Human Capital Accumulation and the Long-Term Effects of Temporary Sectoral Shocks[*][†]

Ekaterina Gurkova[‡]

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Abstract. This paper investigates the impact of temporary sectoral shocks on human capital accumulation and introduces a structural model to quantify their long-term general equilibrium effects. I use Spain's economic boom (1995–2007) as a case study, which represented a positive labor demand shock in construction and low-skill services, and show that it led to a persistent decline in educational attainment among young workers. To evaluate the general equilibrium implications of this shock during the transition, I construct a quantitative lifecycle model in which workers endogenously choose education and sectoral employment under imperfect human capital transferability. The model reproduces the observed decline in educational attainment and sluggish labor reallocation following the boom. The transition, which is driven primarily by new cohorts, entails a persistent decline in aggregate productivity, with cumulative losses of about 7% and convergence to the steady state over roughly 50 years. The findings demonstrate that positive sectoral shocks can generate adverse long-run aggregate outcomes and substantial distributional effects—cohorts born during the boom experience lifetime earnings gains of nearly 11%, while those born before or after incur losses—highlighting the scope for redistributive policy interventions.

Keywords: Human capital, sectoral shocks, housing, boom-bust cycle, education, skill transferability, overlapping-generations model, transition dynamics.

JEL codes: E24, F43, I21, J22, J24.

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[†]This paper uses data from Eurostat, EU Labour Force Survey (1986-2019) and European Community Household Panel (1994-2001). The responsibility for all conclusions drawn from the data lies entirely with the author.

[‡]UCLA Economics and CCPR. Email at gurkova@ucla.edu.

1 Introduction

It has long been recognized that sectoral shocks can significantly affect the aggregate economy through various channels (Lilien 1982, Long and Plosser 1987, Horvath 1998, 2000, Chodorow-Reich and Wieland 2020, Beraja and Wolf 2021). Existing studies emphasize that multiple sectoral shocks can propagate through the production network (Horvath 2000), and that complementarities in demand structure can be equally important in explaining persistent recoveries following a shock (Beraja and Wolf 2021).

However, less attention has been devoted to examining whether human capital accumulation can serve as a source of persistent effects arising from temporary sectoral shocks. Such shocks influence human capital accumulation both by altering incentives to acquire education and by shifting workers' sectoral allocation (Black et al. 2005, Autor et al. 2014, Atkin 2016, Blanchard and Olney 2017, Charles et al. 2018, García-Cabo et al. 2023, Sorá 2024). While prior studies have shown that even temporary sectoral shocks can have permanent effects on individual workers' allocation, it remains an open question whether they can also generate persistent effects at the aggregate level of the economy.

This paper examines the impact of temporary sectoral shocks on human capital accumulation and introduces a structural model to quantify their long-term general equilibrium effects. I use Spain's economic boom from 1995 to 2007 as an example of a positive labor demand shock in construction and low-skill services, and show that it led to a permanent decline in educational attainment and sectoral reallocation among young workers. To study the long-term aggregate effects of this shock and to conduct counterfactual analysis, I develop a lifecycle model in which workers endogenously choose education and sectoral employment under imperfect human capital transferability. The model is then used to analyze the aggregate and distributional effects of the boom and to quantify the contribution of human capital accumulation to Spain's productivity dynamics along the transition.

Spain's economic boom from 1995 to 2007 serves as a clear example of a temporary positive demand shock concentrated in low-skill sectors. The boom followed the convergence of European interest rates and was marked by large capital inflows and rising household debt. Unlike other European countries that experienced similar interest rate declines, Spain underwent a significant construction boom, which coincided with a slowdown in labor productivity growth that did not begin to recover until after the bust in 2008. I decompose the changes in aggregate labor productivity and show that the decline in growth was driven primarily by lower sector-specific productivity rather than by shifts in sectoral composition. Low-skill sectors, such as construction and services, expanded both in terms of GDP and hours worked, and they accounted for most of the sectoral productivity decline.

I use the boom period from 1995 to 2007 to examine the effects of a temporary demand shock to low-skill sectors on human capital accumulation. Using data from the EU Labour Force Survey, I show that both male and female populations experienced higher labor force participation among young cohorts, who, as a result, were less likely to pursue higher education. Specifically, employing a shift-share instrumental variable (IV) strategy, I find that regions more exposed to the construction boom experienced a greater decline in enrollment, supporting the hypothesis that improved labor market opportunities were the main driver of the reduction in educational attainment. Finally, I present evidence of persistence in the educational outcomes of the affected cohorts, indicating a permanent reduction in their human capital accumulation, which has long-term implications for their lifetime employment trajectories.

To study the economy's transition following the shock, I propose an overlapping-generations model in which workers make decisions about education and sectoral allocation that jointly determine their human capital. Building on the approach of Dvorkin and Monge-Naranjo (2019), I extend their framework to include two skill types of workers and endogenize worker type through the decision to acquire education. The model imposes no restrictions on the timing of education decisions and features rising opportunity costs of education due to finite lifetimes and increasing mobility costs. The framework is rich enough to capture differential mobility and the transferability of sector-specific human capital across skill groups, allowing it to account for the asymmetric responses of different skill groups to shocks in their sectors of comparative advantage. Finally, I incorporate static sector-specific productivity spillovers that depend on the share of skilled workers' human capital and generate inefficiencies in educational attainment and sectoral allocation.

The quantitative model is calibrated using Spanish data and applied to counterfactual analyses of the economy's transition dynamics following the boom. In particular, I estimate key model parameters—such as human capital transferability rates, switching costs, and productivity spillovers across sectors—by combining data from the European Community Household Panel (1994–2001) and national accounts to match lifetime earnings dynamics and gross worker flows across sectors. The shock in the model is represented by a temporary change in the discount factor and sectoral demand shifters, calibrated using the Simulated Method of Moments (SMM) to replicate the initial increase in total GDP and sectoral GDP shares during the boom. The remaining model predictions for the transition, including the responses of enrollment and productivity, are untargeted and are used to assess the role of the human capital mechanism.

The main results are as follows. First, the model replicates an immediate decline in educational attainment among young workers during the boom, followed by rapid labor reallocation into the construction sector. However, under the perfect foresight assumption, enrollment rates rise toward the end of the boom as new cohorts anticipate the bust. Existing workers, however, face high opportunity costs and are unable to reallocate, so employment dynamics after the bust are primarily driven by incoming cohorts. Moreover, the model generates a persistent decline in aggregate productivity throughout the transition, which lasts nearly 50 years, and predicts cumulative productivity losses of about 7%. The initial productivity decline is driven by changes in labor force composition, as younger workers with lower average human capital enter less productive sectors. After the bust, imperfect human capital mobility becomes the key mechanism sustaining the productivity slowdown, as affected cohorts remain locked in sectors with lower human capital externalities. Finally, the model predicts sizable distributional effects across cohorts, with net gains in lifetime earnings, leaving scope for redistribution policies that could compensate workers who incur losses while still benefiting those who gain.

The counterfactual analysis examines the relative contributions of discount factor shocks and sectoral demand shocks to the observed employment and productivity dynamics. I find that sectoral demand shocks are the primary drivers of employment and skill premium dynamics across sectors, while a discount factor shock that generates the aggregate demand increase is necessary to replicate the observed declines in enrollment and labor force participation rates. Rising aggregate demand also emerges as the main driver of the initial productivity decline: when employment and output expansion is driven by younger, less experienced workers with lower accumulated human capital, sectoral productivity falls. By contrast, changes in sectoral composition play a more significant role in sustaining the productivity decline after the bust. The human capital "lock-in" mechanism prevents existing workers from reallocating to sectors with higher relative demand and thus serves as the main source of persistence.

In the quantitative analysis, I also examine the role of human capital spillovers to sectoral productivity in shaping the model's predictions. These spillovers take the form of external returns arising from the share of skilled workers' human capital and differ between low-skill sectors (construction and low-skill services) and high-skill sectors (manufacturing and high-skill services). Because workers do not internalize these spillovers, they result in underinvestment in higher education, both in the long-run equilibrium and during the boom. At the same time, they mitigate aggregate productivity losses, playing a differentiated role along the transition. In particular, they partially offset the initial productivity decline, as older skilled workers reallocate to high-skill services and generate productivity gains in that sector. After the bust, however, imperfect transferability amplifies productivity losses in the presence of spillovers, since the average human capital of workers locked in low-skill sectors rises but generates only limited external returns.

Related Literature This paper contributes to the existing literature on the impact of sectoral shocks on human capital accumulation (Black et al. 2005, Emery et al. 2012, Guren et al. 2015, Atkin 2016, Basso 2017, Blanchard and Olney 2017, Cascio and Narayan 2022). It examines the effects of temporary sectoral shocks, such as the construction boom in Spain, and contributes by analyzing their long-term general equilibrium effects, showing that human capital accumulation plays a crucial role in explaining the persistent impact on aggregate productivity dynamics. The empirical findings of this paper are closely related to those of Charles et al. (2018), who study the effects of the U.S. housing boom on educational attainment. I find that, due to the magnitude of the Spanish boom—which was substantially larger than the U.S. one[1]—the estimated effects on higher education enrollment are larger and persist even in the annual-frequency analysis.

Moreover, this paper complements existing research on skill specificity and labor market transitions following aggregate shocks (Dix-Carneiro 2014, Guren et al. 2015, Dvorkin and Monge-Naranjo 2019, García-Cabo et al. 2023, Sorá 2024, Adão et al. 2024) by emphasizing the role of education as a mechanism for acquiring general skills during economic transitions. It highlights that educational attainment, in the presence of differential skill composition across sectors, can play a crucial role in constraining worker mobility in response to sector-level shocks. In particular, the rising opportunity cost of education over a worker's lifecycle leads to a persistent reduction in cohort-level human capital accumulation. Emphasizing these lifecycle dynamics is essential for accurately assessing the distributional effects of temporary shocks.

Following Autor et al. (2014), Ferriere et al. (2018), Porzio et al. (2022) and others, this paper leverages regional exposure to shocks to assess the effects of the construction boom on educational attainment. It employs a shift-share instrumental variable design, originally introduced by Bartik (1991) and further developed by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022), to examine how shocks to construction employment influence higher education enrollment. The analysis uses pre-shock regional occupational composition as an exogenous measure of exposure and shows that regions experiencing larger expansions in construction employment also exhibited greater declines in higher education enrollment.

Finally, this paper contributes to the broader literature on the productivity slowdown during European convergence and boom-bust cycles (Blanchard and Giavazzi 2002, Burnside et al. 2016, Gopinath et al. 2017, Brunnermeier et al. 2018, Kaplan et al. 2020, Chodorow-Reich et al. 2023, Carreno 2023). It highlights the significance of labor supply composition throughout the cycle, with particular emphasis on human capital accumulation and investment in education. The paper emphasizes the dynamic nature of educational attainment and incorporates the concept of imperfect human capital mobility across sectors. Furthermore, it provides detailed empirical evidence on the effects of temporary sectoral shocks on education and labor allocation, proposing a novel mechanism to explain their long-term aggregate and distributional effects.

[1]Construction + FIRE employment among male workers in Spain increased to 27% for ages 16–65 at its peak, while construction employment in the U.S. reached at most 12–13%.

Roadmap The remainder of the paper is structured as follows. Section 2 documents the main empirical facts on productivity dynamics, labor reallocation, and educational attainment in Spain between 1995 and 2007. It analyzes the effects of the construction boom on higher education enrollment, cohort-specific attainment, and productivity growth. Section 3 introduces the lifecycle model, which incorporates dynamic education decisions and imperfect human capital mobility, and discusses its implications for long-term productivity growth. Section 4 outlines the calibration strategy for the model parameters and evaluates model fit. Section 5 presents the main results of the quantitative simulations and describes the economy's transition during and after the boom. Section 6 examines the relative contributions of discount factor shocks and sectoral demand shocks to employment and productivity dynamics, and analyzes the role of human capital spillovers. Section 7 concludes.

2 Empirical Facts on Spanish Boom

In this section, I present key motivating facts about labor productivity dynamics and human capital accumulation during Spain's boom period from 1995 to 2007. I decompose labor productivity to identify the sectors that contributed most to its decline during this period. Furthermore, I document that the economic boom was characterized by increased employment in low-skill sectors, which led to a decline in young workers' enrollment in higher education and a rise in labor force participation. Moreover, I show that post-bust increase in educational attainment occur primarily through new cohorts, leaving the affected cohorts with permanently lower education levels.

The empirical analysis presented in this paper relies on multiple data sources. First, for cross-country comparisons, I use labor productivity data from the OECD Productivity Statistics Database. For the decomposition of Spanish productivity, I employ GDP and hours worked data from national accounts, along with growth accounts data provided by the EUKLEMS & INTANProd database[2]. Lastly, I use data from the EU Labour Force Survey, covering the period from 1995 to 2019. This dataset consists of annual cross-sections of Spanish households and provides individual-level information on employment, labor force participation, educational attainment, and demographic characteristics. For further details on the data sources, see Appendix A.

[2]EUKLEMS & INTANProd database, Release 2025, by the Luiss Lab of Economics and Energy Transition at Luiss University in Rome, Italy.

2.1 Spanish Economic Boom and Productivity Decline

Between 1995 and 2007, many European countries experienced a decline in interest rates, following the Maastricht Treaty of 1992, which established interest rate convergence as one of the criteria for joining the eurozone. This decline was particularly pronounced in Southern European countries such as Greece, Italy, Portugal, and Spain, which had historically run current account deficit and faced higher interest rates.

Unlike other European countries, Spain experienced a decline in labor productivity growth during this period, which did not begin to recover until 2008 (see Figure 1). Prior to this, Spain had been characterized by a very extensive rental market and high borrowing costs.[3] A significant decrease in mortgage rates lowered barriers to homeownership, leading to an increase in housing demand and a surge in aggregate consumption. As a result, the Spanish economy underwent a demand-driven boom, accompanied by large capital inflows, which were primarily concentrated in non-traded, low-skill sectors.

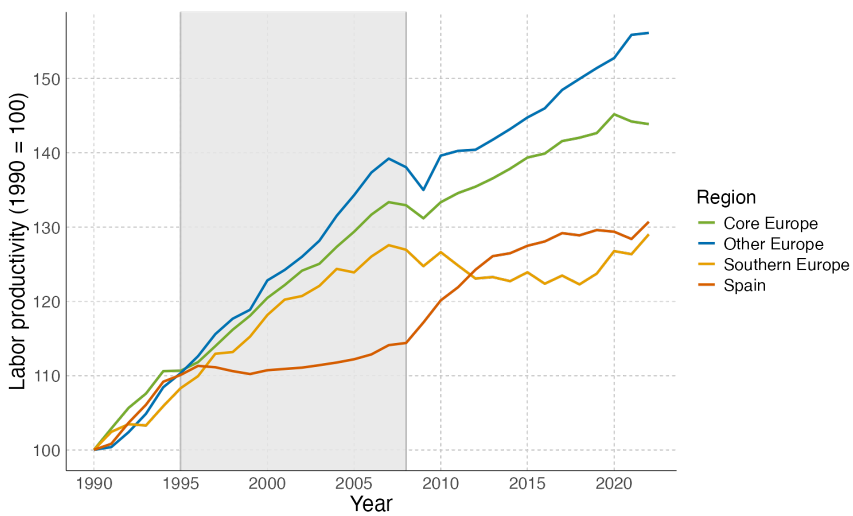


Figure 1: Labor productivity in Europe, 1990-2022

Note: Data Source: OECD Productivity Statistics Database. Core Europe average is unweighted average for Austria, Belgium, France and Germany. South Europe includes Greece, Italy, and Portugal, and Other Europe includes Denmark, Finland, Sweden, and Switzerland. Labor productivity is computed as real GDP per hour worked, PPP adjusted, and is normalized to 1990. The shaded region is the period of the boom in Spain, 1995-2007.

The housing boom in Spain began slightly later, around 1998, and by 2007, real housing prices had more than doubled. During this period, the construction sector experienced its most significant expansion, both in terms of the number of units produced and the increase in employment. For instance, in 2006 alone, 554,000 new residential units were built in Spain—equivalent

[3]The share of the rental market decreased from 30% to 10% of the housing stock between 1995 and 2002.

to 75% of the total residential units constructed in both France and Germany combined that year. The bust occurred in 2008, and both housing prices and construction activity remained stagnant until they began to rise again in 2014.[4]

2.2 Decomposition of Labor Productivity Growth

To understand the nature of Spain's productivity decline during the boom period, I examine the sectoral composition and sector-specific productivity dynamics more closely.

FACT 1. *The decline in labor productivity in Spain during the period 1995–2007 was primarily driven by low-skill sectors.*

First, I decompose Spain's aggregate labor productivity by sector to highlight the contribution of low-skill sectors during the period 1995–2007. Figure 2 plots average labor productivity across European countries (excluding Spain), as well as a counterfactual productivity measure that excludes low-skill sectors[5] both for Spain and Europe. In this exercise, I completely exclude low-skill sectors, meaning that the counterfactual productivity reflects both changes in sector-specific productivity and sectoral composition over time.

As evident from the graph, in the absence of low-skill sectors, Spanish labor productivity dynamics would have closely followed the average European trend and more closely resembled those of other Southern European countries after the 2007 recession (see Figure 1). While in other European countries low-skill sectors did not play a significant role in productivity growth during this period (as the two black lines nearly coincide), excluding low-skill sectors from the Spanish data almost entirely closes the gap between Spanish productivity and the European average[6].

Notably, both construction and low-skill services, especially wholesale and retail trade (included in low-skill) represented a substantial share of employment—10% and 20% respectively—and can be characterized by a low share of workers with higher education. While construction primarily employed young non-college educated male workers, the wholesale sector saw an increase in the employment of young low-skill female workers during this period. Specifically, the employment rate of 16- to 20-year-old men in construction rose from 12.5% to nearly 25% between 1995 and 2007, while the employment rate of 16- to 20-year-old women in wholesale increased from 13% to 24% over the same period. To examine in greater detail whether changes in aggregate productivity were driven by sectoral productivity shifts or changes in the share of

[4]See Appendix B.1 for cross-country comparison of new construction.

[5]By low-skill sectors I mean construction and low-skill services.

[6]For the decomposition of Spanish labor productivity using real GDP and hours worked by industry groups, see Appendix B.

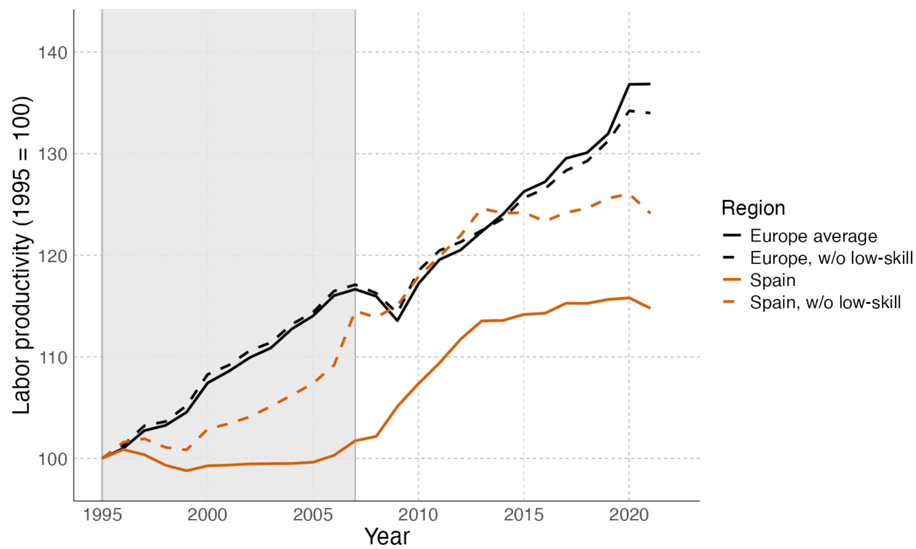


Figure 2: Productivity in Spain VS Europe, contribution of low-skill sectors

Note: Data Source: EU KLEMS Database. Low-skill sectors include (NACE Rev. 2): Construction (F), Wholesale and retail (G), transport (H), accomodation and food services (I), other services (R-S). Labor productivity is computed as real GDP per hour worked, and is normalized to 1995 (real GDP is computed using the price index that includes low-skill sectors in both cases). Europe average includes Austria, Belgium, France, Germany, Denmark, Finland, Sweden, Greece, Italy, and Portugal. The shaded region is the period of the boom in Spain, 1995-2007.

low-skill sectors, I turn to the decomposition exercise below.

FACT 2. *Declines in sector-specific productivity accounted for most of the decline in aggregate labor productivity.*

Let me now conduct a decomposition exercise to identify the factors driving changes in aggregate labor productivity during this period. Aggregate labor productivity can be written as

$$\text{GDPh}_t = \sum_i \alpha_{it}\text{GDPh}_{it}, \tag{1}$$

where $\text{GDPh}_t = \text{GDP}_t/\text{Hours}_t$ is the aggregate labor productivity measured as real GDP per hour worked, GDPh_{it} corresponds to the labor productivity in sector i in period t, and weights $\alpha_{it} = \text{Hours}_{it}/\sum_n \text{Hours}_{nt}$ correspond to the share of sector i in total hours worked.[7]

[7]To get equation (1),

$$\text{GDPh}_t = \frac{\text{GDP}_t}{\text{Hours}_t} = \frac{\sum_i \text{GDP}_{it}}{\sum_i \text{Hours}_{it}} = \frac{\sum_i \text{Hours}_{it} \times \text{GDPh}_{it}}{\sum_i \text{Hours}_{it}} = \sum_i \frac{\text{Hours}_{it}}{\sum_n \text{Hours}_{nt}} \times \text{GDPh}_{it} = \sum_i \alpha_{it}\text{GDPh}_{it},$$

where $\alpha_{it} = \text{Hours}_{it}/\sum_n \text{Hours}_{nt}$.

To illustrate the contribution of changes in sectoral labor productivity and sectoral employment shares, I plot counterfactual productivity series in Figure 3. In one counterfactual scenario, I keep the employment shares of each sector fixed at their 1995 levels while allowing sectoral productivity to change. The difference between the two lines accounts for the changes in sectoral composition.

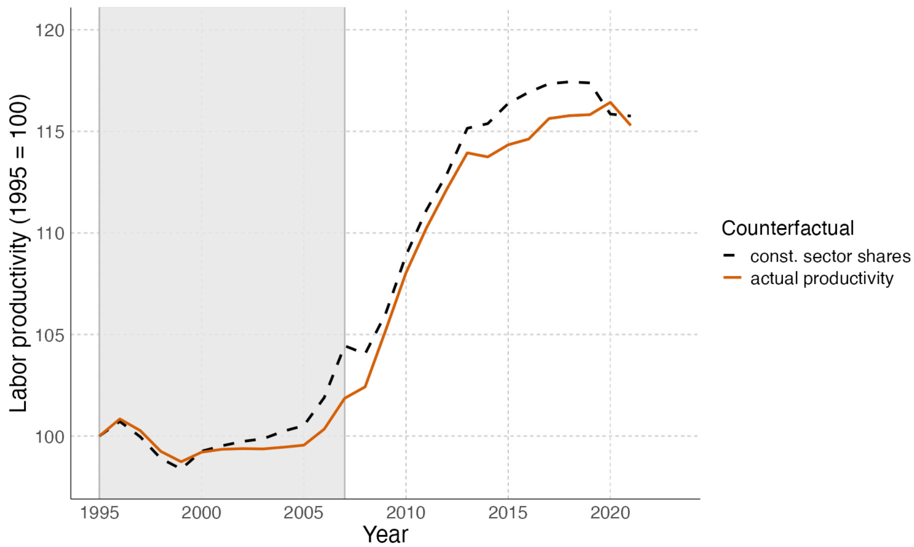


Figure 3: Counterfactual changes in labor productivity in Spain, 1995-2020

Note: Data Source: EU KLEMS Database, national accounts. Productivity with constant shares is computed keeping the employment sector shares fixed at their 1995 level. The shaded region is the period of the boom in Spain, 1995-2007.

The changes in aggregate labor productivity growth over the entire period from 1995 to 2020 are driven almost exclusively by changes in the level of sector-specific productivity. The counterfactual series that uses constant sectoral employment shares closely tracks aggregate productivity, even exhibiting a larger decline during the boom period between 1995 and 2007. In contrast, changes in sectoral composition played only a minor role in aggregate dynamics. Although low-skill sectors expanded during the boom, the corresponding counterfactual shows that aggregate productivity would not have changed much, given the initial productivity levels in those sectors.

In Appendix C.1, I conduct a formal variance decomposition exercise, where I compute the contributions of changes in sector-specific productivity, changes in sectoral composition, and their interaction to the variance of annual percentage changes in labor productivity. The results show that the largest contributor to aggregate changes in labor productivity is the change in within-sector productivity, accounting for over 94% of the aggregate productivity variance. The next largest factor is sectoral composition component, which includes both the within-sector variance in employment shares and the cross-sector covariance term. Still, it is relatively small and accounts for around 12% of the overall variation.

Labor productivity dynamics by industry are presented in Appendix Figure A3. During the period 1995–2000, the largest declines in productivity were observed in the low-skill sectors, which include construction and low-skill services. Among these, construction contributed approximately 10% of annual GDP in 2000[8], and the initial decline in Spanish labor productivity, as evident from cross-country comparisons, was largely driven by the construction sector. From 2000 onward, a decline in low-skill services productivity also became more apparent.[9] This group of sectors is the largest in the Spanish economy, and it accounted for 25% of annual real GDP at the beginning of the 2000s.

The decline in labor productivity was driven by changes in both real GDP and hours worked. As shown in Appendix Figure A4, the construction sector experienced a large increase in GDP and an even greater spike in total hours between 1995 and 2007. During this period, both low-skill and high-skill services also saw significant growth; however, this increase in production was not outpaced by an expansion in hours worked.

Even though aggregate labor productivity initially declined between 1995 and 1998—and significantly decreased in some industries throughout the 2000s—aggregate productivity remained relatively stable from 1998 to 2007. It is more precise to describe this period as one of declining productivity growth, which was particularly pronounced compared to the pre-shock trend in Spain and the productivity growth observed in other European countries at that time.

2.3 Participation and Sectoral Reallocation in the Labor Market

As discussed in the previous section, the decline in aggregate labor productivity was primarily driven by changes in sectoral productivity, particularly that of low-skilled sectors such as construction and low-skill services. In this section, I focus on the labor supply adjustment as a transmission mechanism and examine how individual workers' decisions regarding sector allocation and skill accumulation changed during the boom and after the bust.

FACT 3. *Young workers increased their labor force participation and primary went to work in low-skill sectors during the boom.*

As discussed above, low-skill sectors expanded significantly, primarily through an increase in total hours worked. This growth was largely driven by the extensive margin, where employment in these sectors increased while hours worked per worker remained relatively constant

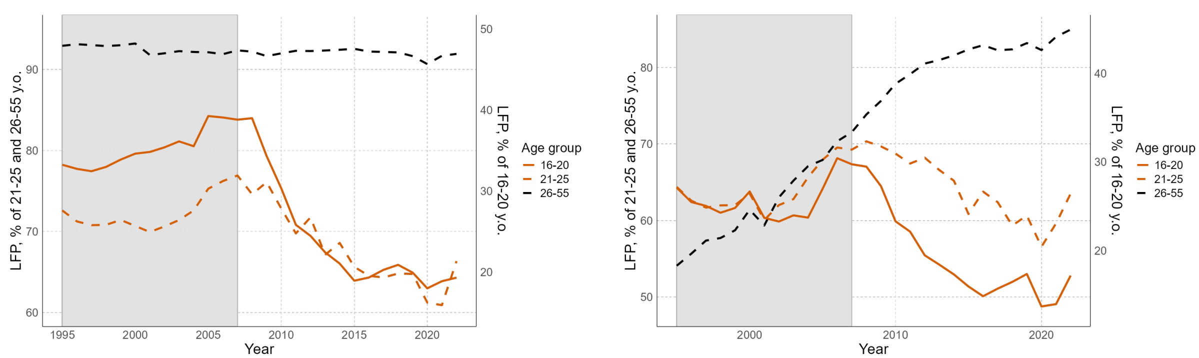
[8]National accounts data from INE.

[9]By low-skill services, I denote wholesale and retail trade, accomodation and food sector, which corresponds to G, H, I sectors in NACE Rev. 2 classification.

over time.

Employment growth was driven primarily by young workers who entered the labor force at the beginning of the boom period. While the labor force participation of older age groups remained stable throughout the economic cycle—with a slight increase for those aged 26–55 after 2008—it changed significantly for workers aged 16–20 and 21–25. During the boom, the labor force participation rate for male workers aged 16–20 increased from 33% to 39%, while for those aged 21–25, it rose from 70% to 77% (left panel of Figure 4), reflecting improved labor market opportunities for young, predominantly unskilled workers. A similar but slightly weaker effect is observed for the female population, with the labor force participation rate for 16–20-year-olds increasing from around 25% to 30% (right panel of Figure 4).

Importantly, following the bust in 2008, the labor force participation of 16–20-year-olds declined. This suggests that new incoming cohorts opted to pursue further education before entering the labor force, and that the boom period represented a temporary change in labor demand rather than a structural change in the economy.



(a) male population

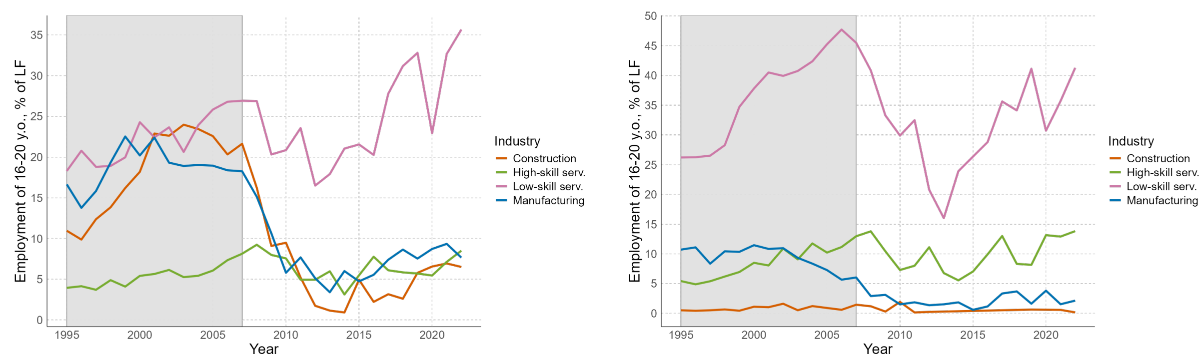
(b) female population

Figure 4: Labor fore participation, by age groups

Note: This figure displays the labor force participation rates for male and female workers, calculated as the percentage of the population that is either employed or unemployed (actively searching for a job). The sample is divided into three age groups: 16-20 years old, 21-25 years old, and 26-55 years old. The shaded region is the period of the boom, 1995-2007. The data used in the figure is sourced from the EU Labour Force Survey.

The boom period was accompanied by a substantial increase in employment within low-skill sectors—particularly in construction for male workers and in low-skill services for female workers. This trend was especially pronounced among younger individuals who were on the verge of entering college but instead chose to join the labor force. As shown in the right panel of Figure 5, low-skill services consistently remained the primary employer of female workers aged 16–20 from 1995 to 2020, with wholesale and retail trade being the largest sector. During the boom years from 1995 to 2007, the share of young female workers employed in low-skill sectors surged from 25% to over 45%, before rapidly declining to its initial level following the bust in 2007.

For male workers, the left panel of Figure 5 illustrates the employment dynamics of 16-20-year-old males in Spain. In the early years, low-skill services and manufacturing each employed more male workers than construction. However, beginning in 1995, employment in construction sector grew the most—rising from 10% to a peak of 24% in 2007—before sharply declining after the bust. In contrast, employment in low-skill services and manufacturing remained relatively stable throughout the period, with manufacturing experiencing a slight decline during the 2000s.



(a) male population

(b) female population

Figure 5: Employment rates, by industry

Note: This figure displays the employment rates for male and female workers, calculated as the the percentage of the population in the labor force that are employed in a particular sector. Industry classification using NACE Rev. 2 is: construction (F), low-skill services (G-I and R-U), manufacturing (B-E), and high-skill services (J-Q). The shaded region is the period of the boom, 1995-2007. The data used in the figure is sourced from the EU Labour Force Survey.

When comparing absolute numbers, the increase in construction employment for male workers was of the same magnitude as the rise in labor force participation among the 16-20 age group. Furthermore, as shown in the Appendix, this increase in construction employment was almost entirely driven by the native-born population and cannot be attributed to rising migration flows. This highlights the importance of understanding the reallocation of native-born workers and changes in their incentives to work throughout the economic cycle.

Dynamics of employment among 21-65-year-old male and female workers is shown in Appendix B. For female workers, there was an increase in employment in high-skill services, almost entirely driven by real estate and financial and insurance activities, while for male workers construction employment rose. Although both low-skill services and construction primarily employ unskilled workers and thus experienced the largest increases in young employment, real estate tends to hire workers with higher education. As a result, real estate employment remained very low among young workers despite the housing boom.

These empirical facts provide evidence that younger workers face a trade-off between working in low-skill jobs and staying out of the labor force to pursue higher education. During the economic boom in 1995-2007, increased demand for low-skilled labor raised the opportunity cost of education, incentivizing younger workers to enter the labor force.

2.4 Changes in Educational Attainment During the Boom

To further explore the trade-offs faced by young workers during the boom, I turn to an analysis of educational attainment. Specifically, I show that enrollment rates in higher education declined during the boom, suggesting that the expansion of the construction and low-skill services attracted young individuals who might have otherwise pursued a college education, prompting them to enter the labor force earlier. Moreover, I demonstrate that educational attainment rates remained low for the affected cohorts even after the bust, indicating that these early decisions had lasting consequences.

FACT 4. *Enrollment in higher education declined in response to a boom in low-skill sectors.*

First, I examine the dynamics of aggregate higher education enrollment rates over the course of the economic cycle in Spain. Figure 6 shows that enrollment rates of both male and female 16-20-year-olds decreased significantly during the housing boom and increased right after the bust in 2008. The effect is most pronounced for the 16-20-year-old male population, for whom enrollment declined from 34% pre-shock to 20% around 2007. Following the bust in 2008, the enrollment of both male and female population started to slowly increase and reached the pre-shock level only by 2022.

For the next set of results, I focus on the male population whose labor force participation was influenced by the expansion of the construction sector and the housing boom. During the boom, construction employment surged, primarily attracting young, unskilled male workers, thereby increasing their labor force participation. To investigate whether the improving opportunities for unskilled workers affected their educational attainment, I leverage the fact that spikes in regional housing prices were correlated with the expansion of construction employment[10]. Below, I present reduced-form evidence suggesting that this expansion was accompanied by lower enrollment in higher education.

Figure 7 presents the correlation between changes in construction and FIRE employment[11] and higher education enrollment across autonomous communities from 1997 to 2007. The figure

[10] See Appendix B for empirical evidence on regional housing prices and employment.

[11] FIRE refers to the finance, insurance, and real estate sectors.

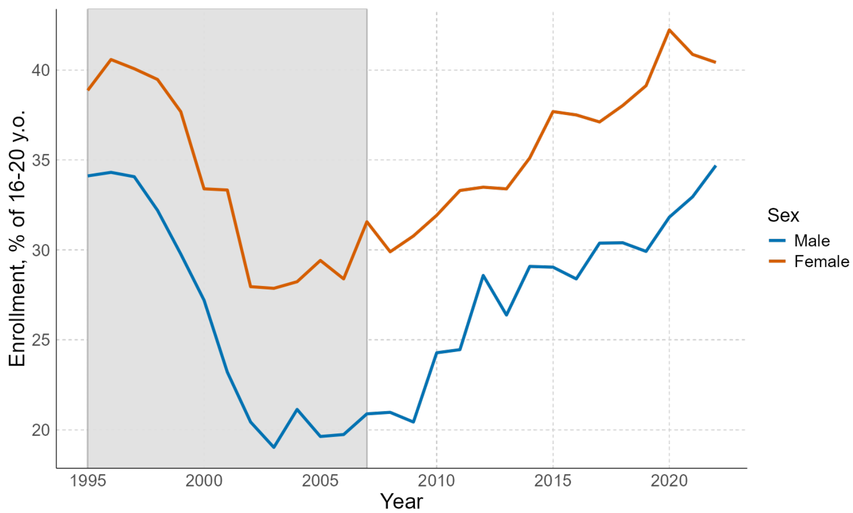


Figure 6: Enrollment of 16-20 y.o. in higher education, by sex

Note: This figure plots enrollment rates for male and female population in 1995-2019. Enrollment is defined as a positive answer to question whether an individual has attended school in the past 4 weeks. The enrollment rates are calcualted as % of 16-20 y.o. native-born male and female population enrolled in higher education. The shaded region is the period of the boom, 1995-2007. The data used in the figure is sourced from the EU Labour Force Survey.

shows a slightly negative relationship between construction employment and enrollment rates, which cannot be solely attributed to a mechanical composition effect, as employment is measured using the working population aged 21–65. Autonomous communities that experienced a larger increase in construction employment during the boom were also those that saw the most significant declines in higher education enrollment.

In order to determine whether the trends in enrollment are correlated with the exposure to the housing boom in a more structural way, I employ annual variation in construction employment and enrollment by region. I estimate the following regression

$$\Delta\text{enrollment}_{it} = \alpha + \beta\Delta\text{constr\_emp}_{it} + X_{it}'\gamma + \epsilon_{it} \tag{2}$$

where all observations correspond to region i and year t. $\Delta\text{enrollment}_{it}$ represents the growth rate of enrollment for the 16-20-year-old male population, $\Delta\text{constr\_emp}_{it}$ is the construction employment growth rate for all 21-65-year-old male workers, and other controls include the share of the female labor force, labor force participation rate, the share of the foreign-born population, and the average age in a given region and lagged by one year.

There are two potential sources of bias in this regression. First, the housing boom followed a decline in interest rates, which increased credit affordability. This could have influenced higher

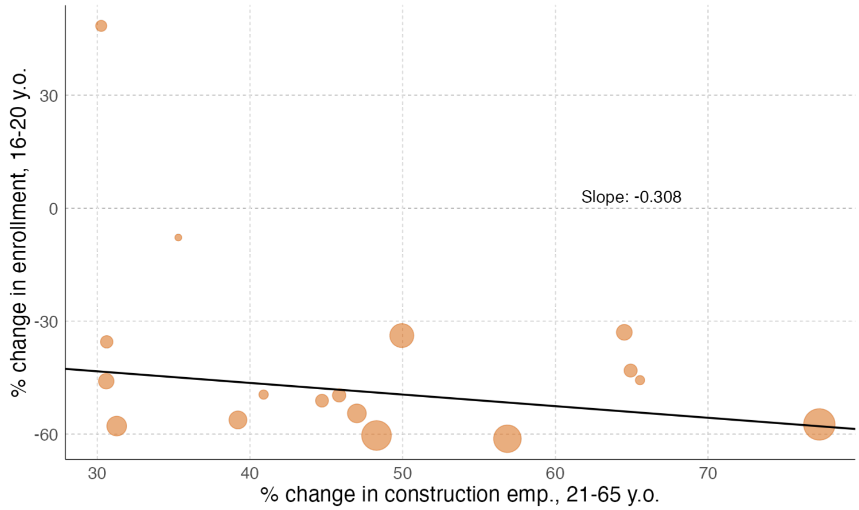


Figure 7: Change in construction employment and male enrollment, 1997-2007

Note: This figure plots the correlation between % changes in construction + FIRE employment of 21-65 y.o. male workers and the % changes in higher education enrollment of 16-20 y.o. male population. Each observation is an autonomous community in Spain, and the % change is measured between 1997 and 2007 for each regions. The size of each dot is proportional to the population in that region in 1997. This figure uses data from the EU Labour Force Survey. Ceuta (Ciudad Autónoma de Ceuta) and Melilla (Ciudad Autónoma de Melilla) are excluded as the data was not available for one of the years.

education enrollment either directly, by making it easier for individuals to borrow for college expenses, or indirectly, by improving job market opportunities in a demand-led economy, thereby increasing the opportunity cost of education. The direct effect is positive but likely small, given that higher education in Spain is highly subsidized, whereas the indirect effect is expected to be negative. Consequently, the estimated negative coefficient might be biased upwards. Second, other regional shocks during the boom could have negatively impacted enrollment, leading to an influx of workers into the construction sector. In this scenario, reverse causality would reinforce the relationship between construction employment and enrollment, biasing the estimated coefficient downwards.

To isolate the effect of the labor demand shock and obtain a consistent estimate of the housing cycle's impact on enrollment rates, I propose a shift-share instrumental variable design that exploits regional variation in occupational composition to predict each region's exposure to the construction boom. I decompose construction employment in each region and year into employment by occupation[12]. The shift-share instrumental variable (IV) is then constructed using nationwide changes in construction employment as the magnitude of the shock, while pre-

[12] Occupations are classified according to the ISCO08 1-digit classification, excluding code 60 (agricultural workers), as they are not employed in industries outside of agriculture.

shock occupation shares—those not directly affected by the housing shock—serve as a measure of region i's exposure. The resulting variable is

$$\Delta \text{constr IV}_{it} = \sum_{c} \Delta \text{constr\_emp}_{ct} \times \text{share}_{ci\tau} \tag{3}$$

where $\Delta\text{constr\_emp}_{ct}$ is the construction employment growth of occupation c in year t across the whole of Spain, and $\text{share}_{ci\tau}$ is the share of occupation c in employment of region i in the pre-shock period τ (I choose $\tau = 1995$).

The identifying assumption for the shift-share instrument is that regions with different occupational compositions experience similar trends in higher education enrollment but are differentially exposed to the housing boom. In other words, regions with a higher concentration of manual workers[13] have a greater capacity to expand construction when demand rises and, consequently, are more likely to experience a larger drop in enrollment during the boom.

One potential concern is that this analysis involves regressing two equilibrium outcomes rather than directly measuring the shock on the right-hand side. To address this, I use employment in the 21–65 age group as a proxy for the demand for unskilled labor, which, in the absence of the shock, would be positively correlated with enrollment among 16–20-year-olds. For now, I interpret these results as purely reduced-form evidence. However, future analysis could rely on estimated changes in housing prices and use geographical constraints as instruments for housing supply, as well as employ more geographically disaggregated data.

Following Goldsmith-Pinkham et al. (2020), I run several tests to determine the plausibility of this exogeneity assumption. In particular, I show that the lagged occupation shares are not correlated with any other region-specific characteristics and, therefore, my instrument only affects enrollment rates through the proposed labor demand mechanism. Moreover, I check that there are no pre-trends in enrollment rates that are correlated with the region occupation composition. I demonstrate that pre-shock enrollment is not correlated with the instrument. For details, see Appendix B.

The estimation results are presented in Table 1[14]. The results include estimates for three time periods: the boom period (1996–2007), the bust period (2008–2019), and the pooled sample (1996–2019). The effect of increased construction employment is negative and statistically significant for both the boom period and the overall sample, with the largest effect observed during the boom. Interestingly, the OLS estimate for the boom period (column 1) yields a coefficient with a smaller absolute value than the IV estimate (column 4). This suggests that attenuation

[13]The expansion of construction in regions experiencing a larger housing boom primarily occurred through increased employment in elementary occupations and craft-related trades. See Appendix B.

[14]For estimation results with an alternative set of controls, see Table A5.

bias is stronger than the bias from reverse causality; otherwise, the coefficient obtained via IV would have been smaller than the OLS estimate.

As a robustness check, I run the same regressions using enrollment among 21–25-year-olds as the dependent variable instead of 16–20-year-olds. The results indicate no significant effect of changes in construction employment on enrollment. Additionally, there is no significant impact on the completion rates of 21–25-year-olds, confirming that the educational attainment of older cohorts is not affected by the construction shock. For additional robustness checks, see Table A6 in the Appendix.

Table 1: Effects of labor demand shock on enrollment rates

	Dependent variable: Δ enrollment$_{it}$ for 16-20 y.o.					
	OLS			IV		
	1996-2007	2008-2019	1996-2019	1996-2007	2008-2019	1996-2019
	(1)	(2)	(3)	(4)	(5)	(6)
Δ construction emp.	-0.584^{***}	-0.302	-0.297^{*}	-1.090^{*}	-0.470	-0.292
	(0.167)	(0.254)	(0.161)	(0.597)	(0.530)	(0.269)
first stage				1.128^{***}	0.725^{***}	0.782^{***}
				(0.285)	(0.078)	(0.052)
# observations	216	213	429	216	213	429

Note: This table presents the results of estimation of the model in (2) using OLS and IV estimators. Columns 1-3 present the estimators for parameter of interest for OLS regression, while columns 4-6 shows the results of IV estimation, using TSLS estimation procedure. All results are presented for three time periods: the boom 1995-2007, the bust 2008-2019, and the full period 1995-2019. All models use region-year data, constructed using EU Labour Force Survey. Each observation is weighted by the 15-64 y.o. population in the region, standard errors are bootstraped.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Another notable result from Table 1 is that while the effects of the construction boom on educational enrollment are significant for both the boom period and the full sample (1996–2019), there are no significant effects during the bust period when examined separately (columns 2 and 5). One potential explanation for this result is that it likely driven by the overarching influence of the broader economic cycle rather than an adverse shock to a specific sector. A large body of literature on educational attainment during recessions, including Kahn (2010), Oreopoulos et al.

(2012), provides further insights into this phenomenon. However, this paper primarily focuses on the effects of a sectoral boom and its impact on education and labor allocation, which have long-term consequences for the economy's transition following the bust.

FACT 5. *Educational attainment of the affected cohorts stayed lower after the bust.*

To determine whether the effect on educational attainment was permanent for the affected cohorts, I plot the higher education completion rates by birth year. Figure 8 shows that for cohorts born before the boom—those individuals who were 21 and older when the boom started—there is an increasing trend in educational attainment for both the male and female populations. For individuals who were 16-20 years old during the boom period (cohorts born between 1979-1986), higher education completion rates flattened and even declined for the male population. Finally, for cohorts born later and not affected by the shock, there is some mean reversion back to the trend.

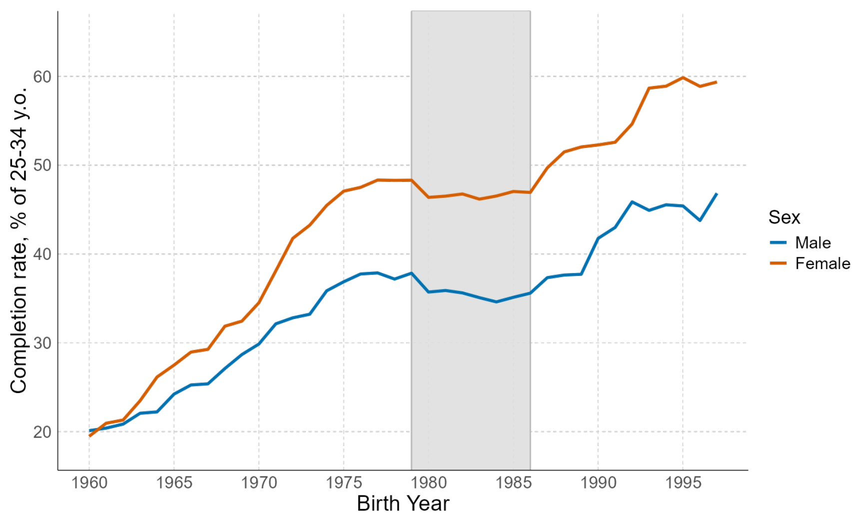


Figure 8: Higher education completion rates, by cohort

Note: This figure plots the higher education completion rates by cohort and sex, for individuals born between 1960 and 1995. Completion rate is defined as a % of individuals born in each year who completed higher education by the age of 35. The shaded region corresponds to the cohorts that were 16-20 y.o. during the boom period. The data is from the EU Labour Force Survey.

We can summarize this evidence in two key points. First, enrollment in higher education declined among young individuals during the boom, reflecting the increasing opportunity cost of education. This decline was accompanied by a rise in their labor force participation and employment rates, with the most significant increases observed in the construction and low-skill services. Second, the decline in educational attainment among cohorts affected by the boom appears to be permanent. Individuals who were 16–20 years old at the onset of the boom did not return to education even after the bust, despite a dramatic rise in unemployment across all age groups. This conclusion is supported by the dynamics of higher education completion rates of the affected cohorts compared to individuals born earlier or later and not affected by the boom.

In conclusion to this section, I summarize the empirical findings, which later serve as motivation for the quantitative model. First, the boom period in Spain was accompanied by a significant decline in productivity growth, primarily driven by the expansion of low-skill sectors such as construction and low-skill services. Second, this expansion led to a substantial increase in demand for unskilled labor, particularly among younger cohorts, resulting in higher labor force participation and a decline in higher education enrollment. In the model section, I show that an expansion driven by the entry of young, less experienced, and less educated workers translates can lead to a decline in sectoral productivity. Finally, I show that the impact of the boom on educational attainment was permanent for the affected cohorts, leading to a persistent deviation in their completion rates from the pre-existing trend.

3 Model

In this section, I introduce a lifecycle model that incorporates dynamic educational attainment decisions and imperfect human capital mobility. The model's lifecycle structure captures changes in the opportunity cost of education faced by different cohorts during and after the boom. Furthermore, imperfect mobility of human capital across sectors generates a "lock-in" mechanism, particularly for older cohorts who entered low-skill sectors during the boom, in contrast to incoming cohorts. For the worker's problem, I build on Dvorkin and Monge-Naranjo (2019), generalizing their framework to include multiple types of workers and endogenizing worker type through education decisions, while imposing a finite lifecycle to analyze cohort-specific allocations along the transition.

In this model, an infinite-horizon closed economy is populated by overlapping generations of workers who acquire education and supply labor to different sectors. Time is discrete and indexed by t. Each worker is born at age $a = 1$ and lives for A periods, and the size of each cohort is assumed to remain constant over time. Workers' human capital consists of their skill type and their stock of efficiency units, both determined by their decisions regarding education and sectoral allocation.

3.1 Consumers Preferences

The economy consists of J production sectors, a non-employment sector, and education. I denote the set of production sectors + non-employment as $\mathcal{J} = \{1, \ldots, J+1\}$, where non-employment corresponds to $J+1$, and denote education as sector 0. The consumers are hand-to-mouth (not allowed to borrow) and discount ther future with $\beta \in (0,1)$. The flow utility of a worker in each period is given by

$$u(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma} \tag{4}$$

where CRRA parameter is assumed to be $\gamma > 1$. Utility of the consumer in each period t depends on consumption of the composite good, which is given by a constant-elasticity-of-substitution (CES) aggregator over consumption goods in the production sectors $1, \ldots, J$

$$c_t = \left(\sum_{j=1}^{J} \varphi_j^{\frac{1}{\zeta}} c_{j,t}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}}, \tag{5}$$

where the elasticity of substitution across all the goods is given by ζ, while the preferences of consumers over various goods are given by demand shifters φ_j (which can be varying over time). Education is viewed purely as an investment in future human capital and, therefore, is not part of the aggregate consumption.

Since all the consumers have identical preferences at time t, the aggregate demand in the economy can be written as a CES aggregator of the same form

$$C_t = \left(\sum_{j=1}^{J} \varphi_j^{\frac{1}{\zeta}} C_{j,t}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}},$$

where each $C_{j,t}$ is the aggregate consumption of good j. Aggregate demand for good j in the economy can be written as a function of the aggregate variables (aggregate consumption and ideal price index, P_t) and the price of good j, $P_{j,t}$, in a standard form:

$$C_{j,t} = \varphi_j P_{j,t}^{-\zeta} P_t^{\zeta} C_t, \qquad \text{where} \quad P_t = \left(\sum_{j=1}^{J} \varphi_j P_{j,t}^{1-\zeta} \right)^{\frac{1}{1-\zeta}}. \tag{6}$$

3.2 Workers Allocation

Now, let's define the workers' optimization problem, which includes dynamic decisions about educational attainment and the choice of employment sector in the presence of imperfect human capital mobility and idiosyncratic preference shocks.

A worker's human capital is described by a tuple (ℓ, h), where $\ell \in \{u, s\}$ denotes the skill level and h represents the stock of efficiency units. There are two skill types of workers in the economy—unskilled and skilled. All individuals are born unskilled, with an initial stock of efficiency units $h = 1$, and can become skilled by acquiring education. In each period, an unskilled worker chooses both the sector in which to work and whether to pursue higher education. Once a worker attains higher education, she becomes skilled and receives a skill premium on each unit of her human capital in every sector.

For both unskilled and skilled workers, their stock of efficiency units changes according to the law of motion below, which is a slight modification of assumption introduced by Dvorkin and Monge-Naranjo (2019). When a worker with initial stock of efficiency units h_t is moving from sector j to i between periods t and $t+1$, her efficiency units in $t+1$ are given by

$$h_{t+1} = \tau^{\ell}_{j_t, i_{t+1}} h_t. \tag{7}$$

The stock of efficiency units h represents the absolute advantage of a worker within their skill type. Transition matrix τ^{ℓ} reflects how much efficiency units can be transferred from one sector to the other. Here, parameter $\tau^{\ell}_{ji} \geq 1$ means that there is potential human capital accumulation when staying or switching sector, and $\tau^{\ell}_{ji} \leq 1$ represents human capital depreciation when a worker switches to a new sector.

Introducing this law of motion, as well as the general form of the value function, I follow Dvorkin and Monge-Naranjo (2019) with several generalizations: (i) introducing two skill types of workers, (ii) adding an education sector and making a worker's type endogenous, and (iii) explicitly modeling the finite lifetime of overlapping cohorts. Moreover, in this model, idiosyncratic shocks are treated as preference shocks rather than productivity shocks,[15] and workers choose the sectors of employment rather than occupations. The elements of the transition matrices τ^{ℓ} will later be calibrated to match the growth rates of lifetime earnings across various sectors of the economy.

In each period t, a worker receives a realization of her preferences for working in each sector $\epsilon_t = \{\epsilon_{j,t}\} \in \mathbb{R}_+^{J+2}$ (or $\mathbb{R}_+^{J+1}$ in case of a skilled worker), where each $\epsilon_{j,t}$ is drawn from Weibull distribution with CDF $F_j(\epsilon) = 1 - \exp\left(-(\epsilon/\lambda_j)^{\kappa}\right)$, with the shape parameter $\kappa > 0$ (common

[15] This assumption is particularly useful when estimating the matrix τ in the data, as it allows to abstract from selection bias based on productivity draws.

for all sectors) and scale parameter $\lambda_j > 0$ (can be sector-specific). The idiosyncratic shock can be viewed as an unexpected shock to a preferences of a worker for a given sector, or in other words, it represents a random draw of utility that a worker receives when working in each sector in a given period.[16] The shocks are assumed to be i.i.d. across workers and time.

The value function of a worker with skill level $\ell \in \{u, s\}$, stock of efficiency units h, of age a, employed in sector j is then given by

$$\tilde{V}_{\ell,t}(h,a,j) = \frac{(w_{\ell,j,t}h)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_\epsilon \left[\max_i \left\{ \chi_{ji}^{\ell'}(a+1) \tilde{V}_{\ell',t+1}(h', a+1, i)\epsilon_i \right\} \right], \tag{8}$$

where $w_{\ell,j,t}$ is a wage rate for efficiency unit in sector j, and the stock of efficiency units in the next period h' is detemined by (7). The new skill level of a worker ℓ' is determined by

$$\ell' = \begin{cases} \ell, & \text{if } j \neq 0, \\ s, & \text{if } j = 0. \end{cases} \tag{9}$$

Matrix $\chi^\ell(a)$ is the matrix of switching costs, with $\chi_{ji}^\ell(a)$ being the utility cost of moving from sector j to sector i for a worker of age a with skill ℓ. I assume no cost of staying in the same sector, i.e. $\chi_{jj}^\ell(a) = 1, \forall j \in \mathcal{J}$. By allowing this matrix to be skill- and age-specific, I am making the model more flexible to match the lifetime reallocation patterns, in particular low gross flows of older workers across sectors and in and out of the labor force.

The first term in equation (8) represents the flow utility of consumption in period t, while the second part is the continuation value, which depends on the choice of sector i and the realization of the sector-specific preference shocks, ϵ_i. For unskilled workers ($\ell = u$), the choice set for the next period consists of $J + 2$ sectors and includes education sector, while skilled workers only choose one of $J + 1$ sectors to go to (production or non-employment).

Proposition 1. *For a given worker's problem specification in* (8) *and the law of motion of human capital* (7)*, one can show that the worker's value function is homogenous of degree* $(1-\gamma)$ *in* h*, i.e.*

$$\tilde{V}_{\ell,t}(h,a,j) = V_{\ell,t}(a,j)h^{1-\gamma}.$$

Hence, the worker's problem can be solved separate from the human capital distribution. See proof in Appendix C.2.[17]

[16] This type of a shock can be thought of as a sector-specific amenity, which also differs across workers. Alternatively, one can write the model in which the idiosyncratic shock directly affects human capital stock and, therefore, represents productivity shock.

[17] This proposition is generalized version of the result proved in Dvorkin and Monge-Naranjo (2019), with the extensions to multiple endogenous worker types and finite lifetime assumption.

Proposition 1 relies on three key assumptions. First, CRRA per-period utility from consumption with parameter γ gives rise to homogeneity of degree $1-\gamma$. The other two assumptions are the absence of borrowing and income being proportional to human capital (no lump sum taxes). In particular, I assume that both the subsidy received while in education and in non-employment are proportional to a worker's human capital, which is not always a realistic assumption. I allow the non-employment rate to differ by skill group. As for the education subsidy, the proportionality assumption reflects the fact that workers with more human capital are more likely to select into education (given that the subsidy is small relative to the unskilled wage rate), which serves as a proxy for selection based on ability. Since the stock of human capital is directly linked to income in any sector of the economy, this selection also implies that workers with initially higher income are more likely to pursue education, a pattern supported by the vast empirical literature on intergenerational mobility.

Applying Proposition 1 and using the law of motion (7), we can rewrite the value function in (8) as

$$V_{\ell,t}(a,j) = \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{\epsilon}\left[\max_{i}\left\{\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\epsilon_i\right\}\right]. \tag{10}$$

Proposition 2. *Assume that the value function of a worker of age $a = 1, \ldots, A-1$, with skill $\ell \in \{u, s\}$, employed in sector j is defined in (10). CRRA parameter satisfies $\gamma > 1$, and the preference shocks have distribution $\epsilon_j \sim Weibull\,(\kappa, \lambda_j)$. Then, the value function of a worker can be rewritten as*

$$V_{\ell,t}(a,j) = \begin{cases} \dfrac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} - \beta\,\Gamma\big(1+\frac{1}{\kappa}\big) \\ \quad \times\Big(\sum_i\big(-\chi_{ji}^{\ell'}(a+1)\,V_{\ell',t+1}(a+1,i)\,(\tau_{ji}^{\ell'})^{1-\gamma}\,\lambda_i\big)^{-\kappa}\Big)^{-1/\kappa}, & \textit{for } a = 1,\ldots,A-1, \\ \dfrac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma}, & \textit{for } a = A. \end{cases} \tag{11}$$

subject to (7) and (9).

and probability of switching from sector j to sector i between time periods t and $t+1$ is equal to

$$\mu_{ji,t}^{\ell}(a) = \frac{\big(-\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\lambda_i\big)^{-\kappa}}{\sum_n\big(-\chi_{jn}^{\ell'}(a+1)V_{\ell',t+1}(a+1,n)(\tau_{jn}^{\ell'})^{1-\gamma}\lambda_n\big)^{-\kappa}} \tag{12}$$

for $a = 1, \ldots, A-1$. *See Appendix C.3 for detailed derivations.*[18]

In this paper, I focus on the case $\gamma > 1$ and use it as the benchmark for quantification. However, Proposition 1 holds for CRRA utility with any parameter γ (including log utility), and therefore the model can be extended to arbitrary CRRA preferences. In such cases, one needs to modify the assumption about the distribution of idiosyncratic preference shocks. Specifically, for $\gamma < 1$ the shocks must follow a Fréchet distribution, while for $\gamma = 1$ they should be drawn from a Gumbel distribution, with switching costs $\chi_{ij}(a)$ assumed to be additive. See Appendix C.2 for further discussion.

Evolution of employment shares and aggregate human capital Now we can characterize worker's distribution across sectors. Let's denote the fraction of unskilled and skilled workers of age a in sector j as $\theta_{u,t}(a, j)$ and $\theta_{s,t}(a, j)$ respectively, then

$$\theta_{u,t+1}(a, j) = \sum_{i=1}^{J+1} \mu_{ij,t}^{u}(a-1)\theta_{u,t}(a-1, i), \tag{13}$$

$$\theta_{s,t+1}(a, j) = \sum_{i=1}^{J+1} \mu_{ij,t}^{s}(a-1)\theta_{s,t}(a-1, i) + \mu_{0j,t}^{u}(a-1)\theta_{u,t}(a-1, 0). \tag{14}$$

Here the incoming unskilled workers are switching from other sectors, while skilled workers either switch from other sectors or enter the labor force after receiving education. Before moving to describe the evolution of aggregate human capital across sectors, it is useful to show the following result.

Given the probabilites of switching across sectors and transferability matrices τ^{ℓ}, we can define matrix $\mathcal{M}^{\ell}(a)$, which elements $\mathcal{M}_{ji}^{\ell}(a)$ determine how much human capital all workers with skill $\ell \in \{u, s\}$ from sector j bring on average to sector i:

$$\mathcal{M}_{ji}^{\ell}(a) = \tau_{ji}^{\ell}\mu_{ji}^{\ell}(a). \tag{15}$$

Using this matrix $\mathcal{M}^{\ell}(a)$, we can write the evolution of *aggregate human capital* of workers

[18] Notice that this solution is equivalent to the case of the idiosyncratic productivity shocks, which are distributed $Frechet(\kappa, \lambda_j)$. In this case, $\epsilon_j^{1-\gamma}$ will appear in the expectation, and one can show it is distributed Weibull with shape parameter $\kappa/(\gamma-1)$ and scale parameter $\lambda_j^{1-\gamma}$. Formally, we can define a new variable $y = \epsilon^{1-\gamma}$, which CDF is equal to

$$\begin{aligned} F_y(y) &= \mathbb{P}(\epsilon^{1-\gamma} \le y) = \mathbb{P}(\epsilon \ge y^{\frac{1}{1-\gamma}}) = 1 - F(y^{\frac{1}{1-\gamma}}) \\ &= 1 - \exp\left(-(y^{\frac{1}{1-\gamma}}/\lambda)^{-\kappa}\right) = 1 - \exp\left(-(y/\lambda^{1-\gamma})^{-\frac{\kappa}{1-\gamma}}\right). \end{aligned}$$

of age a in sector j as

$$H_{u,t+1}(a,j) = \sum_{i=1}^{J+1} \mathcal{M}_{ij}^{u}(a-1) H_{u,t}(a-1,i), \tag{16}$$

$$H_{s,t+1}(a,j) = \sum_{i=1}^{J+1} \mathcal{M}_{ij}^{s}(a-1) H_{s,t}(a-1,i) + \mathcal{M}_{0j}^{u}(a-1) H_{u,t}(a-1,0). \tag{17}$$

Aggregate human capital and the number of workers of skill level ℓ in sector j at time t are defined as

$$L_{\ell,j,t} = \sum_{a=1}^{A} H_{\ell,t}(a,j) \quad \text{and} \quad N_{\ell,j,t} = \sum_{a=1}^{A} \theta_{\ell,t}(a,j) N, \tag{18}$$

where N is the size of one cohort (assumed to be constant).

Workers of age 1 The cohort of workers of age $a = 1$ entering the economy in period t starts being unskilled in one of $\{0, 1 \ldots, J, J+1\}$ sectors. The share of workers in each sector j for this cohort upon entry is given by

$$\theta_{u,t}(1,j) = \frac{\left(-\chi_j^0 V_{u,t}(1,j) \lambda_j (\tau_j^0)^{1-\gamma}\right)^{-\kappa}}{\sum_{n=0}^{J+1} \left(-\chi_n^0 V_{u,t}(1,n) \lambda_n (\tau_n^0)^{1-\gamma}\right)^{-\kappa}}, \tag{19}$$

where χ_j^0 denotes the costs of choosing sector j as the starting sector. Vector χ^0 is calibrateed to match the allocation of 16-20 y.o. workers, and τ^0 drives the cross-sector differences in earnings.

Let me briefly summarize the key advantages of this framework for analyzing the effects of sectoral shocks. First, by allowing workers to choose their sector in every period, I do not impose restrictions on their ability to receive education at any age. As a result, the fact that most workers acquire education early in life emerges as an optimal strategy, explained by the increasing opportunity costs of education for older workers. Second, workers must remain outside the labor force while receiving education. This feature of the model highlights the time cost of education and naturally implies that enrollment declines when more young workers join labor force in response to a positive demand shock. Finally, by allowing preference shocks to be iid across time and workers, I obtain a closed-form solution for switching probabilities, which simplifies the quantitative analysis.

3.3 Production

The production in the economy is presented by sectors $\{1, \ldots, J\}$ that combine unskilled and skilled labor using a constant-returns-to-scale technology. Production technology in sector j is given by

$$Y_{j,t} = Z_{j,t} L_{u,j,t}^{\alpha_j} L_{s,j,t}^{1-\alpha_j} \tag{20}$$

where the aggregate stock of unskilled and skilled human capital is defined as in (18). Each of the workers supplies their stock of human capital h.

I assume that sectoral technology can vary over time due to spillovers from human capital. Consider the aggregate technology in a sector j of a form

$$Z_{j,t} = Z_j \left(\frac{L_{s,j,t}}{L_{s,j,t} + L_{u,j,t}} \right)^{\eta_j}, \tag{21}$$

where Z_j is the constant exogenous component of sector-specific productivity, and parameter η_j measures the spillover effects that depends on the share of skilled human capital in sector j. This form assumes positive spillovers to a sector productivity and, therefore, a positive effect on labor income of both skilled and unskilled workers employed in a sector with higher share of skilled human capital.

The existence of positive technological spillovers can be motivated by the various knowledge diffusion and innovation processes. The specification in which the technological spillovers depend on the average human capital in the industry date back to Lucas Jr (1988), and the spillovers from share of skilled workers are discussed in Moretti (2004a,b,c).

Competitive unitary wages of unskilled and skilled workers in sector j are equal to

$$w_{u,j,t} = \alpha_j \frac{P_{j,t} Y_{j,t}}{L_{u,j,t}} \quad \text{and} \quad w_{s,j,t} = (1-\alpha_j) \frac{P_{j,t} Y_{j,t}}{L_{s,j,t}}, \tag{22}$$

and skill premium is then driven by the relative abundance of skilled human capital in sector j

$$\frac{w_{s,j,t}}{w_{u,j,t}} = \frac{(1-\alpha_j) L_{u,j,t}}{\alpha_j L_{s,j,t}}.$$

Finally, the aggregate nominal GDP is this economy is defined as

$$P_t Y_t = \sum_{j=1}^{J} P_{j,t} Y_{j,t}, \tag{23}$$

where P_t is the aggregate price index in the economy derived from the consumers preferences, and Y_t is the real GDP in period t.

3.4 General Equilibrium

The general equilibrium structure of this model allows us to analyze the transition of the economy following the boom, while accounting for the endogenous changes in the opportunity cost of education coming from the endogenous labor supply composition.

Let's close the model by introducing a set of market clearing conditions, consisting of goods market and labor market clearing, and defining the competitive equilibrium. Market clearing for each sector j is given by

$$Y_{j,t} = C_{j,t}, \tag{24}$$

where $Y_{j,t}$ is production defined in (20) and $C_{j,t}$ is the aggregate consumption of good j defined in (6).

Workers employment shares in each sector j are specified in (13)-(14). The size of each cohort is normalized to a unit measure, so that

$$\sum_{a=1}^{A} \frac{1}{A} \left(\sum_{\ell \in \{u,s\}} \sum_{j=1}^{J+1} \theta_{\ell,t}(a,j) + \theta_{u,t}(a,0) \right) = 1. \tag{25}$$

Now let's define equilibrium in this economy.

Definition 1 (Temporary Competitive Equilibrium)**.** *Given model parameters* $\{\gamma, \varphi_j, \zeta, \kappa, J, A, Z_j, \alpha_j, \eta_j\}$ *and aggregate state variables* $\{H_{\ell,t}(a,j), \theta_{\ell,t}(a,j)\}_{\ell,j}$*, a* temporary competitive equilibrium *at date* t *consists of a set of prices* $\{w_{\ell,j,t}, P_{j,t}\}_{\ell,j}$*, and aggregate sectoral output and consumption* $\{Y_{j,t}, C_{j,t}\}_j$*, such that:*

(i) ***Individual optimization:*** *given prices* $\{w_{\ell,j,t}, P_{j,t}\}$*, workers' decisions satisfy the intratemporal optimality conditions (each worker consumes her income); firms' labor demand is consistent with wage setting* (22)*; sectoral output and consumption satisfy* (6) *and* (20)*.*

(ii) ***Market clearing:*** *in every sector* j*, both the goods market and the labor market clear according to* (18) *and* (24)*.*

Definition 2 (Dynamic Competitive Equilibrium)**.** *Given the full set of model parameters*

$$\{\beta, \gamma, \varphi_j, \zeta, \kappa, J, A, \lambda_j, Z_j, \alpha_j, \eta_j, \tau^0, \tau^u, \tau^s, \chi^0, \chi^u(a), \chi^s(a)\},$$

and the initial stock of human capital for each worker, a dynamic competitive equilibrium *is a sequence*

$$\{w_{\ell,j,t}, P_{j,t}, V_{\ell,t}(a,j), \mu^{\ell}_{ij,t}(a), \mathcal{M}^{\ell}_{ij,t}(a), Y_{j,t}, C_{j,t}, \theta_{\ell,t}(a,j), H_{\ell,t}(a,j)\}^{\infty}_{\ell,a,j,i,t=0}$$

such that:

(i) For each t, $\{w_{\ell,j,t}, P_{j,t}, Y_{j,t}, C_{j,t}\}$ constitute a temporary competitive equilibrium *given state variables $\{H_{\ell,t}(a,j), \theta_{\ell,t}(a,j)\}$.*

*(ii) **Intertemporal consistency:** workers' decisions satisfy lifetime optimization across all periods, as described by* (11)–(12)*, and* (19).

*(iii) **State evolution:** aggregate labor allocations and human capital evolve according to the laws of motion* (13)–(14) *and* (16)–(17)*, with population given by* (25).

*(iv) **Market clearing:** in every period t, goods and labor markets clear in all sectors as in* (18) *and* (24).

4 Model Calibration

In this section, I briefly outline the set of parameters required for the quantitative analysis and discuss the estimation strategy. Table 2 summarizes all the parameters of the model for the benchmark model described in Section 3.

4.1 Parameters Estimation

Most of the parameters are calibrated using standard procedures in the literature. Some are externally calibrated using the values obtained by other studies or set to commonly used values in the macroeconomic literature on finite-lifetime overlapping-generations models (see the first block). The key parameters for this paper are the transition matrices for human capital, τ^u and τ^s, the age-dependent switching cost matrices $\chi^u(a)$ and $\chi^s(a)$, and the spillover parameters η_j. The strategy for calibrating these parameters is outlined below.

One period in the model is equivalent to five years, so all parameters are chosen for a five-year frequency. The lifetime of the household, A, is chosen to be 10, which corresponds to roughly 50 years that a person can spend in the labor market (from age 16, when the mandatory part of education ends, to age 65, when they retire).

Table 2: Model Parameters

Parameter	Description	Value	Note
A	Worker lifetime	10	lifetime 50 years (16-65 y.o.)
β	Discount factor	0.77	annual 0.95
γ	CRRA parameter	2	Dvorkin and Monge-Naranjo (2019)
J	Production sectors	4	constr., manufact., low- and high-skill serv.
ζ	Across-sectors CES	2	standard value in macro literature
κ	Weibull shape parameter	0.8	5-year equivalent to Caliendo et al. (2019)
λ_j	Weibull scale parameters	$[1,1,1,1]$	Dvorkin and Monge-Naranjo (2019)
τ^0, χ^0	Age-0 allocation		allocation and income of 16-20 y.o.
τ^u, τ^s	Transferability matrices		lifetime earnings dynamics
$\chi^u(a), \chi^s(a)$	Switching costs		gross flows of workers
α_j	Cobb-Douglas unskilled share		ECHP
Z_j	Sectoral productivity		see below
η_j	Within-sector spillover		see below
φ_j	CES demand shifters		SMM

Note: This table presents the summary of model parameters. One period in the model is 5 years.

The discount factor, β, is chosen to match the annual discount factor of 0.95, and the relative risk-aversion parameter, γ, is assumed to be equal to 2, which is also a standard value for models focusing on macroeconomic implications. Specifically, I am following Dvorkin and Monge-Naranjo (2019), who instead consider an occupation-choice model with overlapping generations. The constant elasticity of substitution across various sectors, ζ, is chosen following the tradition of many papers in international trade. Parameters α_j, which represent the share of unskilled labor by sector, are calibrated using data from European Community Household Panel[19].

In the benchmark quantification, I assume that the Weibull shape parameter, which represents the inverse of the migration elasticity, equals 0.8. This value corresponds to the five-year equivalent of the annual elasticity estimated in the literature. For instance, Diamond (2016) and Monte et al. (2018) estimate an annual parameter of around 3 using Gumbel and Fréchet shocks, while Artuç et al. (2010) focus on mobility across industries and find an inverse elasticity of about 2.8 at an annual frequency. Similarly, Caliendo et al. (2019) examine sectoral switching and show that the elasticity increases—and the shape parameter declines—from 5.34 to 2.02 (a

[19]More information on the data sources can be found in Appendix A.

factor of 2.6) when moving from quarterly to annual frequency. Since no established benchmark exists for a five-year frequency, I set the parameter κ to be smaller than the estimated annual analogue by the same factor and later conduct a sensitivity analysis. Moreover, I abstract from some of the framework's richness and assume that all idiosyncratic preference shocks are drawn from the same Weibull distribution with a common scale parameter λ.

In the case of a closed economy, the consumers' expenditure shares and nominal GDP shares coincide, therefore, I calibrate the steady-state demand shifters φ_j to match the average sectoral GDP shares over the period 1995-2000, using the data from the Spanish national acconuts. In particular, I employ simulated method of moments (SMM) and calibrate the parameters to target the share of construction around 10%, 23% for manufacturing, 29% for low-skill services, and around 38% for high-skill services.

Transferability Matrices τ^u and τ^s In order to estimate the elements of human capital transferability matrices, I employ data from the European Community Household Panel, in particular information on workers' income changes between the two periods, together with information on their sector of employment in those two periods[20].

According to the model introduced in Section 3, when a worker with a stock of human capital h and skill level ℓ moves from sector j to sector i between periods t and $t+1$, her earnings change according to

$$\frac{w_{h,\ell,i,t+1}}{w_{h,\ell,j,t}} = \frac{\bar{w}_{\ell,i,t+1}\overbrace{\tau^{\ell}_{ji}h_t}^{=h_{t+1}}}{\bar{w}_{\ell,j,t}h_t} = \tau^{\ell}_{ji}\frac{\bar{w}_{\ell,i,t+1}}{\bar{w}_{\ell,j,t}}, \tag{26}$$

where $\bar{w}$ is the wage per unit of human capital, and the stock of human capital changes according to the law of motion in (7). However, wage per unit of human capital is not observed in the data, and instead we can compute the average wage, which is denoted by $\tilde{w}_{\ell,j,t}$ and is equal to the average wage income of all workers in sector j period t:

$$\tilde{w}_{\ell,j,t} = \bar{w}_{\ell,j,t}\int hdG_{\ell,j,t}(h) = \bar{w}_{\ell,j,t}\frac{L_{\ell,j,t}}{N_{\ell,j,t}}, \tag{27}$$

which is a function of the unitary wage and the average human capital $L_{\ell,j,t}/N_{\ell,j,t}$ (both $L_{\ell,j,t}$

[20]For workers with a known sector of employment but missing wages, I impute wages as the average wage in the corresponding sector and year for the relevant education-sex group. This rule affects only around 4% of the observations. For workers switching into and out of the labor force (the non-employment sector in the model), I normalize the element of the matrix τ for transitions into non-employment to 1, and estimate the element for transitions out of non-employment using the wage from the last recorded job as the initial wage, adjusted for the duration of non-employment.

and $N_{\ell,j,t}$) are defined in (18).

Then, using this notation we can express the adjusted change in worker's income between the two periods t and $t+1$ as

$$\ln\left(\frac{w_{h,\ell,i,t+1}/\tilde{w}_{\ell,i,t+1}}{w_{h,\ell,j,t}/\tilde{w}_{\ell,j,t}}\right) = \ln(\tau_{ji}^{\ell}) + \ln\left(L_{\ell,j,t}/N_{\ell,j,t}\right) - \ln\left(L_{\ell,i,t+1}/N_{\ell,i,t+1}\right) \tag{28}$$

where the left-hand side is observed (denoted by $\ln\left(y_{h,\ell,t}^{j,i}\right)$). Since the average stock of human capital, $\ln\left(L_{\ell,j,t}/N_{\ell,j,t}\right)$ and $\ln\left(L_{\ell,i,t+1}/N_{\ell,i,t+1}\right)$, is unobservable, I will treat it as sector-time-specific fixed effects. Including such fixed effects also absorbs any other sector-time-varying characteristics, such as sectoral productivity or demand shocks not reflected in average wages. This is desirable, as it allows us to separate those effects from the τ_{ji} coefficients, which are time-invariant.

Estimating equation is then given by

$$\ln\left(y_{h,\ell,t}^{j,i}\right) = \alpha_{ji}^{\ell} + \mathrm{FE}_{\ell,j,t} - \mathrm{FE}_{\ell,i,t+1} + X_{h,t}'\gamma + \epsilon_{h,t}, \tag{29}$$

from which elements of the transferability matrix can be computed as $\tau_{ji}^{\ell} = \exp(\alpha_{ji}^{\ell})$, and $X_{h,t}$ includes individual-level controls like age, gender, etc. Since estimating this equation requires some normalization, I choose one of the elements τ_{ji} to be equal to 1.

The results of the estimation are presented in Appendix D.1. I choose to normalize the accumulation rate of unskilled workers in low-skill services to 1 and, therefore, the remaining elements should be interpreted relative to this normalization.

First, the resulting transferability rates for both unskilled and skilled workers present considerable variation, ranging from 0.44 to 1.48. Less skill-intensive sectors (such as construction and low-skill services) display higher accumulation rates for unskilled workers, whereas skill-intensive sectors like manufacturing and high-skill services exhibit higher accumulation rates for skilled workers. Moreover, some transferability rates for switching between sectors exceed 1, reflecting the fact that switching sectors always entails changing jobs, while remaining in the same sector often implies retaining the current job and therefore lower wage growth. Finally, since the panel used to estimate these matrices covers 1994–2000 and includes the very beginning of the housing boom, transferability rates from all other sectors into construction turned out to be greater than 1 for unskilled workers, which may be due to rising relative wages in construction and a declining skill premium at that time.

Surprisingly, the rates upon returning to the labor market from non-employment are greater than 1 for unskilled workers, implying an additional boost to human capital. This result can be attributed to the fact that the decision to reenter the labor market is often associated with improved job opportunities and that the workers employed in low-skill manual jobs do not really experience depreciation of their human capital while staying out of the labor force.[21] Nevertheless, these rates remain lower than some of the transferability rates across sectors.

Switching Cost Matrices $\chi^u(a)$ and $\chi^s(a)$ Recall that upon switching from sector j to sector i, a worker of age a incurs a multiplicative utility flow cost $\chi^{\ell}_{ji}(a)$. The switching probability between sectors j and i is described in equation (12) and equal to

$$\mu^{\ell}_{ji,t}(a) = \frac{\left(-\chi^{\ell'}_{ji}(a+1)V_{\ell',t+1}(a+1,i)\lambda_i(\tau^{\ell'}_{ji})^{1-\gamma}\right)^{-\kappa}}{\sum_n \left(-\chi^{\ell'}_{jn}(a+1)V_{\ell',t+1}(a+1,n)\lambda_n(\tau^{\ell'}_{jn})^{1-\gamma}\right)^{-\kappa}}. \tag{30}$$

I compute the steady-state population flows $\mu^{\ell}_{ji}(a)$ using European Community Household Panel, by pooling together all observations between 1994-2000, and splitting workers into age groups $a \in \{16-20, 21-25, 26-30, \text{ etc.}\}$ and by skill groups. Then, from equation (30)

$$\chi^{\ell}_{ji}(a) = \frac{(\tau^{\ell}_{ii})^{1-\gamma}(\mu^{\ell}_{ii}(a-1))^{1/\kappa}}{(\tau^{\ell}_{ji})^{1-\gamma}(\mu^{\ell}_{ji}(a-1))^{1/\kappa}}, \tag{31}$$

where we use the elements of matrix τ^{ℓ} estimated in the previous step and normalize $\chi_{ii}(a) = 1$ for all $i \in \mathcal{J}$[22]. Here I do not jointly estimate switching elasticity κ and take its value from the literature as discussed above.

Human Capital Spillovers η_j and Productivity Z_j As introduced in Section 3.3, the aggregate sectoral productivity is assumed to take form

$$Z_{j,t} = Z_j \left(\frac{L_{s,j,t}}{L_{s,j,t} + L_{s,j,t}}\right)^{\eta_j} \tag{32}$$

where Z_j is fixed exogenous productivity component, and η_j reflects the static externality from share of aggregate human capital of skilled workers.

From the Cobb-Douglas assumption, the aggregate payments to both unskilled and skilled

[21] I separately consider unemployment and "out-of-labor-force" spells for this estimation. The interpretation of the non-employment sector in the model is closer to the "out-of-labor-force" state; therefore, I estimate all parameters using this definition. Using unemployment spells yields qualitatively similar results but implies slightly lower accumulation rates, reflecting the fact that workers reenter the labor force only upon receiving a better job offer with a higher wage than in their previous employment, whereas starting a job after unemployment often involves a trade-off between finding a job quickly and holding out for a better offer.

[22] Since workers only stay in education for one period, I normalize the moving cost from education to non-employment for skilled workers to 1.

workers are equal to the total sector revenue,

$$\text{Wage bill}_{j,t} = Z_{j,t} L_{u,j,t}^{\alpha_j} L_{s,j,t}^{1-\alpha_j} \tag{33}$$

where the total wage bill is observed in the national accounts data, parameter α_j is calibrated separately, and the aggregate stock of human capital $L_{\ell,j,t}$ can be recovered from the fixed effects from τ^ℓ estimation. Using this equation, we can then recover the sector-level productivity $Z_{j,t}$:

$$\ln(Z_{j,t}) = \ln\left(\text{Wage bill}_{j,t}\right) - \alpha_j \ln(L_{u,j,t}) - (1-\alpha_j)\ln(L_{s,j,t}), \tag{34}$$

where $\ln(L_{\ell,j,t}) = \ln\left(L_{\ell,j,t}/N_{\ell,j,t}\right) + \ln(N_{\ell,j,t}) = \text{FE}_{\ell,j,t} + \ln(N_{\ell,j,t})$.

Finally, once we recover $\ln(Z_{j,t})$ from the equation above, we can use the definition of the spillover to estimate

$$\ln(Z_{j,t}) = \text{FE}_j + \eta_{\mathcal{J}(j)} \ln\left(\frac{L_{s,j,t}}{L_{s,j,t} + L_{s,j,t}}\right) + \epsilon_{j,t}, \tag{35}$$

where $\mathcal{J}(j) = \{\text{low-skill}, \text{high-skill}\}$. Notice that in this regression, the FE_j represents a time-invariant sectoral primitive productivity $\ln(Z_j)$, and the share of human capital of skilled workers in sector j is computed from the fixed effects estimated previously. I estimate the spillover parameters for two groups of sectors: low-skill (construction and low-skill services) and high-skill (manufacturing and high-skill services).

Importantly, this estimation strategy heavily relies on the ability to recover the sector-level aggregate stock of human capital. Therefore, the fact that the estimated sector-year fixed effects may capture other sector-time-varying shocks is problematic and can potentially to an upward bias in the estimation of the spillover parameter.

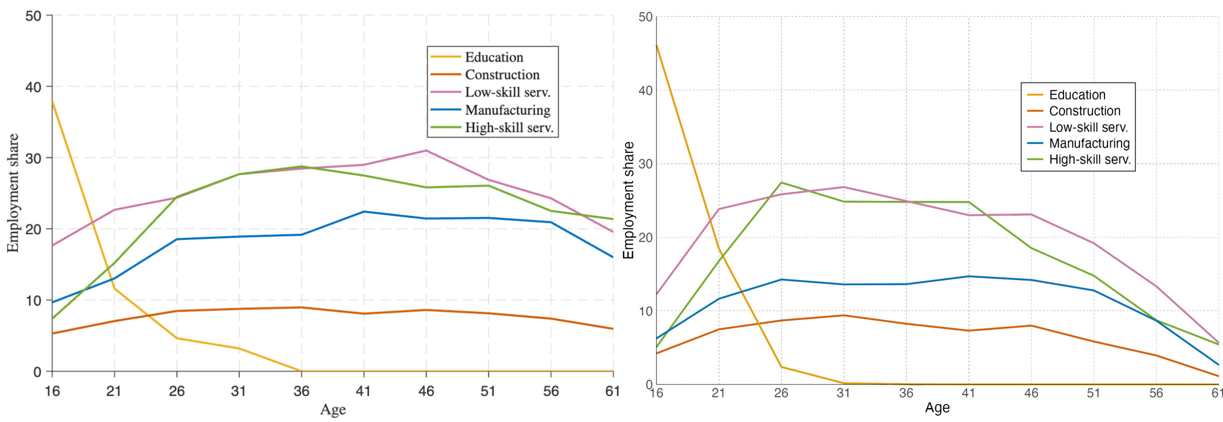
One crucial assumption made in this estimation is that the primitive TFP of each sector, represented by Z_j, is constant over time. As is evident from Figure A10, this assumption does not hold, and the utilization-adjusted TFP declined for most sectors during the period 1995–2000. Including it directly as a control allows me to abstract from the changes in sectoral productivity that are not coming from the changes in human capital, and therefore, the predictions of model simulations will only speak to the changes in labor productiivity driven by human capital reallocation, not changes in TFP.

The estimation results are presented in Table A11. In my preferred specification, the spillover parameter is about 0.64 for low-skill sectors and about 0.99 for high-skill sectors. Robustness checks consistently yield lower values for low-skill sectors compared to high-skill sectors, in the range of 0.4–0.65 for the former and 0.8–1.3 for the latter. Notably, these estimates are consistent with the literature on human capital spillovers. For example, Moretti (2004a) reports average estimates of 0.6–1.2 (without distinguishing by sector), while Moretti (2004c) documents a range of 0.5–1.3 for the manufacturing sector.

4.2 Model Fit

Now I solve for the steady state equilibrium in this economy using the parameter values discussed above. The four production sectors used in the benchmark simulations are construction, low-skill services, manufacturing, and high-skill services. Solution algorithm 1 used to solve for the steady state is described in Appendix C.4.

Let's first describe the steady-state allocation of workers. Workers enter the economy as unskilled, and the parameters driving their lifetime allocation are the transferability matrices τ and the age-specific moving costs $\chi(a)$. One simplifying assumption of the model is that everyone spends only one period in education before entering the skilled labor force. This assumption does not hold in reality, since for some individuals obtaining a college degree takes more than four years due to pre-college preparation programs and/or gap years. Moreover, many individuals continue with more advanced degrees after college. Therefore, the employment rates simulated by the model might be slightly inaccurate due to a constraint in the education sector.



(a) steady state, model

(b) data, 1995-2000

Figure 9: Long-run equilibrium, enrollment and employment rates

Note: This figure plots the steady-state workers allocation for both skill types, for each age, aggregated by sectors. Workers live for 10 periods, corresponding to 50 years from finishing high school until the retirement. The shares for all sectors + non-employment (not shown on the graph) add up to 1.

The steady-state lifetime allocation of workers is presented in Figure 9. First, the majority of young workers enter either education or low-skill services, and a large share remains out of the labor force for the first few periods of their life[23]. Throughout their lifetime, a nearly constant fraction of workers remains in the construction sector, primarily consisting of unskilled workers.

Table 3: Model partially targeted moments vs data

Moment	Model	Data
% in education	5.8	8.2
% in construction	7.8	6.4
% in manufacturing	18.2	11.8
% in low-skill serv.	25.2	20.4
% in high-skill serv.	22.3	17.3
% in non-employment	18.7	35.9
rel. skill premium, construction	1.4	1.2
rel. skill premium, manufacturing	1.3	1.2
rel. skill premium, high-skill serv.	1.5	1.1

Note: This table compares the untargeted moments in the data with the model steady state. Data moments are copmuted using ECHP 1995-2000. Skill premium is computed as a ratio of average wage of skilled and unskilled workers, and all skill premiums are relative to the one in low-skill services.

Low-skill services constitute the largest employment sector for younger workers, while both low-skill and high-skill services together employ nearly 50% of the older population. Although the employment shares in the model are slightly larger than those in the data, the model captures the relative sizes of all sectors fairly well, as shown in Panel (b). In the model, workers have no incentive to exit the labor force toward the end of their lifetime. To replicate the exit pattern observed in the data, I impose exogenous human capital deterioration during the final periods of the workers' lifecycle. This assumption is consistent with the literature on lifecycle earnings dynamics, which shows that individual wage income typically peaks in the 50s and declines thereafter.[24] Nevertheless, the model still generates less labor force exit than is observed in the data.

The steady-state aggregate employment shares in the model and the data are shown in Table 3. Aside from the non-employment sector being larger in the model than in the data, the relative

[23] The non-employment sector is not explicitly shown in the graph but can be inferred as the remaining fraction of the population at any given age.

[24] Murphy and Welch (1990) and Lagakos et al. (2018), among many others, find that workers' productivity and wages peak after about 30 years of experience ($\approx$ 50 years of age) and decline slightly thereafter.

employment sizes of all sectors align closely with the data. The education sector, by contrast, is larger in the data, due to the constraint in the model that all agents spend only one period to become skilled.

However, the model has limited ability to replicate the relative skill premium, since the Cobb–Douglas assumption fixes the income proportions of skilled and unskilled workers across sectors. Both the model and the data show the smallest skill premium in low-skill services and the same premium in manufacturing. Yet, the model simulations produce a larger relative skill premium in high-skill services than is observed in the data.

5 Economic Transition During and After the Boom

In this section, I describe the main results from the quantitative model simulations. I calibrate the path of demand shocks that match the initial change in the agregate demand and consumers' expenditure shares and solve for the transition path of the economy. Solution algorithm 2 used to solve for the transition path is described in Appendix C.4.

5.1 Demand Shock

For the case of a closed economy, I model the boom as a shock to: (i) sectoral demand shifters, φ_j, which enter the consumers' preferences for sectoral goods; and (ii) the discount factor, β. Intuitively, a shock to the demand shifters alters the relative demand for specific sectors and captures an expansion in low-skill sectors, particularly construction and low-skill services. On the other hand, a shock to the discount factor drives aggregate demand in the economy, allowing me to generate an increase in aggregate consumption.

For the benchmark case, I normalize the change of one of the demand shifters to 1, and use Simulated Method of Moments (SMM) to estimate the shocks to other demand shifters and discount rate. In particular, I solve for the whole transition path to match the initial increase in total GDP and the share of GDP of each sector during the boom. For the counterfactual analysis, I calibrate these parameters for two alternative scenarios: (a) change in sectoral shares with constant aggregate GDP, and (b) change in aggregate GDP with constant sectoral shares.

I consider an unanticipated temporary demand shock that increases aggregate demand and shifts consumption towards low-skill sectors, and focus on the economy's transition back to the initial steady state. I assume that the economy starts from the steady state and workers do not anticipate the shock. However, once the shock is realized, workers have perfect foresight about its duration.

5.2 Employment During and After the Boom

The dynamics of employment rates are presented in Figure 10. During the boom, workers reallocate toward construction and low-skill services and away from manufacturing and high-skill services. This pattern arises as both the aggregate demand shock and composition changes increase demand for construction and low-skill services. However, this pattern changes if look at the employment to population shares, as opposed to the employment rates which are normalized by the size of the labor force. In Appendix E, the dynamics of the employment-to-population ratios is depicted, and it is clear that employment in all sectors of the economy increases during the period of the boom.

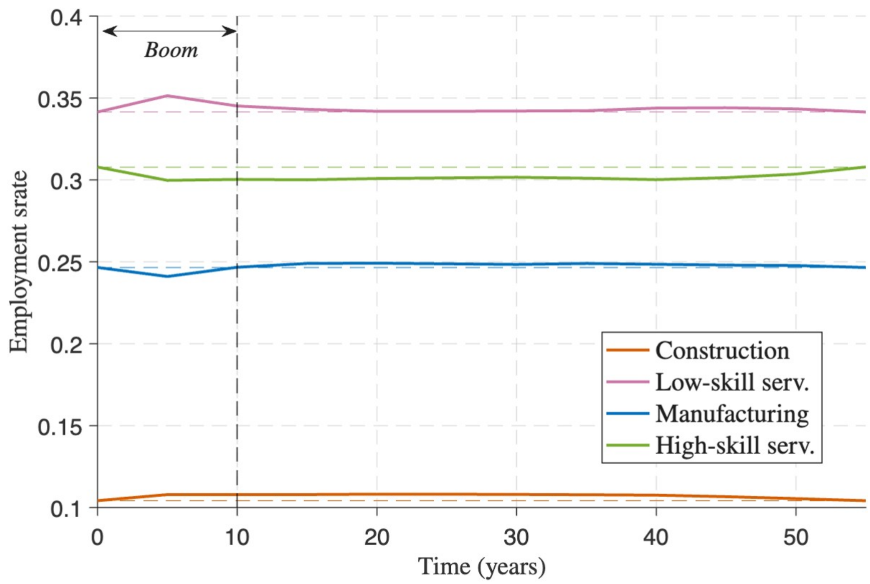


Figure 10: Employment rates during transition

Note: This figure plots the dynamics of the employment rates, computed as a percentage of the labor force, throughout the transition. The transition period consists of 5-year time periods, which are converted into years.

Reallocation after the bust occurs at a slow pace, with employment shares converging back to the steady state only after 50 years. This slow adjustment arises because, when the bust occurs, a lock-in mechanism prevents existing workers from reallocating away from the previously booming sectors. Both the potential loss of accumulated human capital and the rising switching costs hinder older workers from reallocating. As a result, in the short run, employment in low-skill sectors remains elevated, and the adjustment occurs primarily through new cohorts choosing different allocations.

Enrollment rates of workers of age 1 initially decline following the shock, as reflected in Figure 11. In the second period of the boom, workers anticipate the coming bust and increase their enrollment back to the steady-state level, as they expect an increase in the skill premium in the following period. The model matches the magnitude of the initial decline quite well, predicting 14.5pp drop in the enrollment rate, compared to 15pp in the data.

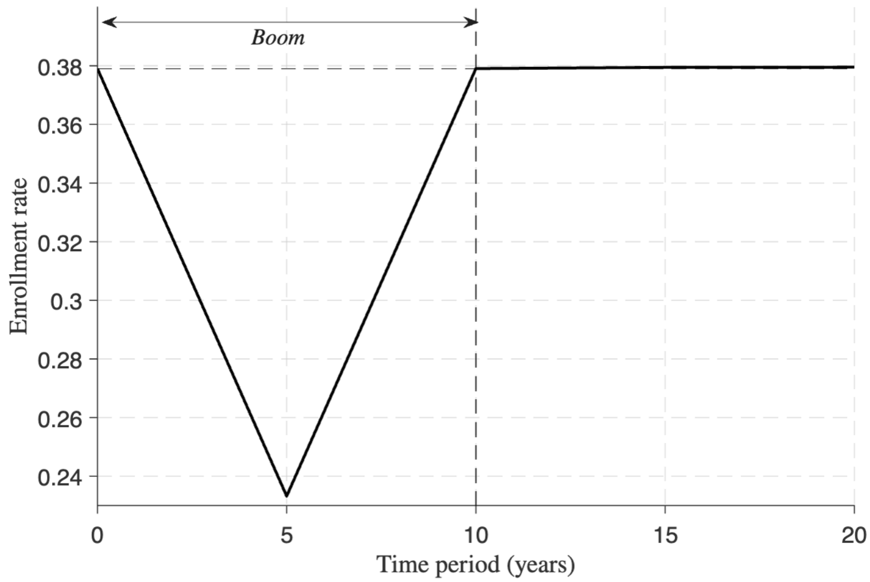


Figure 11: Enrollment during transition

Note: This figure plots the dynamics of the enrollment rates throughout the transition. The transition period consists of 5-year time periods, which are converted into years.

The labor force participation turns out to be a much stickier margin, as it affects workers of all ages. The share of workers in the non-employment sector (not in the labor force) is presented in Figure 12. Even though the initial decline in the non-employment rate is not as large as the changes in enrollment, it remains below the steady-state level for almost 45 years after the boom. This result can be attributed to the fact that affected cohorts permanently stay in the labor force once they join it, which is consistent with the empirical evidence presented in Section 2.

Next, consider the lifetime employment and enrollment trajectory of the cohort born at the beginning of the boom. Figure 13 shows that this cohort reduces educational attainment during the boom and reallocates toward the low-skill sectors. Importantly, they do not return to education after the bust, as indicated by the yellow line in the graph, which never overshoots the steady-state level at any age. Moreover, this cohort remains permanently more employed in construction and low-skill services even after the bust, driven by the opportunity cost of switching to a different sector. At the same time, they are consistently less employed in high-skill services throughout their lifecycle, reflecting lower skill acquisition rates. Consequently, the overall increase in high-skill services employment observed in Figure 10 is primarily driven by the reallocation of older cohorts, while younger workers disproportionately join low-skill

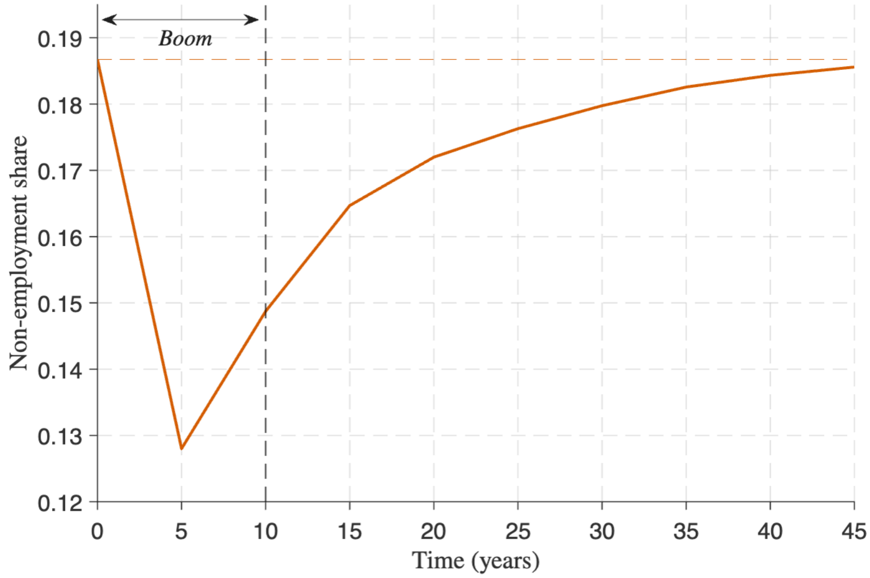


Figure 12: Non-employment sector during transition

Note: This figure plots the dynamics of the share of workers not in the labor force throughout the transition. The transition period consists of 5-year time periods, which are converted into years.

sectors.

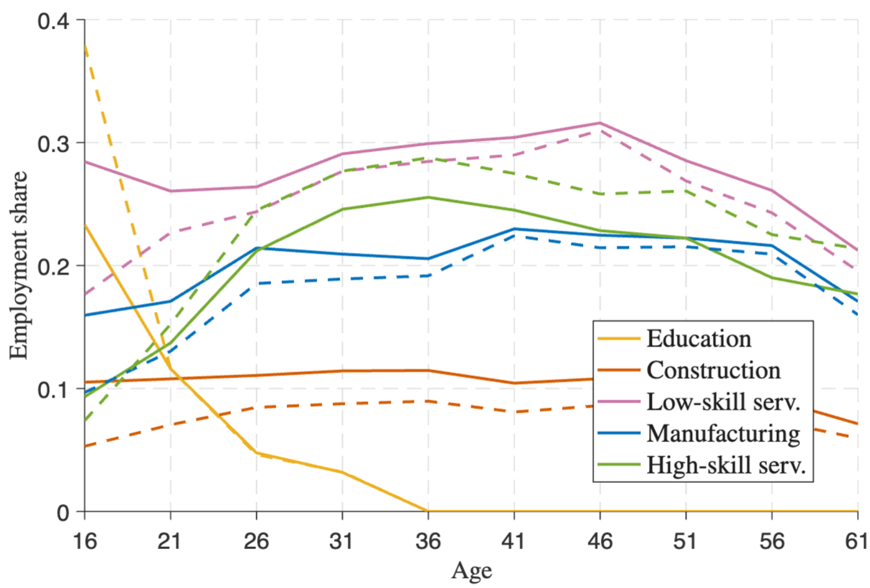


Figure 13: Lifetime allocation of affected cohort

Note: This figure plots the lifetime employment shares and enrollment of the cohort born during the first period of the boom. The dashed lines represent steady-state allocation, while the solid lines correspond to the actual allocation of this cohort.

5.3 Productivity Dynamics During and After the Boom

Now let's compute the changes in aggregate labor productivity along the transition. Since the proposed shock is the shock to consumers' preferences, I follow Baqaee and Burstein (2023) and express the *change in real GDP* (equal to real consumption) using the chain-weighted index:

$$\Delta \log Y_t = \log \frac{I_t}{I_{t_0}} - \int_{t_0}^{t} \sum_j s_j d \log P_j \tag{36}$$

which depends in the whole path of sectoral prices $P_{j,t}$, weighted by the expenditure shares $s_{jt} = \frac{P_{j,t}Y_{j,t}}{\sum_j P_{j,t}Y_{j,t}}$ reflecting changing preferences in every period.

Definition 3 (Change in Labor Productivity)**.** *Consider the economy's equilibrium definied in 2, with a path of preferences across sectors given by demand shifters $\varphi_{j,t}$ and discount factor β_t for all j and t. The change in real GDP is computed using formula in (36). Then:*

(a) The change in aggregate labor productivity (LP) at time t is defined as

$$\Delta \log(LP_t) = \Delta \log \left(\frac{Y_t}{N_t} \right) = \Delta \log Y_t - \Delta \log N_t, \tag{37}$$

where $I_t = \sum_{j=1}^{J} \sum_{\ell} w_{\ell,j,t} L_{\ell,j,t}$ is the total nominal income of all workers in the economy, and $N_t = \sum_{j=1}^{J} \sum_{\ell} N_{\ell,j,t}$ is the aggregate number of workers employed in production sectors.

(b) The change in multifactor productivity (MFP) at time t is defined as

$$\Delta \log(MFP_t) = \Delta \log Y_t - \int_{t_0}^{t} \sum_{j=1}^{J} s_{j,t} \sum_{\ell} \frac{w_{\ell,j,t} L_{\ell,j,t}}{\sum_{\ell} w_{\ell,j,t} L_{\ell,j,t}} d \log N_{\ell,j,t}, \tag{38}$$

where the change in the number of workers employed in each sector and each skill group is now weighted by corresponding expenditure and wage shares, and according to a Cobb-Douglas assumption the wage shares stay constant over time $\frac{w_{u,j,t} L_{u,j,t}}{\sum_{\ell} w_{\ell,j,t} L_{\ell,j,t}} = \alpha_j$.

Here, my definition of multifactor productivity coincides with that of the OECD, since the only input is labor. To compute the changes in labor productivity numerically, I employ mid-point Rieman sums approach, also regerred to as chained Tornqvist index. The reason I define these two measures is that both are usually computed in the data and, therefore, can be easily compared to the predictions of the model.

Definition 4 (Numerical Change in Labor Productivity)**.** *Consider the economy's equilibrium definied in 2, with a path of preferences across sectors given by demand shifters $\varphi_{j,t}$ for all j and*

t. The change in real GDP is computed using formula in (36), and the change in aggregate labor productivity is defined as in (37) and (38). Then:

(a) The change in aggregate labor productivity (LP) at time t can be numerically approximated as

$$\Delta \log(LP_t) = \Delta \log\left(\frac{Y_t}{N_t}\right) \approx \log \frac{I_t}{I_{t_0}} - \sum_{k=t_0+1}^{t} \sum_j \frac{1}{2}(s_{j,k} + s_{j,k-1}) \log \frac{P_{j,k}}{P_{j,k-1}} - \log \frac{N_k}{N_{k-1}}. \tag{39}$$

(b) The change in multifactor productivity (MFP) at time t can be numerically approximated as

$$\Delta \log(MFP_t) \approx \log \frac{I_t}{I_{t_0}} - \sum_{k=t_0+1}^{t} \sum_j \frac{1}{2}(s_{j,k} + s_{j,k-1}) \log \frac{P_{j,k}}{P_{j,k-1}} - \sum_{k=t_0}^{t} \sum_j \frac{1}{2}(s_{j,k} + s_{j,k-1}) \sum_\ell \frac{w_{\ell,j,k} L_{\ell,j,k}}{\sum_\ell w_{\ell,j,k} L_{\ell,j,k}} \log \frac{N_{\ell,j,k}}{N_{\ell,j,k-1}}. \tag{40}$$

The dynamics of cumulative changes in aggregate labor productivity are presented in Figure 14. I compute both the aggregate labor productivity and the multifactor productivity measures, as defined in 3 and numerically approximated as in 4. During the boom, both measures show an initial decline by around 1.2%. This decline can be attributed to two factors. First, as the aggregate demand goes up the labor force grows primarily through younger workers with lower accumulated human capital. Second, as the relative demand for low-skill sectors increases, they expand generating lower external return from human capital compared to the high-skill sectors.

Following the bust, both measures of productivity stay below their initial levels and converge to the long-term equilibrium only after 50 years (10 periods). This transition is driven by both the drop in aggregate demand, which affects low-skill and high-skill sectors alike, and the lock-in mechanism, which prevents existing workers from relocating to more productive sectors and results in persistently low aggregate productivity until the cohorts born during the boom exit the economy completely. Overall, a 10-year boom in the model generates cumulative losses in multifactor productivity of roughly 6.6% over the transition.

Sectoral labor productivity dynamics are presented in Figure 15. Similar to the data, the calibrated shock generates a large decline in construction productivity and a smaller decline in low-skill services productivity. However, whereas high-skill services productivity remains nearly constant in the data, the model predicts a large increase, driven by the increasing share of older workers in this sector that generate substantial human capital externality.

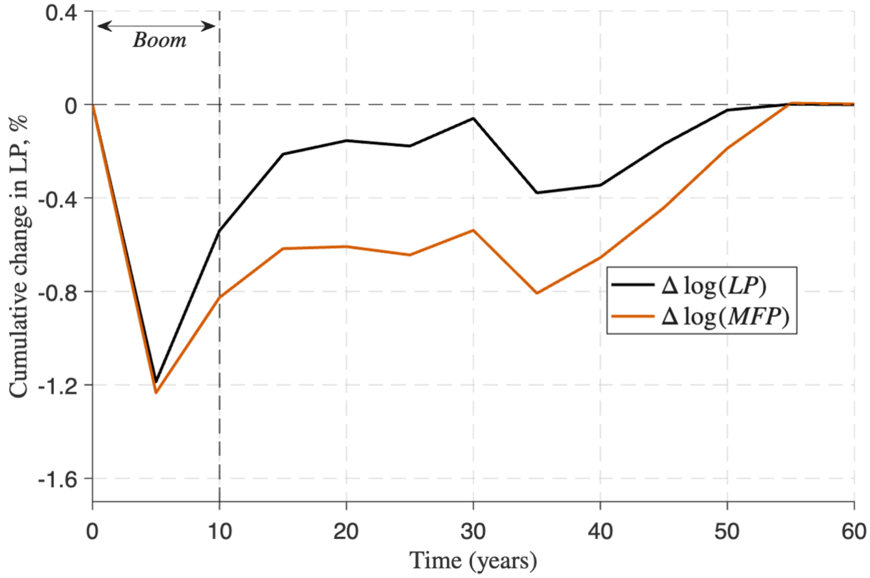


Figure 14: Aggregate labor productivity dynamics

Note: This figure plots the dynamics of cumulative change in aggregate labor productivity, computed using the formula in (37) and numerical approximation by mid-point Rieman sums. The labor productivity change in each time period is constructed as the change in real GDP divided by the labor force (i.e. excluding fraction of population in education and non-employment).

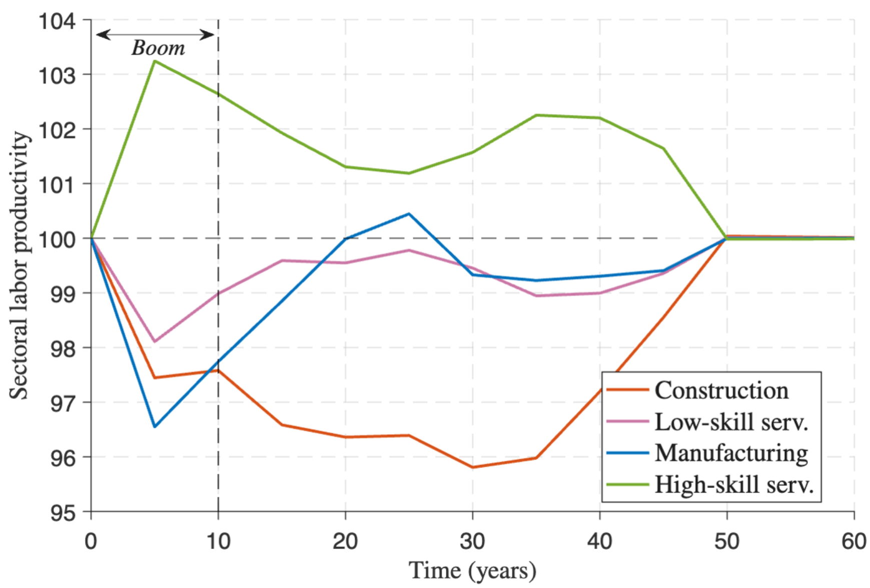


Figure 15: Sectoral labor productivity dynamics

Note: This figure plots the dynamics of sectoral labor productivity, copmuted as real GDP divided by the number of employed workers. Productivity in each sector is normalized to 100 in the steady state.

It is worth noting that although the model generates realistic employment and productivity patterns, it does not reproduce changes of the same magnitude as those observed in the data. The model's predictions should be interpreted as capturing only the portion of employment and productivity dynamics driven by the demand shock. Nevertheless, other factors during this period—such as declining interest rates and rising investment and household debt—likely also contributed to production and employment outcomes.

5.4 Distributional Effects of the Boom

Next, I analyze the model's predictions for the distributional effects of the temporary low-skill boom. Because the shock is modeled as a change in consumer preferences, a welfare analysis is not straightforward. Instead, I examine changes in lifetime earnings across cohorts. In Figure 16, I plot the percentage change in each cohort's total lifetime earnings relative to the steady-state level.[25]

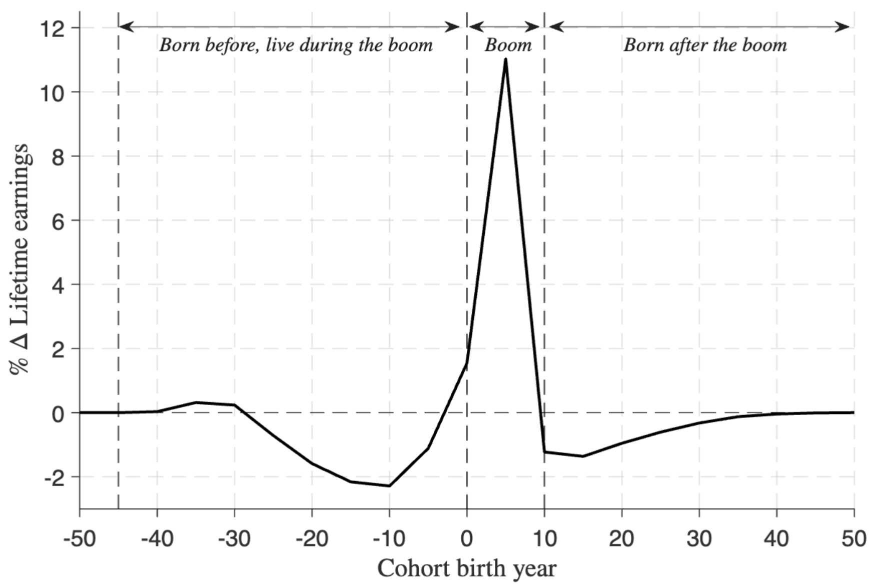


Figure 16: Lifetime earnings by cohort

Note: This figure plots the total lifetime earnings by cohort birth year, computed as the % change relative to the steady-state lifetime earnings. Negative numbers on the x-axis correspond to the cohorts born before the boom, 0 denotes the cohort born at the beginning of the boom, and postivie numbers correspond to the cohorts born during and after the boom.

Cohorts born before the boom suffer the most: they have already accumulated substantial human capital by the time the boom begins, yet they are unable to reallocate to low-skill sectors

[25]Total lifetime earnings are computed without discounting.

as much. Moreover, they incur losses because the skill premium falls during the boom, even though these cohorts have already invested in education. Cohorts born immediately after the bust are also worse off, as they enter the labor market during a period of depressed aggregate demand and do not benefit from the boom in the same way as cohorts born during the boom.

In contrast, cohorts born during the boom gain, as they are able to adjust both their educational attainment and sectoral allocation, while also benefiting from high wages in low-skill sectors. For the cohort born at the very beginning of the boom (cohort 0), these positive effects are partially offset by lower earnings after the bust. By comparison, the cohort born immediately before the bust, which increases educational attainment in anticipation and is therefore more flexible, experiences the largest gains, with lifetime earnings exceeding the steady-state level by nearly 11%.

Interestingly, the sum of the earnings changes is positive, reflecting an overall increase in workers' earnings due to the boom. This implies that a redistribution policy could be designed to compensate cohorts that experience earnings losses while still leaving cohorts born during the boom better off. Although I do not pursue such a policy analysis in this paper, the framework readily allows for it.

6 Drivers of the Boom and the Role of Spillovers

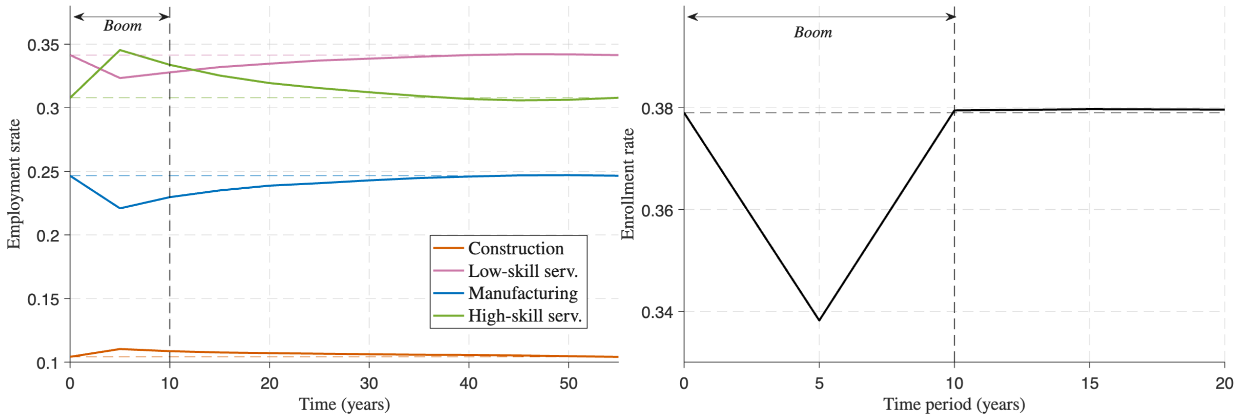
In this section, I investigate how aggregate demand dynamics and sectoral composition changes separately affect employment and productivity during the economic transition, and assess the contribution of spillovers to aggregate productivity dynamics.

6.1 Economy without Discount Factor Shock

First, let's consider an economy without a discount factor shock, which keeps aggregate demand constant, and the boom is just the change in the sector composition. I calibrate the new paths for both demand shifters and discount factor for such an economy and present the transition patterns below.

In this economy, employment dynamics looks different, with employment in high-skill services increasing and in low-skill services declining. In the benchmark, the main reason for expansion of low-skill services is the increase in aggregate demand, while in reality the GDP share of high-skill services slightly expands during the boom. Moreover, the aggregate demand increase is the driver of labor force participation increase and educational attainment decline, and in this counterfactual economy enrollment almost stays at its steady-state level.

Regarding productivity dynamics, Figure 18 shows that during the boom both measures



(a) employment rates

(b) enrollment

Figure 17: Employment and enrollment rates dynamics

Note: This figure plots dynamics of employment and enrollment rates for the case of constant aggregate demand and changing sectoral composition.

predict initial increase in labor productivity. This occurs because labor reallocation is driven primarily by older workers, while younger cohorts still acquire education and stay out of the labor force. Following the bust, productivity decreases and stays lower than its long-run level before converging to the long-run equilibrium. That dynamic is driven by the fact that older cohorts stay locked in the sectors with decreasing demand.

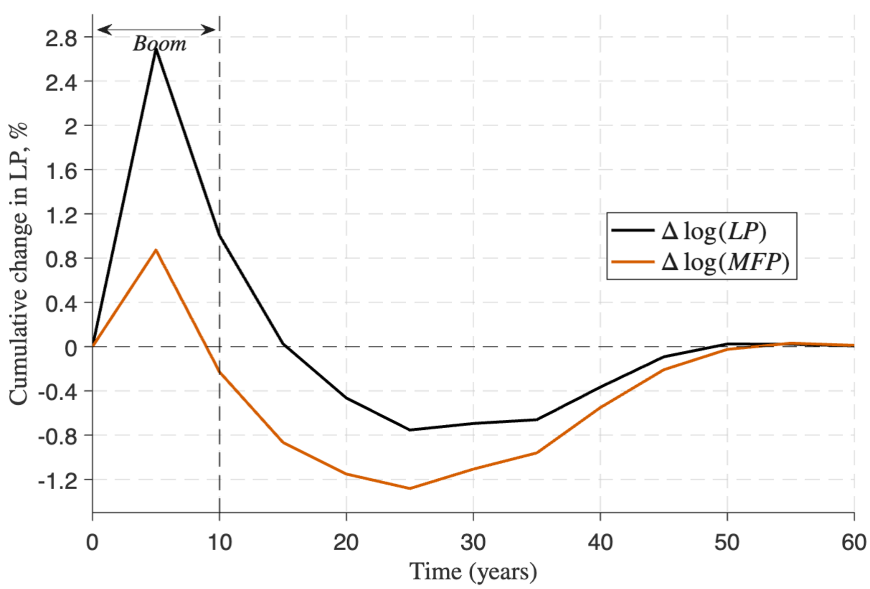


Figure 18: Aggregate labor productivity dynamics

Note: This figure plots the dynamics of cumulative change in aggregate labor productivity for the case of constant aggregate demand and changing sectoral composition.

I highlight two main takeaways from this counterfactual. First, generating quantitatively significant responses of enrollment and labor force participation along the transition requires either a change in aggregate demand or a much larger shift in sectoral composition. The observed changes in sectoral shares alone cannot explain the enrollment and productivity dynamics observed in the Spanish economy. Second, employment dynamics cannot be explained by the sectoral changes alone, as the low-skill services were affected by the aggregate demand. Finally, aggregate productivity dynamics flips, which is both the result of not matching the correct sectors reallocation and increase in the labor force. Therefore, it is crucial to consider both the boom–bust cycle of aggregate demand and the change in sectoral composition when analyzing this period.

6.2 Economy without Sectoral Shocks

Now consider a different counterfactual in which sector GDP shares remain constant throughout the transition, and the boom is driven solely by the shock to an aggregate demand. As before, I calibrate the path of the discount factor to match the initial increase in aggregate demand and then solve for the transition dynamics of the economy.

Unlike the benchmark economy, under constant sectoral demand an increase in aggregate demand leads to a proportional increase in employment across all production sectors and an increase in labor force participation, so employment rates change only slightly. The temporary rise in real wages relative to non-employment subsidies incentivizes workers of all ages to enter the labor force. For older workers, this transition is accompanied by a decline in the non-employment rate, while younger workers reduce their investment in education. The length of the transition in both employment and enrollment rates is quite similar to that in the benchmark economy, although the decline in educational attainment is even larger in this case.

As opposed to the benchmark case, the skill premium increases during the boom and remains elevated throughout the transition when the aggregate demand shock is the sole driver of the boom. When both aggregate demand and sectoral composition change, the relative increase in demand for low-skill sectors raises demand for unskilled workers and thus lowers the skill premium, while higher aggregate demand encourages younger workers to forgo education and join the labor force as unskilled workers. Following the bust, the abundance of unskilled labor and the higher relative demand for skilled workers push the skill premium upward until it converges back to its initial steady-state level. By contrast, when only aggregate demand changes, demand for both skilled and unskilled workers rises proportionally. In this case, more workers enter the labor force before completing their education due to rising wages, and the resulting abundance of unskilled labor drives the skill premium up even during the boom.

Aggregate labor productivity dynamics are presented in Figure 19. With constant sectoral composition, both productivity measures predict an initial decline during the boom. This pattern is driven by the disproportionate entry of unskilled workers into the labor force across all sectors, while skilled workers shift more toward high-skill sectors. Consequently, the average human capital of unskilled workers declines, and the share of skilled human capital falls, causing sectoral productivity decrease further through the spillover channel. In this counterfactual, the initial decline is even larger than in the benchmark case.

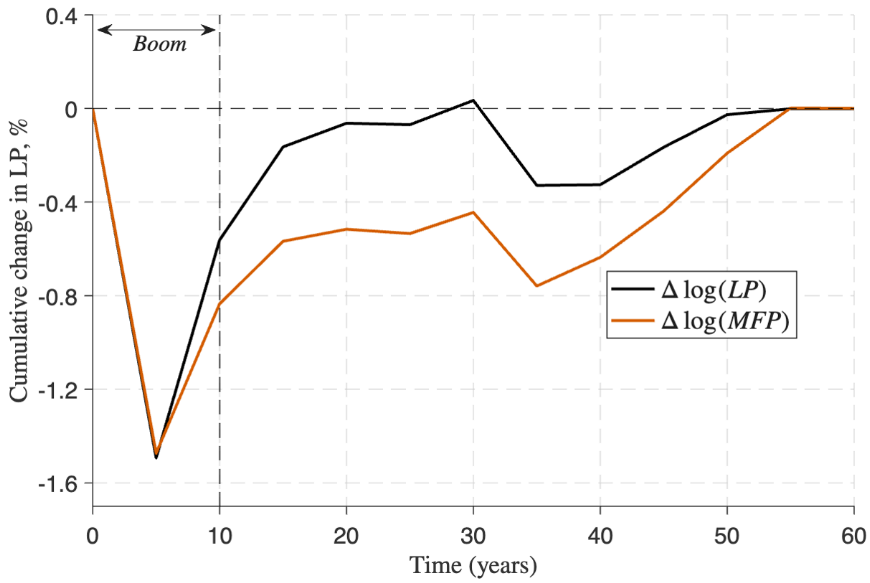


Figure 19: Aggregate labor productivity dynamics

Note: This figure plots the dynamics of cumulative change in aggregate labor productivity for the case of constant sectoral composition and changing aggregate demand.

Summing up, the analysis of these two counterfactual scenarios highlights the contributions of aggregate demand and sectoral composition changes to the transition dynamics of the economy. While changes in sectoral composition are the key mechanism for explaining employment and skill premium dynamics across sectors, temporary shocks to aggregate demand are necessary to generate declines in enrollment and non-employment rates. Regarding aggregate productivity dynamics, rising aggregate demand is the main driver of the initial productivity decline. In particular, when increases in employment and output are driven by younger, less experienced workers with lower accumulated human capital, productivity in each sector falls. By contrast, changes in sectoral composition play a larger role in sustaining the productivity decline after the bust. The human capital "lock-in" mechanism prevents existing workers from reallocating to sectors with higher relative demand and thus constitutes the main source of persistence.

6.3 The Role of Human Capital Spillovers

Here, I analyze the role of productivity spillovers from human capital under each of the three scenarios and provide further insights into their implications for the transition dynamics of the economy. For each counterfactual, I abstract from human capital spillovers and compute the cumulative productivity losses, with the results reported in Table 4.

Table 4: Counterfactual Productivity Losses

Scenario	Spillovers	No spillovers
Benchmark	6.55%	8.36%
Constant agg. demand	5.47%	3.39%
Constant sector composition	6.39%	8.04%

Note: This table compares the aggregate productivity losses, measured as a multifactor productivity, for three counterfactuals with and without spillovers.

First, cumulative productivity losses are largest in the benchmark economy, where both aggregate demand and sectoral composition change. The losses in the other two scenarios do not add up to the benchmark case, since the steady state is solved separately each time, but they roughly capture the relative contributions of aggregate demand declines and sectoral composition changes.

At any point in time, labor productivity dynamics in each sector are affected both directly by the average human capital of employed workers and indirectly through the external returns to skilled human capital in the form of static spillovers. A temporary increase in aggregate demand reduces the average human capital of unskilled workers, as more young individuals enter production rather than education. At the same time, skilled workers increase their labor force participation, and the resulting spillovers mitigate the direct negative effects on sectoral productivity. By contrast, a relative increase in demand for low-skill sectors induces a reallocation of unskilled workers toward those sectors and away from high-skill sectors. Consequently, productivity declines in low-skill sectors and rises in high-skill sectors, yielding only very small changes in aggregate productivity.

As shown by comparing the first and second columns of Table 4, and under the assumption of no spillovers from human capital, productivity losses are larger in the benchmark economy and the economy with constant sectoral composition, while they are smaller in the economy with constant aggregate demand. One reason is that under constant aggregate demand, productivity initially increases and spillovers further amplify this increase, as opposed to offsetting the decline.

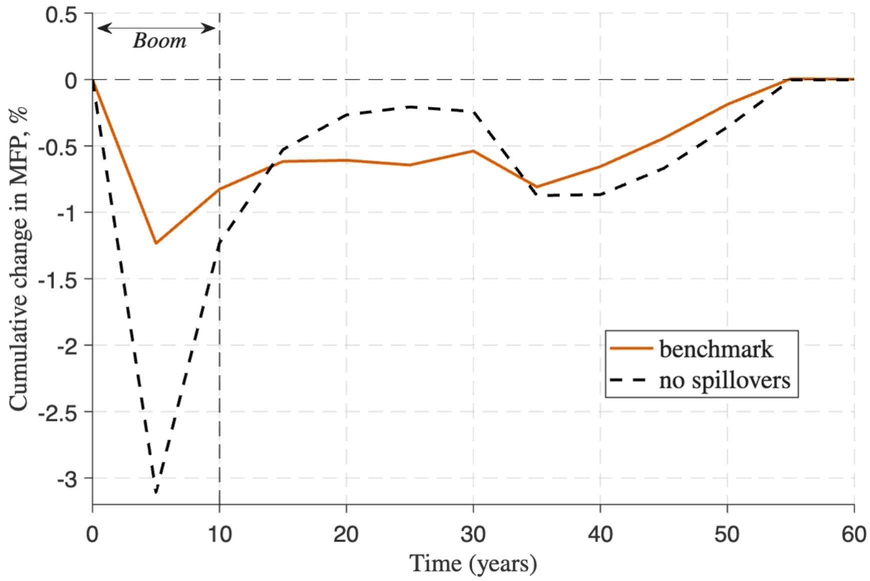


Figure 20: Labor productivity dynamics w/ and w/o spillovers

Note: This figure plots the dynamics of cumulative change in quality-adjusted aggregate labor productivity for the benchmark case and the case without spillovers.

When focusing on the role of spillovers, one can see that their relative influence varies over time. As shown in Figure 20, during the boom the direct effect dominates: as educational attainment declines, young workers enter low-skill sectors with less accumulated human capital, which drives productivity downward. Spillovers partially offset this decline, as older skilled workers reallocate to high-skill services and generate productivity gains in that sector. However, after the bust, imperfect transferability produces even larger productivity losses in the presence of spillovers. In particular, as existing workers face high opportunity costs and are unable to reallocate away from low-skill sectors, average human capital in those sectors rises but yields low external returns, while the average human capital in high-spillover sectors remains low and increases only through incoming cohorts.

7 Conclusion

This paper addresses an important question: whether human capital accumulation can serve as a source of persistent aggregate effects arising from temporary sectoral shocks. While the existing literature provides evidence that such shocks can have permanent effects on individual workers' educational attainment and sectoral allocation, it remains an open question whether they can also generate long-term aggregate effects on the economy.

In this paper, I analyze the impact of temporary sectoral shocks on human capital accumulation and introduce a framework to quantify their effects on long-term economic growth. Using the 1995–2007 boom in Spain as an example of a positive demand shock to low-skill sectors, I provide evidence that the boom had a lasting negative effect on cohort-specific educational attainment. I propose a lifecycle model with endogenous decisions regarding education and sectoral allocation, which is used to study the economy's transition following the shock and its distributional effects. The paper highlights the pivotal role of labor supply skill composition in shaping workers' opportunity costs and driving long-term changes in aggregate productivity.

I calibrate the model to the Spanish economy and solve for the full transition path following a temporary shock to low-skill sectors. The model replicates the employment and productivity dynamics observed during the expansion of low-skill sectors, albeit with smaller magnitudes of change. It highlights the importance of human capital accumulation and the rising opportunity cost of education in driving workers' reallocation across sectors and in explaining the long-term decline in aggregate labor productivity after the bust. Furthermore, the counterfactual analysis shows that productivity spillovers from human capital play a critical role in mitigating the impact of shocks on aggregate productivity, thereby reducing cumulative losses along the transition.

The main takeaways from this paper are as follows. First, it highlights that human capital is a key mechanism driving the persistence of temporary shocks. Both changes in workers' sectoral allocation and in educational attainment shape the transition: the decline in education is the main driver of the initial downturn, while imperfect human capital mobility contributes to sluggish reallocation after the bust. Second, even positive shocks can generate adverse aggregate effects—although all agents make individually optimal choices, the economy as a whole may still experience productivity losses along the transition. Finally, temporary shocks generate heterogeneous effects across cohorts, leaving room for redistribution policies to offset losses while preserving overall efficiency.

There are several potential channels through which temporary demand shifts may exert long-term effects on aggregate productivity that are not examined in this paper and could motivate future research. For instance, some studies highlight distinctive features of the Spanish labor market, which tends to favor experienced workers over younger college graduates and promotes fixed-term contracts. In addition, changes in consumption–savings behavior, driven by lower mortgage rates and the consumption boom, likely encouraged workers to remain in the labor force even after the bust. Finally, examining the joint effects of demand and supply shocks—where declining interest rates are explicitly accounted for as a driver of the investment boom—could provide a more comprehensive picture of the economic forces behind the transition.

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A Data Appendix

A.1 OECD Productivity Statistics Database

The OECD database[26] provides annual data on real GDP and total hours worked, which are homogenized and can be used for cross-country comparisons. This data is used to motivate the significance of the boom in low-skill sectors for aggregate-level productivity growth in Spain. Productivity is calculated as GDP per hour worked. Total hours worked is used instead of salaried hours to abstract from cross-country differences in labor market regulations regarding overtime and sick pay. The analysis includes data for the following European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and Switzerland.

A.2 EUKLEMS & INTANProd database

The integrated EUKLEMS & INTANProd database updates the original EUKLEMS productivity database and extends it with new estimates of intangible investment, following the methodology outlined in Bontadini et al. (2023). The EUKLEMS database provides a comprehensive set of national accounts data, including output, value added, employment (measured in both hours worked and number of persons), and capital inputs disaggregated by asset type. These data are harmonized across countries using standard industry classifications (NACE Rev. 2) and are consistent with the European System of Accounts (ESA), allowing for robust cross-country and cross-industry comparisons.

In addition to the national accounts, EU KLEMS includes growth accounts, applying a Solow-based growth accounting framework. This framework decomposes output growth into contributions from capital input, labor input, and total factor productivity (TFP). Importantly, labor input is not treated as a homogenous factor, it is adjusted for changes in labor composition or quality, reflecting differences in education, age, experience, and gender across the workforce. This adjustment allows for a more accurate measure of the contribution of labor to productivity growth.

This data used in this analysis covers the period from 1995 to 2020. The data from growth accounts is used to construct measures of quality-adjusted labor productivity at the national level. The data on GDP and hours worked at the national level by economic activity (using NACE Rev. 2 classification) is used to perform decoposition of productivity growth at the industry level.

[26] https://www.oecd-ilibrary.org/employment/data/oecd-productivity-statistics_pdtvy-data-en

A.3 EU Labour Force Survey

The EU-LFS[27] is a household sample survey that provides quarterly and annual results on the labor participation, as well as information on individuals outside the labor force. The survey covers persons aged 15 years and older who live in private households and includes employees across all industries and occupations. Conducted by national statistical institutes across Europe since 1983, the survey includes approximately 1 million individuals each year[28].

The data used in this paper is primarily Spanish, and the data on other countries is used for cross-country comparisons of educational attainment in the motivation section only. Spanish survey covers the years 1986–2019, with an unrestricted sample consisting of around 5 million individual observations. It is representative in terms of gender, age, and labor force composition, and includes both individuals within and outside the labor force. Additionally, it closely mirrors the fraction of the foreign-born population compared to administrative data, provided by INE.

After restricting the sample to include the years for which all the crucial variables are available, I obtain a sample of roughly 2.6 million individuals aged 16–65, covering the period from 1995 to 2019. Years after 2019 are excluded due to the start of COVID-19 pandemic. The survey provides individual yearly weights, which are used to make comparisons across different years. The summary statistics for this sample are presented in Table A1.

A.4 European Community Household Panel

The European Community Household Panel (ECHP) was an annual panel survey conducted over eight years (1994–2001) across 14 EU countries. It collected comprehensive data on households and individuals, covering income, employment, housing, health, social relations, and demographics, providing valuable insights into living conditions across Europe.

The data on workers' labor force participation, employment, enrollment, and earnings is used to estimate the parameters of the model, including human capital transferability matrices, moving costs matrices, and human capital spillovers.

A.5 FRED Database

Data from FRED[29] is used to analyze the dynamics of housing prices and new residential construction during the period between 1995 and 2007. The housing price index (HPI) and new

[27] https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

[28] The number slightly varies by year. For example, in 2021, the quarterly EU-LFS sample size was around 1.1 million people.

[29] https://fred.stlouisfed.org

Table A1: LFS Data Summary Statistics

	Time period: 1995-2019	
Statistics	Unweighted sample	Weighted sample
# of observations (thousands)	$2,611$	$2,611$
% of female	50.8	49.9
mean age	40.6	40.2
% of 16-20 y.o.	9.5	8.5
% of 21-25 y.o.	10.1	9.4
% of foreign-born	5.3	11.6
% of urban	68.7	75.7
% of completed high education	23.4	26.4
% enrolled (any level)	17.5	17.2
labor force participation, %	65.0	69.2
unemployment, %	15.4	16.8

Note: This table provides the means for the key characteristics of the population of 16-65 y.o. for period 1995-2019, observed in the EU Labour Force Survey. The sample is obtained after keeping observaitons, for which we know the country of birth, age, sex, level of urbanization of the place of residence, current school enrollment status, previous educational level, labor force participation, and yearly weight used for aggregation. The left column presents the results computed without using the weights, while the right columns weighs every observation using weights provided by Eurostat.

residential construction data for the period 1995 to 2018 for several European countries including Spain are shown in the Empirical Appendix B, with new residential construction measured by the number of thousands of new construction sites started each year.

A.6 Instituto Nacional de Estadística (INE)

The Spanish National Statistics Institute (INE)[30] provides data on GDP, total hours worked, and population at the level of autonomous communities. Specifically, it covers 19 administrative divisions, consisting of 17 autonomous communities and 2 autonomous cities (Ceuta and Melilla). GDP and hours data are sourced from the regional national accounts, with GDP measured in current prices, which I convert to constant prices using annual CPI data. Population data is categorized by age and gender groups. I also use data on the total number of workers to compute

[30] https://www.ine.es

an alternative measure of labor productivity – GDP per worker – for robustness exercises. The data on hours worked is only available during the period between 2000 and 2020.

B Empirical Appendix

B.1 Productivity and Housing Boom across Countries

As shown in Figure 1, Spain was the only country that experienced such a large decline in labor productivity following the interest rates convergence period in 1995-2007. The next Figure A1 shows that it was also the only country to experience such a big boom in the construction industry during the period, confirming that the housing boom in Spain played an important role in determining the productivity dynamics. During the later 2000s, France also slightly increased its construction, however this increase was much smaller than in Spain and the new level was maintained after 2007.

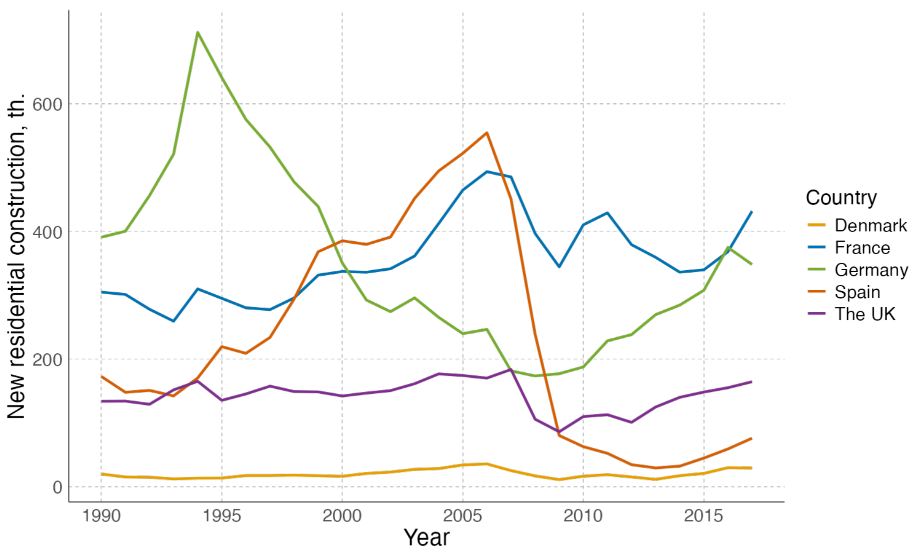
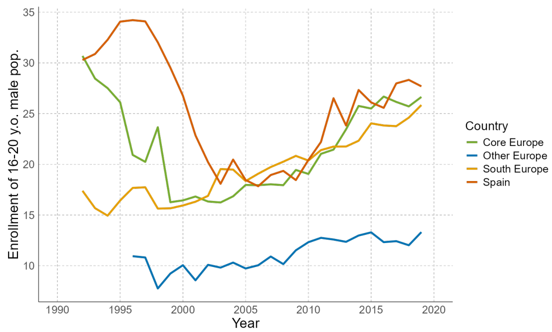


Figure A1: New residential construction by country

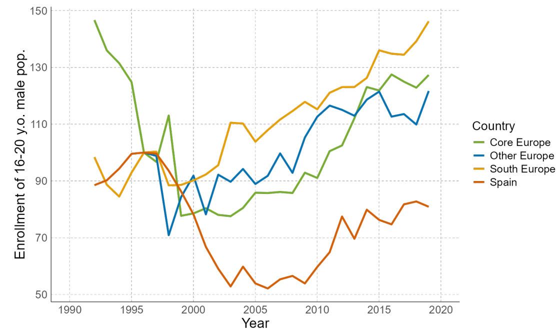
Note: Data Source: FRED. New residential construction is measured in thousands of new units and, therefore, represents the flow of new housing in each year.

In terms of enrollment, Spain was also the only country that experienced such a sharp decline in enrollment rates during the boom. First, from the left panel of Figure A2, we can see that Spain had the highest enrollment rates prior to the boom, significantly exceeding those in Southern and Northern Europe. Between 1992 and 1995, Spain's enrollment rates even surpassed those of Central European countries such as Germany and France.

From the right panel of Figure A2, it is evident that the decline in Spanish enrollment after 1995 was twice as large as in any other country. Core European countries experienced a decline in higher education attainment before the shock, which can be attributed to reforms in vocational training—a system that was not highly developed in Spain.



(a) enrollment



(b) enrollment, normalized

Figure A2: Enrollment rates by country

Note: This figure plots enrollment rates of 16-20 y.o. male population in different countries. The left panel plots the actual enrollment rates, while the right panel plots enrollment rates normalized to 100 in 1995 for all countries. Both panels use data from the EU Labour Force Survey. Core Europe average is unweighted average for Austria, Belgium, France and Germany. South Europe includes Greece, Italy, and Portugal, and Other Europe includes Denmark, Finland, Sweden, and Switzerland. The data for most countries is available starting from 1992, while some countrues only appeared in the survey in 1995.

Labor productivity dynamics by industry are presented in Figure A3. During the period 1995–2000, the largest declines in productivity were observed in the low-skill sectors, which include construction and low-skill services. Among these, construction contributed approximately 10% of annual GDP in 2000.[31], and the initial decline in Spanish labor productivity, as evident from cross-country comparisons, was largely driven by the construction sector. From 2000 onward, a decline in low-skill services productivity also became more apparent.[32] This group of sectors is the largest in the Spanish economy, and it accounted for 25% of annual real GDP at the beginning of the 2000s.

[31] National accounts data from INE.

[32] By low-skill services, I denote wholesale and retail trade, accomodation and food sector, which corresponds to G, H, I sectors in NACE Rev. 2 classification.

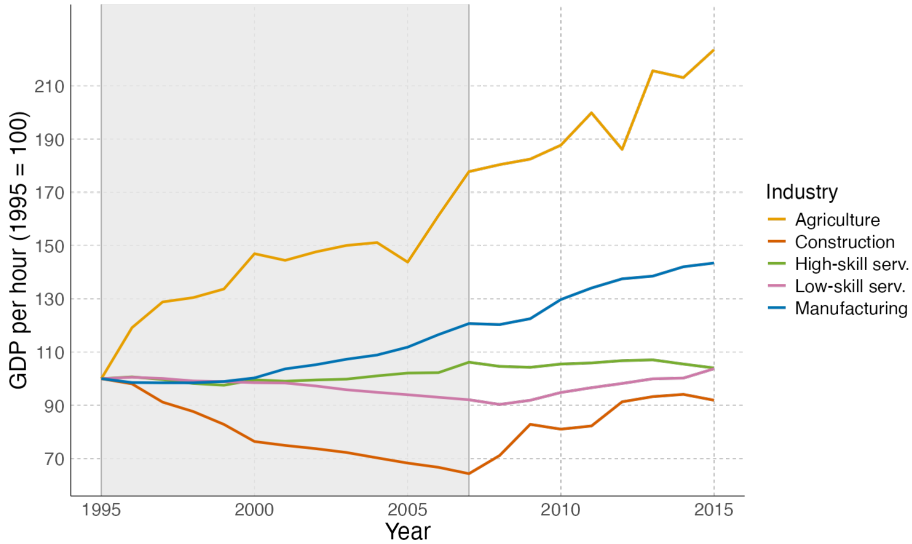
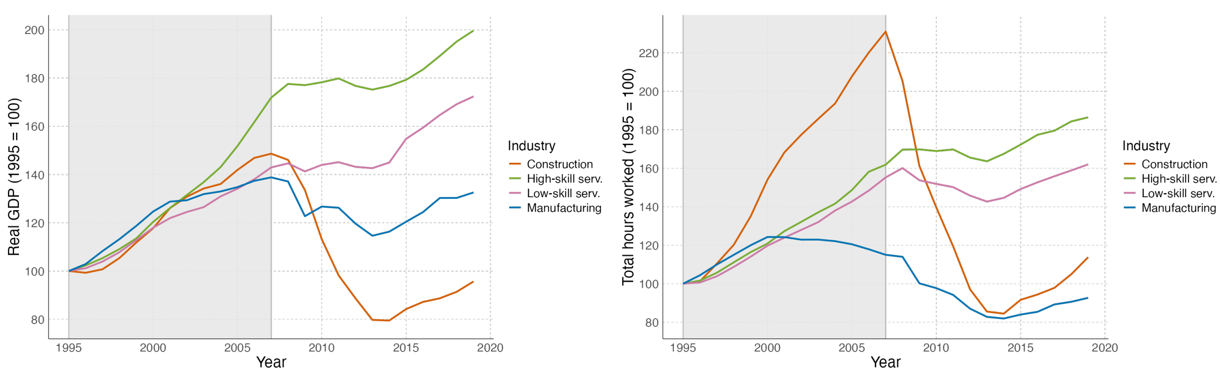


Figure A3: Labor productivity in Spain, by industry

Note: Data Source: EU KLEMS Database, national accounts. Industry classification using NACE Rev. 2 is: agriculture (A), manufacturing (B-E), construction (F), low-skill services (G-I and R-S), and high-skill services (J-Q). Labor productivity is computed as real GDP per hour worked, and is normalized to 1995. The shaded region corresponds to the boom period in 1995-2007.

The next Figure A4 has both real GDP and hours by industry group. This figure emphasizes the increase in both GDP and hours worked in construction sector, and allows to assess the size of the particular industry for the whole economy.



(a) real GDP

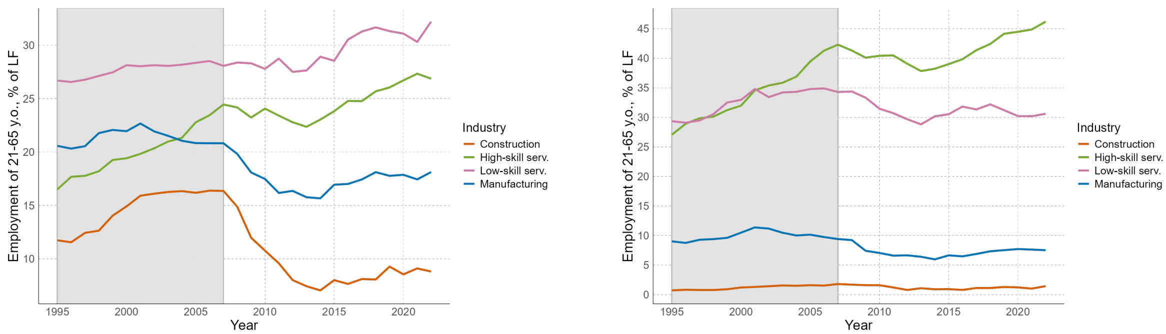
(b) total hours worked

Figure A4: Real GDP and hours by industry, 1995-2020

Note: Data Source: EU KLEMS Database, national accounts. Industry classification using NACE Rev. 2 is: manufacturing (B-E), construction (F), low-skill services (G-I and R-S), and high-skill services (J-Q). Both real GDP and hours worked are normalized to 100 in 1995 for all sectors.

B.2 Labor Allocation and Educational Attainment

Employment rates of 21-65 y.o. male and female workers is presented in Figure A5.

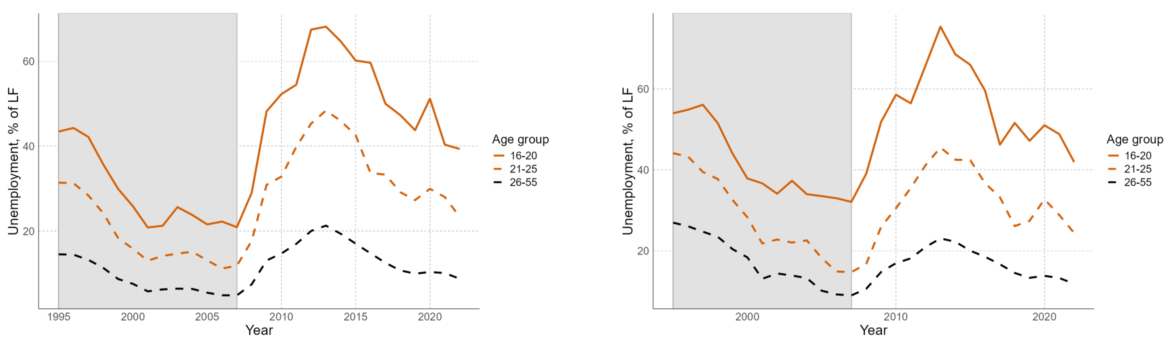


(a) 21-65 y.o., male pop.

(b) 21-65 y.o., female pop.

Figure A5: Employment rates of 21-65 y.o. male and female workers, by sector

Note: This figure plots employment rates of male and female workers, computed as the percentage of labor force employed in various sectors of the economy. The left panel plots employment rates for 21-65 y.o. male workers, while the right panel plots employment rates for 21-65 y.o. female workers. Both panels use data from the EU Labour Force Survey. Sectors' classification is based on NACE Rev. 2 classification.



(a) male pop.

(b) female pop.

Figure A6: Unemployment rates, by age group

Note: This figure plots unemployment rates of 16-55 y.o. male and female workers, computed as the percentage of the labor force who are unemployed (searching for a job). The whole sample is divided into age groups 16-20 y.o., 21-25 y.o., and 26-55 y.o. The figure uses data from the EU Labour Force Survey.

Since construction is one of the sectors that employs low-skilled labor, a positive shock to this sector can potentially influence migration patterns. As can be observed from Figure A7, the significant increase in construction employment during the housing boom was primarily driven by the reallocation of native-born workers and was not fully absorbed by migration flows.

In Figure A8, I show that the changes in reginoal employment in low-skill sectors during

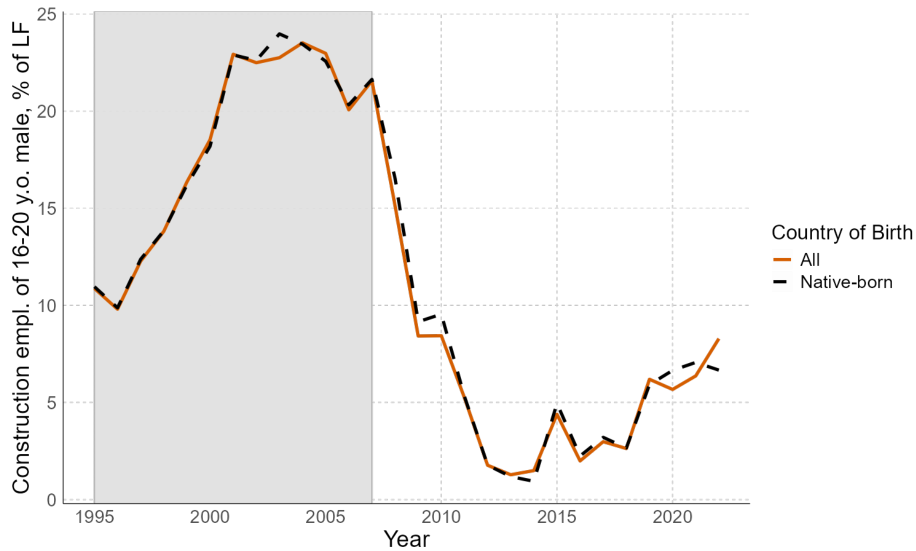
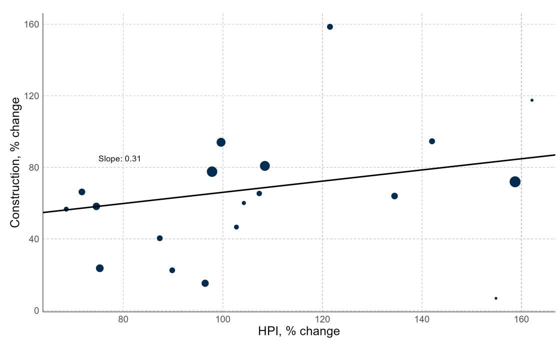


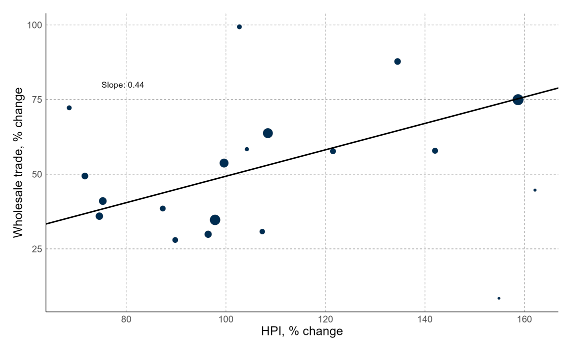
Figure A7: Construction employment of 16-20 y.o. male workers

Note: This figure plots construction employment rates of 16-20 y.o. male workers, computed as % of the labor force employed in construction. The orange line reflects construction employment of both native- and foreign-born male workers, while the blue line plots construction employment rates of the native-born workers only. The figure uses data from the EU Labour Force Survey.

the boom was positively correlated with the increases in housing prices, providing the evidence that the housing boom led to improvinf opportunities in the labor market for unskilled workers.



(a) construction



(b) wholesale

Figure A8: Employment and housing prices

Note: This figure plots the changes in employment rates of 21-65 y.o. male and female workers in construction and wholesale respectively, against the changes in regional housing prices. The plot uses data from the EU Labour Force Survey and BBVA foundation and Ivie.

Shift-Share IV

Construction employment of 16-20 y.o. male workers by ISCO08 occupation is below.

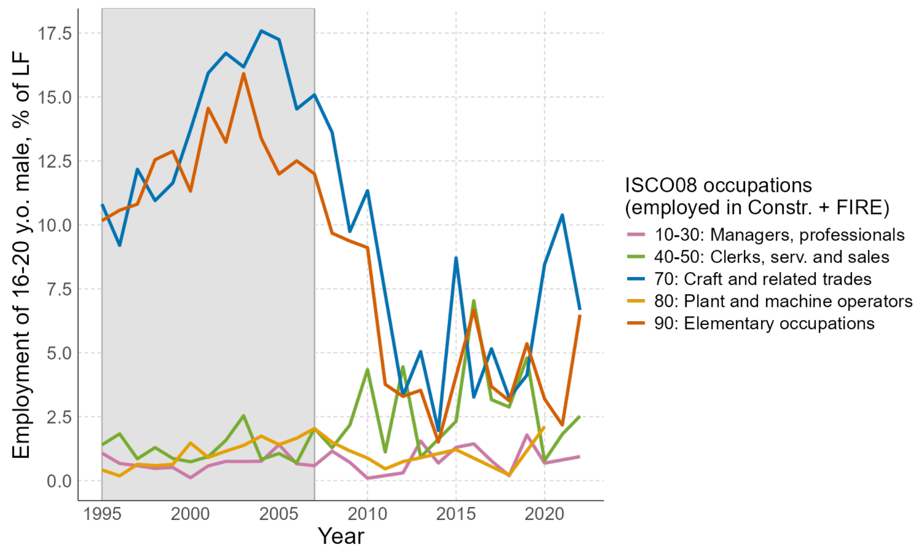


Figure A9: Construction employment, by occupation

Note: This figure plots construction employment rates of 16-20 y.o. male workers, by ISCO-8 1-digit occupation. The figure uses data from the EU Labour Force Survey.

Table A2: Rotemberg weights summary

	Sum	Mean	Share
Panel A. Negative and positive weights			
Positive	30.241	0.315	0.542
Negative	−29.241	−0.305	0.458
	$\hat{\alpha}_h$	g_h	$\hat{\beta}_h$
Panel B. Top three Rotemberg weight occupations			
70: Craft and related trades (1999)	5.061	9.646	−4.744
70: Craft and related trades (2003)	1.840	4.500	−3.719
70: Craft and related trades (1996)	1.578	2.430	−2.569

Note: This table shows summary of the Rotemberg weights, where the data is for the boom period.

Table A3: Correlates of occupation composition pre-shock

	70: Craft and related trade	90: Elementary occ.	Shift-share IV
% of female pop	-0.045	-0.082^{**}	2.109^{*}
	(0.068)	(0.034)	(1.253)
female employment	0.003	-0.001	0.034
	(0.005)	(0.004)	(0.094)
LFP, %	0.006	-0.009	0.150
	(0.011)	(0.006)	(0.182)
% of foreign-born pop	-0.027	0.015	-0.119
	(0.026)	(0.025)	(0.625)
$\overline{\text{age}}$	-0.006	-0.032	0.415
	(0.044)	(0.034)	(0.904)
Adj. R^2	0.057	0.605	0.405
# observations	18	18	18

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: This table presents the results of regressing top-2 Rotemberg weights occupations shares and the final shift-share IV on the regional characteristics. All models use regional cross-section for the pre-shock period, 1995, constructed using EU Labour Force Survey. Each observation is weighted by the aggregate population in the region, standard errors in parentheses are bootstraped.

To test whether IV predicts lagged construction employment or enrollment, I estimate the following regression

$$\Delta y_{it-2} = \gamma \Delta \text{shift\_share\_iv}_{it} + \epsilon_{it}$$

where Δy_{it-2} is twice lagged annual change in enrollment or construction employment (with and without other regional controls).

Table A4: Placebo test

	Dependent variable:			
	Δ constr_emp$_{it-2}$		Δ enrollment$_{it-2}$	
	(1)	(2)	(3)	(4)
Δ shift share iv$_{it}$	-0.920^{***}	1.020^{***}	-0.425	-0.527
	(0.296)	(0.280)	(0.542)	(0.434)
other region controls		✓		✓
# observations	216	216	216	216

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Robustness checks

Other specifications of the regression in (2) is presented below.

Table A5: Effects of housing cycle on enrollment rates: other specifications

	Dependent variable: Δ enrollment$_{it}$ for 16-20 y.o.					
	OLS			TSLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ construction emp	-0.584^{***}	-0.588^{***}	-0.616^{***}	-1.090^{*}	-1.140^{*}	-3.624
	(0.167)	(0.184)	(0.187)	(0.597)	(0.628)	(34.255)
other region controls	✓	✓	✓	✓	✓	✓
region FE		✓	✓		✓	✓
year FE			✓			✓
# observations	216	216	216	216	216	216

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: Each observation is weighted by the aggregate population in the region, standard errors in parentheses are bootstraped.

Table A6: Effects of housing cycle on education: robustness

	Dependent variable:			
	Δ enrollment$_{it}$ of 21-25 y.o.		Δ completion$_{it}$ of 21-25 y.o.	
	OLS	TSLS	OLS	TSLS
	(1)	(2)	(3)	(4)
Δ construction emp	0.107	−0.383	0.153	0.518
	(0.171)	(0.502)	(0.232)	(0.655)
other region controls	✓	✓	✓	✓
# observations	216	216	216	216

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Note: This table presents the results of estimation of the model in (2) using other endogenous variables. Standard errors in parentheses are bootstraped.

C Theory Appendix

C.1 Productivity Variance Decomposition

Here, I conduct a variance decomposition exercise, where I compute the contributions of changes in sector-specific productivity, changes in sectoral composition, and their interaction to the variance of annual percentage changes in labor productivity. We start from equation (1), and take a first-approximation for $d\text{GDPh}_t$:

$$d\text{GDPh}_t = \sum_i d\alpha_{it} \times \text{GDPh}_{it} + \sum_i \alpha_{it} \times d\text{GDPh}_{it}. \tag{A1}$$

Then, using that $\Delta\text{GDPh}_t = d \ln \text{GDPh}_t \approx \frac{d\text{GDPh}_t}{\text{GDPh}_t}$, we get

$$\begin{aligned}
\Delta\text{GDPh}_t &= \sum_i d\alpha_{it} \times \frac{\text{GDPh}_{it}}{\text{GDPh}_t} + \sum_i \frac{\alpha_{it}}{\text{GDPh}_t} \times d\text{GDPh}_{it} \\
&= \sum_i \frac{d\alpha_{it}}{\alpha_{it}} \times \frac{\alpha_{it}\text{GDPh}_{it}}{\text{GDPh}_t} + \sum_i \frac{\alpha_{it}\text{GDPh}_{it}}{\text{GDPh}_t} \times \frac{d\text{GDPh}_{it}}{\text{GDPh}_{it}} \\
&= \sum_i s_{it}\Delta\alpha_{it} + \sum_i s_{it}\Delta\text{GDPh}_{it}, \qquad \text{(A2)}
\end{aligned}$$

which is equivalent to equation (A6) in the main text. Here we use that

$$\frac{\alpha_{it}\text{GDPh}_{it}}{\text{GDPh}_t} = \frac{\frac{\text{Hours}_{it}}{\text{Hours}_t} \cdot \frac{\text{GDP}_{it}}{\text{Hours}_{it}}}{\frac{\text{GDP}_t}{\text{Hours}_t}} = \frac{\text{GDP}_{it}}{\text{GDP}_t} = s_{it}. \tag{A3}$$

Now we can derive the formula for the variance of the changes in aggregate labor productivity over time:

$$\begin{aligned}
\text{Var}(\Delta\text{GDPh}_t) &= \text{Var}\left(\sum_i s_{it}\Delta\alpha_{it} + \sum_i s_{it}\Delta\text{GDPh}_{it}\right) \\
&= \text{Var}\left(\sum_i s_{it}\Delta\alpha_{it}\right) + \text{Var}\left(\sum_i s_{it}\Delta\text{GDPh}_{it}\right) + 2\text{Cov}\left(\sum_i s_{it}\Delta\alpha_{it}, \sum_i s_{it}\Delta\text{GDPh}_{it}\right)
\end{aligned}$$

Here I am going to leave the first term as it is, for the second one

$$\text{Var}\left(\sum_i s_{it}\Delta\text{GDPh}_{it}\right) = \sum_i \text{Var}(s_{it}\Delta\text{GDPh}_{it}) + \sum_i \sum_{j\neq i} \text{Cov}(s_{it}\Delta\text{GDPh}_{it}, s_{jt}\Delta\text{GDPh}_{jt}),$$

where the double-sum takes into account all pairs (i, j) as well as (j, i), and the first term measures variance of sector-specific productivity. The last term can be rewritten as

$$2\text{Cov}\left(\sum_i s_{it}\Delta\alpha_{it}, \sum_i s_{it}\Delta\text{GDPh}_{it}\right) = 2\sum_i\sum_j \text{Cov}(s_{it}\Delta\alpha_{it}, s_{jt}\Delta\text{GDPh}_{jt}).$$

Finally, combining all the terms together we get

$$\begin{aligned}\text{Var}(\Delta\text{GDPh}_t) = &\underbrace{\sum_i \text{Var}(s_{it}\Delta\text{GDPh}_{it})}_{\text{within sector var.}} + \underbrace{\sum_i\sum_{j\neq i}\text{Cov}(s_{it}\Delta\text{GDPh}_{it}, s_{jt}\Delta\text{GDPh}_{jt})}_{\text{across-sector cov.}} \\ &+ \underbrace{\text{Var}\left(\sum_i s_{it}\Delta\alpha_{it}\right)}_{\text{sectoral composition}} + \underbrace{2\sum_i\sum_j \text{Cov}(s_{it}\Delta\alpha_{it}, s_{jt}\Delta\text{GDPh}_{jt})}_{\text{interaction term}},\end{aligned} \tag{A4}$$

which is equivalent to equation (A7) in the main text. In the initial decomposition of the productivity changes I drop the higher-order terms, which would make equation (A6) look like

$$\Delta\text{GDPh}_t = \underbrace{\sum_i s_{it}\Delta\alpha_{it} + \sum_i s_{it}\Delta\text{GDPh}_{it}}_{\text{1st-order term}} + \underbrace{\epsilon_t}_{\text{high-order term}}$$

and would appear in the variance decomposition

$$\begin{aligned}\text{Var}(\Delta\text{GDPh}_t) = &\underbrace{\sum_i \text{Var}(s_{it}\Delta\text{GDPh}_{it})}_{\text{within sector var.}} + \underbrace{\sum_i\sum_{j\neq i}\text{Cov}(s_{it}\Delta\text{GDPh}_{it}, s_{jt}\Delta\text{GDPh}_{jt})}_{\text{across-sector cov.}} \\ &+ \underbrace{\text{Var}\left(\sum_i s_{it}\Delta\alpha_{it}\right)}_{\text{sectoral composition}} + \underbrace{2\sum_i\sum_j \text{Cov}(s_{it}\Delta\alpha_{it}, s_{jt}\Delta\text{GDPh}_{jt})}_{\text{interaction term}} \\ &+ \underbrace{\text{Var}(\epsilon_t) + 2\text{Cov}\left(\epsilon_t, \text{1st-order term}\right)}_{\text{residual}}.\end{aligned} \tag{A5}$$

Now, let's summarize what we have. From equation (1), to a first-order approxmation, the changes in labor productivity GDPh_t can be written as[33]

$$\Delta\text{GDPh}_t = \sum_i s_{it}\Delta\text{GDPh}_{it} + \sum_i s_{it}\Delta\alpha_{it}, \tag{A6}$$

where the first term characterizes the changes due to sector-specific productivity and the sec-

[33]Here I define $d\text{GDPh}_t = \text{GDPh}_{t+1} - \text{GDPh}_t$ and take first-order approximation around $(\alpha_{it}, \text{GDPh}_{it})$.

ond term reflects changes in sectoral composition of the economy. Here the change in labor productivity is defined as a percentage change, i.e. $\Delta \text{GDPh}_{it} = d \ln \text{GDPh}_{it}$, and the weights $s_{it} = \text{GDP}_{it}/\text{GDP}_t$ are defined as the share of sector's GDP. Using this result, the variance of changes over time can be expressed as

$$\begin{aligned} \text{Var}(\Delta \text{GDPh}_t) = & \underbrace{\sum_i \text{Var}(s_{it} \Delta \text{GDPh}_{it})}_{\text{within sector var.}} + \underbrace{\sum_i \sum_{j \neq i} \text{Cov}(s_{it} \Delta \text{GDPh}_{it}, s_{jt} \Delta \text{GDPh}_{jt})}_{\text{across-sector cov.}} \\ & + \underbrace{\text{Var}\left(\sum_i s_{it} \Delta \alpha_{it} \right)}_{\text{sectoral composition}} + \underbrace{2 \sum_i \sum_j \text{Cov}(s_{it} \Delta \alpha_{it}, s_{jt} \Delta \text{GDPh}_{jt})}_{\text{interaction term}} . \end{aligned} \tag{A7}$$

Table A7: Variance decomposition of labor productivity

Component	% of $\text{Var}(\Delta \text{GDPh}_t)$
Within-sector GDPh variance	94.8
Cross-Sector GDP covariance	-2.3
Sectoral composition term	12.1
Interaction term	-8.7
Residual term	4.1
Total changes in labor productivity	100%

Note: The residual term arises since the decomposition formula in (A7) drops the higher-order terms to begin with.

The results of the decomposition are presented in Table A7. First, we can see that the largest contributor to aggregate changes in labor productivity is the change in within-sector productivity, accounting for over 94% of the aggregate productivity variance. The next largest factor is sectoral composition component, which includes both the within-sector variance in employment shares and the cross-sector covariance term. Still, it is relatively small and accounts for around 12% of the overall variation.

C.2 Value Function Homogeneity

The value function of a worker with skill level $\ell \in \{u, s\}$, stock of human capital h, of age a, employed in sector j is then given by

$$\tilde{V}_{\ell,t}(h,a,j) = \frac{(w_{\ell,j,t}h)^{1-\gamma}}{1-\gamma} + \beta\mathbb{E}_{\epsilon}\left[\max_i \left\{\chi_{ji}^{\ell'}(a+1)\tilde{V}_{\ell',t+1}(h',a+1,i)\epsilon_i\right\}\right], \tag{A8}$$

which corresponds to equation (8) in the text. Here the new stock of human capital, h', is detemined by the law of motion (7) and the new skill level is determined by (9).

This result is driven by the fact that workers are not allowed to borrow or save, are not subject to lump sum taxes, their labor income is proportional to the stock of human capital, and CRRA utility function is homogeneous of degree $(1-\gamma)$ in h. I assume that the education subsidy and unemployment benefits are financed through proportional taxes, in which case one can think about the wage rate $w_{\ell,j,t}$ as an after-tax wage.

In this paper, I focus on the case $\gamma > 1$ and use it as the benchmark for quantification. However, this property holds for CRRA utility with any parameter γ (including log utility), and therefore the model can be quantified in all such cases. Analogous to Dvorkin and Monge-Naranjo (2019), who assume idiosyncratic productivity shocks that are distributed Frechet and derive the implied distributions for continuation value shocks, in this setting one needs to assume Fréchet preference shocks when $\gamma \in (0,1)$ and Gumbel shocks for log utility, instead of the Weibull shocks described here.

We will guess and verify that the following holds for the worker's value fucntion (Proporition 1):

$$\tilde{V}_{\ell,t}(h,a,j) = V_{\ell,t}(a,j)h^{1-\gamma}.$$

This guess implies that the value function in (8) can be rewritten as

$$V_{\ell,t}(a,j)h^{1-\gamma} = \frac{(w_{\ell,j,t}h)^{1-\gamma}}{1-\gamma} + \beta\mathbb{E}_{\epsilon}\left[\max_i \left\{\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(h')^{1-\gamma}\epsilon_i\right\}\right], \tag{A9}$$

and applying the law of motion (7),

$$V_{\ell,t}(a,j)h^{1-\gamma} = \left(\frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} + \beta\mathbb{E}_{\epsilon}\left[\max_i \left\{\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\epsilon_i\right\}\right]\right)h^{1-\gamma},$$

from which we can factor out $h^{1-\gamma}$ from both sides and confirm that the value function is homogeneous of degree $1-\gamma$ in h. Hence, we get

$$V_{\ell,t}(a,j) = \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{\epsilon}\left[\max_{i}\left\{\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\epsilon_i\right\}\right], \tag{A10}$$

which is the same as the equation (10) in the text.

For the last period of a worker's lifetime, $a = A$, we have

$$\tilde{V}_{\ell,t}(h,A,j) = \frac{(w_{\ell,j,t}h)^{1-\gamma}}{1-\gamma}, \tag{A11}$$

which is also homogeneous of degree $1-\gamma$ in h and, therefore, Proposition 1 holds for all $a = 1,\ldots,A$.

C.3 Workers Sectoral Choice

The optimization problem of a worker of age a, skill $\ell \in \{u,s\}$, employed in sector j at time period t is given by

$$V_{\ell,t}(a,j) = \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{\epsilon}\left[\max_{i}\left\{\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\epsilon_i\right\}\right], \tag{A12}$$

which corresponds to equation (10) in the main text.

Now we can use the distribution of the preference shocks, ϵ, and derive the analytical expression for the switching probabilities and the expectation of the future value of a worker.

Switching probabilities, $\mu_{ji,t}^{\ell}(a)$. Let me simplify the notation and denote $v_i = V_{\ell',t+1}(a+1,i)$ and $\chi_{ji} = \chi_{ji}^{\ell'}(a+1)$, where I assume that a worker of age a starts from sector j in period t and decides on a sector for period $t+1$ (when she is of age $a+1$). Also note that since CRRA parameter is chosen to be $\gamma > 1$, both the per-period utility and the value function are negative.

The probability of switching from sector j to sector i can then be written as

$$\begin{aligned}
\mu_{ji} &= \mathbb{P}\left(\max_{n\in\mathcal{J}} \chi_{jn} v_n \tau_{jn}^{1-\gamma}\epsilon_n = \chi_{ji} v_i \tau_{ji}^{1-\gamma}\epsilon_i\right) \\
&= \mathbb{P}\left(\max_{n\neq i} \chi_{jn} v_n \tau_{jn}^{1-\gamma}\epsilon_n \leq \chi_{ji} v_i \tau_{ji}^{1-\gamma}\epsilon_i\right) \\
&= \mathbb{P}\left(\max_{n\neq i} \epsilon_n \geq \frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{jn} v_n \tau_{jn}^{1-\gamma}}\epsilon_i\right)
\end{aligned}$$

Using the CDF of Weibull distribution with shape parameter κ and scale parameter λ_j, so that its CDF is given by $F_j(\epsilon) = 1 - \exp(-(\epsilon/\lambda_j)^\kappa)$, we can write

$$
\begin{aligned}
\mu_{ji} &= \int_0^\infty \prod_{n\neq i} \left(1 - F_n\left(\frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{jn} v_n \tau_{jn}^{1-\gamma}} \epsilon_i\right)\right) f_i(\epsilon_i) d\epsilon_i \\
&= \int_0^\infty \prod_{n\neq i} \exp\left(-\left(\frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{jn} v_n \tau_{jn}^{1-\gamma}} \epsilon_i/\lambda_n\right)^\kappa\right) \frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1} \exp(-(\epsilon_i/\lambda_i)^\kappa) d\epsilon_i \\
&= \int_0^\infty \frac{\prod_{n\in\mathcal{J}} \exp\left(-\left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa} (\epsilon_i/\lambda_i)^\kappa\right)}{\exp(-(\epsilon_i/\lambda_i)^\kappa)} \frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1} \exp(-(\epsilon_i/\lambda_i)^\kappa) d\epsilon_i \\
&= \int_0^\infty \exp\left(-\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa} (\epsilon_i/\lambda_i)^\kappa\right) \frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1} d\epsilon_i
\end{aligned}
$$

Now we can multiply and divide this integral by a constant $\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}$ and integrate

$$
\begin{aligned}
\mu_{ji} = &\left(\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1} \\
&\times \int_0^\infty \exp\left(-\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa} \left(\frac{\epsilon_i}{\lambda_i}\right)^\kappa\right) \left(\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right) \frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1} d\epsilon_i \\
= &\left(\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1} \left[1 - \exp\left(-\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa} \left(\frac{\epsilon_i}{\lambda_i}\right)^\kappa\right)\right]\Bigg|_0^\infty \\
= &\left(\sum_{n\in\mathcal{J}} \left(\frac{\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1} = \frac{(\chi_{ji} v_i \tau_{ji}^{1-\gamma}\lambda_i)^{-\kappa}}{\sum_{n\in\mathcal{J}}(\chi_{jn} v_n \tau_{jn}^{1-\gamma}\lambda_n)^{-\kappa}}.
\end{aligned}
$$

Going back to the original notation, it can be rewritten as

$$
\mu^\ell_{ji,t}(a) = \frac{\left(-\chi^{\ell'}_{ji}(a+1)V_{\ell',t+1}(a+1,i)(\tau^{\ell'}_{ji})^{1-\gamma}\lambda_i\right)^{-\kappa}}{\sum_{n\in\mathcal{J}}\left(-\chi^{\ell'}_{jn}(a+1)V_{\ell',t+1}(a+1,n)(\tau^{\ell'}_{jn})^{1-\gamma}\lambda_n\right)^{-\kappa}}, \tag{A13}
$$

which corresponds to equation (12) in the main text. Here I multiply both the numerator and the denominator by -1 for convenience, since all value functions $V_{\ell,t+1}(a+1,i)$ are negative.

Expected future value. Now I turn to deriving the expression for the expected future value. From now on, I will use the same notation as for deriving the switching probabilites.

$$\mathbb{E}_\epsilon\left[\max_{i\in\mathcal{J}} \chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon_i\right] = \sum_{i\in\mathcal{J}}\int_0^\infty (\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon_i)\prod_{n\neq i}\left(1-F_n\left(\frac{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}{\chi_{jn}v_n\tau_{jn}^{1-\gamma}}\epsilon_i\right)\right) f_i(\epsilon_i)d\epsilon_i$$

$$= \sum_{i\in\mathcal{J}}\int_0^\infty (\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon_i)\frac{\prod_{n\in\mathcal{J}}\exp\left(-\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa}\right)}{\exp(-(\epsilon_i/\lambda_i)^\kappa)}$$

$$\times\frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1}\exp(-(\epsilon_i/\lambda_i)^\kappa)d\epsilon_i$$

$$= \sum_{i\in\mathcal{J}}\int_0^\infty (\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon_i)\exp\left(-\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}(\epsilon_i/\lambda_i)^\kappa\right)\frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1}d\epsilon_i$$

Now we can use the same trick as before and multiply and divide this expression by a constant $\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}$. Then we get

$$\mathbb{E}_\epsilon\left[\max_{i\in\mathcal{J}} \chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon_i\right] =$$

$$= \sum_{i\in\mathcal{J}}\left\{\left(\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1}(\chi_{ji}v_i\tau_{ji}^{1-\gamma})\right.$$

$$\left.\times\int_0^\infty \epsilon_i\exp\left(-\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}(\epsilon_i/\lambda_i)^\kappa\right)\left(\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)\frac{\kappa}{\lambda_i}\left(\frac{\epsilon_i}{\lambda_i}\right)^{\kappa-1}d\epsilon_i\right\}$$

$$= \sum_{i\in\mathcal{J}}\left(\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1}(\chi_{ji}v_i\tau_{ji}^{1-\gamma})\left(\sum_{n\in\mathcal{J}}\left(\frac{\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i}\right)^{-\kappa}\right)^{-1/\kappa}\lambda_i\Gamma\left(1+\frac{1}{\kappa}\right)$$

$$= \sum_{i\in\mathcal{J}}\frac{(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i)^{-\kappa}}{\sum_{n\in\mathcal{J}}(\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n)^{-\kappa}}(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i)\left(\frac{\sum_{n\in\mathcal{J}}(\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n)^{-\kappa}}{(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i)^{-\kappa}}\right)^{-1/\kappa}\Gamma\left(1+\frac{1}{\kappa}\right)$$

$$= \Gamma\left(1+\frac{1}{\kappa}\right)\left(\sum_{i\in\mathcal{J}}(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i)^{-\kappa}\right)^{-1/\kappa},$$

where I use that $\lambda_i\Gamma(1+1/\kappa)$ is the mean of Weibull distribution, and computing this integral is equivalent to computing the expectation of a random variable with $Weibull\left(\kappa,\left(\frac{\sum_{n\in\mathcal{J}}(\chi_{jn}v_n\tau_{jn}^{1-\gamma}\lambda_n)^{-\kappa}}{(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\lambda_i)^{-\kappa}}\right)^{-1/\kappa}\lambda_i\right)$

Finally, going back to the original notation, I get

$$\mathbb{E}_\epsilon\left[\max_{i\in\mathcal{J}} \chi_{ji} v_i \tau_{ji}^{1-\gamma}\epsilon_i\right] = \Gamma\left(1+\frac{1}{\kappa}\right)\left(\sum_{i\in\mathcal{J}}(\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\lambda_i)^{-\kappa}\right)^{-1/\kappa}, \tag{A14}$$

and the value function can be written as

$$V_{\ell,t}(a,j) = \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} - \beta\Gamma\left(1+\frac{1}{\kappa}\right)\left(\sum_{i\in\mathcal{J}}(-\chi_{ji}^{\ell'}(a+1)V_{\ell',t+1}(a+1,i)(\tau_{ji}^{\ell'})^{1-\gamma}\lambda_i)^{-\kappa}\right)^{-1/\kappa}, \tag{A15}$$

which corresponds to equation (**??**) in the main text.

C.4 Solution Algorithm

The algorithm used to compute both the steady state of the economy and its transition path is based on backward and forward loops. For the steady state, it relies on the terminal condition of the value function. For the transition path, I assume that the economy begins and ends in the same steady state[34], while incorporating the path of temporary shocks.

[34]Since the benchmark case assumes a temporary demand shock to construction, the initial and the final long-term equilibria are identical. One could potentially explore the case of a permanent shock, in which the final long-term equilibrium is different from the initial one.

Algorithm 1 Steady State in Closed Economy

Require: Parameters: $\{\beta, \gamma, \zeta, \kappa, J, A, N, tax\}$,
sector-specific $\{\varphi_j, \lambda_j, Z_j, \alpha_j, \eta_j\}$, and
skill- and age-specific $\{\tau^0, \tau^u, \tau^s, \chi^0, \chi^u(a), \chi^s(a)\}$

Result: Steady state $\{P_j, w_{\ell,j}, Y_j, V_\ell(a,j), \mu^\ell_{ji}(a), \mathcal{M}^\ell_{ji}(a), \theta_\ell(a,j), H_\ell(a,j)\}$

Initialize guess for prices and employment shares $\{P^0_j, L^0_{\ell,j}, N^0_{\ell,j}\}$;
Denote iterations as $i = 0, 1, 2, \ldots$;
while not converged **do**
  Given $\{P^i_j, L^i_{\ell,j}, N^i_{\ell,j}\}$ compute wages using (20) and (22);
  Compute education subsidy and unemployment benefits per unit of human capital;
  Set the terminal value $V^i_\ell(A+1, j) = 0$;
  for $a = A$ **downto** 1 **do**
    Given $V^i_\ell(a+1, j)$, compute $\{V^i_\ell(a,j), \mu^{\ell,i}_{ji}(a)\}$ using (11) and (12);
    Compute human capital transition matrices $\mathcal{M}^{\ell,i}_{ji}(a)$ using (15);
  end for
  Compute initial employment shares and human capital $\{\theta^i_\ell(1,j), H^i_\ell(1,j)\}$ using (19);
  for $a = 2$ to A **do**
    Given shares and stocks of human capital $\{\theta^i_\ell(a-1,j), H^i_\ell(a-1,j)\}$ and matrices $\{\mu^{\ell,i}_{ji}(a-1), \mathcal{M}^{\ell,i}_{ji}(a-1)\}$, compute $\{\theta^i_\ell(a,j), H^i_\ell(a,j)\}$ using (13)–(14) and (16)–(17);
  end for
  Compute aggregate shares and human capital $\{N^i_{\ell,j}, L^i_{\ell,j}\}$;
  Compute aggregate consumption and sectoral production;
  Solve for new prices P^{i+1}_j using (6) and market clearing conditions;
  if $\{P^{i+1}_j, L^{i+1}_{\ell,j}, N^{i+1}_{\ell,j}\}$ close to $\{P^i_j, L^i_{\ell,j}, N^i_{\ell,j}\}$ **then**
    break;
  else
    Update guess for $\{P^{i+1}_j, L^{i+1}_{\ell,j}, N^{i+1}_{\ell,j}\}$;
  end if
end while
return result

Algorithm 2 Transition Path in Closed Economy

Require: Parameters: $\{\gamma, \zeta, \kappa, J, A, N, tax\}$,
sector-specific $\{\lambda_j, Z_j, \alpha_j, \eta_j\}$,
skill- and age-specific $\{\tau^0, \tau^u, \tau^s, \chi^0, \chi^u(a), \chi^s(a)\}$, and
time-variant $\{\beta_t, \varphi_{j,t}\}$ and the length of the transition T

Result: Transition path $\{P_{j,t}, w_{\ell,j,t}, Y_{j,t}, V_{\ell,t}(a,j), \mu^{\ell}_{ji,t}(a), \mathcal{M}^{\ell}_{ji,t}(a), \theta_{\ell,t}(a,j), H_{\ell,t}(a,j)\}$

Compute initial and final steady states using Algorithm 1;
Initialize guess for tha path of prices and employment shares $\{P^0_{j,t}, L^0_{\ell,j,t}, N^0_{\ell,j,t}\}$;
Denote time as $t = 0, 1, \ldots, T+1$ and assign employment shares at $t = 0$ and value functions at $t = T+1$ to their steady-state values;
Denote iterations as $i = 0, 1, 2, \ldots$;
while not converged **do**
  for $t = 1$ to T **do**
    Given $\{P^i_{j,t}, L^i_{\ell,j,t}, N^i_{\ell,j,t}\}$ compute wages $w_{\ell,j,t}$ using (20) and (22);
    Compute education subsidy and unemployment benefits per unit of human capital;
  end for
  for $t = T$ **downto** 1 **do**
    Set the terminal value $V^i_{\ell,t}(A+1, j) = 0$;
    for $a = A$ **downto** 1 **do**
      Given $V^i_{\ell,t+1}(a+1, j)$, compute $\{V^i_{\ell,t}(a,j), \mu^{\ell,i}_{ji,t}(a)\}$ using (11) and (12);
      Compute human capital transition matrices $\mathcal{M}^{\ell,i}_{ji,t}(a)$ using (15);
    end for
  end for
  for $t = 1$ to T **do**
    Compute initial employment and human capital $\{\theta^i_{\ell,t}(1,j), H^i_{\ell,t}(1,j)\}$ using (19);
    for $a = 2$ to A **do**
      Given shares and stocks of human capital $\{\theta^i_{\ell,t-1}(a-1,j), H^i_{\ell,t-1}(a-1,j)\}$ and matrices $\{\mu^{\ell,i}_{ji,t-1}(a-1), \mathcal{M}^{\ell,i}_{ji,t-1}(a-1)\}$, compute $\{\theta^i_{\ell,t}(a,j), H^i_{\ell,t}(a,j)\}$ using (13)–(14) and (16)–(17);
    end for
    Compute aggregate shares and human capital $\{N^i_{\ell,j,t}, L^i_{\ell,j,t}\}$;
    Compute aggregate consumption and sectoral production;
    Given $\{\varphi_{j,t}\}$, solve for new prices $P^{i+1}_{j,t}$ using (6) and market clearing conditions;
  end for
  if $\{P^{i+1}_{j,t}, L^{i+1}_{\ell,j,t}, N^{i+1}_{\ell,j,t}\}$ close to $\{P^i_{j,t}, L^i_{\ell,j,t}, N^i_{\ell,j,t}\}$ **then**
    break;
  else
    Update guess for path $\{P^{i+1}_{j,t}, L^{i+1}_{\ell,j,t}, N^{i+1}_{\ell,j,t}\}$;
  end if
end while
return result

D Model Estimation

D.1 Transferability Matrices

The results of the estimation strategy described in Section 4 and specifically estimation of equation (29) for both unskilled and skilled workers is provided below[35].

Table A8: Human Capital Transition Matrix for Unskilled Workers, τ^u

From \ To	Non-employment	Construction	Low-skill serv.	Manufacturing	High-skill serv.
Non-employment	1	1.11	1.34	1.21	1.18
Construction	1	1.03	0.81	0.80	0.60
Low-skill serv.	1	1.06	1	0.89	0.85
Manufacturing	1	1.32	1.12	1.01	1.26
High-skill serv.	1	1.48	1.00	1.12	0.98

Table A9: Human Capital Transition Matrix for Skilled Workers, τ^s

From \ To	Non-employment	Construction	Low-skill serv.	Manufacturing	High-skill serv.
Non-employment	1	0.50	0.55	0.50	0.44
Construction	1	0.84	1.35	0.68	0.69
Low-skill serv.	1	1.03	0.97	0.86	0.81
Manufacturing	1	1.25	1.30	1.25	1.19
High-skill serv.	1	1.03	1.07	0.77	0.97

[35] Both for unskilled and skilled workers the coefficient from non-enmployment to manufacturing is not identified, and for the quantitative exercise I am using the average of coefficients from non-employment to all other sectors.

D.2 Spillover Parameters

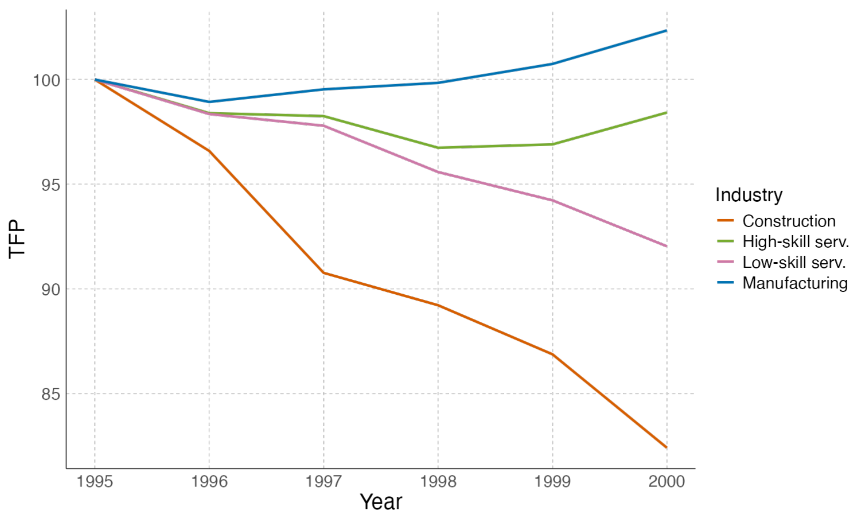


Figure A10: Utilization-adjusted TFP

Note: Data Source: EU KLEMS Database. Industries are defied using NACE Rev. 2 classification: Construction (F), Manufacturing (B-E), Low-skill services (G-I and R-S), and High-skill services (J-Q). TFP for each industry is normalized to 1995.

Table A10: Spillover and sectoral productivity parameters

Parameter	Construction	Low-skill serv.	Manufacturing	High-skill serv.
Z_j	0.69	0.42	1	0.41
η_j	0.64	0.64	0.99	0.99

Note: Productivity of manufacturing is normalized to 1. The spillover parameters are estimated for two groups of sectors—low-skill (construction and low-skill services) and high-skill (manufacturing and high-skill services), and are chosen from specification (4) of Table A11.

Table A11: Spillovers Estimation

	Dependent variable: Z_jt			
	(1)	(2)	(3)	(4)
Z_j Construction	2.726	−0.374	5.937**	−0.881*
	(2.059)	(0.307)	(2.769)	(0.470)
Z_j High-skill serv.	6.303***	−0.890**	6.398***	−1.039***
	(1.176)	(0.296)	(1.125)	(0.305)
Z_j Low-skill serv.	4.461**	−0.858**	7.317***	−1.357**
	(1.902)	(0.322)	(2.511)	(0.475)
log(TFP)			−13.272	1.836
			(8.054)	(1.322)
High-skill η_j	−9.903***	0.987**	−10.476***	1.272**
	(1.700)	(0.442)	(1.662)	(0.473)
Low-skill η_j	−4.270***	0.638***	−1.757	0.380
	(0.713)	(0.194)	(1.670)	(0.264)
Year FE		✓		✓
Observations	24	24	24	24
R^2	0.802	0.997	0.829	0.998
Adjusted R^2	0.747	0.995	0.769	0.995

Note: *p<0.1; **p<0.05; ***p<0.01

Table A12: Spillovers Estimation: Robustness

	Dependent variable: ln(Z_jt)			
	(1)	(2)	(3)	(4)
Panel A. Benchmark				
High-skill η_j	0.987**	0.886*	0.841*	0.577
Low-skill η_j	0.638***	0.634***	0.631***	0.649***
Panel B. Controling for TFP				
High-skill η_j	1.272**	1.046*	0.997*	0.878*
Low-skill η_j	0.380	0.490*	0.491*	0.377

Note: *p<0.1; **p<0.05; ***p<0.01. Column (1) uses the same data from INE as Table A11. Column (2) employs data from INE, but utilizies data on salaried employees only. Columns (3) and (4) use data from KLEMS, and column (4) adjusts total wages for changes in sector-specific price indices.

E Quantitative Results

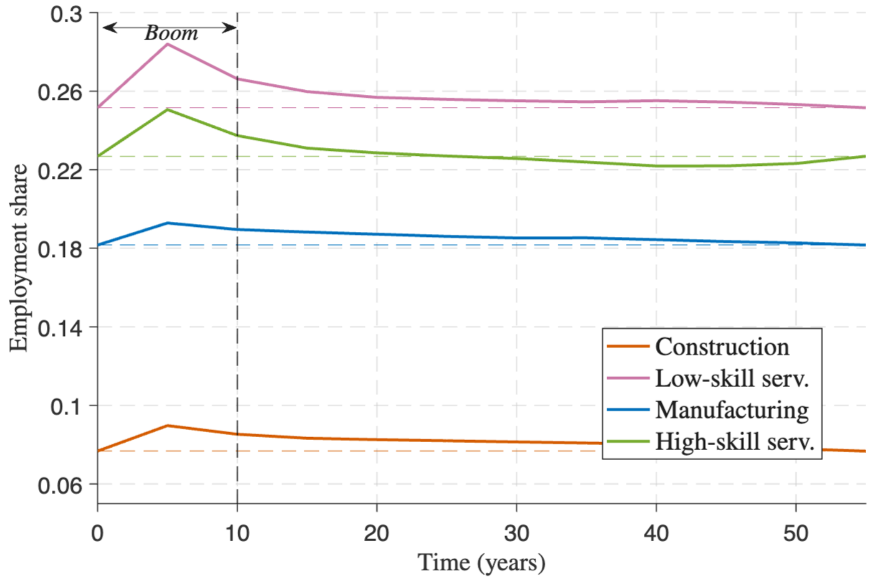


Figure A11: Employment during transition

Note: This figure plots the dynamics of the employment shares throughout the transition. The transition period consists of 5-year time periods, which are converted into years.