should also experience a long-term wage discount.

This intuition can be formalized in our model. The difference in the ICT wage premium between the boom cohort ($c = B$) and the pre-boom cohort ($c = B - 1$) in year $t \geq B$ is:

$$\Delta\overline{w}_{B,t} - \Delta\overline{w}_{B-1,t} = \underbrace{\left(\Delta\overline{\theta}_B - \Delta\overline{\theta}_{B-1}\right)}_{\text{selection}} - \underbrace{\frac{1-(\rho_h)^{t-B+1}}{1-\rho_h}\Delta\varepsilon^h_B}_{\substack{\text{human capital shock} \\ \text{to pre-boom cohort}}}. \tag{17}$$

The first term reflects selection during the boom relative to the pre-boom level of selection. This term is constant over time, so negative selection during the boom implies that the average wage of the boom cohort should display a time-invariant discount relative to the pre-boom cohort. The second term is the long-term impact of the human capital shock experienced by the pre-boom cohort when the boom starts. If non-zero, this shock leads to a differential trend between the boom cohort and the pre-boom cohort.

We estimate the panel regression equation (14) on the pre-boom cohort 1994–1996.[16]

[16]We exclude 1997 from the pre-boom cohort because it might be argued that the ICT boom has

The estimated coefficients β_t are plotted in Figure 3. Skilled workers starting in the ICT sector in the period preceding the ICT boom earn similar wages to that of workers starting in other sectors until the beginning of the boom. This pattern is consistent with workers starting in ICT before the boom having similar intrinsic productivity to those starting in other sectors ($\Delta\overline{\theta}^* = 0$ in the model). Then, these workers experience rapid wage growth during the boom and earn at the peak of the boom an average 6% wage premium. Crucially, when the boom ends, the pre-boom cohort experiences a similar wage dynamics to that of the boom cohort in Figure 2. The relative wage of ICT entrants declines over time. By 2015, workers who started in the ICT sector before the boom earn 6% lower wage on average relative to workers of the same cohort who started outside the ICT sector.

Regression results reported in Table 6 confirm the graphical analysis when worker fixed effects are not included (column (1)), and when worker fixed effects are included (column (2)). We also estimate the difference between the boom cohort and the pre-boom cohort by estimating the panel regression equation (14) on the pooled sample of the pre-boom and boom cohorts, and interacting the explanatory variables with a dummy variable equal to one if the worker belongs to the boom cohort. The interaction terms between ICT_0 and the boom cohort dummy are economically and statistically insignificant in all years (column (3)).[17] Therefore, skilled workers going into ICT before the boom experience a qualitatively and quantitatively similar long-run wage dynamics to that of workers who go into ICT during the boom.

This evidence is at odds with a selection effect. A more subtle explanation based on a combination of negative selection during the boom (first term of (17) negative) and a negative human capital shock to the pre-boom cohort (second term of (17) negative), which would offset each other, is also inconsistent with the data, because selection generates a time-invariant wage shift whereas a human capital shock generates a wage trend. We will show an additional piece of evidence against the selection hypothesis in Section 6.1.

5.3 Ruling Out Declining Labor Demand

An alternative explanation for the ICT boom-cohort discount is that wages are structurally low in the ICT sector ($\Delta w^* < 0$), but these structurally low wages were masked by the boom ($\Delta w_B > 0$), and only became apparent when the boom ends. This explanation is not consistent with the fact that the entry wage of the pre-boom cohort is not lower in the ICT sector than in other sectors (see Figure 3 and column (1) of Table 6).

Another explanation is that there is a structural break after the bust, driving ICT sector wages down in the long run; that is, there is a persistent negative shock to Δz

already started in 1997 (see Figure 1). The results are robust to including 1997 in the pre-boom cohort.

[17] The regression does not include the years 2000 and before, because not all workers of the boom cohort have entered the labor market in 2000.

leading to persistently low Δw_t.

We exploit the post-boom cohort to test this hypothesis. If the ICT sector experiences an overall wage decline after the boom, the post-boom cohort should also experience it. This prediction is obtained naturally in our simple model. The difference in the ICT wage premium between the boom cohort ($c = B$) and the post-boom cohort ($c = B + 1$) is:

$$\Delta\overline{w}_{B,t} - \Delta\overline{w}_{B+1,t} = \underbrace{\left(\Delta\overline{\theta}_B - \Delta\overline{\theta}_{B+1}\right)}_{\text{selection}} + \underbrace{\frac{1-(\rho_h)^{t-B}}{1-\rho_h}\Delta\varepsilon^h_{B+1}}_{\substack{\text{human capital shock} \\ \text{to boom cohort}}}. \tag{18}$$

We estimate the panel regression equation (14) on the post-boom cohort 2003–2005.[18] The estimated coefficients β_t are plotted in Figure 4. Workers starting in the ICT sector in the post-boom period have slightly lower starting wages than workers starting in other sectors. Crucially, this wage gap does not widen but, to the contrary, closes over time.

Regression results reported in Table 7 confirm the graphical analysis. Column 1 shows that post-boom entrants starting in the ICT sector earn 2.2% (significant at 5%) lower wages than entrants in other sectors, and catch up over time such that the wage difference is small and insignificant by 2015. The specification with worker fixed effects in column 2 yields a similar conclusion. In column 3, we estimate the difference between the boom cohort and the post-boom cohort, using the same specification as in Section 5.2. The interaction terms between ICT_0 and the boom cohort dummy are negative and statistically significant from 2010 on. In 2015, there is a 6.6% ICT wage discount for skilled individuals who started during the boom relative to those who started after the boom.

The evidence is inconsistent with a secular decline of ICT sector wages in the wake of the ICT bust. Instead, the result that the post-boom cohort experiences an opposite wage dynamics to that of the pre-boom and boom cohorts is consistent with a shock to the human capital of workers exposed to the ICT sector during the boom.

6 Explaining Human Capital Depreciation

Why does the human capital of skilled workers allocated to the ICT sector during the boom progressively depreciate over time? We investigate three hypotheses. First, human capital acquired during technology booms depreciates faster, because technology changes rapidly during these periods. Second, workers are more likely to lose firm-specific human capital, because there is a high rate of job termination when a technology boom ends. Third, large entry of workers of the same cohort in a sector leads to a demographic

[18] We exclude 2002 from the post-boom period in order to leave a gap year between the boom period and post-boom period. The results are robust to including 2002 in the post-boom period.

imbalance, which reduces the scope for promotions to management positions. In the rest of this section, we provide evidence consistent with the first mechanism but not with the latter two.

6.1 Skill Obsolescence

Skilled workers starting in the booming ICT sector may accumulate human capital early in their career that rapidly becomes obsolete, because technology evolves fast during technology booms. If the ICT boom-cohort discount is explained by this mechanism, we expect it to be larger for workers holding a job with a higher technological content or working in firms more intensive in technology, because human capital accumulated on these jobs depreciates faster as technology changes.

We test this hypothesis using several proxies for jobs' technological content. The first proxy is constructed using the occupation held by the worker at entry. The two-digit occupation classification in the data distinguishes between occupations with a STEM skill content (hereafter "STEM workers") and those with a managerial, non-STEM content (hereafter "managers"). We define $STEMOccupation$ as the dummy variable equal to one if the worker holds a STEM occupation in her first job.

The second proxy aims at capturing the technological intensity of firms in which skilled workers start their career. We define $TechFirm$ as the fraction of STEM workers among the skilled workforce of the individual's initial employer. The third proxy aims at capturing the technological intensity of specific (four-digit) sectors of the broad ICT sector in which workers start their career. We define $TechSector$ as the fraction of STEM workers among skilled workers in the four-digit sector in which the individual holds her first job.

Table 8 shows how long-run wage growth depends on jobs' technological content. In column 1, we estimate the long-difference regression equation (15) adding the interaction term between ICT_0 and the STEM occupation dummy as an explanatory variable.[19] The coefficient on the interaction term shows that STEM workers who started in ICT have 9.9 percentage points (significant at 5%) lower wage growth than managers who started in ICT and relative to the same difference in other sectors. By contrast, the coefficient on the non-interacted ICT dummy is small and insignificant, showing that managers starting in ICT do not have lower wage growth than managers starting in other sectors. Thus, consistent with the skill obsolescence hypothesis, the ICT boom-cohort discount is concentrated on STEM workers.

In column 2, we include the interaction of ICT_0 with $TechFirm$. The coefficient on the interaction term is negative and significant at the 1% level. Thus, the discount

[19]The non-interacted variable STEM occupation dummy is not included, because the baseline specification already has fixed effects for the initial occupation.

is stronger for workers who started in more-tech firms. One concern could be that the result is driven by a more general pattern by which skilled workers starting in more-tech firms even outside the ICT sector would experience lower wage growth, for instance because workers are in more STEM related skills. In column 3, we add the dummy $(1-ICT_0)$ interacted with $TechFirm$. Two results appear. First, the impact of the firm's technological intensity for workers starting in ICT is barely affected by the inclusion of that variable. Second, the firm's technological intensity has no significant impact for workers starting outside ICT. Thus, patterns of wage dynamics are consistent with rapid obsolescence of technical skills acquired specifically in the ICT sector during the boom, but not with a general trend of obsolescence of technical skills in the rest of the economy.

A similar pattern emerges when we use the proxy for the sector's technological intensity.[20] Column 4 shows that the ICT boom-cohort discount is stronger for workers who started in more-tech sectors. Column 5 shows that the result is not explained by the fact that workers starting in more-tech sectors even outside the ICT sector experience slower wage growth.

On a different note, the evidence that STEM workers but not managers experience the ICT boom-cohort discount goes against a selection mechanism by which individuals with low unobserved ability would select into the booming ICT sector, as discussed in Section 5.2. Indeed, there is no obvious reason why STEM workers' sectoral choice would be more responsive to market conditions than managers'. By contrast, the skill obsolescence mechanism naturally generates the prediction that STEM workers should be more affected by the ICT boom-cohort discount than managers.

6.2 Job Termination

Within-jobs/between-jobs wage growth decomposition. As an elementary test of the job loss channel, we focus on the boom cohort and decompose workers' wage growth from entry to 2015 into a within-jobs and a between-jobs components. If lower wage growth is explained (economically) by workers forced to change jobs and in the process losing human capital, then it should be explained (statistically) by the between-jobs component. Indexing by $t = 0, \ldots, T$ the years in which we observe worker i and denoting by $F_{i,t}$ her employer in year t, we construct within-jobs wage growth as $\sum_{t=1}^{T} 1_{\{F_{i,t}=F_{i,t-1}\}}\big(\log(w_{i,t}) - \log(w_{i,t-1})\big)$, and between-jobs wage growth as: $\sum_{t=1}^{T} 1_{\{F_{i,t}\neq F_{i,t-1}\}}\big(\log(w_{i,t}) - \log(w_{i,t-1})\big)$. We estimate the long-difference regression equation (15) using these two components of wage growth as dependent variables.

Table 9 shows that the ICT boom-cohort discount comes almost entirely from the within-jobs component. Of the total 10.5 percentage point discount, 8.8 percentage points

[20] The top three ICT industries in terms of technological intensity are "IT consultancy", "Software", and "Other IT-related activities", while the bottom three are "Manufacturing of insulated wires and cables", "Manufacturing of capacitors", and "Manufacturing of office devices except computers".

(significant at 1%) come from lower wage growth within job spells, whereas only 1.7 percentage points (insignificant) come from lower wage growth during job transitions. This result does not arise because wage growth happens only within job spells unconditionally: For skilled entrants (in any sector) during the boom period, within-jobs and between-jobs wage growth explain respectively 39% and 18% of the variation in total wage growth.[21]

The decomposition into a within/between-jobs may still underestimate the effect of job termination if job termination reduces the probability of promotion or increases the risk of mismatch in the new job, thereby weighing on future (within-jobs) wage growth. To address this possibility, we now test directly whether (forced) job termination explains the ICT boom-cohort discount.

Job termination. We construct four variables to measure job termination. The first two do not distinguish between forced and voluntary job termination: (1) a dummy variable equal to one if the worker changes employer within the first four years after entry; and (2) a dummy variable equal to one if the worker has changed employer by 2015. The next two are dummy variables equal to one if the worker experiences a forced job termination within the first four years after entry, where forced termination is defined as a transition to another employer: (3) with a wage decrease; or (4) when the initial employer has negative employment growth in the year of the transition. The unconditional probability of job termination is, for each of the four proxies, 59%, 86%, 17%, and 20%, respectively.

Table 10 shows how the probability of job termination depends on the sector of entry for the pre-boom, boom, and post-boom cohorts. We regress each of the job termination dummy on ICT_0 interacted with dummy variables for each cohort, and the same set of controls as before, all interacted with the cohort dummies. When we consider all types of job termination in columns 1 and 2, skilled workers starting in the ICT sector during the boom are more likely to experience job termination than those of the pre-boom cohort, but not more than those of the post-boom cohort.

When we focus on forced job termination in columns 3 and 4, a clearer pattern emerges. Workers starting in ICT during the boom are more likely to experience forced termination than workers starting in ICT before or after the boom. This result holds for both proxies of forced termination. For instance, column 3 shows that ICT entrants during the boom are 4.6 percentage points (significant at 1%) more likely to experience a transition to a lower-paid job within the first four years of their career than entrants in other sectors. By contrast, there is no significant difference for the pre-boom cohort and

[21] The unconditional contribution of each component to total wage growth is calculated as the R^2 of the cross-sectional regression of total wage growth on the component. The R^2s do not sum to one because within-jobs wage growth and between-jobs wage growth are negatively correlated in the cross-section of workers.

the post-boom cohort.[22]

We go on testing whether the higher probability of job termination explains the ICT boom-cohort discount. We re-estimate the wage growth regression for the boom cohort controlling directly for each of the four proxies of job termination. The odd-numbered columns of Table 11 show that job termination explains a negligible part of the discount. Compared to the baseline discount of 10.5% (column 1 of Table 2), job termination explains at most 0.7 percentage points of this discount (using the first proxy of forced job termination in column 5).[23]

Job termination during a sectoral bust might have a disproportionate impact on wages. The specification in the even-numbered columns of Table 11 includes an interaction term between ICT_0 and job termination to allow job termination to have a different effect on workers starting in the booming ICT sector than on workers starting in other sectors. The coefficient on (non-interacted) ICT_0 can be interpreted as the wage growth difference between workers starting in the ICT sector and experiencing no job termination, and entrants in other sectors experiencing no job termination. With all four proxies of job termination, we find a wage growth discount of the same magnitude (in the range of 8.1% to 11.4%) as in the baseline specification (10.5%). A particularly telling result is the one reported in column 4, showing that workers starting in the ICT sector during the boom and still working with their initial employer in 2015 experience 8.1 percentage points lower wage growth than entrants in other sectors and also working with their initial employer in 2015.

Overall, the evidence is inconsistent with the ICT boom-cohort discount being explained by job losses. Even workers who do not switch employers face as poor a long-term wage growth as those losing their jobs. The evidence suggests that these workers experience a long-run decline in productivity that goes beyond firm-specific effects and that materializes regardless of their career path.

6.3 Demographic Imbalance

Large entry of skilled workers in the ICT sector during the boom may lead to an oversupply of skilled workers of the same cohort. If, as argued for instance by Welch (1979) or Jeong, Kim, and Manovskii (2015), workers from different cohorts are imperfect substitutes, the demographic imbalance created by the boom may explain why wage growth is low for the ICT boom cohort but not for the post-boom cohort. One mechanism by which workers of the boom cohort and workers of the post-boom cohort could be complements rather than substitutes, is that experienced skilled workers become managers of junior

[22]The difference in coefficient between the boom cohort and pre-boom cohort is significant at 1%, and the one between the boom cohort and post-boom cohort is significant at 5%.

[23]A similar conclusion obtains when we include all four proxies of job termination in the same regression. In this specification, job termination explains 0.5 percentage points of the discount.

skilled workers. A distorted age pyramid in the ICT sector may create a bottleneck that makes it less likely for the boom-cohort workers to be promoted.

To test this hypothesis, we focus on workers starting in a STEM occupation and analyze whether these workers are less likely to be promoted to a management position if they start in the ICT sector during the boom. The sample for this test is skilled workers from the boom cohort (1998–2001) and the post-boom cohort (2003–2005) who start as STEM workers based on the two-digit occupation classification described in Section 6.1. We construct a dummy variable *Promotion* equal to one if the worker has become a manager in her starting industry in 2015.[24] The unconditional mean of the promotion dummy is 0.32. To validate the proxy for promotion, we regress wage growth from entry to 2015 on the promotion dummy, the same set of controls as before, and four-digit industry fixed effects. Column 1 of Table 12 shows that STEM workers who follow a career path leading up to a management position in their starting industry experience a 12% (significant at 1%) higher wage growth than STEM workers who follow a different career path.[25] In column 2, we interact the promotion dummy with ICT_0 and find that the interaction term is small and insignificant. Thus, the proxy for promotion is similarly valid for STEM workers starting in or outside the ICT sector.

We go on testing whether STEM workers starting in ICT during the boom have a lower probability of being promoted. We follow a difference-in-difference approach and compare the probability of promotion for STEM workers who started in the ICT sector relative to STEM workers who started in other sectors (first difference) for the boom cohort relative to the post-boom cohort (second difference). We regress the promotion dummy on ICT_0 interacted with a boom cohort dummy. In column 3, the coefficient on the interaction term is small and statistically insignificant.[26] Therefore, the large flow of STEM workers to ICT during the boom does not seem to have reduced these workers' future opportunities of promotion to management positions.

7 Conclusion

We uncover an *ICT boom-cohort discount:* Young talents who started in the ICT sector during the late 1990s Tech Bubble enjoyed 5% higher entry wages, but end up in the long

[24] We use a broad industry classification (with 10 different industries) to determine whether the worker has become a manager in the same industry in which she started her career. We obtain similar results if we use the two-digit industry classification (84 industries) or the four-digit industry classification (476 industries).

[25] Only a small part of this effect comes from the fact that STEM workers who still work in their starting industry in 2015 have higher wage growth even if they do not become managers. When we add a dummy variable equal to one if the worker still works in her starting industry in 2015, the coefficient on this dummy variable is 0.021 (significant at 10%) and the coefficient on the promotion dummy is 0.10 (significant at 1%).

[26] Columns 2 and 3 do not include non-interacted ICT_0 or boom cohort dummy as explanatory variables because the specifications already include industry fixed effects and entry year fixed effects.

run with 6% lower wages, relative to similar skilled workers who started in a different sector. The ICT boom-cohort discount is not explained by selection or by a higher rate of job termination in the bust of the tech sector. Instead, the evidence points to the rapid depreciation of technical skills acquired during the boom, consistent with accelerating skill obsolescence during technology booms. This finding is not consistent with the notion that boom-time tech firms enhance their workers' human capital and long-term productivity.

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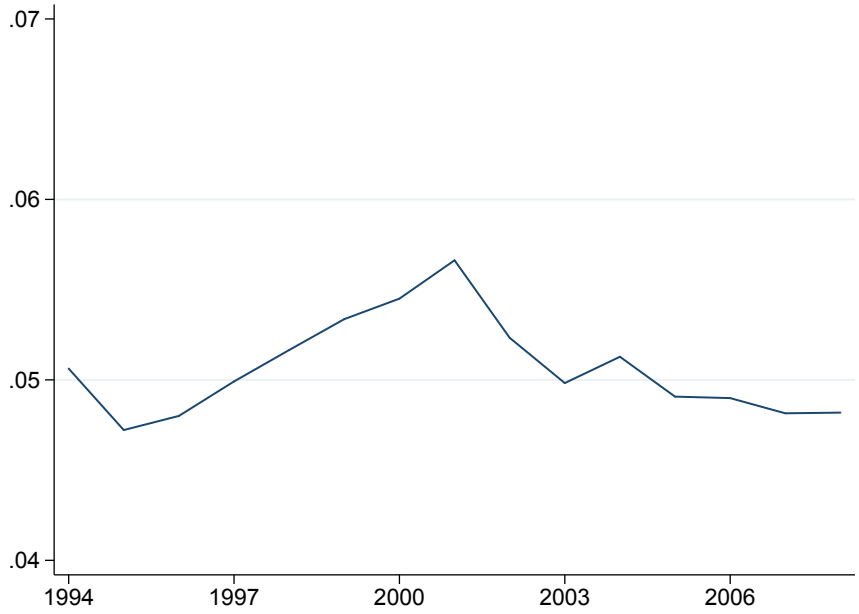
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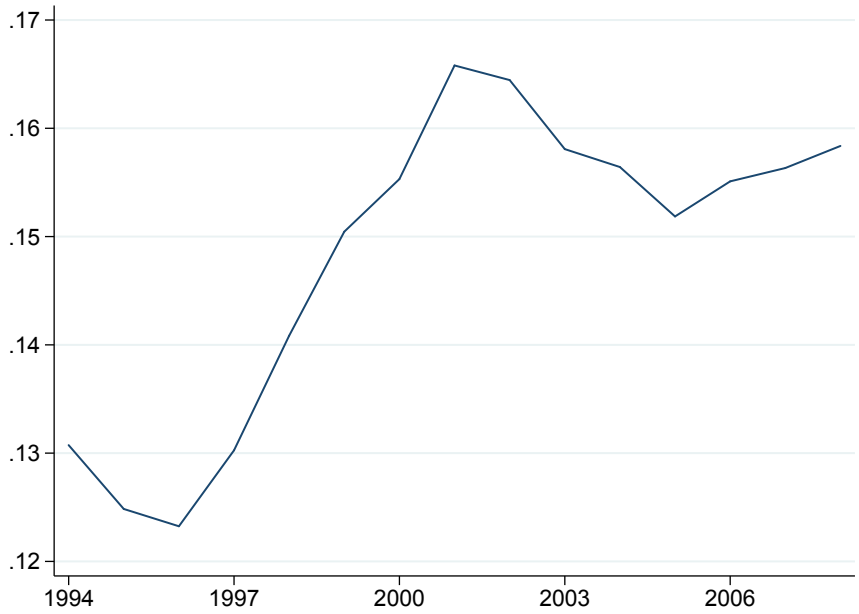
Figure 1: Employment Share of the ICT Sector

Panel A shows the share of the ICT sector in total employment. Panel B shows the share of the ICT sector in skilled employment. Panel C decomposes skilled employment in the ICT sector into workers who entered the labor market five years ago or more (blue line) and those who entered four years ago or less (red line). Panel D plots the share of skilled labor market entrants starting in the ICT sector.

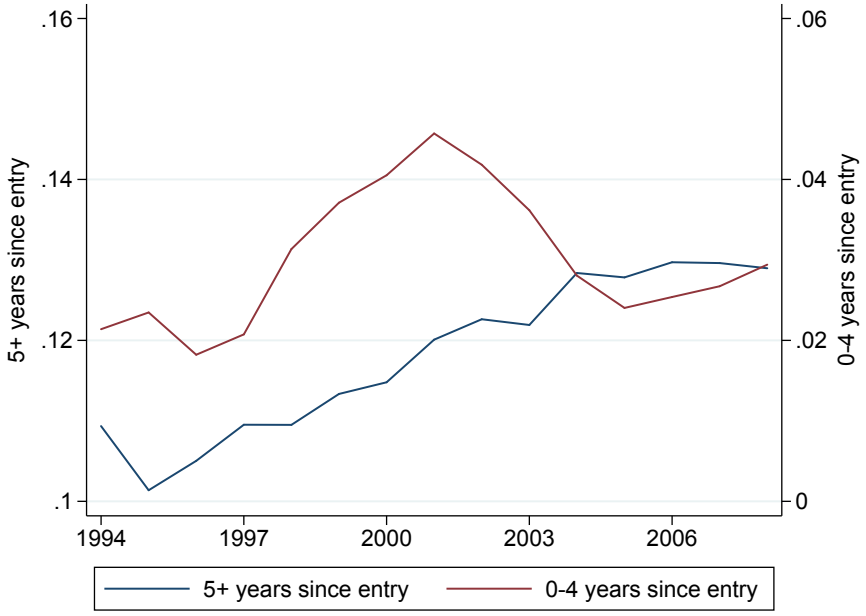
Panel A: All workers



Panel B: Skilled workers



Panel C: Skilled workers: decomposition recent entrants vs. older workers



Panel D: Skilled entrants

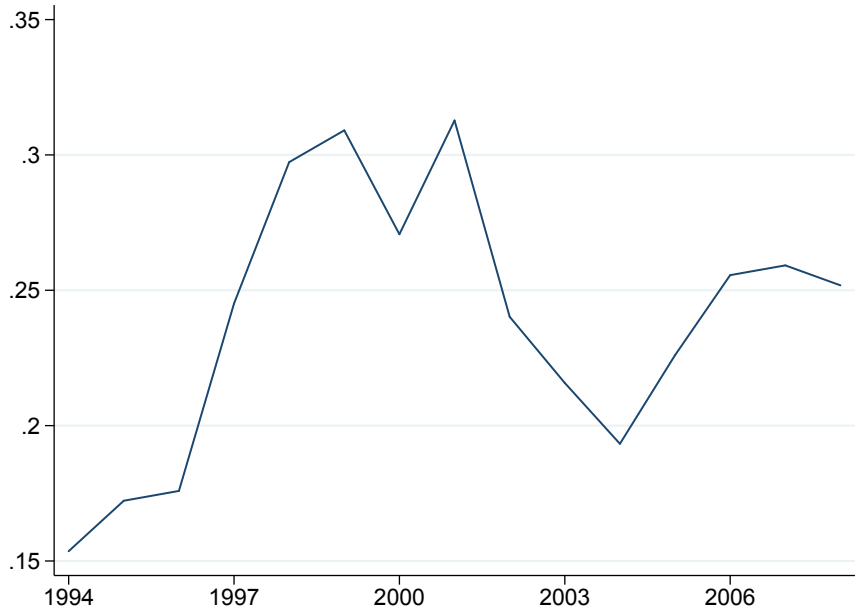


Figure 2: Wage Dynamics of the ICT Boom Cohort

The figure displays the β_t coefficient of the wage regression $\log(w_{i,t}) = \alpha_t + \beta_t ICT_{i,0} + \gamma_t X_i + \epsilon_{i,t}$ where $ICT_{i,0}$ is a dummy variable equal to one if worker i's first employment spell is in a firm in the ICT sector and X_i collects control variables listed in Section 4.1. Dashed lines represent the 95% confidence interval. The regression is estimated over the cohort of skilled workers whose first full-time job was in 1998–2001.



Figure 3: Wage Dynamics of the Pre-Boom Cohort

The figure displays the β_t coefficient of the wage regression $\log(w_{i,t}) = \alpha_t + \beta_t ICT_{i,0} + \gamma_t X_i + \epsilon_{i,t}$ where $ICT_{i,0}$ is a dummy variable equal to one if worker i's first employment spell is in a firm in the ICT sector and X_i collects control variables listed in Section 4.1. Dashed lines represent the 95% confidence interval. The regression is estimated over the cohort of skilled workers whose first full-time job was in 1994–1996.

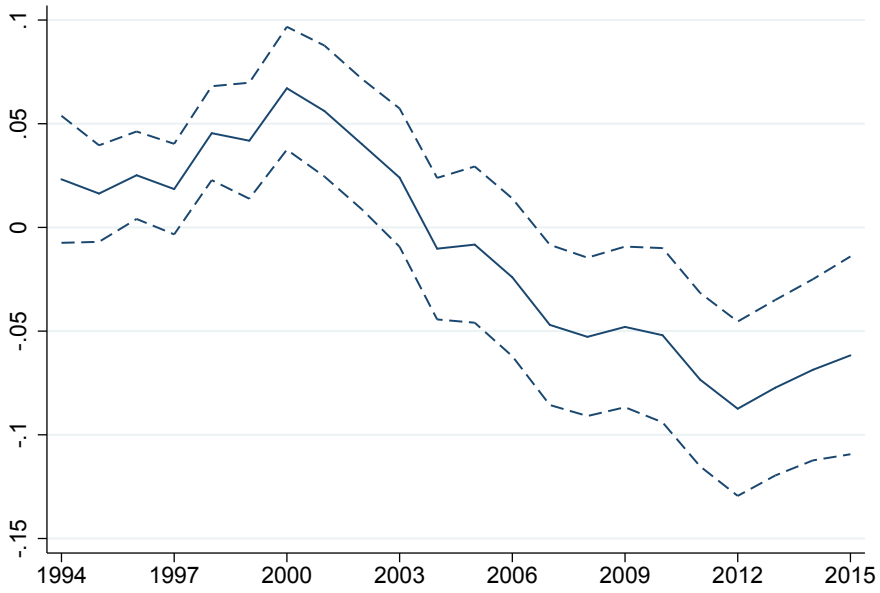


Figure 4: Wage Dynamics of the Post-Boom Cohort

The figure displays the β_t coefficient of the wage regression $\log(w_{i,t}) = \alpha_t + \beta_t ICT_{i,0} + \gamma_t X_i + \epsilon_{i,t}$ where $ICT_{i,0}$ is a dummy variable equal to one if worker i's first employment spell is in a firm in the ICT sector and X_i collects control variables listed in Section 4.1. Dashed lines represent the 95% confidence interval. The regression is estimated over the cohort of skilled workers whose first full-time job was in 2003–2005.



Table 1: Wage Dynamics of the Boom Cohort

The table presents the OLS estimates of β_t in Equation (14) for skilled entrants of the boom cohort 1998–2001. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if worker i started in the ICT sector. (t=Y) is a dummy equal to one if year t is Y = entry year, 2002, 2006, 2010, or 2015. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. Column 2 includes worker fixed effects and use the year of entry as the baseline year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage	
	(1)	(2)
ICT_0 x (t=0)	.046***	
	(.007)	
ICT_0 x (t=2002)	.030***	-.004
	(.007)	(.007)
ICT_0 x (t=2006)	-.025**	-.070***
	(.010)	(.001)
ICT_0 x (t=2010)	-.051***	-.095***
	(.012)	(.011)
ICT_0 x (t=2015)	-.062***	-.109***
	(.015)	(.014)
Worker controls	✓	✓
Worker FE	–	✓
Observations	31,670	30,423

Table 2: Wage Growth of the Boom Cohort

The table presents OLS estimations of Equation (15) for skilled entrants of the boom cohort 1998–2001. The dependent variable is wage growth growth of worker i from entry year to 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. From column 2 on, Commuting Zone fixed effects are included. In column 3, entrants who started in the finance sector are excluded. In column 4, the sample is restricted to workers that can be linked with census data. In column 5, we add two dummy variables for the worker holding a three-year college degree and for the worker holding a five-year college degree. In column 6, the firm's net income is added to the worker's wage if the worker is the CEO of the firm. In column 7, a fraction of the firm's net income equal to the worker's share in total wage bill is added to the worker's wage. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry						
						Incl. firm CEO	profit for all emp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICT_0	-.105***	-.113***	-.104***	-.154***	-.152***	-.133***	-.130***
	(.015)	(.016)	(.016)	(.044)	(.043)	(.016)	(.016)
Worker controls	✓	✓	✓	✓	✓	✓	✓
Commuting Zone FE	–	✓	✓	✓	✓	✓	✓
Education	–	–	–	–	✓	–	–
Observations	4,972	4,972	4,599	537	537	4,948	4,968
Sample	All	All	Excl. finance	Census	Census	All	All

Table 3: Wage Growth and Firm Characteristics

The table presents OLS estimations of Equation (15) for skilled entrants of the boom cohort 1998–2001. The dependent variable is wage growth growth of worker i from entry year to 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. Log(Employees), Value added/Worker, and Startup are variables defined for the initial employer of worker i and equal to the log number of employees, value added per worker, and a dummy equal to one if the firm is two year old or less, respectively. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. In column 2, we restrict the sample to workers whose initial employer is the subsidiary of a US company. In column 3, we restrict the sample to workers whose initial employer has sales growth in the subsequent five years above 40%. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry		
	(1)	(2)	(3)
ICT_0	-0.11***	-0.15***	-0.095***
	(.015)	(.045)	(.032)
Log(Employees)	0.0026		
	(.0032)		
Value added/Worker	0.00085***		
	(.00015)		
Startup	0.042		
	(.026)		
Worker controls	✓	✓	✓
Observations	4,282	530	879
Sample	All	US firms	High growth firms

Table 4: Quantiles of Wage Growth

The table presents quantile regressions of Equation (15) for skilled entrants of the boom cohort 1998–2001. The dependent variable from column 1 to 5 is the 10th, 25th, 50th, 75th, and 90th percentile, respectively, of wage growth of worker i from entry year to 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Wage growth quantiles				
	P10	P25	P50	P75	P90
	(1)	(2)	(3)	(4)	(5)
ICT_0	-.105***	-.105***	-.107***	-.121***	-.110***
	(.026)	(.019)	(.010)	(.018)	(.029)
Worker Controls	✓	✓	✓	✓	✓
Observations	4,972	4,972	4,972	4,972	4,972

Table 5: Cumulative Earnings

The table presents the OLS estimates of β_t in Equation (14) for skilled entrants of the boom cohort 1998–2001. The dependent variable is discounted cumulative earnings of worker i from entry year to year t, in log in column 1 and in level in column 2. In column 3, earnings include unemployment benefits assuming a 60% replacement rate for one year. ICT_0 is a dummy equal to one if worker i started in the ICT sector. (t=Y) is a dummy equal to one if year t is Y = entry year, 2002, 2006, 2010, or 2015. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cumulative Earnings		
	Log	Level (in Euro)	Level (in Euro) incl. UB
	(1)	(2)	(3)
ICT_0 x (t=0)	.038***	810 ***	810***
	(.008)	(222)	(222)
ICT_0 x (t=2002)	.023***	1748	2060**
	(.011)	(949)	(923)
ICT_0 x (t=2006)	-.003	-948	-1260
	(.015)	(2184)	(2155)
ICT_0 x (t=2010)	-.024	-8393**	-9016**
	(.018)	(3702)	(3664)
ICT_0 x (t=2015)	-.043***	-18381***	-19387***
	(.021)	(5968)	(5946)
Worker controls	✓	✓	✓
Observations	45,695	45,695	45,695

Table 6: Wage Dynamics of the Pre-Boom Cohort

The table presents the OLS estimates of β_t in equation (14) for skilled entrants of the pre-boom cohort 1994–1996. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if worker i started in the ICT sector. (t=Y) is a dummy equal to one if year t is Y = entry year, 1997, 2000, 2002, 2006, 2010, or 2015. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. Column 2 includes worker fixed effects and use the year of entry as the baseline year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage		
	(1)	(2)	(3)
$\text{ICT}_0 \times$ (t=0)	.028***		
	(.0098)		
$\text{ICT}_0 \times$ (t=1997)	.018*	.0017	
	(.011)	(.0096)	
$\text{ICT}_0 \times$ (t=2000)	.067***	.056***	
	(.015)	(.014)	
$\text{ICT}_0 \times$ (t=2002)	.04**	.028**	.04**
	(.016)	(.014)	(.016)
$\text{ICT}_0 \times$ (t=2006)	-.024	-.041**	-.024
	(.019)	(.018)	(.019)
$\text{ICT}_0 \times$ (t=2010)	-.052**	-.063***	-.052**
	(.021)	(.019)	(.021)
$\text{ICT}_0 \times$ (t=2015)	-.062**	-.086***	-.062**
	(.024)	(.022)	(.024)
$\text{ICT}_0 \times$ (t=2002) $\times$ Boom cohort			-.010
			(.018)
$\text{ICT}_0 \times$ (t=2006) $\times$ Boom cohort			-.001
			(.022)
$\text{ICT}_0 \times$ (t=2010) $\times$ Boom cohort			.001
			(.024)
$\text{ICT}_0 \times$ (t=2015) $\times$ Boom cohort			-.001
			(.028)
Worker controls	✓	✓	✓
Worker FE	–	✓	–
Observations	24,546	23,403	34,017
Sample	Pre-boom cohort	Pre-boom cohort	Pre-boom+Boom cohorts

Table 7: Wage Dynamics of the Post-Boom Cohort

The table presents the OLS estimates of β_t in equation (14) for skilled entrants of the post-boom cohort 2003–2005. The dependent variable is log wage of worker i in year t. ICT_0 is a dummy equal to one if worker i started in the ICT sector. (t=Y) is a dummy equal to one if year t is Y = entry year, 2006, 2010, or 2015. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. Column 2 includes worker fixed effects and use the year of entry as the baseline year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage		
	(1)	(2)	(3)
ICT_0 x (t=0)	-.022**		
	(.0096)		
ICT_0 × (t=2006)	-.02*	.0091	-.02*
	(.011)	(.0092)	(.011)
ICT_0 × (t=2010)	-.002	.026**	-.002
	(.014)	(.012)	(.014)
ICT_0 × (t=2015)	.0036	.027	.0036
	(.019)	(.017)	(.019)
ICT_0 × (t=2006) × Boom cohort			-.005
			(.015)
ICT_0 × (t=2010) × Boom cohort			-.049***
			(.018)
ICT_0 × (t=2015) × Boom cohort			-.066***
			(.024)
Worker controls	✓	✓	✓
Worker FE	–	✓	–
Observations	15,424	14,815	26,260
Sample	Post-boom cohort	Post-boom cohort	Boom+Post-boom cohorts

Table 8: Wage Growth and Job Skill Content

The table presents OLS estimations of Equation (15) for skilled entrants of the boom cohort 1998–2001. The dependent variable is wage growth growth of worker i from entry year to 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. STEM occupation is a dummy equal to one if worker i has a STEM (as opposed to management/business) occupation in her first job. TechFirm is the fraction of STEM workers in worker i's initial employer. TechSector is the fraction of STEM workers in worker i's initial four-digit industry. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry				
	(1)	(2)	(3)	(4)	(5)
ICT_0	-.027	-.044	-.05	-.034	-.043
	(.039)	(.032)	(.034)	(.04)	(.041)
ICT_0 × STEM occupation	-.099**				
	(.042)				
ICT_0 × TechFirm		-.11***	-.12***		
		(.043)	(.043)		
$(1 - ICT_0)$ × TechFirm			-.032		
			(.036)		
ICT_0 × TechSector				-.16**	-.16**
				(.077)	(.077)
$(1 - ICT_0)$ × TechSector					-.085
					(.08)
Worker controls	✓	✓	✓	✓	✓
Observations	4,972	4,897	4,897	4,970	4,970

Table 9: Within-Jobs/Between-Jobs Wage Growth Decomposition

The table presents the decomposition of workers' wage growth from entry to 2015 into a within-jobs component and a between-jobs component as defined in the text, for skilled entrants of the boom cohort 1998–2001. ICT_0 is a dummy equal to one if worker i started in the ICT sector. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry	
	Within-jobs	Between-jobs
	(1)	(2)
ICT_0	-.088***	-.017
	(.015)	(.013)
Worker controls	✓	✓
Observations	4,972	4,972

Table 10: Job Termination

The table presents OLS regressions for skilled entrants of the pre-boom cohort 1996-1998, boom cohort 1998–2001, and post-boom cohort 2003–2005. The dependent variable is a dummy equal to one if worker i experiences job termination. In column 1, job termination equals one if the worker switches job within the first four years after entry. In column 2, job termination equals one if the worker has a different employer in 2015 than at entry. In column 3, job termination equals if the worker switches job during the first four years after entry and this switch is associated with a wage drop. In column 4, job termination equals if the worker switches job during the first four years after entry and the initial employer has negative employment growth in the year of the switch. ICT_0 is a dummy equal to one if worker i started in the ICT sector. Pre-boom cohort, Boom cohort, and Post-boom cohort are dummy variables equal to one if the worker enters the labor market over 1994–1996, 1998–2001, and 2003–2005 respectively. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	=1 if job terminated			
	forced or voluntary		forced	
	Within four years	Diff. employer in 2015	Within 4y & Δwage<0	Within 4y & Δemp<0
	(1)	(2)	(3)	(4)
(Pre-boom cohort) × ICT_0	.051**	-.008	-.0069	-.025
	(.024)	(.016)	(.019)	(.021)
(Boom cohort) × ICT_0	.075***	.058***	.046***	.028**
	(.016)	(.0097)	(.013)	(.014)
(Post-boom cohort) × ICT_0	.084***	.057***	-.0017	-.014
	(.024)	(.018)	(.019)	(.015)
Worker controls	✓	✓	✓	✓
Observations	10,464	10,464	10,464	10,464

Table 11: Wage Growth and Job Termination

The table presents OLS estimations of Equation (15) for skilled entrants of the boom cohort 1998–2001. The dependent variable is wage growth growth of worker i from entry year to 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. In odd-numbered columns, we include each of the four proxies for job termination used in Table 10 as an explanatory variable. In even-numbered columns, we also include the interaction between ICT_0 and the proxy for job termination. Worker controls include sex, age and age squared at entry, entry year, and two-digit occupation at entry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry							
Proxy for job termination:	Within four years		Diff. employer in 2015		Within 4y & Δwage<0		Within 4y & Δemp<0	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT_0	-.102***	-.114***	-.102***	-.081*	-.098***	-.099***	-.104***	-.114***
	(.015)	(.022)	(.015)	(.042)	(.015)	(.016)	(.015)	(.016)
Job termination	-.035***	-.04**	-.053***	-.048**	-.14***	-.15***	-.028*	-.044**
	(.013)	(.016)	(.018)	(.021)	(.017)	(.022)	(.017)	(.021)
ICT_0 × Job termination		.019		-.023		.005		.042
		(.027)		(.043)		(.035)		(.034)
Worker controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,972	4,972	4,972	4,972	4,972	4,972	4,972	4,972

Table 12: Promotion Up the Hierarchy

The table presents OLS regressions for skilled entrants of the boom cohort 1998–2001 and post-boom cohort 2003–2005. In columns 1 and 2, the dependent variable is wage growth growth of worker i from entry year to 2015. Promotion is a dummy equal to one if worker i has become a manager in her initial industry in 2015. ICT_0 is a dummy equal to one if worker i started in the ICT sector. In column 3, the dependent variable is the promotion dummy. Boom cohort is a dummy equal one if the worker enters the labor market over 1998–2001. Worker controls include sex, age and age squared at entry, entry year, two-digit occupation at entry, and four-digit industry fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log wage 2015 − log wage entry		=1 if Promotion
	(1)	(2)	(3)
Promotion	.12***	.14***	
	(.019)	(.023)	
Promotion × ICT_0		-0.29	
		(.041)	
ICT_0 × Boom Cohort			-.027
			(.029)
Worker controls	✓	✓	✓
Industry FE	✓	✓	✓
Observations	4,228	4,228	4,228

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 Tables

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 matched employer-employee panel who hold a full-time job. Panel B reports summary statistics for the subsample of skilled workers who enter the labor force over 1994–2005.

	N	Mean	P25	P50	P75
	Panel A: All skilled workers				
Annual wage	1,980,099	50,406	32,137	41,414	56,468
Male	1,980,099	0.69	0	1	1
Age	1,980,099	43	35	43	51
	Panel B: Skilled workers entering the labor force over 1994–2005				
Annual wage	244,139	44,770	29,769	38,331	50,962
Male	244,139	0.68	0	1	1
Age at entry	244,139	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	*7210*	0.7	3.4
Software	*7220*	0.7	3.1
Data processing	*7230*	0.3	0.8
Maintenance computers	*7250*	0.1	0.2
Other data/computer-related services	*7123,7240,7290*	0.1	0.2
ICT: Telecommunications		**1.2**	**2.1**
Telecommunications	*6420*	1.2	2.1
ICT: Manufacturing		**1.6**	**3.7**
Electronic/communication equipment	*3210,3220,3230*	0.8	1.7
Measurement/navigation equipment	*3312,3313*	0.5	1.2
Accounting/computing equipment	*3000*	0.2	0.7
Insulated wire and cable	*3130*	0.1	0.1
ICT: Wholesale		**0.5**	**1.2**
Computers, electronics, telecoms	*5151,5152*	0.5	1.2
ICT: Total		**5.1**	**14.6**

Table B.3: Employers' Characteristics

The table reports summary statistics on the characteristics of the employers of skilled labor market entrants in the ICT sector (column 1) and in other sectors (column 2) over 1998–2001 (Panel A) and over 2003–2005 (Panel B). Column 3 reports the difference between column 1 and column 2. Employees is the number of full-time equivalent employees. Value added/Worker is value added in thousand euro per worker. Startup is a dummy equal to one if the firm is two year old or younger. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ICT firms	**Non-ICT firms**	**(1) minus (2)**
	(1)	(2)	(3)
	Panel A: Boom cohort		
Log(Employees)	5	5.2	-.24**
Value added/Worker	61	67	-5.5**
Startup	.15	.074	.074***
	Panel B: Post-boom cohort		
Employees	4.8	5.1	-.24*
Value added/Worker	66	70	-4.8*
Startup	.089	.05	.039**

C Model Solution

C.1 Proof of Proposition 1

Law of motion of old labor. Let

$$L_{k,t}^{new} = \int_{i \in E_{k,t}} H_{k,t,i,t} di \tag{C.1}$$

denote the efficient quantity of labor supplied by new workers in sector k in period t. (9) implies that $L_{k,t}^{new}$ is a function of the expected wage differential between the two sectors:

$$L_{k,t}^{new} = L_k^{new}\Big(\sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}[\Delta w_\tau]\Big), \quad L_1^{new}(\mathcal{W}) = \int_{\gamma_i < \mathcal{W}} e^{\theta_i} di, \quad L_2^{new}(\mathcal{W}) = \int_{\gamma_i \geq \mathcal{W}} e^{\theta_i} di. \tag{C.2}$$

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

$$L_{k,t+1} = (1-\delta)dH\big(L_{k,t} + L_{k,t}^{new}\big) + \sum_{c=-\infty}^{t-1} (1-\delta)^{t+1-c}\Big(\int_{i \in E_{k,c}} H_{k,c,i,t} di\Big)\big(dH_{k,c,t+1} - dH\big) + (1-\delta)L_{k,t}^{new}\big(dH_{k,t,t+1} - dH\big). \tag{C.3}$$

Steady state. We denote steady values with *. The steady state 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:

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

(C.3) at steady state implies:

$$L_k^* = g(L_k^* + L_k^{new*}) = \frac{g}{1-g} L_k^{new*}, \tag{C.4}$$

where $g \equiv (1-\delta)dH < 1$. Substituting into the labor demand function (6):

$$\Delta w^* = \Delta a - \frac{1}{\sigma}\log\left(\frac{L_1^{new}\left(\frac{\Delta w^*}{1-\beta}\right)}{L_2^{new}\left(\frac{\Delta w^*}{1-\beta}\right)}\right). \tag{C.5}$$

Since $(L_1^{new}/L_2^{new})(.)$ is an increasing function, going to zero at $-\infty$ and going to infinity at $+\infty$, (C.5) uniquely pins down Δw^*.

In the special case where θ_i and γ_i are independent, we have $w_1^* - w_2^* = 0$ and $L_k^{new*} = A_k^\sigma \int e^{\theta_i} di$. Indeed, independence between θ_i and γ_i implies $L_k^{new*} = E_k^* \int e^{\theta_i} di$. The result then follows from the assumption that sectoral entry shares are proportional

to sector shares in the production function when expected wages are equalized across sectors, that is, $E_{1,c}/E_{2,c} = A_1^\sigma/A_2^\sigma$ if $\sum_{t=c}^{\infty} \beta^{t-c}\mathbb{E}[\Delta w_t] = 0$.

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

$$\Delta w_t - \Delta w^* \simeq w_z.\Delta z_t + w_\ell.\big(\Delta \ell_t - \Delta \ell^*\big) + w_h.\Delta \overline{dh}_t, \tag{C.6}$$

where $\overline{dh}_{k,t} = \sum_{c=-\infty}^{t} q_{t-c}(dh_{k,c,t+1} - dh)$ 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 (4), and write the total efficient quantity of labor as the sum over old workers and new workers:

$$x_{k,t} = z_{k,t} + \log\left(L_{k,t} + L_{k,t}^{new}\right). \tag{C.7}$$

We linearize the log efficient quantity of labor:

$$\begin{aligned}\log\left(L_{k,t} + L_{k,t}^{new}\right) - \log\left(L_{k,t}^* + L_{k,t}^{new*}\right) &\simeq \frac{L_{k,t}^*\big(\ell_{k,t} - \ell_k^*\big) + L_{k,t}^{new*}\big(\ell_{k,t}^{new} - \ell_k^{new*}\big)}{L_{k,t}^* + L_{k,t}^{new*}} \\ &= g.\big(\ell_{k,t} - \ell_k^*\big) + (1-g).\big(\ell_{k,t}^{new} - \ell_k^{new*}\big), \end{aligned} \tag{C.8}$$

where the latter equality follows from (C.4). We calculate the difference between (C.7) for $k = 1$ and (C.7) for $k = 2$, and use (C.8) to substitute $\log(L_{k,t} + L_{k,t}^{new})$. We obtain:

$$\Delta x_t \simeq \Delta z_t + \log\left(\frac{L_{1,t}^* + L_{1,t}^{new*}}{L_{2,t}^* + L_{2,t}^{new*}}\right) + g.\big(\Delta \ell_t - \Delta \ell^*\big) + (1-g).\big(\Delta \ell_t^{new} - \Delta \ell^{new*}\big). \tag{C.9}$$

Using (C.4) and (C.5), the term in big parenthesis in (C.9) is equal to $\sigma\Delta a - \sigma\Delta w^*$. Plugging (C.9) into the labor demand function (6), we obtain:

$$\Delta w_t - \Delta w^* \simeq \frac{\sigma - 1}{\sigma}\Delta z_t - \frac{g}{\sigma}\big(\Delta \ell_t - \Delta \ell^*\big) - \frac{1-g}{\sigma}\big(\Delta \ell_t^{new} - \Delta \ell^{new*}\big). \tag{C.10}$$

We combine (C.6) and (C.10) to obtain:

$$\Delta \ell_t^{new} - \Delta \ell^{new*} \simeq \frac{\sigma - 1 - \sigma w_z}{1-g}\Delta z_t - \frac{g + \sigma w_\ell}{1-g}\big(\Delta \ell_t - \Delta \ell^*\big) - \frac{\sigma w_h}{1-g}\Delta \overline{dh}_t. \tag{C.11}$$

Expected future wages. We consider (C.6) evaluated at time $t + \tau$, and take expectations conditional on beginning of period t information. We obtain:

$$\mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] \simeq w_z\mathbb{E}_t\big[\Delta z_{t+\tau}\big] + w_\ell\mathbb{E}_t\big[\Delta \ell_{t+\tau} - \Delta \ell^*\big] + w_h\mathbb{E}_t\big[\Delta \overline{dh}_t\big]. \tag{C.12}$$

We linearize the law of motion of the efficient quantity of labor supplied by old workers, given by (C.3):

$$\ell_{k,t+1} - \ell_k^* \simeq g.\big(\ell_{k,t} - \ell_k^*\big) + (1-g).\big(\ell_{k,t}^{new} - \ell_k^{new^*}\big) + \overline{dh}_{k,t+1}, \tag{C.13}$$

where

$$\begin{aligned}\overline{dh}_{k,t+1} = \sum_{c=-\infty}^{t-1} \frac{(1-\delta)^{t+1-c} dH \int_{i\in E_{k,c}} H_{k,c,i,t} di}{L_k^*}\big(dh_{k,c,t+1} - dh\big) \\ + \frac{(1-\delta) dH L_{k,t}^{new}}{L_k^*}\big(dh_{k,t,t+1} - dh\big) \equiv \sum_{c=-\infty}^{t} q_{t-c}\big(dh_{k,c,t+1} - dh\big).\end{aligned} \tag{C.14}$$

A first-order approximation of the weights is:

$$q_{t-c} \simeq \frac{(1-\delta)^{t+1-c} dH^{t+1-c} L_k^{new*}}{L_k^*} = (1-g)g^{t-c}. \tag{C.15}$$

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

$$\overline{dh}_{k,t+1} = g\rho_h \overline{dh}_{k,t} + g\varepsilon_{k,t+1}^h. \tag{C.16}$$

We calculate the difference between (C.13) for $k=1$ and (C.13) for $k=2$:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq g.\big(\Delta\ell_t - \Delta\ell^*\big) + (1-g).\big(\Delta\ell_t^{new} - \Delta\ell^{new*}\big) + \Delta\overline{dh}_{t+1}. \tag{C.17}$$

Using (C.11) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (C.17), we obtain:

$$\Delta\ell_{t+1} - \Delta\ell^* \simeq -\sigma w_\ell\big(\Delta\ell_t - \Delta\ell^*\big) + (\sigma - 1 - \sigma w_z)\Delta z_t + \Delta\overline{dh}_{t+1}. \tag{C.18}$$

Therefore:

$$\Delta\ell_{t+\tau} - \Delta\ell^* \simeq (-\sigma w_\ell)^\tau\big(\Delta\ell_t - \Delta\ell^*\big) + \sum_{s=0}^{\tau-1}(-\sigma w_\ell)^{\tau-1-s}\Big[(\sigma - 1 - \sigma w_z)\Delta z_{t+s} + \Delta\overline{dh}_{t+s+1}\Big]. \tag{C.19}$$

We use (C.19) to substitute $\Delta\ell_{t+\tau} - \Delta\ell^*$ in (C.12), and we use $\mathbb{E}_t[z_{k,t+s}] = \rho_z^s z_{k,t}$ and $\mathbb{E}_t[\overline{dh}_{k,t+s+1}] = (g\rho_h)^{s+1}\overline{dh}_{k,t}$ for $s \geq 0$, to obtain:

$$\begin{aligned}\mathbb{E}_t\big[\Delta w_{t+\tau} - \Delta w^*\big] \simeq \left[w_z\rho_z^\tau + w_\ell(\sigma - 1 - \sigma w_z)\frac{(-\sigma w_\ell)^\tau - \rho_z^\tau}{(-\sigma w_\ell) - \rho_z}\right]\Delta z_t \\ + w_\ell(-\sigma w_\ell)^\tau\big(\Delta\ell_t - \Delta\ell^*\big) + \left[w_h(g\rho_h)^{\tau+1} + w_\ell g\rho_h\frac{(-\sigma w_\ell)^\tau - (g\rho_h)^\tau}{(-\sigma w_\ell) - g\rho_h}\right]\Delta\overline{dh}_t\end{aligned} \tag{C.20}$$

if $(-\sigma w_\ell) \neq \rho_z$ and $(-\sigma w_\ell) \neq g\rho_h$. The fraction on the first line of (C.20) is equal to

$\tau\rho_z^{\tau-1}$ if $(-\sigma w_\ell) = \rho_z$. The fraction on the second line of (C.20) is equal to $\tau(g\rho_h)^{\tau-1}$ if $(-\sigma w_\ell) = g\rho_h$.

We use (C.20) to calculate the intertemporal wage difference between the two sectors:

$$\sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*] \simeq \left[\frac{w_z}{1-\beta\rho_z} + w_\ell(\sigma - 1 - \sigma w_z)\frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta\rho_z)}\right]\Delta z_t$$
$$+ \frac{w_\ell}{1+\beta\sigma w_\ell}\big(\Delta\ell_t - \Delta\ell^*\big) + \left[\frac{w_h g\rho_h}{1-\beta g\rho_h} + w_\ell g\rho_h \frac{\beta}{(1+\beta\sigma w_\ell)(1-\beta g\rho_h)}\right]\Delta\overline{dh}_t, \quad \text{(C.21)}$$

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

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

$$E_{1,t} - E_1^* = -\big(E_{2,t} - E_2^*\big) \simeq \sigma\eta \sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*]. \quad \text{(C.22)}$$

We linearize the efficient quantity of labor supplied by new workers in sector k, given by (C.1):

$$\big(\ell_{k,t}^{new} - \ell_k^{new*}\big)L_k^{new*} \simeq \big(E_{k,t} - E_k^*\big)\mathbb{E}\big[e^{\theta_i}|\gamma_i = \Delta^*\big]. \quad \text{(C.23)}$$

We use (C.22) to substitute $E_{k,t} - E_k^*$ in (C.23), and we use $L_1^{new*} + L_2^{new*} = \mathbb{E}\big[e^{\theta_i}\big]$. We obtain:

$$\Delta\ell_t^{new} - \Delta\ell^{new^*} \simeq \sigma\eta\alpha \sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}_t[\Delta w_\tau - \Delta w^*], \quad \text{(C.24)}$$

where

$$\alpha = \frac{\mathbb{E}\big[e^{\theta_i}\big]\mathbb{E}\big[e^{\theta_i}|\gamma_i = \Delta^*\big]}{L_1^{new*}L_2^{new*}} \quad \text{(C.25)}$$

and the intertemporal sectoral wage difference in (C.24) is given by (C.21).

In the special case where θ_i and γ_i are independent, $\alpha = 1/(A_1^\sigma A_2^\sigma)$.

Solving for (w_z, w_ℓ, w_h). Equalizing (C.11) and (C.24), we obtain that the sectoral wage differential is given by (10). 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:

$$w_z = \left[\frac{1-\beta\rho_z}{\alpha\eta(1-g)} + \frac{-\beta\sigma w_\ell}{1+\beta\sigma w_\ell}\right]\left(\frac{\sigma-1}{\sigma} - w_z\right) \quad \text{(C.26)}$$

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

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

$$w_h = \frac{-w_\ell \beta g \rho_h \alpha \eta (1-g)}{(1+\beta\sigma w_\ell)(1-\beta g\rho_h + (1-g) g \rho_h \alpha \eta)}. \tag{C.27}$$

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 (C.22) and (C.24), we obtain:

$$\Delta E_t - \Delta E^* \simeq \frac{2}{\alpha}\big(\Delta \ell_t^{new} - \Delta \ell^{new*}\big). \tag{C.28}$$

Using (C.11) to substitute $\Delta\ell_t^{new} - \Delta\ell^{new*}$ in (C.28), we obtain that entry is given by (11), where

$$E_z = \frac{2\sigma}{\alpha(1-g)}\left(\frac{\sigma-1}{\sigma} - w_z\right) > 0, \tag{C.29}$$

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

$$E_\ell = -\frac{2(g+\sigma w_\ell)}{\alpha(1-g)} < 0, \tag{C.30}$$

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

$$E_h = -\frac{2\sigma w_h}{\alpha(1-g)} \leq 0, \tag{C.31}$$

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

Solving for ℓ_E. Using (C.28) to substitute $\ell_{k,t}^{new} - \ell_k^{new*}$ in (C.17), we obtain that the law of motion of efficient quantity of old labor is given by (12), where

$$\ell_E = \frac{1}{2}\alpha(1-g) > 0, \tag{C.32}$$

and the law of motion of $\Delta\overline{dh}_t$ is given by (C.16).

C.2 The Determinants of Selection

When worker skill, θ_i, and worker sectoral preference, γ_i, are independent, the average worker skill is always the same in both sectors, that is, $\Delta\overline{\theta}_c = 0$. By contrast, when θ_i and γ_i are not independent, worker selection into sectors leads to composition effects that affect the average skill in each sector, that is, $\Delta\overline{\theta}_c$ may be nonzero. Two different moments of the joint distribution of (θ_i, γ_i) determine, on the one hand, the direction of the selection effect at the steady state, and on the other hand, the change in selection induced by variation in the sectoral allocation of entry around the steady state.

At the steady state level of entry, the average skill difference between the two sectors, $\Delta\overline{\theta}^*$, depends on the correlation between worker skill and worker sectoral preference.

More precisely, $\Delta\overline{\theta}^*$ has the same sign as the correlation between θ_i and $1_{\{\gamma_i<\Delta w^*/(1-\beta)\}}$. Intuitively, if workers with an idiosyncratic preference for sector 1 tend to have above-average skills, the average skill is higher in sector 1, that is, $\Delta\overline{\theta}^* > 0$; and vice versa.

To see how variation in the sectoral allocation of entrants changes the pool of entrants in each sector, define $\theta^{marg} = \mathbb{E}[\theta_i|\gamma_i = \Delta w^*/(1-\beta)]$ as the skill of the marginal entrant who is just indifferent between sector 1 and sector 2 at the steady state, and $\theta^{avg} = E_2^*\overline{\theta}_1^* + E_1^*\overline{\theta}_2^*$ as a weighted average worker skill across both sectors. The average skill difference between the two sectors is given by:

$$\Delta\overline{\theta}_c \simeq \Delta\overline{\theta}^* + \frac{\theta^{marg} - \theta^{avg}}{2E_1^*E_2^*}\big(\Delta E_c - \Delta E^*\big). \tag{C.33}$$

The effect of sectoral reallocation on sectoral worker composition depends on how the skill of the marginal entrant (who has a weak sectoral preference) compares to the skill of the average entrant. If the marginal worker has low skill ($\theta^{marg} < \theta^{avg}$), reallocation of entry towards sector 1 ($\Delta E_c - \Delta E^* > 0$) worsens the pool of entrants in sector 1. Conversely, if the marginal worker has high skill, then sectoral reallocation towards sector 1 improves the pool of entrants in sector 1.