Technology Boom, Labor Reallocation, and Human Capital Depreciation

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Abstract

We study the long-run effect on productivity of labor reallocation during a technology boom. Using French matched employer-employee data, we examine the large cohort of workers who enter the Information and Communication Technology sector during the late 1990s 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 in other sectors. The long-run wage discount is concentrated on STEM occupations, consistent with a skill obsolescence mechanism. Other moments of the wage distribution are inconsistent with selection effects and negative demand shocks.

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1 Introduction

Examples of large sectoral booms triggering important reallocation of labor abound across time, countries and sectors. Such episodes are often followed by sharp reversals. Recent examples include the boom-bust cycle in the technology sector in the late 1990s in the US and other high-income economies, that in the real estate sector in the mid 2000s in the US and some other countries, and that in commodity sectors in the late 2000s in several Latin American countries. Such sectoral booms can have short-term implications for the business cycle, for instance because labor market frictions hinder the reallocation of workers when the boom reverses (Lilien, 1982). But do they also have long-term effects?

Sectoral booms can have long-term effects through their impact on the accumulation of human capital of workers joining the booming sector. If workers drawn into a sector acquire skills that are useful (resp. useless) in other sectors, reallocation of labor towards that sector will have a positive (resp. negative) impact on their long-term productivity. Evidence supporting this hypothesis exists for booms in low-skill sectors, which pull workers into low-skill occupations, weighing on their accumulation of human capital and long-term productivity.[1] What about booms in high-skills sectors?

Booms in technology sectors might foster the accumulation of human capital. Employees may be exposed to new technologies, allowing them to acquire new skills, which can be used in other sectors when the technology booms reverses. Hence, even if technology booms are possibly fueled by over-optimism about the sector's prospects and by asset over-valuation (Ofek and Richardson, 2003; Brunnermeier and Nagel, 2004), the labor reallocation these booms involve might still boost human capital accumulation and long-term productivity of reallocated workers.

This paper empirically explores that idea: We study how joining a booming technology sector affects workers' long-term productivity. Carrying out this analysis necessitates: (i) a boom in a technology sector large enough to trigger significant labor reallocation, and (ii) panel worker-level data tracking workers over a long period of time after the boom. These requirements lead us to focus on the "dot-com bubble" that took place in the Information and Communication Technology (ICT) sector in the late 1990s. We use French administrative matched employer-employee data for the period 1994–2015, which can be linked to the universe of firms' financial statements from tax filings, providing us with high quality, longitudinal information on the wages, career paths, and occupational and sectoral choices of workers exposed to the ICT boom.[2] We measure workers' productivity at various horizons using wages.

[1] See Black, McKinnish, and Sanders (2005) on booms in the coal sector, Cascio and Narayan (2015) in the oil and gas sector, Charles, Hurst, and Notowidigdo (2018) in the real estate sector, and Carrillo (2019) in the coffee growing sector.

[2] These data are made available to researchers via a distant server. The reproducibility of results obtained using these confidential administrative data can be certified by a certification agency. See Appendix A for information about data access and reproducibility certificate.

To inform our empirical analysis, we first outline a dynamic two-sector model with worker sectoral choice and on-the-job human capital accumulation. Before starting their careers, workers are heterogeneous in their taste for sectors and in their initial stock of human capital, reflecting innate ability and education. They decide which sector to enter, based on expected lifetime earnings, and cannot switch sector thereafter. On the job, workers are exposed to two types of sectoral shocks: productivity shocks that shift labor demand and thus equilibrium wages of all workers in the sector, and human capital shocks that affect the rate at which individuals working in the sector accumulate human capital. The model provides an intuitive decomposition of the average wage in a sector-cohort into three components: the (sector-specific) wage rate that reflects the unbalance between labor demand and the stock of workers in the sector, (sector-cohort-specific) human capital accumulated since labor market entry, and a (sector-cohort-specific) selection term that depends on the endogenous composition of the workforce in the sector. The model highlights how the human capital accumulation component can be backed out by comparing the wage dynamics of different cohorts of workers.

Our first empirical finding is that the large reallocation of skilled labor towards the ICT sector during the late 1990s boom, and then away from this sector in the subsequent bust, is almost entirely driven by workers who recently entered the labor market. 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. By contrast, inter-sectoral flows of incumbent workers barely contribute to aggregate labor reallocation. This finding justifies the assumption in the model that incumbent workers do not switch to the technology sector when wages are higher in this sector.

Next, we turn our attention to the long-run wage dynamics of skilled workers who enter the labor market during the ICT boom period, which we define to be 1998–2001 based on the years in which the share of skilled entrants starting in the ICT sector is significantly above trend. We compare the wage dynamics of workers starting their career in the booming ICT sector to that of individuals with same demographics, starting their career in the same year with the same broad occupation (e.g., STEM vs. management), but in a different sector. Starting in the booming ICT sector yields a 5% higher wage on average at the time of entry. The wage difference vanishes when the boom ends in the early 2000s. Remarkably, even after the bust, the wage difference keeps decreasing, turns significantly negative and remains so in the long run. 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. A present value calculation shows that the entry wage premium does not compensate for the long-term discount, leading to significantly lower cumulative earnings.

This result is quantitatively robust to controlling for education, 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' long-term earnings such as size, productivity, or age. The long-term wage 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, inconsistent with a winners-take-all interpretation.

As shown by the model, the wage discount can be decomposed into three components: human capital depreciation, negative selection, and persistently low labor demand after the bust. Our next results rule out selection and low labor demand. We have two results against a selection effect by which workers attracted to the booming ICT sector have low intrinsic productivity. First, such selection 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, the model shows that selection can be detected by comparing the wage dynamics of the boom cohort to that of the pre-boom cohort of workers who entered the labor market just before the boom started. Indeed, these slightly older workers have a fairly similar experience to that of the boom cohort, but to the extent that the boom was not anticipated, these workers did not self-select into ICT because of the boom. Thus, the difference in outcomes between the boom cohort and the pre-boom cohort reflects the selection effect of the boom. Inconsistent with selection, the pre-boom cohort has a quantitatively similar wage dynamics to that of the boom cohort, in particular it has the same long-term wage discount.

The model also delivers an empirical strategy to separate human capital depreciation from persistently low labor demand in the ICT sector: comparing the wage dynamics of the boom cohort to that of the post-boom cohort of workers who start after the bust. If the discount is explained by persistently low labor demand in the ICT sector after the bust, the post-boom cohort should also experience the discount. Inconsistent with this hypothesis, post-boom entrants in the ICT sector experience no long-term wage discount.

The wage dynamics of each cohort of workers are instead consistent with rapid depreciation of human capital accumulated in the ICT sector during the boom. Indeed, only those workers who experience the ICT boom (the pre-boom and boom cohorts) experience the long-term wage discount, whereas workers who joined later do not.

In the final part of the paper, we explore potential mechanisms by which human capital accumulated during the boom weighs on long-term productivity. First, skills acquired during a technology boom may become rapidly obsolete as a result of technological acceleration (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 lower long-term earnings (Gibbons and Katz, 1991; Jacobson, LaLonde, and Sullivan, 1993; von Wachter and Bender, 2006; Jarosch, 2015; Kogan et al., 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 skill obsolescence. We hypothesize that if human capital acquired by young workers during the boom depreciates rapidly because of technological change, skill obsolescence should be an increasing function of workers' job technological intensity. 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 among workers starting in the booming ICT sector, only those with a STEM occupation experience low long-run wage growth. The second proxy 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 worker takes her first job. In both cases, the discount is larger for workers who started in more tech-intensive firms or sectors.

Our results do not imply that skill obsolescence is caused by labor reallocation. Instead, our results are consistent with technological change (regardless of what causes it) driving both firms' investment decisions and thus labor reallocation on the one hand, and accelerating skill obsolescence on the other hand. Sectoral labor reallocation matters however, because workers allocated to the booming technology sector are exposed to human capital depreciation. Therefore, the quantity of labor allocated to the technology sector during the boom matters for long-term aggregate productivity, implying that short-term fluctuations can have long-lasting consequences.

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.

Related literature We contribute to the literature on vintage human capital, which emphasizes that several vintages of knowledge can co-exist, and that technological change makes old vintages obsolete (Chari and Hopenhayn, 1991; MacDonald and Weisbach, 2004). Deming and Noray (2018) provide evidence using job vacancy data that skill requirements of STEM occupations can 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 technology sector, implying that boom-induced labor reallocation can have long-lasting consequences.

The effects of sectoral booms on workers' choices and outcomes have been studied outside the technology sector, such as in the financial sector (Oyer, 2008; Gupta and Hacamo, 2018), mining (Cascio and Narayan, 2015), real estate (Charles, Hurst, and Notowidigdo, 2018), agriculture (Carrillo, 2019), and across all sectors (Choi, Lou, and Mukherjee, 2017). By contrast, we study a (large and well-identified) boom in the technology sector. The human capital implications of booms in low-tech sectors do not necessarily extend to booms in high-tech sector, because workers allocated to a booming technology sector may be exposed to new technologies and acquire skills that can be redeployed in other firms or sectors even if the technology sector contracts. Our results, however, reject this view since workers exposed to the booming technology sector have low long-term wage growth. Beaudry, Green, and Sand (2016) also focus on the late 1990s boom and argue that the overall demand for cognitive tasks declined after the boom. Among other differences with our paper, they do not distinguish between cohorts of workers, and they do not distinguish between ICT-related tasks and other cognitive tasks.

Another strand of literature studies how the aggregate state of the economy affects labor market entrants' long-run outcomes. This literature shows that workers starting in a recession have persistently lower earnings (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 (Oyer (2006) on academics, Schoar and Zuo (2017) on CEOs). Our focus is different: We study how sectoral booms affect long-run outcomes of workers allocated to the booming sector relative to same-cohort workers allocated to other sectors.

Finally, our results contribute to the literature studying how labor reallocates in response to sectoral shocks, starting with Lilien (1982) and Rogerson (1987). The recent literature has focused on reallocation induced by negative sectoral shocks induced, for instance, by trade shocks (Dix-Carneiro, 2014; Autor et al., 2014) and real estate shocks (Pilossoph, 2014). Fewer papers have focused on positive shocks (Carrington, 1996; Kline, 2008). Consistent with these papers, we find that labor quickly reallocates across sectors in response to demand shocks and that substantial wage premia are necessary to induce such reallocation. Our contribution is to show that reallocation towards a high-tech sector is entirely driven by the new workers, while the net contribution of older workers is negligible. This result matters for two reasons. First, it contributes to our understanding of why workers in sectors hit by negative shocks incur long-term earnings losses, as reallocation of these workers to high-tech growing sectors is scant. Second, if on-the-job learning includes a sector-specific component, the age pattern of sectoral reallocation matters because skills learnt on the job by young workers will be used for longer periods of time.

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 detailed 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.[3] 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 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%.[4] Appendix Table B.1 reports

[3]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.

[4]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

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 registrations with the event date 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 (Panel B). The share of the ICT sector in total skilled employment displays a sharp deviation from an increasing 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 entirely 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.

sector managers and professionals (33); teaching professionals (34); cultural professionals (35), which represent less than 1%, 8%, 9%, and 3%, respectively, of skilled jobs.

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.[5] 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.

To summarize the pattern of labor reallocation, two main facts emerge. First the ICT boom induces a large reallocation of skilled 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 precisely the "ICT boom cohort" of workers, who enter the labor market during the ICT boom, together with the "pre-boom cohort" and the "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.

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

[5] 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.

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:[6]

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

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

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 work in sector k during period $t-1$, which is effective from period t on. Human capital shocks follow the autoregressive process:

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

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.[7] $\varepsilon^h_{k,t}$ is a human capital shock affecting all cohorts of workers in sector k in period $t-1$, similar in spirit to Rogerson (2005). It may reflect on-the-job learning or changes 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 build up progressively in a sector-cohort over time.

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

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

$Z_{k,t}$ 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, $i \in E_{k,c}$.

[6] Throughout the paper, we use lowercase letters to denote logs of uppercase variables.

[7] 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.

The model allows for two types of sectoral shocks: shocks that affect all cohorts in the sector similarly, and shocks that are sector-cohort specific. 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 sector-cohort-specific shock, 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 cohorts 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:

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

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[8]

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

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, that is, $\mathbb{E}_c[w_{1,c,i,t} - w_{2,c,i,t}] = \mathbb{E}_c[w_{1,t} - w_{2,t}]$.

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

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.

Workers' sectoral choices depend on expectations of future wages. These choices and the resulting equilibrium outcomes do not depend on whether workers hold rational or biased expectations. The only difference is that, in the latter case, workers are systematically surprised by the realization of shocks.

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., $\Delta w_t = w_{1,t} - w_{2,t}$. 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, $\Delta\ell_t = \log(L_{1,t}) - \log(L_{2,t})$, where $L_{k,t} = \sum_{c=-\infty}^{t-1}(1-\delta)^{t-c}\int_{i\in E_{k,c}} H_{k,c,i,t}di$. We denote steady state values with *.

Proposition 1 *At the stationary equilibrium:*

$$\begin{aligned} \Delta w_t &\simeq \Delta w^* + w_z \,.\, \Delta z_t + w_\ell \,.\, \big(\Delta\ell_t - \Delta\ell^*\big) + w_h \,.\, \Delta\overline{dh}_t, & (10)\\ \Delta E_t &\simeq \Delta E^* + E_z \,.\, \Delta z_t + E_\ell \,.\, \big(\Delta\ell_t - \Delta\ell^*\big) + E_h \,.\, \Delta\overline{dh}_t, & (11) \end{aligned}$$

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

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

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 $c \leq t$.

Consider first the effect of a positive productivity shock in sector 1 relative to sector 2: $\Delta z_t > 0$. Higher productivity increases the demand for labor in sector 1. Since old workers cannot switch sector, sectoral reallocation takes place through the sectoral choice of labor market entrants. The wage rate increases in sector 1 relative to sector 2 ($w_z > 0$ in (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 dH. Thus, the efficient quantity of labor by old workers mean 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:

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

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 $\overline{\theta}_{k,c} = \sum_{i\in E_{k,c}} \theta_i$. Remember that the Δ operator denotes the difference between sector $k=1$ and sector $k=2$, e.g., $\Delta\overline{w}_{c,t} = \Delta\overline{w}_{1,c,t} - \Delta\overline{w}_{2,c,t}$.

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 sector-cohorts because different cohorts, even in the same sector, 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 her 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.[9]

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 three components of the average wage in a sector-cohort will rely on comparing the wage dynamics across cohorts.

4 The ICT Boom-Cohort Discount

4.1 Wage Dynamics

We study the wage dynamics of skilled workers who enter the labor market during the ICT boom by estimating the panel regression:

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

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 of $\Delta\overline{w}_{c,t}$ for the boom cohort in the model.

Figure 2 plots the time-series of β_t for the boom cohort and the 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. While the divergence-convergence pattern is consistent with a sectoral cycle, the more surprising result is that even though employment in the ICT sector bounces back after 2005 (see Panel B of Figure 1), the wage difference between entrants in the booming ICT sector and entrants in other sectors keeps falling after the bust. 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 eventually becomes negative. In 2015, these workers earn on average 6.2% (significant at

[9]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.

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. We 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 ($-.062 - .046 = -10.8\%$).

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 entry year to 2015 by estimating the long-difference 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.[10]

Up to now, our results could be explained by differences in workers characteristics (location, education) or differences in their first employer characteristics (e.g. age. size). 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.[11] 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 a few other sectors, such as the financial sector as pointed out by Philippon and Reshef

[10]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.

[11]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.

(2012) for the US and Célérier and Vallée (2019) for France. In column 3, we exclude entrants starting in the financial sector, who represent 7% 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 the employer-employee data reports wages but not capital income. Capital income can be significant for entrepreneurs. It may also be relevant for employees granted 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.[12] Alternatively, assuming that employees have ownership stakes in the company, we allocate the firm's net income to all skilled employees in proportion to their share in total skilled-worker wage bill. In both cases, 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.[13] We compare characteristics of ICT employers to that of non-ICT

[12]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.

[13]Evidence that firm characteristics have long lasting consequences on workers' earnings can be found in Garicano, Lelarge, and Van Reenen (2016) and Bloom, Guvenen, Smith, Song, and von Wachter (2018)

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 significantly different from that after the boom, except for the probability that the employer is a startup, which is higher in the ICT sector during the boom. 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 these controls do not affect the magnitude of the wage discount.

Second, while France fully embraced the ICT revolution and produced successful ICT firms, the country has not become the worldwide leader in that sector. As such, 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, implying that 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 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.

for firm 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), Kerr, Nanda, and Rhodes-Kropf (2014), Hurst and Pugsley (2015), Manso (2016)), 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 (including from part-time and short job spells) from the entry year to year t discounted back to the entry year at a rate of 5% per year. We estimate 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.[14]

[14] Since unemployment benefits (UB) are only reported starting in 2008, we assign 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, and 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

As highlighted by the model, three mechanisms 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 design tests based on the model to assess the contribution of each of these three mechanisms to the ICT boom-cohort discount.

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

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

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

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, the selection hypothesis amounts to $\Delta\overline{\theta}_B < 0$. If there is no human capital shock and a positive productivity shock in the ICT sector during the boom, the sectoral difference in average wage of the boom cohort is equal to $\Delta\overline{w}_{B,t} = \Delta\overline{\theta}_B + \Delta w_t$, which 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. This prediction of the selection hypothesis 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 similar human capital and sectoral shocks as the boom cohort, but they 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 experience no long-term wage discount. By contrast, if the 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 comes out naturally from 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, but that the boom cohort does not experience. 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.[15] 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 6.7% 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 6.2% lower wages 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).[16] 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 inconsistent with a selection effect.

A more subtle explanation based on a combination of negative selection during the boom (first term of (17) is negative) and a negative human capital shock to the pre-boom cohort (second term of (17) is also 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.

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

[15] We exclude 1997 from the pre-boom cohort because it might be argued that the ICT boom has already started in 1997 (see Figure 1). The results are robust to including 1997 in the pre-boom cohort.

[16] 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.

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. In the model, this hypothesis would be amount to a persistent negative productivity shock ($\Delta z_t < 0$), leading to a persistently low wage rate ($\Delta w_t < 0$). To test for this hypothesis, we compare the wage dynamics of the boom cohort to that of the post-boom cohort. The intuition for the test is the following. If the ICT boom-cohort discount is explained by persistently low labor demand and low wages in the ICT sector, the post-boom cohort should also experience the discount. By contrast, if the discount is explained by the depreciation of human capital accumulated during the boom, the post-boom cohort should experience no discount.

This prediction obtains naturally in our model. The difference in the ICT wage premium between the boom cohort ($c = B$) and the post-boom cohort ($c = B + 1$) is:

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

The interpretation of Equation (18) parallels that of Equation (17). The key insight is that sectoral shocks Δz_t do not affect the wage difference between the boom cohort and the post-boom cohort, because these shocks affect all cohorts similarly. Having ruled out selection, any persistent wage difference between the boom cohort and the post-boom cohort should therefore be attributed to human capital depreciation.

We estimate the panel regression equation (14) on the post-boom cohort 2003–2005.[17] The estimated coefficients β_t are plotted in Figure 4. Workers starting in the ICT sector in the post-boom period have slightly lower entry 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 column 3 of Table 6. 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

[17] 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.

boom.

The evidence is inconsistent with a secular decline of ICT sector wages in the wake of the ICT bust. Instead, the fact 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 human capital of skilled workers allocated to the ICT sector during the boom progressively depreciate over time? We investigate three hypotheses. First, skills acquired during technology booms become quickly obsolete, 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 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 management/business, non-STEM content (hereafter "managers"). We define *STEM Occupation* 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.[18] 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 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. 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.[19] 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.

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-

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

[19]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".

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 (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.[20]

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 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

[20] 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.

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 the post-boom cohort.[21]

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).[22]

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.

[21] 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%.

[22] 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.

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) and 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 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 and post-boom cohorts 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.[23] 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 22% (significant at 1%) higher wage growth than STEM workers who follow a different career path. 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.[24] 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.

[23] 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).

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

7 Conclusion

We uncover an *ICT boom-cohort discount:* Young talents who started in the ICT sector during the late 1990s tech boom enjoyed 5% higher entry wages, but end up in the long 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 technology sector. Instead, the evidence points to the rapid depreciation of technical skills acquired during the boom, consistent with accelerating skill obsolescence during technology booms. Thus, our findings are not consistent with the notion that boom-time tech firms enhance their workers' human capital and long-term productivity (although positive externalities on other workers are not necessarily ruled out). Our results also establish a connection between short-term fluctuations and long-term growth by showing that labor reallocation at the business cycle frequency can be associated with changes (in our case, a reduction) in long-run human capital accumulation.

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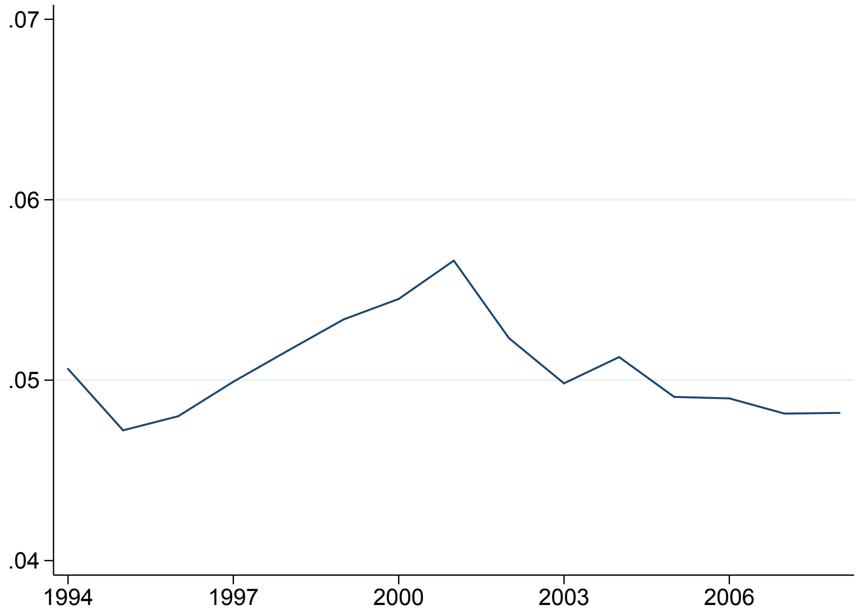
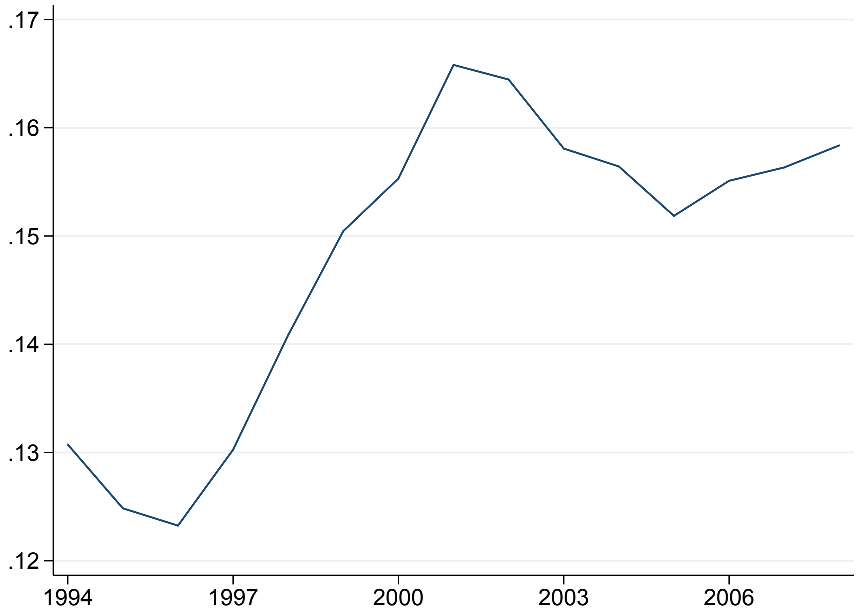
Figure 1: Employment Share of the ICT Sector

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.

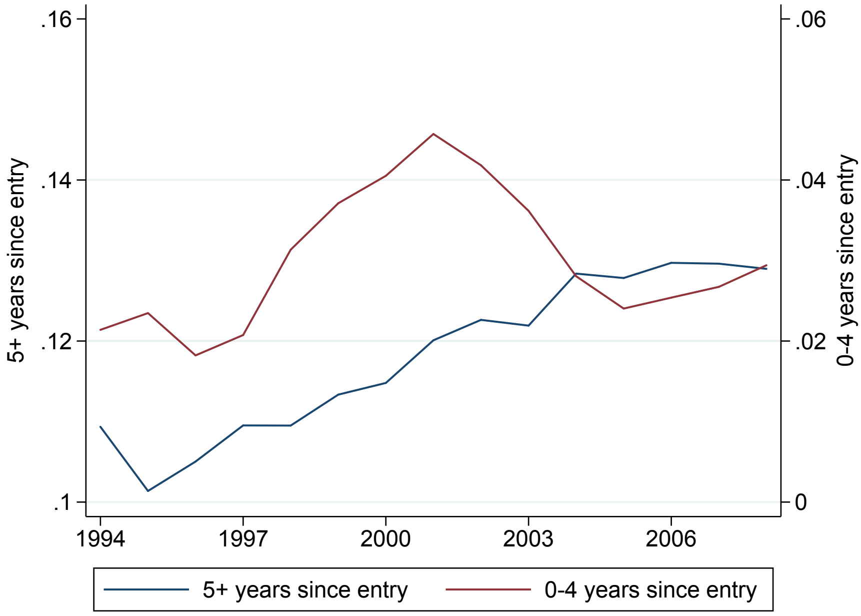
Panel A: All workers



Panel B: Skilled workers



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



Panel D: Skilled entrants

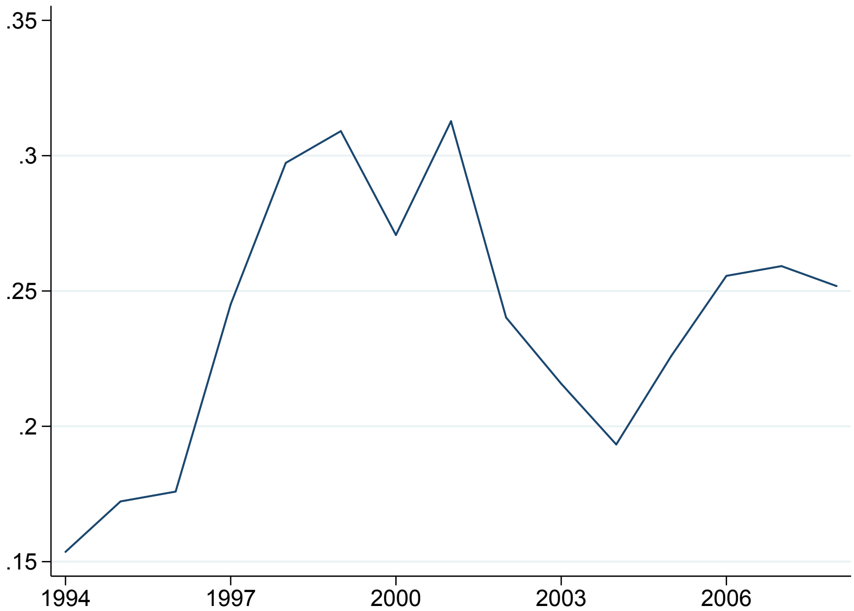


Figure 2: Wage Dynamics of the ICT Boom Cohort

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.

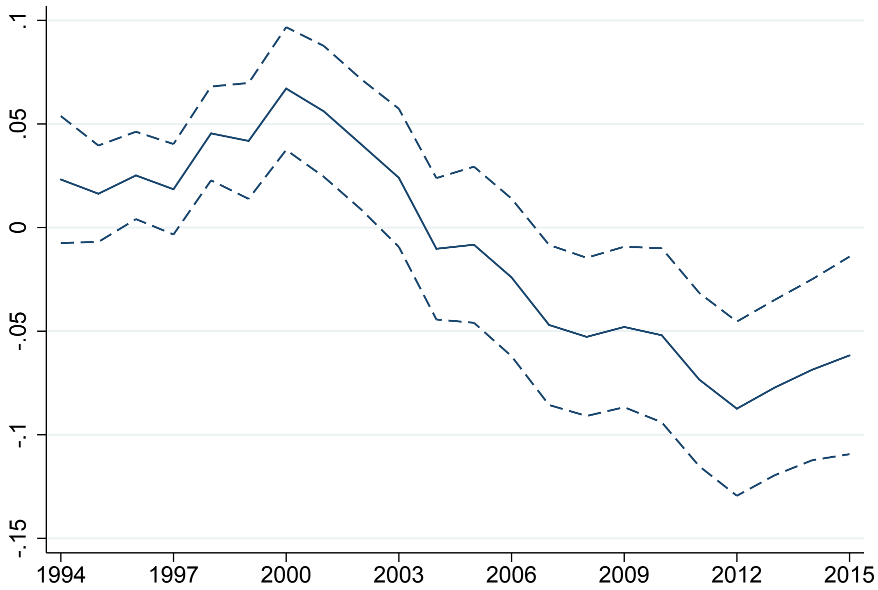


Figure 4: Wage Dynamics of the Post-Boom Cohort

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 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						
						Add firm profit to: CEO	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ICT_0	-.105***	-.113***	-.104***	-.154***	-.152***	-.113***	-.129***
	(.015)	(.016)	(.016)	(.044)	(.043)	(.016)	(.043)
Worker controls	✓	✓	✓	✓	✓	✓	✓
Commuting Zone FE	–	✓	✓	✓	✓	✓	✓
Education	–	–	–	–	✓	–	–
Observations	4,972	4,972	4,599	537	537	4,897	4,972
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 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***	-0.092***
	(.015)	(.045)	(.029)
Log(Employees)	0.0026		
	(.0032)		
Value added/Worker	0.00085***		
	(.00015)		
Startup	0.042*		
	(.026)		
Worker controls	✓	✓	✓
Observations	4,282	530	1,064
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***
	(.027)	(.018)	(.015)	(.018)	(.028)
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)
ICT_0 × (t=0)	.028***		
	(.010)		
ICT_0 × (t=1997)	.018*	.002	
	(.011)	(.010)	
ICT_0 × (t=2000)	.067***	.056***	
	(.015)	(.014)	
ICT_0 × (t=2002)	.040**	.028**	.040**
	(.016)	(.014)	(.016)
ICT_0 × (t=2006)	-.024	-.041**	-.024
	(.019)	(.018)	(.019)
ICT_0 × (t=2010)	-.052**	-.063***	-.052**
	(.021)	(.019)	(.021)
ICT_0 × (t=2015)	-.062**	-.086***	-.062**
	(.024)	(.022)	(.024)
ICT_0 × (t=2002) × Boom cohort			-.010
			(.018)
ICT_0 × (t=2006) × Boom cohort			-.001
			(.022)
ICT_0 × (t=2010) × Boom cohort			.001
			(.024)
ICT_0 × (t=2015) × Boom cohort			-.001
			(.028)
Worker controls	✓	✓	✓
Worker FE	–	✓	–
Observations	24,540	23,397	34,013
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**		
	(.010)		
ICT_0 × (t=2006)	-.020*	.009	-.020*
	(.011)	(.009)	(.011)
ICT_0 × (t=2010)	-.002	.026**	-.002
	(.014)	(.012)	(.014)
ICT_0 × (t=2015)	.004	.027	.004
	(.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 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	-.035	-.044
	(.039)	(.032)	(.034)	(.04)	(.041)
ICT_0 × STEM occupation	-.099**				
	(.042)				
ICT_0 × TechFirm		-.11***	-.12***		
		(.043)	(.043)		
$(1 - \mathrm{ICT}_0)$ × TechFirm			-.031		
			(.036)		
ICT_0 × TechSector				-.16**	-.16**
				(.077)	(.077)
$(1 - \mathrm{ICT}_0)$ × TechSector					-.091
					(.081)
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	-.0078	-.025
	(.024)	(.016)	(.019)	(.021)
(Boom cohort) × ICT_0	.076***	.058***	.046***	.028**
	(.016)	(.0097)	(.013)	(.014)
(Post-boom cohort) × ICT_0	.084***	.057***	-.0017	-.0026
	(.024)	(.018)	(.019)	(.021)
Worker controls	✓	✓	✓	✓
Observations	10,463	10,463	10,463	10,463

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 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***	-.100***	-.104***	-.114***
	(.015)	(.022)	(.015)	(.042)	(.015)	(.016)	(.015)	(.016)
Job termination	-.034***	-.040**	-.053***	-.048**	-.15***	-.15***	-.028*	-.043**
	(.013)	(.016)	(.018)	(.021)	(.017)	(.022)	(.017)	(.021)
ICT_0 × Job termination		.018		-.023		.008		.041
		(.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: Promotions

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 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	.22***	.22***	
	(.023)	(.028)	
Promotion × ICT_0		-0.012	
		(.048)	
ICT_0 × Boom Cohort			-.0088
			(.022)
Worker controls	✓	✓	✓
Industry FE	✓	✓	✓
Observations	4,228	4,228	4,228

Appendix

A Data

A.1 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.

A.2 Reproducibility

The results reported in Figures 1 to 4 and Tables 1 to 12 have been certified by CASCAD (Certification Agency for Scientific Code And Data).[25] The results have been assessed and found to meet the requirements of the CASCAD reproducibility policy for a rating of RRR (perfectly reproducible). The reproducibility certificate can be found at https://www.cascad.tech/certification/88-technology-boom-labor-reallocation-and-human-capital-depreciation/

[25] https://www.cascad.tech/

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

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	70	75	-4.5
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 define the steady state as the equilibrium when $\varepsilon^h = \varepsilon^z = 0$ and denote steady state quantities 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), we obtain:

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

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^*.

NB: 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).

NB: 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.