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

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PRELIMINARY AND INCOMPLETE

March, 2025

Most Recent Version

Abstract. This paper examines the impact of temporary sectoral shocks on human capital accumulation and introduces a structural model to quantify their long-term effects on aggregate productivity. I focus on Spain's economic boom from 1995 to 2007 as an example of a temporary demand shock affecting low-skill sectors such as construction and wholesale. I present novel empirical evidence on labor reallocation patterns across sectors and the decline in educational attainment during this period. Furthermore, I develop a quantitative life-cycle model in which workers make dynamic decisions about educational attainment while facing imperfect human capital mobility across sectors. Using this model, I quantify the role of labor supply adjustments–particularly human capital accumulation–in shaping the persistence of aggregate productivity dynamics after the boom.

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

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

[*]I would like to thank my advisors, Oleg Itskhoki, Lee Ohanian, Ariel Burstein, Jonathan Vogel, and Pierre-Olivier Weill, for their guidance and support throughout my PhD journey. I am also grateful to Pablo Fajgelbaum, Andy Atkeson, David Baqaee, Joao Guerreiro, and Gary Hansen, as well as all participants of the UCLA Macro Proseminar, UCLA Trade Proseminar, and UCLA Macro Reading Group, for their valuable comments and suggestions.

[†]This paper uses data from Eurostat, EU Labour Force Survey 1986-2022. The responsibility for all conclusions drawn from the data lies entirely with the author.

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1 Introduction

It has long been recognized that sectoral shocks, even when temporary, can have significant effects on economic growth (Lilien 1982, Long and Plosser 1987, Horvath 1998, 2000, Atalay 2017). A substantial body of literature explores the contribution of sectoral shocks to aggregate economic dynamics. For example, Horvath (2000) demonstrates that multiple sectoral shocks not only drive resource reallocation but also interact, leading to aggregate economic fluctuations. Similarly, Atalay (2017) highlights how complementarities among sectoral goods in production can amplify shocks within a single sector, substantially increasing aggregate output volatility.

Although the effects of temporary sectoral shocks on economic growth are widely acknowledged, persistence and the mechanisms driving these effects remain unresolved questions. Some studies attribute the persistence of temporary shocks to capital misallocation across firms, driven by inefficiencies in capital accumulation (Gopinath et al. 2017, García-Santana et al. 2020). Yet, while their focus is on cross-firm misallocation within sectors, it does not fully account for the asymmetric responses to shocks originating in different sectors. Other research emphasizes that permanent sectoral shocks, such as structural transformation, can affect human capital accumulation by altering workers' incentives to invest in education (Dvorkin and Monge-Naranjo 2019, Adão et al. 2020, Porzio et al. 2022). However, there is limited evidence on whether temporary shocks operate through similar mechanisms.

This paper examines the impact of temporary sectoral shocks on human capital accumulation and introduces a structural model to quantify their effects on long-term economic growth. It focuses on the economic boom in Spain from 1995 to 2007, which followed European interest rate convergence, and demonstrates that the decline in aggregate labor productivity during that period was primarily driven by a decrease in sectoral productivity and the expansion of low-skill sectors. Using this period as an example of a temporary demand shock to unskilled labor, I document labor reallocation patterns across sectors and the decline in educational attainment following the boom. Furthermore, I develop a quantitative lifecycle model with imperfect human capital mobility, which is used to estimate the role of labor supply adjustments in aggregate economic productivity growth.

The Spanish economic boom from 1995 to 2007 was characterized by large capital inflows and a rise in household debt, following the convergence of European interest rates. However, unlike other European countries that experienced similar declines in interest rates, Spain saw a decline in labor productivity growth during this period, which did not begin to recover until 2007. I decompose the changes in aggregate labor productivity and find that the decline was primarily driven by a reduction in sectoral productivity. Low-skill sectors such as construction and wholesale and retail trade expanded and contributed the most to the aggregate changes. The

housing boom, which began in the early 2000s and was driven by more affordable mortgages, further contributed to the temporary demand shock in the construction sector.

Next, using the boom period from 1995 to 2007 as an example of a temporary shock to low-skill sectors, I provide evidence of its effects 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, did not pursue higher education, leading to a permanent reduction in human capital accumulation. Specifically, employing a shift-share instrumental variable (IV) strategy, I demonstrate that regions more exposed to the housing boom experienced a sharper decline in higher education enrollment. Furthermore, the post-bust dynamics of human capital recovery occur as new cohorts acquire higher education, contributing to a slower economic transition.

Motivated by these findings, I propose an overlapping-generations model in which workers' education decisions and sectoral allocations influence human capital accumulation. The model emphasizes the significance of imperfect human capital mobility and the rising opportunity cost of education in explaining workers' sectoral reallocation and productivity dynamics following the bust. Building on the approach developed by Dvorkin and Monge-Naranjo (2019), I allow workers to choose whether to enter the unskilled or skilled labor force by acquiring education. Moreover, the model accounts for differential mobility and the transferability of sector-specific human capital across skill groups and captures the asymmetric responses of different skill groups to shocks in the sector of their comparative advantage. This quantitative model is calibrated using Spanish data and applied to counterfactual analyses of the economy's transition dynamics following the boom.

The main results are as follows. First, the model predicts an immediate decline in educational attainment among young cohorts during the boom, followed by rapid labor reallocation to the construction sector. It emphasizes that the initial decline in productivity is driven by both a decrease in skill accumulation and the reallocation of workers to less productive sectors of the economy. Second, the model highlights that the post-bust transition is primarily driven by new cohorts acquiring higher levels of education. Following the bust, productivity slowly increases as new cohorts acquire the necessary skills, while older cohorts remain locked in their sectors due to imperfect skill transferability or choose to drop out of the labor force. Finally, the counterfactual analysis demonstrates that human capital mobility across sectors—particularly lower accumulation rates in booming sectors—plays a crucial role in explaining the slow transition of the economy.

The model features static human capital spillovers to sectoral productivity in the form of external returns from the stock of educated workers' human capital, which varies across sectors. In particular, low-skill sectors such as construction and wholesale trade are characterized

by very low spillovers, while high-skill tradable sectors such as manufacturing exhibit large spillovers. The presence of such spillovers, which are not internalized by workers, leads to underinvestment in higher education, both in the long-run equilibrium and during the boom. Moreover, the asymmetry of these spillovers results in an inefficient allocation of workers across sectors in response to the shock and, together with imperfect human capital mobility, generates dynamic inefficiency and influences the entire transition path.

Related Literature This paper contributes to the broader literature on the productivity slowdown during European convergence and housing 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. 2021). It underscores the significance of labor supply composition throughout the cycle, with a particular focus on human capital accumulation and investment in education. The study emphasizes the dynamic nature of educational attainment and incorporates the concept of imperfect human capital mobility across sectors. Furthermore, it presents detailed empirical evidence on the effects of temporary sectoral shocks on education and labor allocation, proposing a novel mechanism to explain their long-term implications for economic growth.

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 housing cycle on educational attainment. It employs a Bartik instrumental variable design, as recently 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, while the national shift in construction employment across different occupations serves as the primary source of the shock.

Finally, this paper complements 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, Charles et al. 2018, Dvorkin and Monge-Naranjo 2019, Adao et al. 2021, Cascio and Narayan 2022). Unlike previous studies, it investigates the effects of temporary sectoral shocks, such as housing booms, and demonstrates that human capital accumulation plays a crucial role in explaining the persistent effects on productivity growth.

Roadmap The remainder of the paper is structured as follows. Section 2 documents the main empirical facts concerning the productivity dynamics, labor reallocation, and educational attainment in Spain during the period between 1995 and 2007. It provides an analysis of the effects of the housing boom on higher education enrollment and cohort-specific educational attainment, as well as the effects on productivity growth. In Section 3, I introduce the lifecycle

model, which incorporates dynamic education decisions and imperfect human capital mobility, and discuss its implications for long-term productivity growth. The main results, illustrated using a numerical example and detailing the effects of the boom on the economy's transition, are presented in Section 4. Section 5 briefly outlines the quantitative model for the case of a small open economy, while Section 6 provides a discussion of the results and future analysis.

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 growth 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, post-bust labor dynamics and the subsequent 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 utilize GDP and hours worked data from Spanish national accounts provided by the Spanish National Statistics Institute (INE, Instituto Nacional de Estadística). 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.

2.1 Labor Productivity Dynamics in Spain

Between 1995 and 2000, 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.

However, unlike other European countries, Spain experienced a decline in productivity growth during this period, which did not begin to recover until 2007 (see Figure 1). Prior to

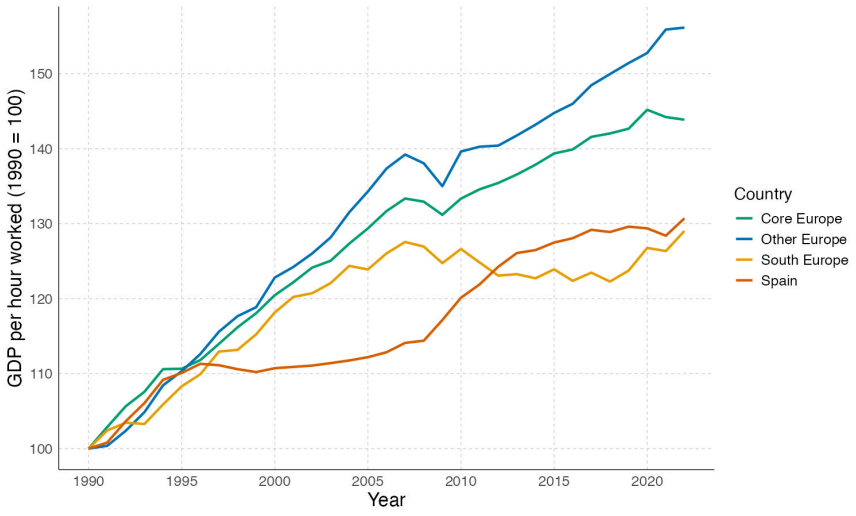


Figure 1: Labor productivity in Europe, 1990-2022

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.

this, Spain had been characterized by a very extensive rental market and high borrowing costs.[1] 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.

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 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.

FACT 1. *Labor productivity decline was 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 labor productivity across groups of European countries, as well as a counterfactual productivity measure for Spain that

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

excludes low-skill sectors. In this exercise, I completely exclude low-skill sectors, meaning that the counterfactual productivity reflects both changes in sectoral productivity and shifts in the shares of different sectors over time.[2]

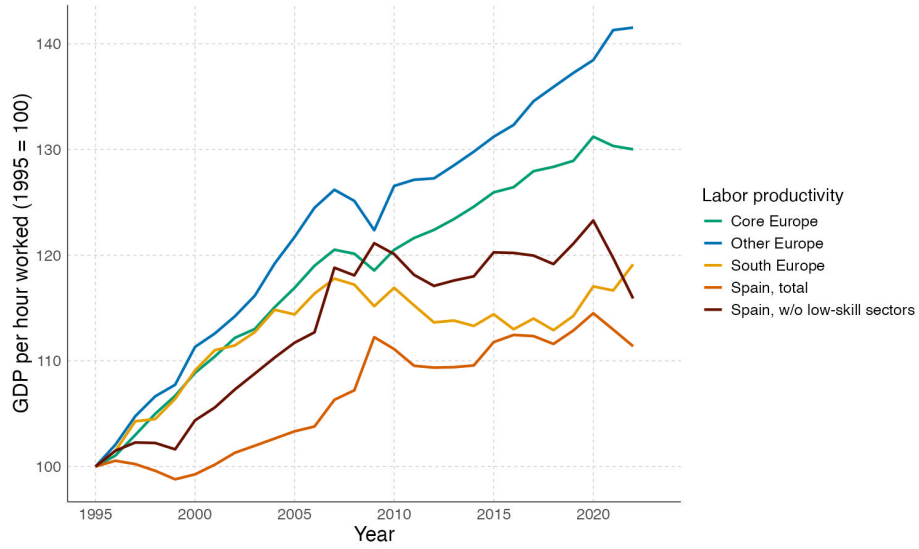


Figure 2: Labor productivity in Spain, 1995-2020

Note: Data Source: OECD Productivity Database and INE, Instituto Nacional de Estadística, National Accounts by branch of activity. Productivity without low-skill sectors excludes industry (B-E), construction (F), and wholesale (G-I). Labor productivity is computed as real GDP per hour worked, and is normalized to 1995.

As evident from this graph, in the absence of low-skill sectors, Spanish labor productivity dynamics would still have followed the average European trend and would have more closely resembled those of other Southern European countries after the 2007 recession.[3]

Notably, both the wholesale and construction sectors (included in low-skill) represented a substantial share of employment—20% and 10% respectively—and can be characterized as relatively low-skill, labor-intensive industries. While construction primarily employed low-skill male workers, the wholesale sector saw an increase in the employment of 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 low-skill sectors, I turn to the decomposition exercise below.

[2]Aggregate productivity for Spain slightly differs from the line in Figure 1, as the data I useis now coming from Spanish National Statistics Institution (INE) and not from OECD Database, and manually adjust for changes in PPP.

[3]For decomposition of Spanish labor productivity, real GDP and hours worked by narrow industry codes, see Appendix B.

FACT 2. *Labor productivity decline was primarily caused by changes in sectoral 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

$$GDPh_t = \sum_i \alpha_{it} GDPh_{it}, \tag{1}$$

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. In the second scenario, I hold sectoral productivity constant, so that all changes are driven by shifts in sectoral composition.

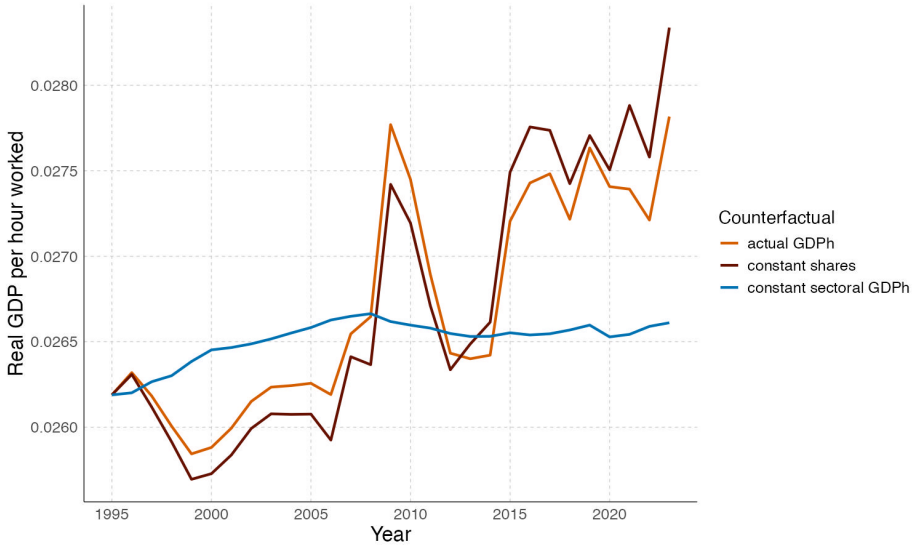


Figure 3: Counterfactual changes in labor productivity in Spain, 1995-2020

Note: Data Source: INE, National Accounts by branch of activity. Productivity with constant shares or sectoral producitivty is computed keeping the share (or sectoral GDPh) fixed at heir 1995 level.

The changes in aggregate labor productivity growth over the entire period from 1995 to 2022 are driven almost exclusively by changes in the level of sectoral 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.

Next, I perform a simple variance decomposition exercise, where I compute the contributions of changes in sectoral productivity, changes in sectoral composition, and their interaction to the variance of annual percentage changes in labor productivity. Using the formula for productivity decomposition above, the variance can be expressed as

$$Var(\Delta GDPh) = \underbrace{\sum_i s_{it}^2 Var(\Delta GDPh_i)}_{\text{within sector var.}} + \underbrace{\sum_i \sum_{j \neq i} s_{it} s_{jt} Cov(\Delta GDPh_i, \Delta GDPh_j)}_{\text{across-sector cov.}}$$
$$+ \underbrace{Var\left(\sum_i s_{it} \Delta \alpha_i\right)}_{\text{sectoral composition}} + \underbrace{\sum_i \sum_{j \neq i} s_{it} s_{jt} Cov(\Delta GDPh_i, \alpha_j)}_{\text{interaction term}} \tag{2}$$

where the weights are the GDP share of sector i in each period t. The results are presented in the table below.

Table 1: Variance decomposition for aggregate labor productivity

Component	% of $Var(\Delta GDPh)$
Within-sector GDPh Variance	87.696
Cross-Sector GDP Covariance	13.435
Sectoral Composition Term	1.999
Interaction Term	−1.749
Total changes in labor productivity	100%

From Table 1, we can see that the largest contributor to aggregate changes in labor productivity is the change in within-sector productivity, which accounts for almost 88% of the variation in aggregate GDPh. The next largest factor is the covariance between sectoral GDPh, which is positive and reflects spillovers between sectors. The sectoral composition component—which includes both the within-sector variance in employment shares and the cross-sector covariance term—is very small, accounting for less than 2% 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 construction, industry, and professional and scientific services sectors. Among these three industries, construction contributed approximately 10% of annual GDP, while professional and scientific activities accounted for about 5%, and industry for around 4% in 2000.[4] Consequently, the initial decline in

[4]National accounts data from INE.

Spanish labor productivity, as evident from cross-country comparisons, was largely driven by the construction sector. From 2000 onward, a decline in wholesale productivity became apparent.[5] This sector, the largest in the Spanish economy, 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 wholesale and construction sectors experienced the largest increases in both GDP and total hours between 1995 and 2007. During this period, public services also saw significant growth; however, this expansion was not accompanied by a corresponding increase 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.

2.2 Labor Reallocation and Educational Attainment

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 wholesale trade. In this section, I focus on labor supply adjustments as a transmission mechanism and examine how individual workers' decisions regarding sector allocation and skill accumulation changed during the boom period.

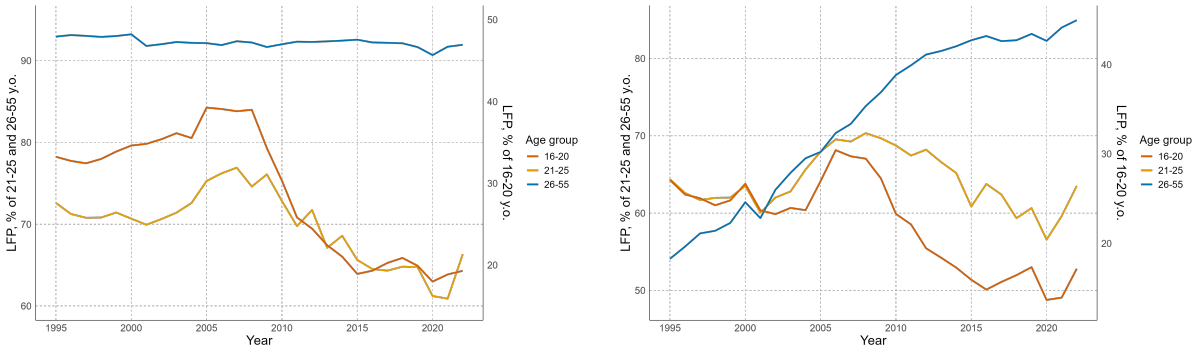
FACT 3. *Young workers increased their labor force participation and primary went to work in low-skill sectors during the boom.*

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 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 rate for older age groups remained stable throughout the housing 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 participation rate for male workers aged 16–20 increased from 33% to 39%, while for those

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

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). However, following the bust in 2008, the participation rate declined, suggesting that new incoming cohorts opted to pursue further education before entering the labor force.



(a) male population (b) female population

Figure 4: Labor fore participation, by age groups

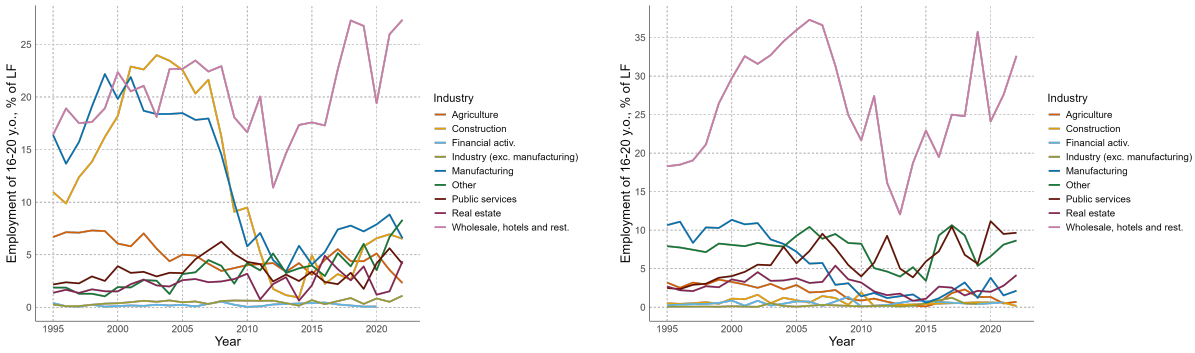
Note: This figure displays the labor force participation rates for male and female workers, calculated as the percentage of the male population that is either employed or unemployed (actively searching for a job). The sample is divided into three age groups: 16-20 years old, 21-25 years old, and 26-55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

The boom period was accompanied by a significant increase in employment within low-skill sectors, particularly construction for male workers and wholesale for female workers. This shift was most pronounced among younger workers 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, wholesale remained the largest employer of 16-20-year-old female workers throughout the period from 1995 to 2020. However, during the boom years between 1995 and 2007, the share of young female workers employed in wholesale surged from 18% to nearly 37%, before rapidly declining back 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. While wholesale and manufacturing employed as many young male workers as construction in the early years, starting in 1995, construction employment grew the most, rising from 12.5% to a peak of 22.5% in 2007 before sharply declining after the bust. In contrast, wholesale and manufacturing employment rates remained relatively stable, with manufacturing experiencing a slight decline during the 2000s.

When comparing absolute numbers, the increase in construction employment 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 throughout the housing cycle and how their opportunity costs evolved during the boom.



(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 percentage of the male population that is either employed or unemployed (actively searching for a job). Industry classification using NACE Rev. 1.1 is: agriculture (A-B), industry (C-E), manufacturing (D), construction (F), wholesale (G-I), financial activities (J), real estate (K), public services (M-N), and other (O-Q).

During the boom, employment among 21-65-year-old male and female workers remained relatively stable (see Appedix B). However, wholesale and real estate employment increased for women, while construction employment rose among older men. Although both wholesale and construction primarily employ unskilled workers and thus experienced the largest increases in young employment, real estate tends to hire women 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.

To further explore the trade-offs faced by young workers during the boom, I turn to an analysis of educational attainment in the next section. Specifically, I show that enrollment rates in higher education declined during the boom, suggesting that the expansion of the construction and wholesale sectors 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.*

Here, I provide evidence of the boom having a negative impact on higher education enrollment rates. 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. However, following the bust in 2008, the enrollment of this group did not completely catch up with the pre-shock levels. In contrast, the post-bust enrollment of female population reached the pre-shock level by 2020.

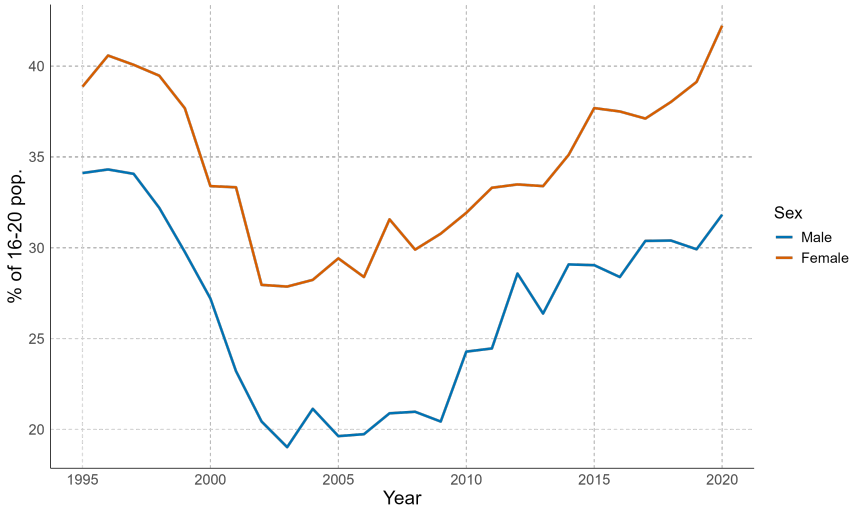


Figure 6: Enrollment of 16-20 y.o. in higher education, by sex

Note: This figure plots enrolllment 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. This figure uses data from the EU Labour Force Survey.

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 housing boom, construction employment surged, primarily by 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[6]. Below, I present reduced-form evidence suggesting that this expansion was

[6]See Appendix B.

accompanied by lower enrollment in higher education.

In order to determine whether the trends in enrollment rates are correlated with the exposure to the housing boom, I employ regional variation in construction employment and enrollment rates. I estimate the following regression

$$\Delta enroll_rate_{it} = X'_{it}\beta + \gamma \Delta constr_emp_{it} + \mu_i + \epsilon_{it} \tag{3}$$

where all observations correspond to region i and year t. $\Delta enroll_rate_{it}$ represents the growth rate of enrollment rates for the 16-20-year-old male population, $\Delta constr_emp_{it}$ 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 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[7]. The shift-share instrumental variable (IV) is then constructed using nationwide changes in construction employment as the magnitude of the shock, while pre-shock occupation shares—those not directly affected by the housing shock—serve as a measure of region i's exposure. The resulting variable is

$$\Delta constr\ IV_{it} = \sum_c \Delta constr_emp_{ct} \times share_{ci\tau} \tag{4}$$

[7]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.

where $\Delta constr_emp_{ct}$ is the construction employment growth of occupation c in year t across the whole of Spain, and $share_{ci\tau}$ 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[8] 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.

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 2[9]. 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 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

[8]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.

[9]For estimation results with an alternative set of controls, see Table **??**.

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 2: 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^{***}	-0.323	-0.318^{**}	-1.090^{**}	-0.475	-0.303
	(0.167)	(0.271)	(0.158)	(0.538)	(0.566)	(0.247)
first stage				1.128^{***}	0.711^{***}	0.783^{***}
				(0.285)	(0.078)	(0.052)
# observations	216	213	429	216	213	429

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: This table presents the results of estimation of the model in (3) using OLS and IV estimators. Columns 1-3 present the estimators for paramter 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 in parentheses are bootstraped.

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

Another notable result from Table 2 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. *Completion rates for 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 7 shows that for cohorts born before the housing 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 when the housing boom started in 1998 (cohorts born between 1978-1988), 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.

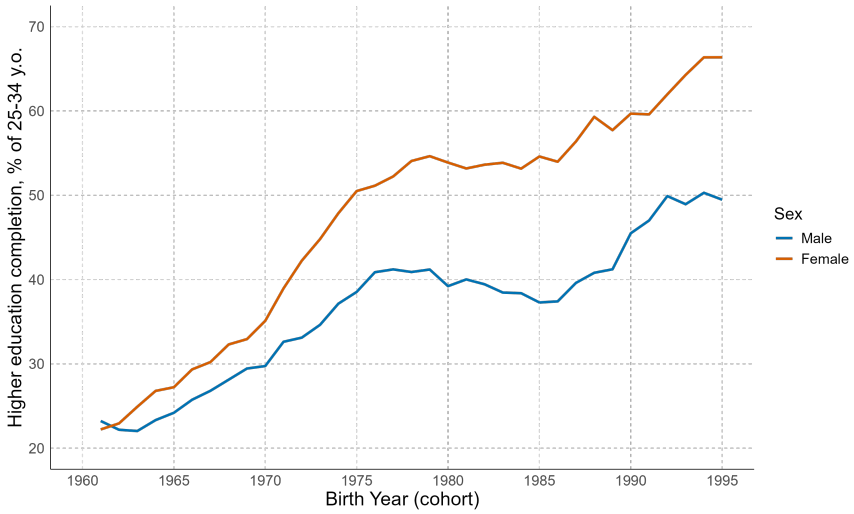


Figure 7: Higher education completion rates, by cohort

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 year *XXXX* who completed higher education by the age of 35. 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 housing 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 wholesale sectors. Second, the decline in educational attainment among cohorts affected by the housing 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.

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 wholesale. 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. Finally, I show that the impact of the housing 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 Setup

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 shifts in the opportunity cost of education for different cohorts during and after the boom. Furthermore, the imperfect mobility of human capital across sectors creates a "lock-in" mechanism, particularly for older cohorts who entered the booming low-skill sector during the boom, in contrast to incoming cohorts. The sluggishness of labor reallocation and human capital investment through education is the key channel driving the persistent effects of the temporary sectoral shock on aggregate productivity.

In this model, an infinite-horizon closed economy is populated by generations of workers who acquire education and supply labor to different sectors of the economy. Time is discrete and indexed by t. Workers' dynamic sector choices influence their human capital and are subject to idiosyncratic productivity shocks. Each worker lives for A periods, and size of each cohort is assumed to remain constant over time.

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 hand-to-mouth consumers have standard CRRA utility with parameter $\gamma > 1$ and discount factor $\beta \in (0, 1)$. In each time period t, the household receives per-period utility

$$u_t = \frac{c_t^{1-\gamma}}{1-\gamma}, \qquad \gamma > 1. \tag{5}$$

Utility of the consumer depends on consumption of the composite good, which is given by a constant-elasticity-of-substitution (CES) aggregator over consumption goods in sectors $1, \ldots, J$

$$c_t = \left(\sum_{j=1}^{J} \varphi_{j,t}^{\frac{1}{\zeta}} c_{j,t}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}}, \tag{6}$$

where the elasticity of substitution between all the goods is given by ζ, while the preferences of consumers over various goods are given by demand shifters $\varphi_{j,t}$ (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.[10]

Aggregating over all the workers in this economy, we can further derive the sectoral demand in the economy 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:

$$C_{j,t} = \varphi_{j,t} P_{j,t}^{-\zeta} P_t^{\zeta} C_t, \qquad \text{where } P_t = \left(\sum_{j=1}^{J} \varphi_{j,t} P_{j,t}^{1-\zeta} \right)^{\frac{1}{1-\zeta}}. \tag{7}$$

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 productivity shocks.

There are two types of workers in the economy – unskilled and skilled. Everyone is born unskilled, with the initial stock of human capital $h = 1$, and can become skilled via acquiring education. In every period, an unskilled worker chooses which sector to work in and whether to get higher education or not. Once a worker receives higher education, she becomes skilled and receives a skill premium for each unit of her human capital in every sector.

In each period t, a worker receives a realization of her labor market opportunities for each sector $\epsilon_t = \{\epsilon_t^j\} \in \mathbb{R}_+^{J+2}$ (or $\mathbb{R}_+^{J+1}$ in case of a skilled worker), where each ϵ_t^j is drawn from Frechet distribution with CDF $F(\epsilon) = \exp\left(-(\epsilon/\lambda)^{-\kappa}\right)$, with the shape parameter $\kappa > 0$ and scale parameter $\lambda > 0$. In this specification, the idiosyncratic shock can be viewed as an unex-

[10] Since all the consumers are identical in terms of their preferences, the aggregate demand in the economy can be written as a CES aggregator of the same form

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

where each $C_{j,t}$ is the aggregate consumption of good j.

pected shock to a productivity of a worker in a given sector, or in other words, it represents a random draw of relative ptoductivities across sectors in a given period (worker's comparative advantage).

For both unskilled and skilled workers, their stock of human capital changes according to the law of motion below. When a worker with initial stock of human capital h_t is moving from sector j to i between periods t and $t+1$, her human capital in $t+1$ is given by

$$h_{t+1} = \tau^{\ell}_{ji} h_t \epsilon^i_t, \tag{8}$$

where h_t and h_{t+1} are the corresponding stocks of human capital in period t and $t+1$, and ϵ_t is the vector of labor market opportunities in period t. The stock of human capital h represents the absolute advantage of a worker. Transition matrix τ^{ℓ} (where $\ell \in \{u, s\}$ denotes the skill level) reflects how much of human capital can be transferred from one sector to the other. A natural assumption would be that $\tau_{jj} \geq 1$ and $\tau_{ji} \leq 1$ (for all $i \neq i$), which means that there is sector-specific human capital accumulation when a worker stays in the same sector and human capital depreciation when a worker switches to a different 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 innovations: (i) introducing two skill types of workers, (ii) adding an education sector and allowing workers to change their type, and (iii) explicitly modeling the finite lifetime of overlapping cohorts. Moreover, in my model, 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.

The value function of a worker with skill level $\ell \in \{u, s\}$, stock of human capital h, of age a, employed in sector $j \in \{0, 1, \ldots, J, J+1\}$ is then given by

$$\tilde{V}_{\ell,t}(h, a, j, \epsilon) = \frac{(w_{\ell,j,t} h \epsilon^j)^{1-\gamma}}{1-\gamma} + \beta \max_i \left\{ \chi_{ji} \mathbb{E}_{\epsilon'} \left[\tilde{V}_{\ell',t+1}(h', a+1, i, \epsilon') \right] \right\}, \tag{9}$$

where $w_{\ell,j,t}$ is a wage rate for unit of human capital stock in sector j, and h' denotes the human capital in the next period (detemined by (8)), while ℓ' is the skill level of a worker in the next period (changes in case a worker acquires education). Matrix χ is the matrix of switching costs, with χ_{ji} being the utility cost of moving from sector j to sector i. I assume no cost of staying in the same sector, $\chi_{jj} = 1, \forall j \in \mathcal{J}$.

The first term 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 labor market opportunities shock, ϵ'. For unskilled workers ($\ell = u$), the choice set of sectors for the

next period 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 (9) and the law of motion of human capital (8), one can show that the worker's value function is homogenous of degree $(1-\gamma)$ in h, i.e.*

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

Hence, the worker's problem can be solved separate from the human capital distribution.

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.

Applying Proposition 1 and using the law of motion (8), we can rewrite the value function in (9) as

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

Now the solution to a worker's problem can be characterized by the random variable $V_{\ell,t}(a,j,\epsilon)$, which depends on the realization of iid shock ϵ. Let's denote $v_{\ell,t}(a,j) \equiv \mathbb{E}[V_{\ell,t}(a,j,\epsilon)]$, then

$$v_{\ell,t}(a,j) = \mathcal{C}_1 \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_{\epsilon} \max_i \left\{ \chi_{ji} (\tau^{\ell}_{ji}\epsilon^i)^{1-\gamma} v_{\ell',t+1}(a+1,i) \right\}, \tag{11}$$

where $\mathcal{C}_1 = \mathbb{E}[(\epsilon^j)^{1-\gamma}]$, and the max operator contains a random variable $(\epsilon^i)^{1-\gamma}$. Let's define a new variable $y = \epsilon^{1-\gamma}$, which, given the Frechet distribution of ϵ, can be shown to be distributed Weibull with shape parameter $\kappa_1 = \kappa/(\gamma-1)$ and scale parameter $\lambda_1 = \lambda^{1-\gamma}$.[11] Therefore, constant $\mathcal{C}_1 = \lambda_1 \Gamma\left(1+\frac{1}{\kappa_1}\right) = \lambda^{1-\gamma}\Gamma\left(1+\frac{\gamma-1}{\kappa}\right)$.

Finally, given the distribution of the shocks $y \sim Weibull\left(\frac{\kappa}{\gamma-1}, \lambda^{1-\gamma}\right)$, the value function of the worker can be solved for as

$$v_{\ell,t}(a,j) = \mathcal{C}_1 \frac{(w_{\ell,j,t})^{1-\gamma}}{1-\gamma} - \beta \mathcal{C}_2 \left[\sum_i (-\chi_{ji} v_{\ell',t+1}(a+1,i))^{\frac{\kappa}{1-\gamma}} (\tau^{\ell}_{ji})^{\kappa} \right]^{\frac{1-\gamma}{\kappa}}, \tag{12}$$

[11] CDF of r.v. y can be derived as

$$\begin{aligned} F_y(y) &= \mathbb{P}(\epsilon^{1-\gamma} \le y) = \mathbb{P}(\epsilon \ge y^{\frac{1}{1-\gamma}}) = 1 - F(y^{\frac{1}{1-\gamma}}) \\ &= 1 - \exp\left(-(y^{\frac{1}{1-\gamma}}/\lambda)^{-\kappa}\right) = 1 - \exp\left(-(y/\lambda^{1-\gamma})^{-\frac{\kappa}{1-\gamma}}\right) = 1 - \exp\left(-(y/\lambda_1)^{\kappa_1}\right). \end{aligned}$$

where $\mathcal{C}_2 = \lambda^{1-\gamma}\Gamma\left(1+\frac{\gamma-1}{\kappa}\right)$ is equal to $\mathcal{C}_1$ if the distribution of labor market opportunities is the same for all ϵ^i, and otherwise both constants are sector specific, with $\mathcal{C}_2$ entering the summation indexed by i.

The probability of switching from sector j to sector i of a worker of age a, with skill level ℓ in time period t can be written as

$$\mu^{\ell}_{ji,t}(a) = \frac{(\tau^{\ell}_{ji}(-\chi_{ji}v_{\ell',t+1}(a+1,i))^{\frac{1}{1-\gamma}})^{\kappa}}{\sum_k(\tau^{\ell}_{jk}(-\chi_{jk}v_{\ell',t+1}(a+1,k))^{\frac{1}{1-\gamma}})^{\kappa}}. \tag{13}$$

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

$$\theta_{u,t+1}(a,j) = \sum_{i=1}^{J+1}\mu^{u}_{ij,t}(a-1)\theta_{u,t}(a-1,i), \tag{14}$$

$$\theta_{s,t+1}(a,j) = \sum_{i=1}^{J+1}\mu^{s}_{ij,t}(a-1)\theta_{s,t}(a-1,i) + \mu^{u}_{0j,t}(a-1)\theta_{u,t}(a-1,0). \tag{15}$$

Here the incoming unskilled workers are switching from other production 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.

Lemma 1. *The expectation of the labor market opportunity shock ϵ^i of a worker who moves from sector j to i is equal to*

$$\mathbb{E}\left[\epsilon^i \middle| i \in \arg\max_k \chi_{jk}(\tau^{\ell}_{jk}\epsilon^k)^{1-\gamma}v_{\ell'}(a+1,k)\right] = \lambda\Gamma\left(1-\frac{1}{\kappa}\right)(\mu^{\ell}_{ji}(a))^{-\frac{1}{\kappa}}, \tag{16}$$

where $\mu^{\ell}_{ji}(a)$ is a switching probability. Hence, the workers who move from j to i bring an average of $\mathcal{M}^{\ell}_{ji}(a)H_{\ell,t}(a,j)$ units of human capital to i, where

$$\mathcal{M}^{\ell}_{ji}(a) = \lambda\Gamma\left(1-\frac{1}{\kappa}\right)\tau^{\ell}_{ji}(\mu^{\ell}_{ji}(a))^{1-\frac{1}{\kappa}}. \tag{17}$$

Using Lemma 1, we can write the evolution of aggregate human capital of workers of age a

in sector j as

$$H_{u,t+1}(a,j) = \sum_{i=1}^{J+1} \mathcal{M}^{u}_{ij}(a-1) H_{u,t}(a-1,i), \tag{18}$$

$$H_{s,t+1}(a,j) = \sum_{i=1}^{J+1} \mathcal{M}^{s}_{ij}(a-1) H_{s,t}(a-1,i) + \mathcal{M}^{u}_{0j}(a-1) H_{u,t}(a-1,0). \tag{19}$$

Workers of age 0 The cohort of workers 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

$$\theta_{u,t}(0,j) = \frac{\left(\tau^0_j(-\chi^0_j v_{u,t+1}(1,i))^{\frac{1}{1-\gamma}}\right)^{\kappa}}{\sum_{k=0}^{J+1}\left(\tau^0_k(-\chi^0_k v_{u,t+1}(1,k))^{\frac{1}{1-\gamma}}\right)^{\kappa}}, \tag{20}$$

where χ^0_j 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 changes 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 productivity shocks to be iid across time and independent across sectors, 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

$$Y_{j,t} = Z_{j,t} L^{\alpha_j}_{u,j,t} L^{1-\alpha_j}_{s,j,t} \tag{21}$$

where the aggregate stock of unskilled and skilled labor is equal to

$$L_{u,j,t} = \sum_a H_{u,t}(a,j) \quad \text{and} \quad L_{s,j,t} = \sum_a H_{s,t}(a,j) \tag{22}$$

Each of the workers supplies the 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 (similar to Faber and Gaubert (2019))

$$Z_{j,t} = Z_j \left(\frac{L_{s,j,t}}{\sum_a \theta_{s,t}(a,j)} \right)^{\eta_j}$$

where Z_j is the constant exogenous component of sector-specific productivity, and parameter η_j measures the spillover effects that depends on the average 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 stock of 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 has become standard in this literature.

Competitive wages in sector j are equal to

$$w_{u,j,t} = \alpha_j \frac{P_{j,t} Y_{j,t}}{L_{u,j,t}}, \quad w_{s,j,t} = (1-\alpha_j) \frac{P_{j,t} Y_{j,t}}{L_{s,j,t}} \tag{23}$$

and the skill premium is then driven by the relative abundance of skill

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

where $w_{u,j,t}$ and $w_{s,j,t}$ are average wages of unskilled and skilled workers.

Finally, the aggregate nominal GDP is this economy is, therefore, given by

$$Y_t P_t = \sum_{j=1}^{J} Y_{j,t} P_{j,t}, \tag{24}$$

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

$$Y_{j,t} = C_{j,t}, \tag{25}$$

where $Y_{j,t}$ is production and $C_{j,t}$ is the aggregate consumption of good j in period t.

Labor market clearing condition for each sector j and skill ℓ is defined in (22), while mobility of workers across sectors is specified in (14)-(15). Since the size of each cohort is normalized to unit measure, so that

$$\sum_{a=0}^{A} \frac{1}{A+1} \left(\sum_{\ell \in \{u,s\}} \sum_{j=1}^{J+1} \theta_{\ell,t}(a,j) + \theta_{u,t}(a,0) \right) = 1, \tag{26}$$

where $A+1$ is the number of cohorts coexisting in each period of time.

Finally, given all the parameters and the initial stock of human capital of each worker, and the exogenous sector-specific productivities $\{Z_j\}_{j=1,\ldots,J}$, we can define a *competitive equilibrium* in this economy as **(i)** a set of prices $\{w_{u,j,t}, w_{s,j,t}, P_{j,t}\}_{j=1,\ldots,J,t=0,\ldots}$; **(ii)** individual worker's allocation decisions $\{v_{\ell,t}(a,j), \mu^{\ell}_{ij,t}(a), \mathcal{M}^{\ell}_{ij,t}(a)\}_{\ell,a,j,i,t}$; **(iii)** aggregate human capital and labor shares across sectors $\{\theta_{\ell,t}(a,j), H_{\ell,t}(a,j)\}_{\ell,a,j,t}$; **(iv)** aggregate output and consumption $\{Y_{j,t}, C_{j,t}\}_{j=1,\ldots,J,t=0,\ldots}$ such that:

(a) Given the fundamentals and the sequence of prices $\{w_{u,j,t}, w_{s,j,t}, P_{j,t}\}_{j,t}$, worker's lifetime optimization decisions $\{v_{\ell,t}(a,j), \mu^{\ell}_{ij,t}(a), \mathcal{M}^{\ell}_{ij,t}(a)\}_{\ell,a,j,i,t}$ are given by equations (12)-(13) and (17); firms' optimal hiring decisions are given by equation (23); sectoral consumption is given by equation (7).

   - Upon solving for $\{\mu^{\ell}_{ij,t}(a), \mathcal{M}^{\ell}_{ij,t}(a)\}$, the fraction of workers moving across sectors can be described by (14)-(15), the evolution of aggregate stock of human capital is described in (18)-(19), and the overall population is given in (26).

(b) Goods market and labor market in every sector $j \in \{1, \ldots, J\}$ clear in every period t, given by equations (22) and (25).

4 Numerical Example: 4-Sector Model

In this section, I provide a numerical example of the model's solution for the case of four sectors. The four sectors are education, non-employment, a skill-intensive sector (manufacturing), and a labor-intensive sector (construction). Later, the model will be extended to the case of multiple sectors and will be estimated using data from the EU Labour Force Survey.

The solution to the four-sector model shows that the human capital accumulation mechanism accounts for both the shifts in aggregate productivity and the economy's delayed recovery after the bust. Moreover, the dynamics of educational attainment after the bust happens through the incoming cohorts acquiring more education, while the older cohorts are more likely to remain in the same sectors or stay out of the labor force.

4.1 Parameters Values

The parameters of the model used in this numerical example are presented in Table 3. 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 3: Parameters Values

Parameter	Variable	Value
Household lifetime	A	10
Discount factor	β	0.77
CRRA parameter	γ	2
Across-sectors CES	ζ	2
Frechet shape parameter	κ	1.5
Transition matrices	τ^u, τ^s	see Tables A7 and A8
Switching costs	χ	see Table A9
Switching costs, age 0	χ^0	$[1.5, 5, 5, 4]$
Transition matrix, age 0	τ^0	$[1.2, 1, 1.01, 1.02]$
Cobb-Douglas unskilled share	α_j	$[0.4, 0.6]$
Sectoral productivity	Z_j	$[1.1, 1]$
Within-sector spillover	η_j	$[0.06, 0.02]$

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. I set the shape parameter of the Frechet distribution for productivity shocks equal to 1.5.

Since the production technology is assumed to have constant returns to scale, the only source of increasing returns is the human capital spillovers to productivity. The spillover parameters in manufacturing and construction are assumed to be equal to 0.08 and 0.02 respectively, similar to Faber and Gaubert (2019), who estimate agglomeration spillover in the manufacturing sector using data from Mexico. Although the value can vary when the parameter is calibrated to match the human capital spillovers in the context of Spain, I rely on the estimation in Faber and Gaubert (2019) for the magnitude.

The transition matrices, τ^u and τ^s, are presented in Tables A7 and A8, where each row corresponds to a sector in period t, and each column corresponds to a sector in period $t+1$. I assume that a skilled worker, while employed in construction, accumulates less human capital then in manufacturing. The matrix of switching costs, χ, is presented in Table A9.

Demand shock For the purpose of this numerical exercise, I define demand shocks as those that alter consumer's sectoral consumption while keeping prices and income fixed. Although the economic boom in 1995-2007 was accompanied by an overall increase in consumption, it disproportionately affected low-skill sectors like construction and wholesale, thereby changing the sectoral composition of aggregate demand. I model this shock as a change in the preference shifters φ. By normalizing the demand shifters in a way that only changes the sectoral composition of consumption and not the total consumption, we establish a benchmark where only the composition effect is present, and the economy's transitional dynamics are driven by relative demand shifts. Additionally, to reflect the changes in aggregate demand evident during the boom in Spain, one can model the intertemporal shock as a shock to the discount factor β. Thus, combining shocks to the demand shifters and the discount factor presents a scenario where the composition effect interacts with agents' intertemporal consumption smoothing, matching the empirically observed changes in consumption. For the purpose of this numerical example, I bypass the calibration of the shock and introduce an ad-hoc change in the demand shifter for construction while keeping the demand shifter for manufacturing constant. This specification incorporates both the aggregate demand shock and the relative increase in demand for construction and will later be adjusted to match the data on aggregate consumption expenditure.

4.2 Long-Run Equilibrium

Let's first examine the steady-state allocation of workers (see Figure 8). Workers enter the economy being unskilled, and the parameters are calibrated to match their lifetime allocation, with a large fraction acquiring education in the first two periods. The parameters are calibrated to feature that young unckilled workers are more likely to go to construction, while older workers reallocate to manufacturing upon acquiring education.

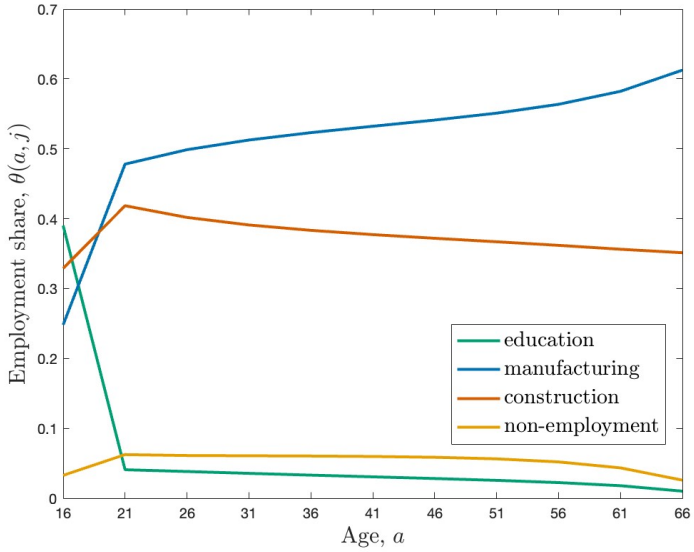


Figure 8: Long-run equilibrium, 4-sector model example

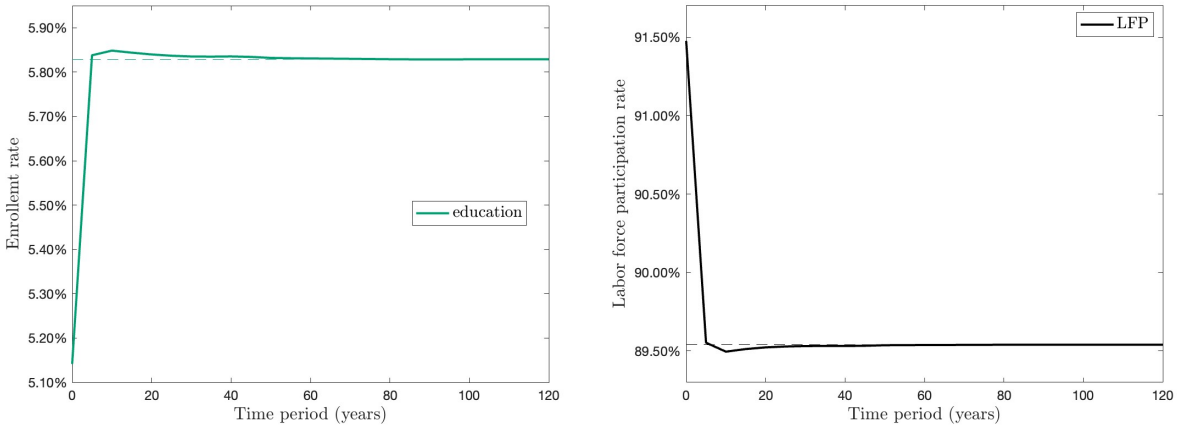
Note: This figure plots the steady-state workers allocation for both skill types, for each age, aggregated by sectors. Workers live for 10 periods, corresponding to 50 years from finishing high school until the retirement.

The steady-state of the model is calibrated to exhibit several key features. First, the manufacturing sector is larger than the construction sector, driven by the underlying exogenous productivity component Z_j and significant productivity spillovers from human capital. Throughout their lifetime, a nearly constant fraction of workers remains in the non-employment sector. The labor force participation rate increases with age, as workers who acquire education transition into the production sectors. The model is calibrated to characterize construction as a sector with greater unskilled labor intensity. Consequently, as workers age and more of them become skilled, they transition to manufacturing, where the skill premium is higher.

4.3 Transition After the Boom

Next, let's consider a temporary demand shock to the construction sector (a one-period unanticipated increase in φ_C) 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.

The dynamics of enrollment rates and labor force participation are presented in Figure 9. Initially, the enrollment rate declines following the shock. However, the transition after the bust exhibits an initial overshooting of the steady-state level of educational attainment, with convergence occurring only after 45–50 years.[12] As the bust happens, lock-in mechanism prevents workers from reallocating away from construction, and as a result, in the short-run the incoming cohorts observe higher skill premium which drives investment in education above the long-run level. The data demonstrates that in the short run, enrollment rates begin to catch up with the pre-trend level, while the model provides additional insights into the long-term dynamics driven by the boom.



(a) enrollment rates, % of all pop.

(b) labor force participation

Figure 9: Enrollment and labor force particiaption

Note: This figure plots the dynamics of the enrollment rates (Panel (a)) and labor force participation (Panel (b)) for a 4-sector model example. The transition period consists of 25 time periods, which are converted into years given that one time period in the model = 5 years.

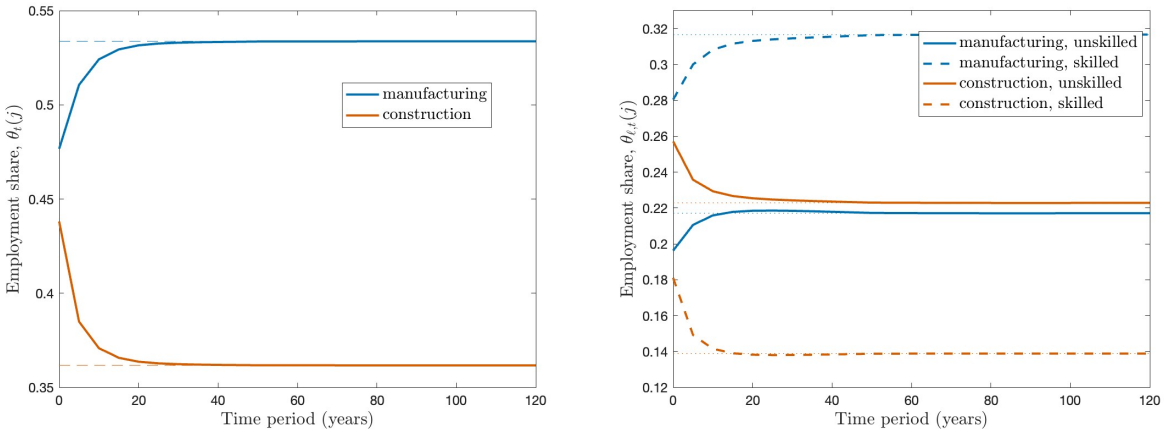
The labor force participation rate is computed as the fraction of the population employed in either the manufacturing or construction sector (excluding those in education or non-employment). Adjustments occur primarily through the education margin, while the non-employment sector remains relatively constant throughout the transition. Labor force participation increases dur-

[12] One period in the model corresponds to 5 years, so 45–50 years represent 9–10 time periods after the shock.

ing the boom as education enrollment declines and returns to its long-run level after approximately 40 years.

Figure 10 focuses on the transition dynamics of employment rates in the production sectors of the economy—manufacturing and construction. Following the shock, construction employment increases while manufacturing employment contracts, with two sectors becoming almost equal in size of employment. Convergence occurs over the next 25–30 years, corresponding to 5–6 periods in the model.

Decomposing employment shares by skill groups reveals that, prior to the shock, the construction sector had a larger share of unskilled workers, while the manufacturing sector had a larger share of skilled workers (panel (b) of Figure 10). During the boom period, the construction sector expands by hiring more workers from both skill groups. Thus, the increase in relative demand for unskilled workers during this period is primarily driven by the lower skill intensity of the construction sector rather than by changes in absolute demand across all sectors.



(a) employment (b) employment, by skill group

Figure 10: Labor reallocation dynamics

Note: This figure plots the dynamics of the aggregate employment rates (Panel (a)) and employment rates by skill groups (Panel (b)) for a three-sector model example.

Next, let's examine the changes in wages—particularly the skill premium—during the transition. Figure 11 shows that the skill premium initially declines in both construction and manufacturing, reflecting how a positive shock to a low-skill sector shifts the relative demand for skill in the economy. Following the bust, wages adjust gradually, returning to their long-run equilibrium after approximately 20–30 years (4–6 periods in the model). This wage persistence can be attributed to older workers becoming locked into the production sectors of the economy, as they face high opportunity costs in leaving the labor market to pursue further education.

Finally, let's compute the changes in aggregate labor productivity along the transition. Since

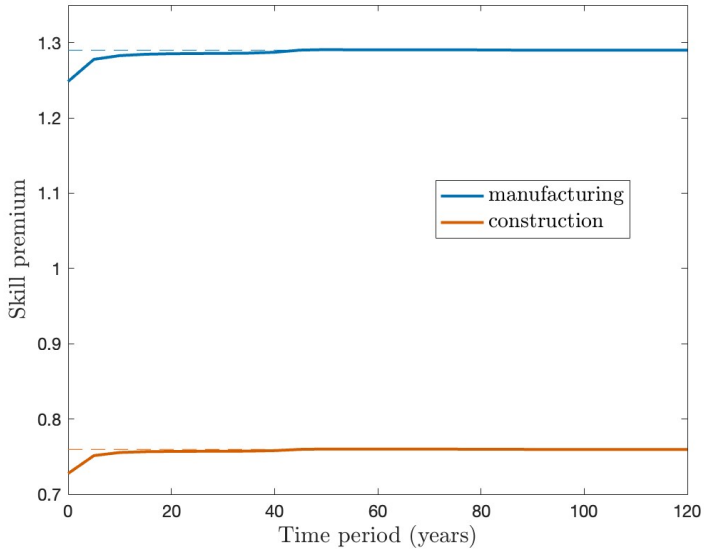


Figure 11: Skill premium dynamics

Note: This figure plots the dynamics of th skill premium, computed as the ratio of average real wages of skilled and unskilled workers in each sector.

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

$$\Delta \log Y_t = \log \frac{I_t}{I_{t_0}} - \int_{t_0}^{t} \sum_j s_j d \log P_j \tag{27}$$

which depends in the whole path of prices, weighted by the relevant expenditure shares reflecting preferfnces in every period.

The change in aggregate labor productivity is then given by

$$\Delta \log \left(\frac{Y_t}{L_t} \right) = \Delta \log Y_t - \Delta \log L_t \tag{28}$$

where I_t is nominal income, s_{jt} are the CES expenditure shares on good j, and L_t is the aggregate labor in production[13].

The dynamics of cumulative changes in aggregate labor productivity are presented in Figure

[13]To compute numerically changes in labor productivity, I use mid-point Rieman sums (Chained Tornqvist index)

$$\Delta \log Y = \log \frac{I_{t_1}}{I_{t_0}} - \sum_{t=t_0+1}^{t_1} \sum_j \frac{1}{2}(s_{jt} + s_{jt-1}) \log \frac{P_{jt}}{P_{jt-1}}$$

12. Initially, aggregate labor productivity declines and remains below its initial level, converging to the long-term equilibrium only after 50 years (10 time periods). Although real GDP initially rises—driving productivity up—this effect is offset by an increase in the labor force, resulting in an immediate drop in aggregate productivity. This result underscores the importance of the sector in which the shock originates for the economy's transition. Since the construction sector primarily employs unskilled workers and is characterized by lower total factor productivity, a large inflow of labor does not translate into a substantial increase in output.

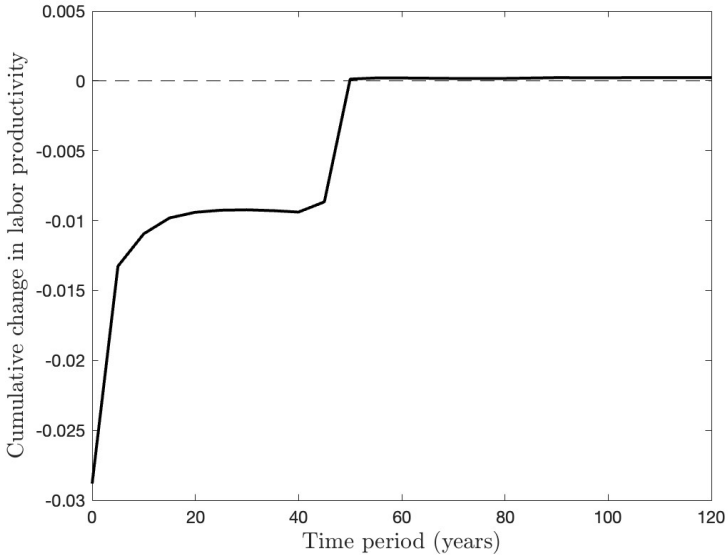


Figure 12: Aggregate labor productivity dynamics

Note: This figure plots the dynamics of cumulative change in aggregate labor productivity, computed using the formula in (28) 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).

Even though labor productivity begins to grow immediately after the shock, it stagnates for several years before eventually recovering to the steady-state level. The initial increase is driven by incoming cohorts acquiring more education and allocating to more productive sectors (in this case, manufacturing). However, the lock-in mechanism prevents the affected cohort from reallocating away from construction and returning to school, keeping aggregate human capital at a lower level. Productivity finally converges to its long-run level 50 years after the shock, coinciding with the complete exit of the affected cohort from the labor market. The sharp increase in productivity at that point is explained by the fact that each cohort accounts for a large share of the population.

5 Quantitative Model *(TBD)*

Now that I have illustrated the main mechanism of the model, I turn to the analysis of the small open economy, which consists of hand-to-mouth workers and a capitalist who can borrow in the foreign asset market. Consumers have preferences over goods from different sectors and consume the services of the housing stock. The small open economy is assumed to run a current account deficit while exporting manufactured goods. A decline in the real interest rate leads to a surge in non-tradable sectors as well as investment, which, in turn, increases the demand for low-skill workers. Consequently, younger cohorts tend to invest less in their human capital and instead enter the labor force.

The mechanism described in the numerical example above is also present in the full quantitative model. However, the dynamics of productivity are more complex, as the housing sector is modeled as durable. Following the bust, investments already made in the housing sector become irreversible, serving as an additional amplification channel. Let me now highlight the key additional assumptions made in this model.

Consumers Preferences Consumers have CRRA utility that depends on the final consumption good, which is a CES aggregator over multiple sectors of the economy

$$c_t = \left(\sum_{j=1}^{J} \varphi_j^{\frac{1}{\zeta}} c_{j,t}^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}}, \tag{29}$$

However, now the demand shifters are fixed, and consumption in the housing sector is modeled to be the services of the capital stock in construction sector.

Capitalist While the workers problem is the same as before, now there is a capitalist who owns all capital in the economy and rents it to various sectors, receives firms profit, and saves/borrows in the foreign asset market. Her preferences are the same as of the workers and budget constraint is given by

$$P_t C_t^c + \sum_j P_t^I I_{j,t} + (1 + r_{t-1}) d_{t-1} = d_t + \sum_j R_{j,t} K_{j,t}^p + \sum_j \Pi_{j,t}$$

where d_t is international debt (savings if $d_t < 0$), and r_t is the real interest rate determined in the international asset market.

Production Each sector's production technology is given by

$$Y_{j,t} = Z_{j,t}\left(L_{u,j,t}^{\alpha_j} L_{s,j,t}^{1-\alpha_j}\right)^{\nu_j} (K_{j,t}^{p})^{1-\nu_j},$$

where parameters $\{\alpha_j, \nu_j\}$ are calibrated using the national accounts by branch of activity. I assume the same form of human capital spillovers as in the numerical example.

Capital Law of Motion and Market Clearing We assume that ψ fraction of consumers are hand-to-mouth workers, while $1-\psi$ are the capitalists. Hence, the goods market clearing condition is

$$\begin{aligned} I_{j,t} + C_{j,t} &= Y_{j,t}, \quad j \text{ is non-tradable} \\ I_{j,t} + C_{j,t} + X_{j,t} &= Y_{j,t}, \quad j \text{ is tradable} \\ I_{j,t} &= Y_{j,t}, \quad j \text{ is housing} \end{aligned}$$

where $\psi C_{j,t}^{w} + (1-\psi) C_{j,t}^{c} = C_{j,t}$, and X denoted export. As for the physical capital dynamics

$$K_{j,t+1} = (1-\delta) K_{j,t} + I_{j,t},$$

and capital used in production in sector j is equal to the aggregate stock $K_{j,t}^{p} = K_{j,t}$ in all sectors excpet for housing, where capital is also rented out for final consumption, i.e. $K_{j,t}^{p} + C_{j,t} = K_{j,t}$.

6 Discussion

This paper analyzes the impact of temporary sectoral shocks on human capital accumulation and introduces a framework to quantify their effects on long-term economic growth. Using the 1995–2007 boom in Spain as an illustrative example of a surge in low-skill sectors—leading to a temporary positive demand shock for unskilled labor—the paper provides evidence that the boom negatively affected cohort-specific educational attainment. First, it documents a decline in enrollment rates in higher education during the boom and employs a shift-share instrument to estimate the causal effects of the housing boom on enrollment. Then, it presents evidence of the permanent impact on the educational attainment of affected cohorts. The paper highlights the pivotal role of labor supply skill composition in shaping workers' opportunity costs and driving long-term changes in aggregate labor productivity.

To shed light on the mechanism underlying the economy's transition, I propose an overlapping generations model in which workers' education decisions and sectoral allocation influence

human capital accumulation. I then present a numerical example of a three-sector model using externally calibrated parameters. The model replicates the decline in educational attainment following the construction expansion and underscores the role of imperfect human capital mobility, along with the rising opportunity cost of education, in shaping workers' reallocation across sectors and the long-term decline in aggregate labor productivity after the bust. Furthermore, the model highlights that the sector in which the shock originates plays a crucial role in determining aggregate labor productivity dynamics.

There are several potential channels through which shifts in human capital accumulation exert long-term effects on aggregate productivity.[14] In future work on this paper, I aim to focus on the mechanism outlined in the quantitative model for the small open economy described in Section 5. In this framework, I model the housing sector as more capital-intensive, providing services as part of the durable capital stock. Consequently, the boom arises from declining interest rates in the presence of borrowing constraints on the consumer side. I will then calibrate this model to match the dynamics of the Spanish economy and quantify the role of the human capital channel in aggregate productivity dynamics.

[14]For example, some literature highlights the unique characteristics of the Spanish labor market, which favors experienced workers over younger college graduates and promotes fixed-term contracts (Alonso-Borrego et al. 2005, OECD 2024).

References

Adão, Rodrigo, Martin Beraja, and Nitya Pandalai-Nayar, "Technological transitions with skill heterogeneity across generations," Technical Report, National Bureau of Economic Research 2020.

Adao, Rodrigo, Martin Beraja, and Nitya Pandalai-Nayar, "Fast and slow technological transitions," Technical Report, Tech. rep., MIT, Mimeo 2021.

Alonso-Borrego, César, Jesús Fernández-Villaverde, and Jose Galdon-Sanchez, "Evaluating labor market reforms: a general equilibrium approach," 2005.

Atalay, Enghin, "How important are sectoral shocks?," *American Economic Journal: Macroeconomics*, 2017, *9* (4), 254–280.

Atkin, David, "Endogenous skill acquisition and export manufacturing in Mexico," *American Economic Review*, 2016, *106* (8), 2046–2085.

Autor, David H, David Dorn, Gordon H Hanson, and Jae Song, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Baqaee, David and Emmanuel Farhi, "Supply and demand in disaggregated Keynesian economies with an application to the Covid-19 crisis," *American Economic Review*, 2022, *112* (5), 1397–1436.

Baqaee, David R and Ariel Burstein, "Welfare and output with income effects and taste shocks," *The Quarterly Journal of Economics*, 2023, *138* (2), 769–834.

Barro, Robert J, "Human capital and growth," *American economic review*, 2001, *91* (2), 12–17.

Basso, Gaetano, "Local labor markets adjustments to oil booms and busts," *Retrieved December*, 2017, *14*, 2021.

Benabou, Roland, "Tax and education policy in a heterogeneous-agent economy: What levels of redistribution maximize growth and efficiency?," *Econometrica*, 2002, *70* (2), 481–517.

Berger, Mark C, "Changes in labor force composition and male earnings: a production approach," *Journal of Human Resources*, 1983, pp. 177–196.

Black, Dan A, Terra G McKinnish, and Seth G Sanders, "Tight labor markets and the demand for education: Evidence from the coal boom and bust," *ILR Review*, 2005, *59* (1), 3–16.

Blanchard, Emily J and William W Olney, "Globalization and human capital investment: Export composition drives educational attainment," *Journal of International Economics*, 2017, *106*, 165–183.

Blanchard, Olivier and Francesco Giavazzi, "Current account deficits in the euro area: the end of the Feldstein-Horioka puzzle?," *Brookings papers on economic activity*, 2002, *2002* (2), 147–209.

_ **and Pedro Portugal**, "What hides behind an unemployment rate: Comparing Portuguese and US labor markets," *American Economic Review*, 2001, *91* (1), 187–207.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-experimental shift-share research designs," *The Review of economic studies*, 2022, *89* (1), 181–213.

Brunnermeier, Markus, Pierre-Olivier Gourinchas, and Oleg Itskhoki, "Consumption-led growth," *Manuscript, Princeton University*, 2018.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, "Understanding booms and busts in housing markets," *Journal of Political Economy*, 2016, *124* (4), 1088–1147.

Burstein, Ariel and Jonathan Vogel, "International trade, technology, and the skill premium," *Journal of Political Economy*, 2017, *125* (5), 1356–1412.

_ **, Javier Cravino, and Jonathan Vogel**, "Importing skill-biased technology," *American Economic Journal: Macroeconomics*, 2013, *5* (2), 32–71.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro, "Trade and labor market dynamics: General equilibrium analysis of the china trade shock," *Econometrica*, 2019, *87* (3), 741–835.

Capelle, Damien, "The great gatsby goes to college: Tuition, inequality and intergenerational mobility in the us," 2019.

Carreno, Jose, "Productivity Hysteresis from the Great Recession," 2023.

Cascio, Elizabeth U and Ayushi Narayan, "Who needs a fracking education? The educational response to low-skill-biased technological change," *ILR Review*, 2022, *75* (1), 56–89.

Chari, Varadarajan V and Hugo Hopenhayn, "Vintage human capital, growth, and the diffusion of new technology," *Journal of political Economy*, 1991, *99* (6), 1142–1165.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo, "Housing Booms and Busts, Labor Market Opportunities, and College Attendance," *American Economic Review*, October 2018, *108* (10), 2947–94.

Chodorow-Reich, Gabriel, Adam M Guren, and Timothy J McQuade, "The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view," Technical Report, National Bureau of Economic Research 2021.

_ **and Johannes Wieland**, "Secular labor reallocation and business cycles," *Journal of Political Economy*, 2020, *128* (6), 2245–2287.

Connelly, Rachel, "A framework for analyzing the impact of cohort size on education and labor earning," *Journal of Human Resources*, 1986, pp. 543–562.

Dvorkin, Maximiliano A, *Heterogeneous Agents Dynamic Spatial General Equilibrium*, Federal Reserve Bank of St. Louis, Research Division, 2023.

_ **and Alexander Monge-Naranjo**, "Occupation mobility, human capital and the aggregate consequences of task-biased innovations," *FRB St. Louis Working Paper*, 2019, (2019-13).

Emery, JC Herbert, Ana Ferrer, and David Green, "Long-term consequences of natural resource booms for human capital accumulation," *Ilr Review*, 2012, *65* (3), 708–734.

Engbom, Niklas, "Labor market fluidity and human capital accumulation," Technical Report, National Bureau of Economic Research 2022.

Faber, Benjamin and Cecile Gaubert, "Tourism and economic development: Evidence from Mexico's coastline," *American Economic Review*, 2019, *109* (6), 2245–2293.

Ferreira, Clodomiro, Julio Gálvez, and Myroslav Pidkuyko, "Housing Tenure, Consumption and Household Debt: Life-Cycle Dynamics During a Housing Bust in Spain," *Documento de Trabajo RedNIE N285*, 2023.

Ferreira, Fernando and Joseph Gyourko, "Anatomy of the beginning of the housing boom: US neighborhoods and metropolitan areas, 1993-2009," Technical Report, National Bureau of Economic Research 2011.

Ferriere, Axelle, Gaston Navarro, Ricardo Reyes-Heroles et al., "Escaping the losses from trade: The impact of heterogeneity on skill acquisition," in "2018 meeting papers," Vol. 1248 Society for Economic Dynamics 2018.

García-Santana, Manuel, Enrique Moral-Benito, Josep Pijoan-Mas, and Roberto Ramos, "Growing like spain: 1995–2007," *International Economic Review*, 2020, *61* (1), 383–416.

Garriga, Carlos, "The role of construction in the housing boom and bust in Spain," *Documento de Trabajo*, 2010, *9*.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," *American Economic Review*, 2020, *110* (8), 2586–2624.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, "Capital allocation and productivity in South Europe," *The Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Guren, Adam, David Hémous, and Morten Olsen, "Trade dynamics with sector-specific human capital," *Journal of International Economics*, 2015, *97* (1), 126–147.

Horvath, Michael, "Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks," *Review of Economic Dynamics*, 1998, *1* (4), 781–808.

_ , "Sectoral shocks and aggregate fluctuations," *Journal of Monetary Economics*, 2000, *45* (1), 69–106.

Jones, Benjamin F, "The human capital stock: a generalized approach," *American Economic Review*, 2014, *104* (11), 3752–3777.

Jr, Robert E Lucas, "On the mechanics of economic development," *Journal of monetary economics*, 1988, *22* (1), 3–42.

_ , "Human capital and growth," *American Economic Review*, 2015, *105* (5), 85–88.

Kahn, Lisa B, "The long-term labor market consequences of graduating from college in a bad economy," *Labour economics*, 2010, *17* (2), 303–316.

Kaplan, Greg, Kurt Mitman, and Giovanni L Violante, "The housing boom and bust: Model meets evidence," *Journal of Political Economy*, 2020, *128* (9), 3285–3345.

Lilien, David M, "Sectoral shifts and cyclical unemployment," *Journal of political economy*, 1982, *90* (4), 777–793.

Long, John B and Charles I Plosser, "Sectoral vs. aggregate shocks in the business cycle," *The American Economic Review*, 1987, *77* (2), 333–336.

Mueller, Andreas I, "Separations, sorting, and cyclical unemployment," *American Economic Review*, 2017, *107* (7), 2081–2107.

OECD, *Reviving Broadly Shared Productivity Growth in Spain*, Paris: OECD Publishing, 2024.

Ohanian, Lee E and Andrea Raffo, "Aggregate hours worked in OECD countries: New measurement and implications for business cycles," *Journal of Monetary Economics*, 2012, *59* (1), 40–56.

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz, "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Porzio, Tommaso, Federico Rossi, and Gabriella Santangelo, "The human side of structural transformation," *American Economic Review*, 2022, *112* (8), 2774–2814.

Redding, Stephen J and David E Weinstein, "Measuring aggregate price indices with taste shocks: Theory and evidence for CES preferences," *The Quarterly Journal of Economics*, 2020, *135* (1), 503–560.

Rodríguez-Clare, Andres, Mauricio Ulate, and Jose P Vasquez, "Trade with Nominal Rigidities: Understanding the Employment and Welfare Effects of the China Shock," Technical Report, CEPR Discussion Papers 2024.

Rodriguez, Francisco and Jeffrey D Sachs, "Why do resource-abundant economies grow more slowly?," *Journal of economic growth*, 1999, pp. 277–303.

Rogerson, Richard, "Indivisible labor, lotteries and equilibrium," *Journal of monetary Economics*, 1988, *21* (1), 3–16.

Schmitt-Grohé, Stephanie and Martin Uribe, "Downward nominal wage rigidity, currency pegs, and involuntary unemployment," *Journal of Political Economy*, 2016, *124* (5), 1466–1514.

A Data Appendix

A.1 EU Labour Force Survey

The EU-LFS[15] 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[16].

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.2 FRED Database

Data from FRED[17] 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 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.3 OECD Productivity Statistics Database

The OECD database[18] 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

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

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

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

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

Table A1: 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. 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.

significance of the housing boom 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.

Furthermore, the data on CPI in Spain is used to compute real GDP later in the analysis.

A.4 Instituto Nacional de Estadística (INE)

The Spanish National Statistics Institute (INE)[19] 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).

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

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 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.

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. This data is available from the Spanish national accounts and covers the period from 1995 to 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.

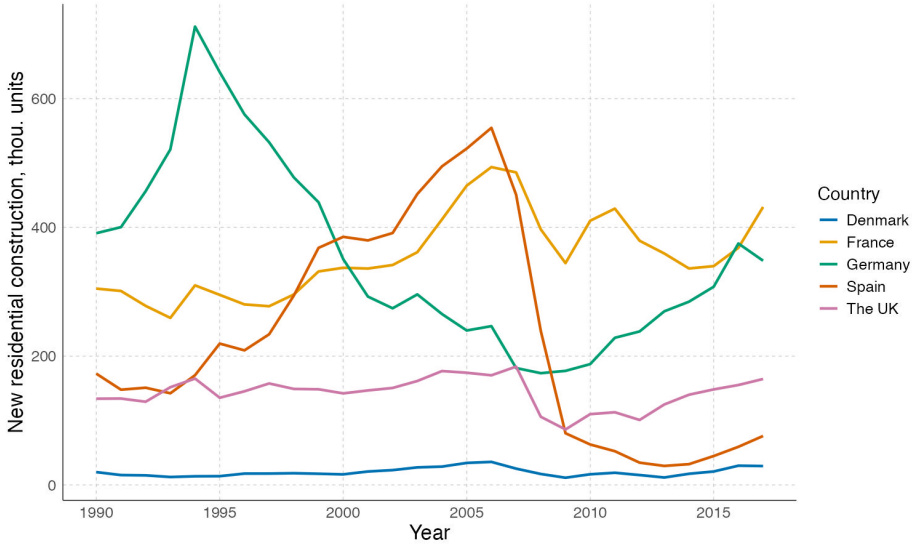
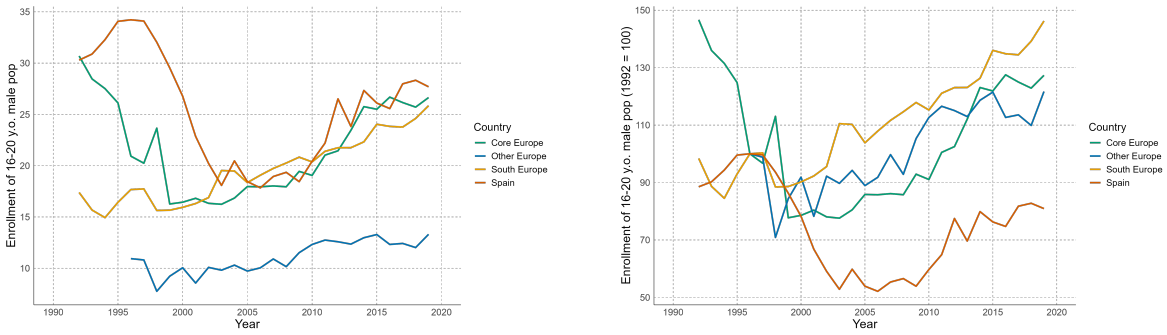


Figure A1: New residential construction by country

Note: Data Source: FRED. New residential construction is measured in thousands of new units.

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 industry, construction and wholesale. Among these three industries, construction contributed approximately 10% of annual GDP, while professional and scientific activities accounted for about 5%, and industry for around 4% in 2000.[20] Consequently, 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 wholesale productivity became apparent.[21] This sector, the largest in the Spanish economy, accounted for 25% of annual real GDP at the

[20]National accounts data from INE.

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

beginning of the 2000s.

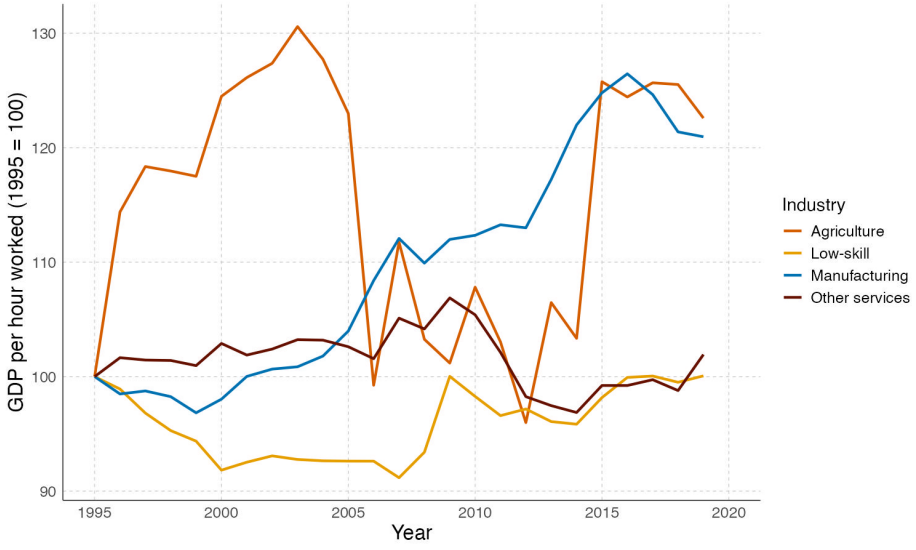


Figure A3: Labor productivity in Spain, 1995-2020

Note: Data Source: INE, Instituto Nacional de Estadística, National Accounts by branch of activity. Industry classification using NACE Rev. 2 is: agriculture (A), industry (B-E), manufacturing (C), construction (F), wholesale (G-I), information and communication (J), professional and administrative activities (M-N), public services (O-Q), and other (R-U). Labor productivity is computed as real GDP per hour worked, and is normalized to 1995.

The next Figure A4 has both real GDP and hours worked decomposed by small industry codes. This figure emphasizes the increase in both GDP and hours worked in construction sector, ans allows to assess the size of the particular industry for the whole economy. For example, one can notice that there was a huge increase in GDP and hours in professional and administrative services, however this sector accounts for 5% of total annual GDP.

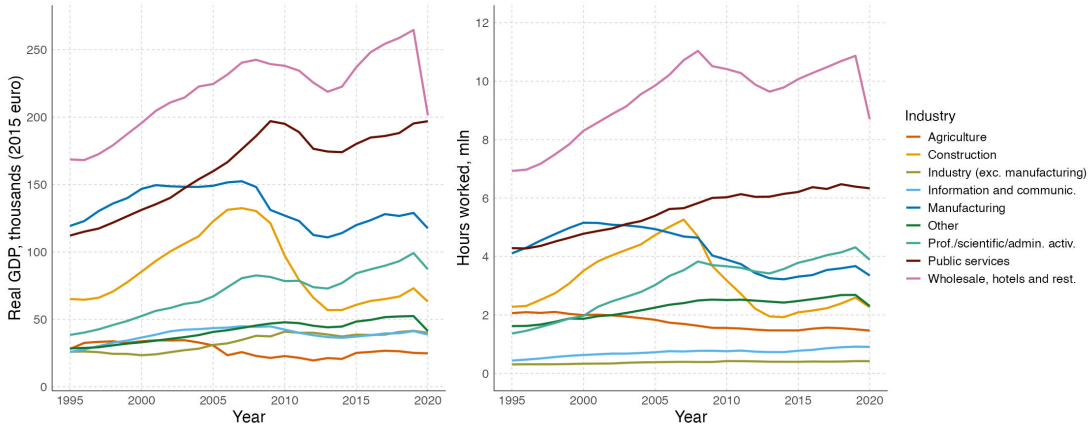
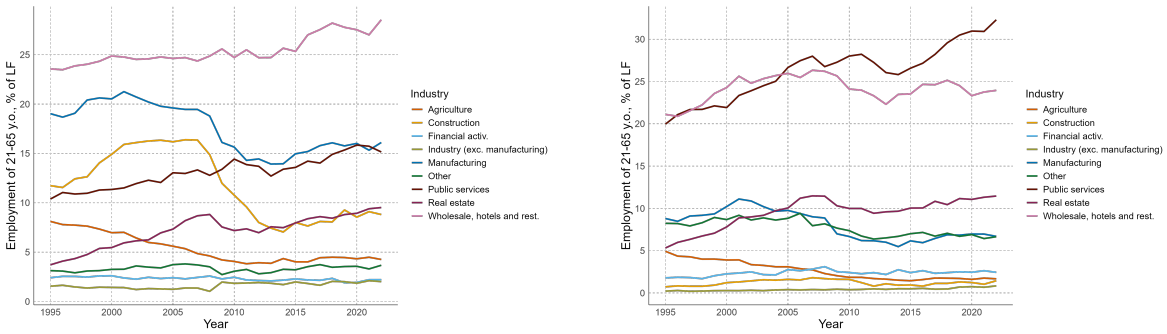


Figure A4: Real GDP and hours by industry, 1995-2020

Note: Data Source: INE, Instituto Nacional de Estadística, National Accounts by branch of activity. Industry classification using NACE Rev. 2 is: agriculture (A), industry (B-E), manufacturing (C), construction (F), wholesale (G-I), information and communication (J), professional and administrative activities (M-N), public services (O-Q), and other (R-U).

B.2 Labor Allocation and Educational Attainment

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

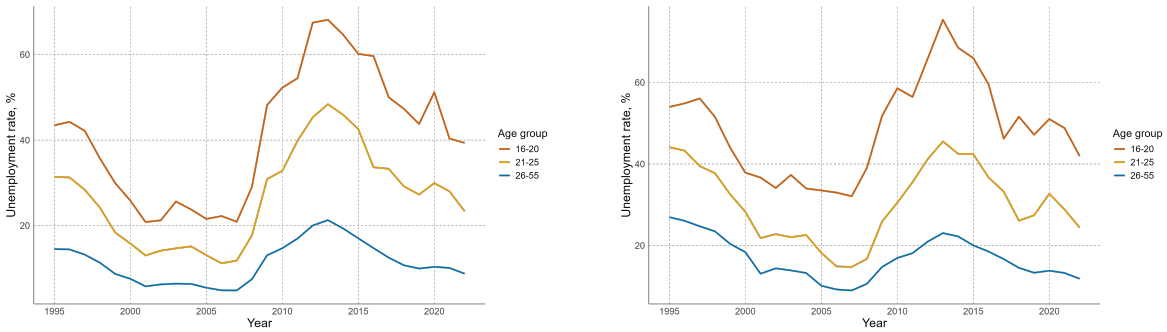


(a) 21-65 y.o., male pop.

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

Figure A5: Employment rates of 16-65 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. 1.1 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.

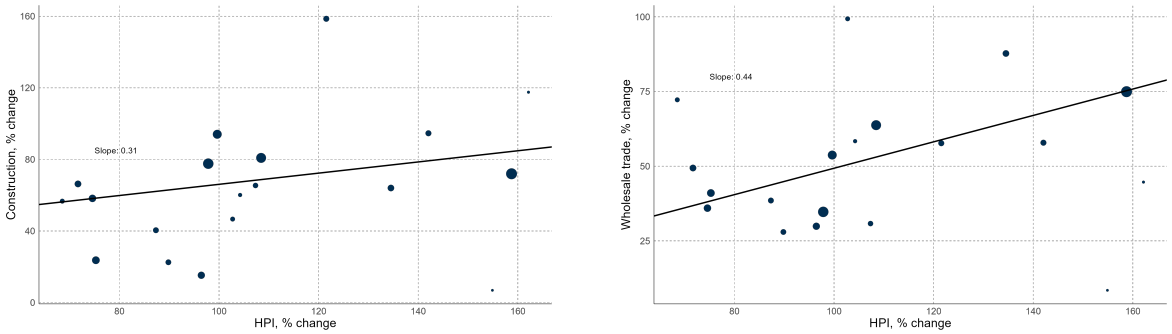


Figure A7: Construction employment of 16-20 y.o. male workers

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.

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

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: Emplotment 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 presented in Figure A9.

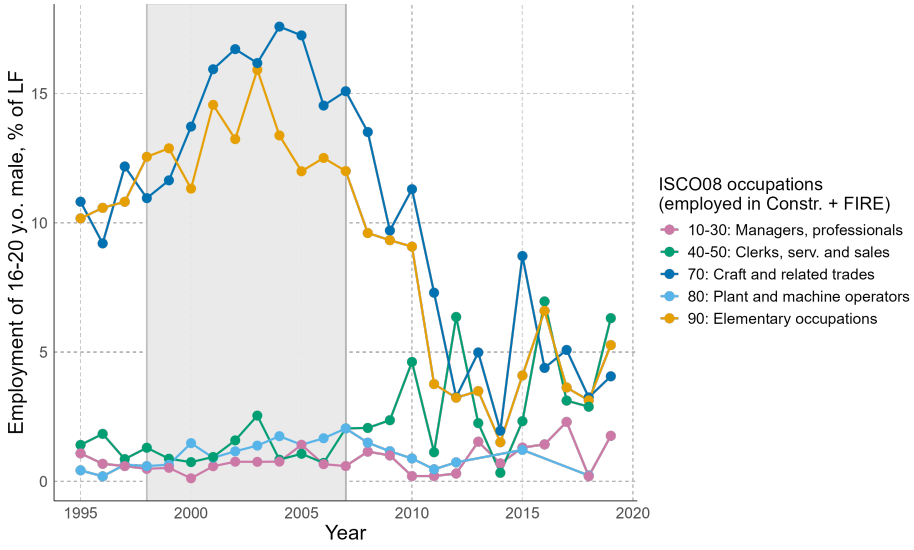


Figure A9: Construction employment, by occupation

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.

Exogeneity tests

Table A2: Rotemberg weights summary

	Sum	Mean	Share
Panel A. Negative and positive weights			
Negative	-1.765	-0.009	0.427
Positive	2.765	0.014	0.573
	$\hat{\alpha}_h$	g_h	$\hat{\beta}_h$
Panel B. Top three Rotemberg weight occupations			
90: Elementary occupations (2003)	0.232	13.730	-0.773
70: Craft and related trades (2009)	0.201	-23.031	-1.447
70: Craft and related trades (2003)	0.175	4.712	-0.382

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**	2.294
	(0.073)	(0.034)	(1.497)
female employment	0.003	−0.001	0.040
	(0.006)	(0.004)	(0.117)
LFP, %	0.006	−0.009	0.140
	(0.012)	(0.006)	(0.228)
% of foreign-born pop	−0.027	0.015	−0.077
	(0.029)	(0.025)	(0.761)
$\overline{\text{age}}$	−0.006	−0.032	0.357
	(0.046)	(0.034)	(1.072)
Adj. R^2	0.057	0.605	0.355
# observations	18	18	18

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

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.

* Significant at the 5% level. ** Significant at the 1% level. *** Significant at the 0.1% level.

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

$$\Delta y_{it-2} = \gamma \Delta shift_share_iv_{it} + \epsilon_{it}$$

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

Table A4: Pre-trends

	Dependent variable:			
	Δ constr_emp$_{it-2}$		Δ enrollment$_{it-2}$	
	(1)	(2)	(3)	(4)
Δ shift share iv$_{it}$	-0.163	-0.137	-1.720^{**}	-1.178
	(0.647)	(0.612)	(0.839)	(0.837)
other region controls		✓		✓
# observations	225	225	225	225

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Standard errors are displayed in parentheses, p-values are in brackets.
* Significant at the 5% level. ** Significant at the 1% level. *** Significant at the 0.1% level.

Robustness checks

Other specifications of the regression in (3) 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^{***}	-0.970^{*}	-1.026^{*}	-3.869
	(0.167)	(0.184)	(0.187)	(0.556)	(0.595)	(46.351)
other region controls	✓	✓	✓	✓	✓	✓
region FE		✓	✓		✓	✓
year FE			✓			✓
# observations	216	216	216	216	216	216

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: Each observation is weighted by the aggregate population in the region, standard errors in parentheses are bootstraped.
* Significant at the 5% level. ** Significant at the 1% level. *** Significant at the 0.1% level.

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	−0.433	0.153	0.500
	(0.171)	(0.504)	(0.232)	(0.651)
other region controls	✓	✓	✓	✓
# observations	216	216	216	216

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Note: This table presents the results of estimation of the model in (3) using other endogenous variables. Standard errors in parentheses are bootstraped.

* Significant at the 5% level. ** Significant at the 1% level. *** Significant at the 0.1% level.

C Theory Appendix

C.1 Workers Sectoral Choice

The optimization problem of a skilled worker of age s, employed in sector j at time period t is given by

$$v_{s,t}(s,j) = \frac{(w_{s,t}(j))^{1-\gamma}}{1-\gamma} - \beta \left[\sum_{i \in \mathcal{J}} (-\chi_{ji} v_{s,t+1}(s+1,i) \tau_{ji}^{1-\gamma})^{-\kappa} \right]^{-1/\kappa}, \tag{A1}$$

which corresponds to equation (12) 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. Let me simplify the notation and denote $v_i = v_{s,t}(s,j)$, where I assume that a worker of age s starts from sector j in period t and decides on a sector for period $t+1$ (when she is of age $s+1$). 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

$$\begin{aligned}
\mu_{ji} &= \mathbb{P}\left(\max_{\ell \in \mathcal{J}} \chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma} \epsilon^\ell = \chi_{ji} v_i \tau_{ji}^{1-\gamma} \epsilon^i \right) \\
&= \mathbb{P}\left(\max_{\ell \neq i} \chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma} \epsilon^\ell \leq \chi_{ji} v_i \tau_{ji}^{1-\gamma} \epsilon^i \right) \\
&= \mathbb{P}\left(\max_{\ell \neq i} \epsilon^\ell \geq \frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}} \epsilon^i \right)
\end{aligned}$$

Using the CDF of Weibull distribution with shape parameter κ and scale parameter $\lambda =$

$1/\Gamma(1+1/\kappa)$[22], we can write

$$\begin{aligned}
\mu_{ji} &= \int_0^\infty \prod_{\ell \neq i} \left(1 - G\left(\frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}} \epsilon^i\right)\right) g(\epsilon^i) d\epsilon^i \\
&= \int_0^\infty \prod_{\ell \neq i} \exp\left(-\left(\frac{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}} \epsilon^i / \lambda\right)^\kappa\right) \frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right)^{\kappa-1} \exp(-(\epsilon^i/\lambda)^\kappa) d\epsilon^i \\
&= \int_0^\infty \frac{\prod_{\ell \in \mathcal{J}} \exp\left(-\left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa} (\epsilon^i/\lambda)^\kappa\right)}{\exp(-(\epsilon^i/\lambda)^\kappa)} \frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right)^{\kappa-1} \exp(-(\epsilon^i/\lambda)^\kappa) d\epsilon^i \\
&= \int_0^\infty \exp\left(-\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa} (\epsilon^i/\lambda)^\kappa\right) \frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right)^{\kappa-1} d\epsilon^i
\end{aligned}$$

Now we can multiply and divide this integral by constant $\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa}$ and integrate

$$\begin{aligned}
m_{ji} &= \left(\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right)^{-1} \int_0^\infty \exp\left(-\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa} (\epsilon^i/\lambda)^\kappa\right) \left(\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right) \frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right) \\
&= \left(\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right)^{-1} \left[1 - \exp\left(-\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa} (\epsilon^i/\lambda)^\kappa\right)\right] \Bigg|_0^\infty = \left(\sum_{\ell \in \mathcal{J}} \left(\frac{\chi_{j\ell} v_\ell \tau_{j\ell}^{1-\gamma}}{\chi_{ji} v_i \tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right)
\end{aligned}$$

Going back to the original notation, it can be rewritten as[23]

$$\mu_{ji,s,t}(s) = \frac{\left(-\chi_{ji} v_{s,t+1}(s+1,i) \tau_{ji}^{1-\gamma}\right)^{-\kappa}}{\sum_{\ell \in \mathcal{J}} \left(-\chi_{j\ell} v_{s,t+1}(s+1,\ell) \tau_{j\ell}^{1-\gamma}\right)^{-\kappa}}, \tag{A2}$$

which corresponds to equation (13) in the main text.

Now I turn to deriving the expression for the expected future value. From now on, I will use

[22] The scale parameter is chosen for mean to equal to 1.

[23] In the final expression, I multiply both the numerator and the denominator by -1 for convenience, since all value functions $v_{s,t+1}(s+1,i)$ are negative.

the same notation as for deriving the switching probabilites.

$$
\begin{aligned}
\mathbb{E}_\epsilon\left[\max_{i\in\mathcal{J}}\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon^i\right] &= \sum_{i\in\mathcal{J}}\int_0^\infty(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon^i)\prod_{\ell\neq i}\left(1-G\left(\frac{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}{\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma}}\epsilon^i\right)\right)g(\epsilon^i)d\epsilon^i \\
&= \sum_{i\in\mathcal{J}}\int_0^\infty(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon^i)\frac{\prod_{\ell\in\mathcal{J}}\exp\left(-\left(\frac{\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-\kappa}(\epsilon^i/\lambda)^\kappa\right)}{\exp(-(\epsilon^i/\lambda)^\kappa)}\frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right)^{\kappa-1}\exp(-(\epsilon^i/\lambda)^\kappa \\
&= \sum_{i\in\mathcal{J}}\int_0^\infty(\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon^i)\exp\left(-\sum_{\ell\in\mathcal{J}}\left(\frac{\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-\kappa}\left(\epsilon^i/\lambda\right)^\kappa\right)\frac{\kappa}{\lambda}\left(\frac{\epsilon^i}{\lambda}\right)^{\kappa-1}d\epsilon^i \\
&= \sum_{i\in\mathcal{J}}\left(\sum_{\ell\in\mathcal{J}}\left(\frac{\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right)^{-1}(\chi_{ji}v_i\tau_{ji}^{1-\gamma})\left(\sum_{\ell\in\mathcal{J}}\left(\frac{\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-\kappa}\right)^{-1/\kappa}\lambda\Gamma(1+1/\kappa) \\
&= \sum_{i\in\mathcal{J}}\frac{(\chi_{ji}v_i\tau_{ji}^{1-\gamma})^{-\kappa}}{\sum_{\ell\in\mathcal{J}}(\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma})^{-\kappa}}(\chi_{ji}v_i\tau_{ji}^{1-\gamma})\left(\frac{\sum_{\ell\in\mathcal{J}}(\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma})^{-\kappa}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-1/\kappa}\lambda\Gamma(1+1/\kappa) \\
&= \left(\sum_{i\in\mathcal{J}}(\chi_{ji}v_i\tau_{ji}^{1-\gamma})^{-\kappa}\right)^{-1/\kappa},
\end{aligned}
$$

where I use that $\lambda\Gamma(1+1/\kappa)=1$ and copmuting this integral is equivalent to computing the expectation of a random variable with $Weibull\left(\left(\frac{\sum_{\ell\in\mathcal{J}}(\chi_{j\ell}v_\ell\tau_{j\ell}^{1-\gamma})^{-\kappa}}{\chi_{ji}v_i\tau_{ji}^{1-\gamma}}\right)^{-1/\kappa}\lambda,\kappa\right)$. Finally, going back to the original notation, I get

$$
\mathbb{E}_\epsilon\left[\max_{i\in\mathcal{J}}\chi_{ji}v_i\tau_{ji}^{1-\gamma}\epsilon^i\right] = \left(\sum_{i\in\mathcal{J}}(\chi_{ji}v_{s,t+1}(s+1,i)\tau_{ji}^{1-\gamma})^{-\kappa}\right)^{-1/\kappa}, \tag{A3}
$$

and the value function can be written as

$$
v_{s,t}(s,j) = \frac{(w_{s,t}(j)h)^{1-\gamma}}{1-\gamma} - \beta\left(\sum_{i\in\mathcal{J}}(-\chi_{ji}v_{s,t+1}(s+1,i)\tau_{ji}^{1-\gamma})^{-\kappa}\right)^{-1/\kappa}, \tag{A4}
$$

which corresponds to equation (12) in the main text.

C.2 Solution Algorithm

Here I describe the general steps that are needed to obtain the solution for the transition path of the model, given the path for the demand shock.

1. Obtain the initial and final steady states.[24]

2. Guess path of prices $\{P_{j,t}\}$ for $j \in \mathcal{J}, t = 1, \ldots, T$:

   (a) Guess path of labor shares $\{\theta_{u,t}(j), \theta_{s,t}(j)\}$ and aggregate human capital $\{H_{u,t(j)}, H_{s,t}(j)\}$ for $t = 1, \ldots, T$[25]:

      i. Compute path of wages $\{w_{u,j,t}, w_{s,j,t}\}_{t=1}^{T}$.

      ii. Assign value functions at $t = T + 1$ to the final steady state.

      iii. Solve for the value functions and switching probabilities backwards for each t.

      iv. Assign the initial steady-state distribution to the distribution at $t = 0$. Solve for labor distribution forward.

   (b) Update path of aggregate human capital (go back to step (a) until convergence).

3. Update path of prices (go back to step 2 until convergence).

Table A7: Human Capital Transition Matrix for Unskilled Workers, τ^u

From \ To	Education	Non-empl	Manufacturing	Construction
Education	1	1	1	1
Non-employment	0.7	1	0.85	0.85
Manufacturing	0.7	0.8	1.1	0.75
Construction	0.7	0.8	0.65	1.08

Table A8: Human Capital Transition Matrix for Skilled Workers, τ^s

From \ To	Education	Non-empl	Manufacturing	Construction
Education	1	1	1	1
Non-employment	1	1	0.9	0.9
Manufacturing	1	0.8	1.15	0.85
Construction	1	0.8	0.75	1.1

[24] 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.

[25] I choose T equal to 15 periods in the benchmark case, but it is easy to show that picking any T that is larger results in the same transition dynamics with the same time of convergence back to the initial steady state.

Table A9: Switching Costs Matrix, χ

From \ To	Education	Non-empl	Manufacturing	Construction
Education	1	1.1	1.1	1.1
Non-employment	1.2	1	1.7	1.6
Manufacturing	1.2	1.1	1	1.45
Construction	1.2	1.1	1.6	1

TO BE COMPLETED