Labor reallocation during booms: The role of duration uncertainty*

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Abstract

A salient aspect of sectoral booms — prevalent in commodities, construction, or tech — is that the end of the boom phase is difficult to predict. I study how this uncertainty shapes labor mobility across sectors during the boom phase. Using a model of sector-specific human capital accumulation I show that workers can exhibit risk-loving attitudes towards duration, leading to ambiguous effects of uncertainty on labor supply. Then, I turn to an empirical investigation of the effects of duration uncertainty during the boom in mineral prices of 2011-2018, driven by a construction boom in China. I estimate the model using financial data and novel administrative micro-data from Australia, an exporter of mineral products to China. I use the quantified model to study a counterfactual perfect foresight economy in which the mining boom was temporary and duration certain. I find that the mining share of employment in Australia would have increased from 3.7% to 4.4%, and the relative wage in the sector would have been substantially lower, leading to a decrease in labor income inequality. Changes in the age composition of the mining sector indicate heterogeneous attitudes towards risk across age groups.

Key words: boom-bust dynamics, human capital, labor reallocation, uncertainty.

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1 Introduction

Regime changes are pervasive in the economic and policy landscape: disruptive technologies make traditional occupations obsolete, protectionist trade policy turns liberal, and commodity prices shift from booms to busts. The perspective of future regime changes should figure prominently in workers' expectations when deciding where to work, as their impact will be different on different sectors, but their timing can be uncertain and difficult to predict. What is the role of this type of uncertainty on workers' labor supply decisions and, ultimately, on aggregate outcomes while a regime lasts? Focusing on booms in commodity prices, I study how uncertainty regarding the length of the boom shapes — through its impact on labor supply elasticities — employment growth in the commodity sector, wage inequality during the boom phase, and which type of workers benefit the most from such booms.

Accounting for uncertainty regarding the duration of commodity booms is crucial to understanding the effects of globalization in commodity-exporting countries, which represent more than half of the countries in the world (UNCTAD 2021). As commodity prices move in low-frequency cycles with large variations between peaks and troughs, workers need to form expectations of future changes in the cycle in an uncertain environment (Erten and Ocampo 2013). Yet, analyses of the labor impact of trade shocks have not focused on how uncertainty about regime duration affects labor supply (Artuç et al. 2010; Dix-Carneiro 2014; Dix-Carneiro and Kovak 2017, 2019; Caliendo et al. 2019; Traiberman 2019). The extent to which trade-related uncertainty can affect economic outcomes has been documented by a different set of studies, which show that the option to wait for the resolution of trade policy uncertainty can prevent firms from starting production or entering new markets (Handley and Limão 2015; Pierce and Schott 2016; Handley and Limão 2022). I build on both strands of the literature to study the role of regime duration uncertainty on labor supply decisions during a commodity boom.

The main goal of the paper is to understand how uncertainty affects labor supply across sectors. First, I tackle the question theoretically by developing a model of sector-specific human capital accumulation. The main insight is that workers exhibit different attitudes towards risk over different durations that the boom could possibly take. The mechanism underlying risk-loving attitudes is that if the boom is short, workers can cut losses by switching to other sectors after the boom ends, but the payoffs associated with longer booms are disproportionately high because of human capital accumulation. The theoretical conclusion is that, depending on the relative likelihood of durations characterized by different attitudes towards risk, workers can be either deterred or incentivized to switch into the booming sectors by uncertainty. Then, I estimate the model combining financial data and novel administrative micro-data from Australia during 2011-2018. This is a well-suited application since, during this period, commodity prices were high yet expected to fall, and Australia specializes in commodities (mineral commodities alone explained 44% of exports during the period). I use the quantified version of the model to simulate a counterfactual perfect foresight economy in which the commodity boom was temporary and duration certain. Employment in mining increases in the counterfactual economy, meaning that during this episode uncertainty deterred workers from switching to the main booming sector at the aggregate level. The age composition of the mining sector changes in the counterfactual scenario, suggesting heterogeneous attitudes towards risk across workers.

The model of the first part of the paper aims to isolate how the value of a worker in the booming sector (mining, from now on) depends on the boom's duration, the random variable over which she needs to form expectations during the boom phase. If values are convex as a function of duration, there is scope for uncertainty to incentivize workers to switch into these sectors. I consider an economy with two sectors: mining and an outside sector. The relative wage in mining is initially high, but, with a constant probability, it falls forever, which stands as the end of the boom. Importantly, workers also accumulate sector-specific human capital which they lose when they switch sectors. Through backward induction, workers anticipate that if the boom ends soon, they will decide to switch to the outside sector when the boom ends. On the other hand, if the duration is long enough, they will optimally decide to stay in mining, even after wages drop, to avoid losing the accumulated human capital.[1] There is a kink in the value function precisely at the duration that induces a change in behavior from leaving to staying in mining upon the end of the boom. Crucially, the value function is convex around this kink as long as there is some human capital accumulation in mining.

The kink will be at different durations for different workers. For workers with higher productivity in mining, the experience of just a couple of years may be enough to induce them to stay in mining even after wages drop. Less productive workers would require longer careers before doing so. The effects of duration uncertainty on labor supply are heterogeneous because all workers face the same boom, but the value function is convex over different durations for different workers.

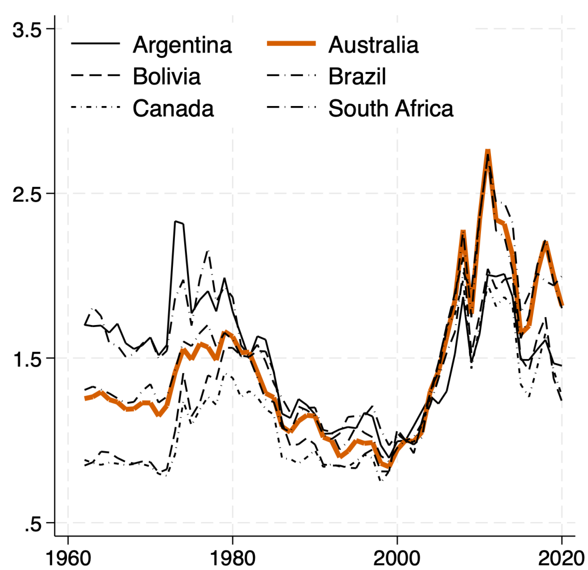
The model serves as a laboratory to study how the value of different sectors would change in an economy identical in every respect to the one just described but without uncertainty about duration. In this economy, workers know the precise date at which the wages in mining will fall. I set this date to be the expected duration from the economy with uncertainty so that both are comparable. The model's insight is that the expected value in mining is lower in the perfect foresight economy if the duration over which a worker's value function is convex are very likely. Once short and long durations are ruled out, workers who were 'betting on the boom' prefer

[1] The logic of the problem is analogous to the one in a call option, where the value goes up when volatility increases (Dixit and Pindyck 1994). Mulligan and Rubinstein (2008) use a similar analogy when explaining how selection patterns across women change when labor market inequality rises. Their model does not incorporate dynamics. The focus on sector-specific human capital derives from recent studies that find it to be an important driver of labor reallocation during trade shocks (Dix-Carneiro 2014; Traiberman 2019).

to start their careers elsewhere. If this behavior characterizes the marginal workers sorting into mining, labor supply into mining will decrease, while if marginal workers are on the concave region of their value function, it will increase. Theoretically, the effects of duration uncertainty are ambiguous.

I then turn to an empirical investigation of the role of duration uncertainty. After the boom in commodity prices of the early 2000s, the prices of mining products remained high throughout 2011-2018. However, the continuity of the boom was not guaranteed during these years, given the tendency of commodity prices to follow cycles with strong variation between the boom and bust phases (Erten and Ocampo 2013). This cautionary view appears in policy reports in mineral exporting countries, which highlight in particular uncertainty about the future state of demand in China (Berkelmans and Wang 2012; Plumb et al. 2013; Rayner and Bishop 2013; Kruger et al. 2016). The construction boom in China had dramatically increased the demand for mineral products used as inputs, but it was expected that construction would stabilize, leading to a fall in mineral imports and prices. For these reasons, the 2011-2018 period represents an ideal setting to study the effects of uncertainty about the duration of a boom, particularly in countries exposed to Chinese demand for mineral products. I will focus on labor markets in Australia, where 44% of exports consisted of mineral products, and approximately half of these were exported to China during these years. Figure 1 shows the average price of exported commodities for a group of commodity exporters, highlighting Australia.

Figure 1: Commodity export prices (Index 2001 = 100)



Sources: *Historical Commodity Export Price Index (Weighted by Ratio of Exports to Total Commodity Exports, Fixed Weights)* from the IMF.

To explore a counterfactual in which uncertainty is stripped out but the boom is still temporary in this empirical setting, I build a quantitative model that incorporates aggregate uncertainty about the duration of the mining boom into a model of sectoral choice with human capital accumulation á la Traiberman (2019). The main new ingredient relative to Traiberman (2019) is that workers observe the hazard rate for the end of the boom and, therefore, the weight they assign to the bust scenario when switching sectors is time-varying. Relative to the stylized model from the first section, the quantitative model incorporates several realistic features that interact meaningfully with risk attitudes toward duration. First, agents live finite lives. This implies, for example, that old workers should be deterred to switch into mining by uncertainty as they would not be able to benefit from long durations (which is key for risk-loving attitudes to arise). I also incorporate other determinants of labor income like age, education, and unobserved heterogeneity. Allowing for a richer set of determinants of labor income is important for correctly estimating the returns to on-the-job human capital accumulation. As I underscored in the discussion of the stylized model, the nature of outside options is crucial to understanding workers' sensitivity to duration uncertainty since wages in sectors other than mining determine workers' payoffs if the boom is short. With this in mind, the quantitative model incorporates tradable and non-tradable sectors. While the price of tradable goods is exogenous in the model, the prices of non-tradable goods could react negatively to the end of the boom, as in Corden and Neary (1982).

My empirical analysis leverages two types of data. I exploit financial data from one of the biggest mining firms in the world, based in Australia, to estimate the hazard rate for the end of the boom. Since asset prices are forward-looking, financial markets are a natural source to look at when estimating this parameter. I estimate the hazard rate by matching the prices of stock and put options on the stock of the firm during the period to their theoretical value, which comes from applying standard formulas to my setting with two states of the world (Dixit and Pindyck 1994; Cochrane 2005). The estimated hazard rate varies between years, with a clear peak in 2015. This peak is associated with the crash in the Chinese stock market, which, in this context, cast doubts about the continuity of the real estate boom and should impact the future price of mining products. My estimate implies that, from the perspective of 2011, the boom was expected to be over by 2015.

My second source is novel administrative micro-data that covers the universe of Australian workers in the formal sector between 2011 and 2018.[2] I construct a panel of workers between 2011 and 2018 by linking data from tax returns across years and to the 2016 census. Given the size and detail of the dataset, I can construct transition matrices between sectors at a fine level of individual characteristics, including sector-specific experience and education. I estimate the

[2]An added advantage of focusing on Australia, among all commodity exporters, is that the coverage of this dataset is relatively high because labor informality is low. According to data from the World Bank, the percentage of the working force in the formal sector in Australia was 90.7% in 2005 (their latest observation), similar to 92.2% in the US.

parameters of labor supply mostly following the approach in Traiberman (2019), which builds on methods original to the empirical industrial organization literature (Rust 1987; Arcidiacono and Miller 2011; Scott 2014). A difference in the estimation stage of the model in my setting comes from the fact that I only observe outcomes during the boom. Still, agents in the model know the hazard rate for the end of the boom and, when making their switching decisions, also consider counterfactual values if the boom were to end. The challenge is disentangling between pure switching costs and counterfactual values in a sector if the boom ends. I tackle this issue by extending the framework in Traiberman (2019) to account for how these 'bust' values enter into expectations in a tractable way, conditional on my estimates of the probability of the commodity boom ending.

I use the estimated model to simulate my counterfactual of interest: a perfect foresight economy in which the last year of the boom is known to be 2014 and compare it to the economy with uncertainty in which the last year of the boom is expected to be 2014. The share of the population working in mining during the period 2012-2014 increased from 3.7% to 4.4%, implying that uncertainty decreased labor supply into mining. However, responses are heterogeneous by age. Young workers increase labor supply into mining the most, while middle-aged workers decrease theirs. Back-of-the-envelope calculations of where the point of convexity for different workers lie, using the estimates, are consistent with these results. For workers aged 40-50, the model-implied kink in the value value function should happen in the early years of the boom. Agriculture and construction are other sectors that grow in the counterfactual economy, while manufacturing shrinks.

The rest of the paper is organized as follows. The remainder of this section discusses the contributions to the literature. Section 2 presents a simple model and discusses risk-loving attitudes towards duration and their effect on labor supply. Section 3 discusses the main features of the mining boom in Australia. Section 4 presents the quantitative model. Section 5 introduces the data sources and Section 6 quantifies the model and discusses the main results. Section 7 shows the results of simulating a counterfactual economy without duration uncertainty and Section 8 concludes.

Related literature. This paper contributes mainly to the literature on labor reallocation following shocks to labor demand that are localized in some sectors or regions, an important strand of which studied trade shocks (Topalova 2010; Artuç et al. 2010; Autor et al. 2013; Dix-Carneiro and Kovak 2017, 2019; Caliendo et al. 2019). The focus in these papers is on how the economy responds to a change in relative prices under the assumption that there are no other regime changes in the future. Recent studies interpret slow and heterogeneous labor reallocation following these types of shocks through the lens of models of sector-specific human capital accumulated on-the-job (Dix-Carneiro 2014; Traiberman 2019). Given these findings, the starting point in this paper is to assume sector-specific human capital acquired on the job, and my contribution is to allow for uncertainty about the future regime of world prices, which translates into uncertainty about labor demand across sectors domestically. At the theoretical level, I show that uncertainty can act as a friction or incentive for workers to switch into booming sectors and that the effects will likely be heterogeneous across workers. Empirically, I show that taking uncertainty into account is important when analyzing the labor market impact of the mining boom in Australia, given the pattern of booms and busts and uncertainty about the length of the boom phase that characterizes commodities.

By incorporating uncertainty about the duration of a trade shock, this paper relates to a strand of the literature in trade that studied firms' responses to trade policy uncertainty. Studies in this area focused on the firms' responses (Handley and Limão 2015; Pierce and Schott 2016; Handley and Limão 2017; Bloom et al. 2019; Graziano et al. 2020). My contribution is to focus on how uncertainty matters for labor supply directly. At the conceptual level, a key difference is that in the settings just mentioned, the firm's problem is an irreversible investment problem, and uncertainty necessarily increases the value of waiting (Handley and Limão 2022). The reason why the effects of uncertainty change in the context I study are two-fold: workers continually decide in which sector to work and they accumulate sector-specific human capital.

This paper also contributes to the varied literature on commodity cycles, particularly to studies focusing on the effects on workers (Kline 2008; Adao 2016; Benguria et al. 2021). None of these studies the interaction between human capital accumulation and duration uncertainty. At the macro level, a strand of the literature has concluded that commodity cycles are an important driver of business cycles in emerging economies (Fernández et al. 2017; Drechsel and Tenreyro 2018). Another strand of the literature focuses instead on 'Dutch-disease' effects, whereby commodity booms can harm long-term income (Corden and Neary 1982; Allcott and Keniston 2018). In all of these papers, a key ingredient is that factors can reallocate between tradable sectors. I focus precisely on this reallocation and highlight duration uncertainty as an important element to determine sectoral labor supply elasticities.

2 Stylized Model

The first step towards understanding the effects of duration uncertainty during a boom is to characterize the attitudes towards duration risk exhibited by workers. I first show that these can be risk-loving or risk-averse in a setting with two main elements: human capital accumulation and boom-bust dynamics. Although marginal utility is constant in the baseline, this result is robust to workers having decreasing marginal utility. Risk-loving attitudes towards the duration of the boom arise from the structure of the environment. In Section 4 I extend the model along several dimensions for the quantitative analysis; in this section, assumptions are kept to a minimum.

2.1 Environment

Time is discrete. The economy is populated by a continuum of heterogeneous infinitely-lived agents indexed by their type θ, distributed according to density $g(\theta) : [\underline{\theta}, \bar{\theta}] \to \mathbb{R}$. At every point in time their problem is to decide in which sector to work between the two sectors in the economy, the commodity and the outside sector ($s = c, o$).

Wages in the commodity sector are high at period 0 — the boom phase — and the only random variable in the economy is τ, the date at which the boom ends. It is convenient to define the aggregate state as $b_t = \mathbb{I}[\tau > t]$. Then, the economy is still booming if $b_t = 1$ and the boom is over if $b_t = 0$, implying that the bust is an absorbing state in the model. In particular, if the economy is in the boom state, wages are higher than 1 in the commodity sector and they fall below 1 when the boom ends. Wages in the outside sector are normalized to 1 at all times and states of nature, namely

$$w_{ot} = 1 \ \forall t, b_t \quad \text{and} \quad w_{ct}(b_t) = \begin{cases} \bar{w} > 1 & b_t = 1 \\ \underline{w} < 1 & b_t = 0 \end{cases} \quad \forall t. \tag{1}$$

The labor income that a worker earns in sector s at period t depends on wages per unit of skill and the human capital she is able to supply in sector s, which depends on her type θ and her tenure. Using $\vec{\Delta}_t = [\Delta_{ot} \ \ \Delta_{ct}]$ to denote a vector of sector-specific tenure at time t, labor income is given by

$$y_{st}(\theta, \vec{\Delta}_t, b_t) \equiv w_{st}(b_t) H_{st}(\theta, \vec{\Delta}) = \begin{cases} \gamma_o^{\Delta_{ot}} & s = o \\ w_{ct}(b_t) \times \theta \times \gamma_c^{\Delta_{ct}} & s = c \end{cases} \quad \forall t. \tag{2}$$

The parameter γ_s measures the rate of human capital accumulation in sector s. I further assume that human capital depreciates fully if some time is spent in other sectors. That is, tenure drops to 0 whenever a worker switches sectors, even if for a single period. Using ℓ_t to denote the sector the worker chooses at t, tenure evolves as

$$\Delta'(\Delta_{st}, s_{t-1}, \ell_t) = \begin{cases} \Delta_{st} + 1 & \ell_t = s_{t-1} \\ 0 & \ell_t \neq s_{t-1}. \end{cases} \tag{3}$$

2.1.1 Sorting

At any point in time a worker with state variables $\{\theta, \vec{\Delta}_t\}$ who was previously employed in sector s_{t-1} observes the state of the economy b_t and then decides where to work. Workers cannot save, the price of the consumption good is normalized to 1 in all periods, utility is linear, and the future is discounted by a factor β.[3] Assuming that the hazard rate for the end of the boom, denoted by μ, is constant, her problem can be written recursively

$$V(\theta,\vec{\Delta}_t,s_{t-1},0) = \max_{\ell_t\in\{c,o\}} \Big\{y_{\ell_t t}(\theta,\vec{\Delta},0) + \beta V(\theta,\vec{\Delta}'(\Delta_{st},s_{t-1},\ell_t),\ell_t,0)\Big\}.$$

$$V(\theta,\vec{\Delta}_t,s_{t-1},1) = \max_{\ell_t\in\{c,o\}} \Big\{y_{\ell_t t}(\theta,\vec{\Delta},1) + \beta\Big[\mu V(\theta,\vec{\Delta}'(\Delta_{st},s_{t-1},\ell_t),\ell_t,0) \ + (1-\mu)V(\theta,\vec{\Delta}'(\Delta_{st},s_{t-1},\ell_t),\ell_t,1)\Big]\Big\},$$

where the last argument in the value function is b_t. The first line describes the deterministic problem of the worker if the boom has ended. The second line describes the problem when the economy is booming and future values depend on the unknown state of the economy at $t+1$. With probability μ the economy will go from boom to bust.

Workers are born in period 0 without experience in any sector, draw their θ and choose where to work. Because the economy is initially booming, $b_0 = 1$, their initial state can be assumed to be $\{\theta,\vec{0},o,1\}$. The following proposition describes the optimal policies for a worker who sorts into the commodity sector when she is born.

Proposition 1. **For all θ such that $\ell_0(\{\theta,\vec{0},o,1\}) = c$ optimal strategies ℓ_t satisfy**

- $\ell_t = c$ **if** $b_t = 1$.
- $\ell_\tau \in \{c,o\}$.
- $\ell_t = \ell_\tau \ \ \forall t > \tau$.

Proof. See Appendix Section A.1.

Proposition 1 states that the optimal strategy for workers that start their career in the commodity sector is to stay until the boom ends, re-optimize when it does, and then never switch again. The logic behind this proposition is that as time goes by, workers accumulate sector-specific human capital that they would lose if they changed sectors. If it was optimal to choose sector one initially, it has to remain optimal when the benefits go up.

When the boom ends at $t = \tau$, workers that originally sorted into the commodity sector would have spent τ consecutive periods in it. The economy is deterministic going forward, so they will choose where to work next by comparing the discounted lifetime earnings in each of them, namely,

$$V(\theta,[0\ \tau],c,0) = \frac{\underline{w}\theta\gamma_c^\tau}{1-\beta\gamma_c} \ \text{ vs. } \ \frac{1}{1-\beta\gamma_o} = V(\theta,[0\ 0],o,0). \tag{4}$$

[3] To complete the model, the outside can be interpreted as the consumption and numeraire which is produced with linear technology so both wages and prices are 1. Mining can be interpreted as a tradable good, also produced with linear technology, which is exported in exchange of the consumption goods. Under this interpretation, $\bar{w}$ would represent the world relative price of minerals. The model in Section 4 is a full general equilibrium dynamic model where world commodity prices are taken as given.

She will choose to stay in the commodity sector if the left-hand side is greater than the right-hand side, switch if it was smaller, and would be indifferent between sectors if both are equal. It is useful to focus on the key driver of this decision: the opportunity cost of leaving the commodity sector — losing sector-specific human capital — which is increasing in the duration of the boom. I define

$$\bar{\tau}(\theta, \cdot) \equiv \min_{\tau} : \frac{\underline{w}\theta\gamma_m^{\tau}}{1-\beta\gamma_m} \geq \frac{1}{1-\beta\gamma_o} \tag{5}$$

as the minimum duration that induces the left-hand side of equation (4) to be greater than the right-hand side, and a change of behavior upon the end of the boom. The value of $\bar{\tau}$ does depend on θ but also, as discussed below, more broadly on parameters like $\beta, \gamma_0, \gamma_1, \underline{w}$ which I summarize with $\cdot$ in equation (5). The following lemma characterizes some useful comparative statics regarding what determines $\bar{\tau}$.

Lemma 1. **The threshold duration $\bar{\tau}(\theta, \cdot)$ is shorter durations for more productive workers**

$$\frac{\partial \bar{\tau}(\theta, \cdot)}{\partial \theta} < 0$$

and, for a given θ, depends on other parameters with the following signs

$$\frac{\partial \bar{\tau}(\theta; \gamma_o, \gamma_c, \underline{w})}{\partial \gamma_o} > 0, \quad \frac{\partial \bar{\tau}(\theta; \gamma_o, \gamma_c, \underline{w})}{\partial \gamma_c} < 0, \quad \frac{\partial \bar{\tau}(\theta; \gamma_o, \gamma_c, \underline{w})}{\partial \underline{w}} < 0.$$

Proof. See Appendix Section A.2.

Lemma 1 becomes important when I compare different economies at the end of this section.

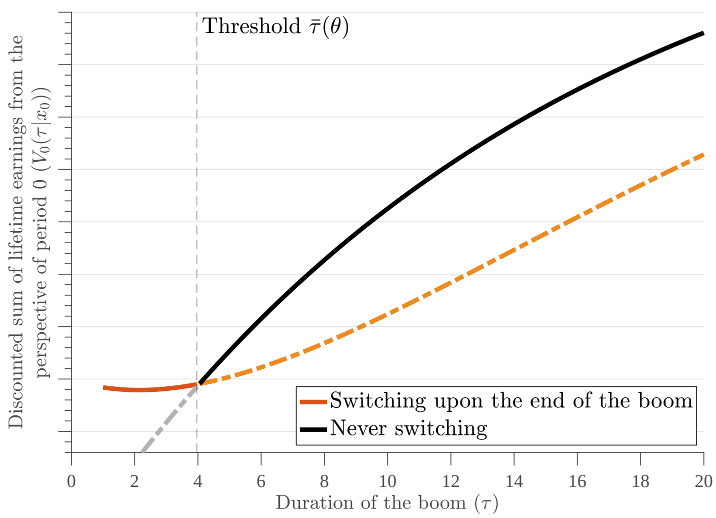
2.2 Attitudes towards Risk

An advantage of the characterization of policy functions in Proposition 1 is that I can now write the discounted value of lifetime earnings in the commodity sector — from the perspective of period 0 — as a function of the duration of the boom, τ. This is a random variable, but workers can, through backward induction, anticipate their lifetime earnings conditional on any duration τ. They are given by

$$\forall \theta : \ell_0(\theta, \cdot) = c \rightarrow V_0(\tau | \theta, \vec{0}, c, 1) = \begin{cases} \frac{\theta\bar{w}(1-(\beta\gamma_c)^{\tau})}{1-\beta\gamma_c} + \frac{\beta^{\tau}}{1-\beta\gamma_o} & \tau < \bar{\tau}(\theta, \cdot) \\ \frac{\theta\bar{w}(1-(\beta\gamma_c)^{\tau})}{1-\beta\gamma_c} + \frac{\underline{w}\theta(\beta\gamma_c)^{\tau}}{1-\beta\gamma_c} & \tau \geq \bar{\tau}(\theta, \cdot). \end{cases} \tag{6}$$

The values in equation (6) reflect that workers recognize that for short durations they will find it optimal to switch sectors upon the end of the boom, but for long durations they will not. The first term of the sum is the same in both cases, reflecting that the worker stays in the commodity sector earning wages $\bar{w}$ at least until the boom ends. The last term of the second line include the term γ_c^τ, human capital accumulated before the boom ended, in the numerator while it does not appear in the first line since human capital depreciates upon switching. For illustration, Figure 2 presents equation (6) as a function of τ.[4]

Figure 2: Risk-loving attitudes towards duration around the kink $\bar{\tau}(\theta)$



Importantly, there is convexity around the kink $\bar{\tau}(\theta)$. The intuition is the following. If the duration of the boom ends up being short, the worker will decide to switch out when the bust happens, cutting losses. On the other hand, if the duration is long enough she will optimally decide to stay even when the boom ends to avoid losing the accumulated human capital. This is a relatively general feature of the environment. The following lemma states sufficient conditions for there to be convexity around the kink.

LEMMA 2. **If $\gamma_c > 1$ and $\frac{\bar{w}}{\underline{w}} \leq \left(\frac{1-\beta}{1-\beta\gamma_c}\right)^2$ then**

$$V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta) - 1) \geq V_0(\bar{\tau}(\theta) - 1) - V_0(\bar{\tau}(\theta) - 2) \tag{7}$$

which implies that the value function is convex at $\bar{\tau}(\theta)$.
Proof. See Appendix Section A.3.

Convexity around the kink is important because it implies that workers have risk-loving attitudes towards duration around $\bar{\tau}(\theta)$. If the process for the boom is such that durations close to the kink are very likely, duration uncertainty would increase the ex-ante expected value in the commodity sector for this worker.

[4]These figures use $\gamma_0 = 1.01, \gamma_1 = 1.04, \beta = 0.9, \underline{w} = 0.6, \bar{w} = 1.03$.

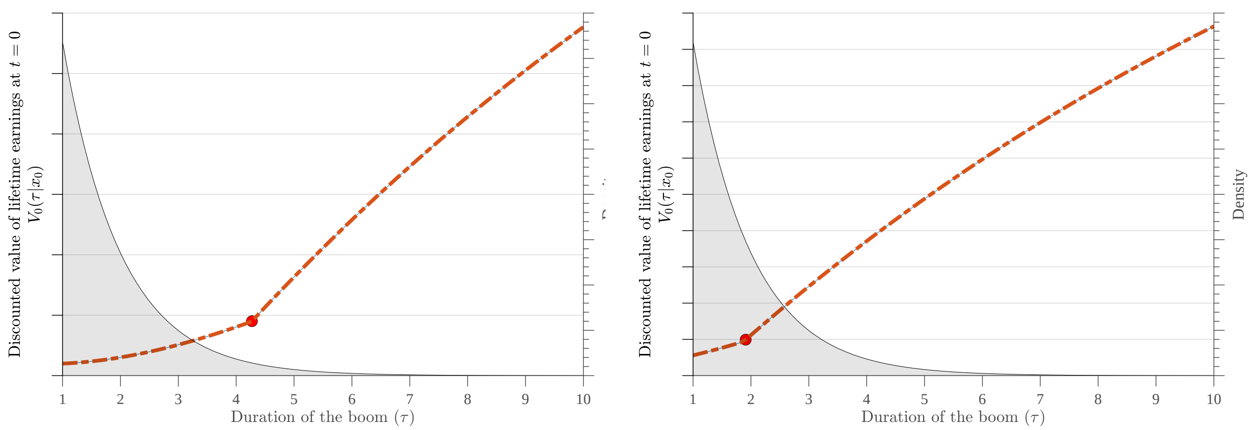
Why is the value function convex around the kink? The crucial difference between an extra period of the boom at $\bar{\tau}(\theta) - 2$ and at $\bar{\tau}(\theta) - 1$ is that in the latter the extra period induces the worker to stay in the booming sector after the boom ends, which means she will carry the human capital accumulated during the boom years throughout her life. This experience increases the level and the returns to human capital accumulation going forward. Human capital accumulation is an important element that makes this setting different from the one studied — for example — in the literature on trade policy uncertainty, where being an older firm does not carry any extra benefits. It is crucial also that the worker can re-optimize: if she was constrained to stay in the booming sector, her value would be given by the dashed gray line (relying on Figure 2), and there would be no convexity. This is another difference with the irreversible investment problem studied in the literature on how trade policy uncertainty affects firms (Handley and Limão 2022). The second condition in the lemma is that the boom can't be too large. This weak condition appears because the model is in discrete time, and is related to the second difference between an extra period of the boom at $\bar{\tau}(\theta) - 2$ and at $\bar{\tau}(\theta) - 1$: in the first case the worker enjoys an extra period of high wages $\bar{w}$ earlier, when they are discounted less.[5]

Because the position of the kink depends on the relative productivity in the commodity sector θ but all workers face the same boom, the impact of duration uncertainty will be different for different workers. Figure 3a shows equation (6) overlapped with the density of the duration for a worker with low θ. Figure 3b shows the same graph for a worker with higher θ. Because the second worker is more productive, the duration starting at which he decides to optimally stay in the commodity sector is shorter than for the first worker and the kink occurs earlier. Given the density for the end of the boom, duration uncertainty is more likely to increase the ex-ante value for the worker that is more productive.

[5]To see that this is related to the model being in discrete time, consider fixing γ_c and taking the limit as $\beta \to \frac{1}{\gamma_c}$, making workers as patient as possible (analogous to period as short as possible) while keeping the problem well-behaved. Then, the upper bound would increase to infinity.

Figure 3: Heterogeneous risk-loving attitudes

(a) Low productivity in the commodity sector (b) High productivity in the commodity sector



2.3 Labor Supply: The Role of Duration Uncertainty

I now study how workers with different productivities decide their sector of employment at time 0. The value at birth of sorting into commodities is equal to the expected value of equation (6), where the expectation is taken over duration τ. The value of sorting into the outside is equal to the discounted value of lifetime earnings staying in that sector forever.[6] Then, a worker of type θ sorts into the commodity sector if the following inequality holds

$$\mathbb{E}_\tau(V(\tau)) \geq \frac{1}{1-\beta\gamma_o} \Rightarrow \ell_0(\theta, \vec{0}, o, 1) = c.$$

Figure 4 shows how different types θ sort across sectors in economies with low and high rates of human capital accumulation in the commodity sector γ_c. The orange solid lines in each panel show the expected value of sorting into the booming sector at time 0. These lines are increasing in θ, as higher θ types have higher productivity. The black solid line is the discounted value of sorting into the outside sector at time 0. Workers at the right of the intersection between the solid lines sort into the commodity sector. The solid orange line is also higher in the right panel, with a higher rate of human capital accumulation. This translates into the threshold shifting to the left and a higher labor supply in the booming sector at time zero.

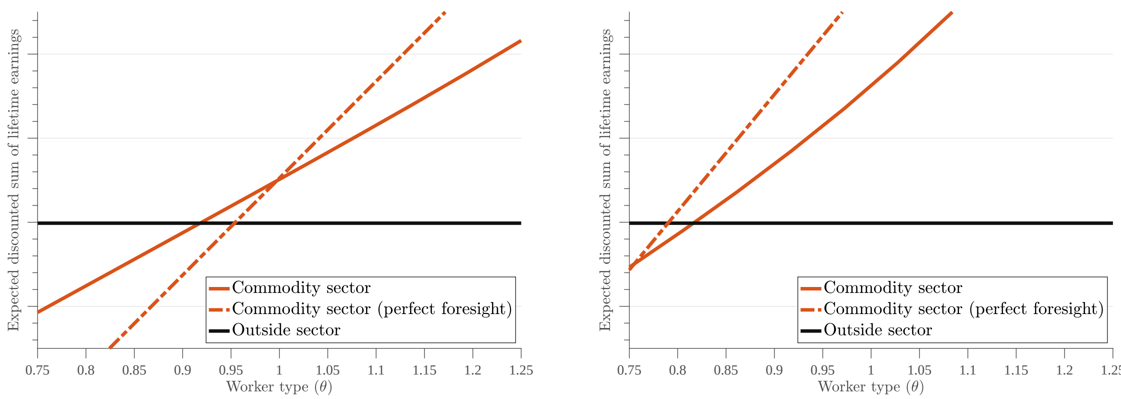
This environment serves as a laboratory for the following thought experiment, where I isolate the role of duration uncertainty. I compare the economy just described with a perfect foresight economy in which the duration of the boom is fixed and set to $\tau^{pf} = \frac{1}{\mu}$, which is the expected duration in the baseline economy. The dashed lines in both panels of Figure 4 show how the

[6] The argument of why a worker never switches out of the outside sector is analogous to the one for commodities but simpler because the sector is not affected directly by the end of the boom.

ex-ante value of sorting into the booming commodity sector changes.

Figure 4: Aggregate effects of duration uncertainty on labor supply

(a) Low rate of human capital accumulation (b) High rate of human capital accumulation



The first thing to note is that the dashed lines rotate and can be below or above the solid lines for different values of θ. This parallels the idea illustrated in Figure 3 that the kink will happen at different points for different workers, leading their expected value to react to duration uncertainty differently.

The main corollary following from that observation is that labor supply in the booming commodity sector can either increase or decrease once the economy has no uncertainty about duration. In the example shown in Figure 4a, workers close to the initial cut-off between sectors were benefiting from the possibility of long booms (in this sense 'betting on the boom'). Once the duration is fixed and known in advance, they find it optimal to sort into the outside sector instead. Figure 4b shows how, keeping all parameters the same except for a higher γ_c, the effects of duration uncertainty on labor supply in this economy flip. In this economy, duration uncertainty discourages labor supply on the margin and employment in the commodity sector increases once there is no uncertainty.

Importantly, the emergence of risk-loving attitudes towards duration does not hinge on the assumption of linear utility, as long as the conditions in Lemma 2 hold. To see this, consider the case in which utility is given by y_{st}^{σ} with $\sigma < 1$. The right-hand side of equation (2) for the commodity sector, now interpreted as utils, would become: $u_{ct} = (w_{ct}\theta\gamma_c^{\Delta_{ct}})^{\sigma} = w_{ct}^{\sigma}\theta^{\sigma}(\gamma_c^{\sigma})^{\Delta_{ct}}$. From here it follows that the problem would be equivalent to having started with these alternative definitions of wages, types, and rates of human capital accumulation (which would never fall below one if they initially were).

The key takeaway from the stylized model is that the effects of duration uncertainty — both qualitatively and quantitatively — are an empirical matter. It is crucial to know whether marginal workers exhibit risk-loving attitudes towards duration or not, as the comparison in

Figure 4 shows. I now turn to describe the context I focus on for the rest of the paper.

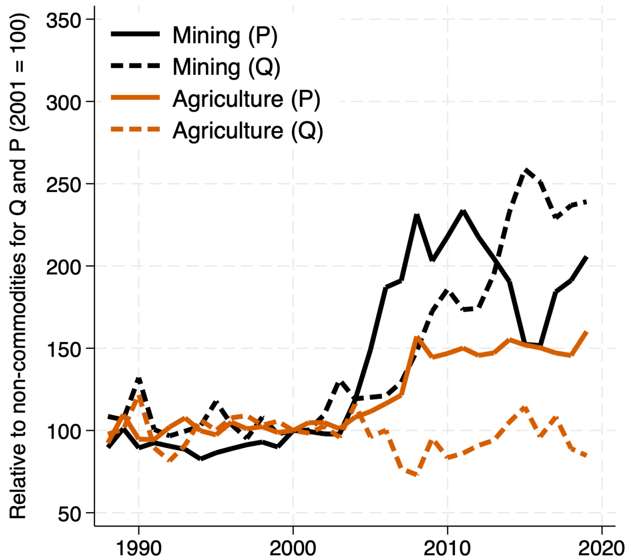
3 The Mining Boom in Australia

Rapid growth and urbanization in China during the early years of the century pushed up demand for commodities, leading to the highest commodity prices in decades. As shown in Figure 1, commodity exporters around the world benefited from the boom. The literature studying commodity super-cycles puts this episode, in terms of its impact on commodity prices, at par with the industrial revolution in the UK, the US and post-war reconstruction in Europe (Erten and Ocampo 2013). Between 2000 and the 2010s, Chinese imports of ores and metals surged, leaping from 5% to 30% of global imports for these commodities.[7] These commodities were being used as inputs in construction as China's population moved to cities and the real estate market was liberalized. Urban population in China increased from 26% of the total population in 1990 to 36% in 2000 and 49% in 2010. Moreover, reforms to the housing market in the late 1990s led to a boom in private construction and an increase in the quality and size of buildings that increased demand for inputs beyond what the urban population numbers suggest (Berkelmans and Wang 2012). Due to the geographical proximity and the quality and quantity of mineral reserves, Australia became a key exporter of mineral products like iron ore and coal used for steel production, an input in the construction sector (Berkelmans and Wang 2012). Between 2011 and 2019, approximately half of the mineral exports of Australia went to China.

Although Australia also produces other commodities, the boom was concentrated in the mining sector. Figure 5 shows, in solid lines, the evolution in the export price of both mining and agricultural commodities in Australia, relative to the price of all other exports. In dashed lines, the same panel shows the growth in exported quantities of both types of commodities during the period, relative to non-commodity exports. Relative exports in mining commodities from Australia increased substantially during this period, especially after 2005. The economy responded to an increase in the relative price of mining products by exporting more of these commodities. Given that the increase in exported quantities was focused on mining products, from now on I will refer to mining as the booming sector.

[7] The facts in this paragraph come from World Bank data accessed online.

Figure 5: Relative export prices and quantitities



In order to test the common view, outlined in the previous paragraphs, that the increase in export prices experienced by Australia was driven by construction in China, I collected data on construction activity in China and test how well it can predict export prices of different goods in Australia. I find that an increase of 1% in planned constructed floor space in China predicts a 0.45% increase in the export prices of mineral and metal prices one year later, while there is no effect for either agricultural or manufactured goods. There is also no effect on mining prices of other proxies of economic activity, like retail sales, suggesting that construction plays an independent role. See Table 4 in the Appendix, Section B.1.

The temporary nature of the boom, as China would eventually converge to the new steady state housing stock, was perceived by key institutional actors in Australia and other commodity exporters and raised questions about how sustainable the boom would be.[8] Consider the following quote from Rayner and Bishop (2013), two researchers from the Reserve Bank of Australia

> *In terms of the path of the terms of trade, an important unknown is the extent to which the growth in the demand for commodities (...) might ease over the longer term as the emerging economies in Asia mature. For example, the rate of urbanisation in Asia, which has driven much of the demand for iron ore and coal, is expected to eventually slow and then stabilise...*

Although temporary, the precise duration of the boom was not known ex-ante. To show this, Figure 10a in the Appendix Section B shows IMF forecasts in the World Economic Outlook

[8] A separate issue is whether growth in the Chinese real estate sector was also driven by speculative forces. For the goals of this paper it doesn't matter; in either case the phenomenon is temporary.

for the prices of coal and iron ore, key products in Australia, between 2010 and 2018. These forecasts were consistently negative, suggesting that the boom phase was expected to end. However, the realized price changes, also shown in Figure 10a, were far from the forecasts.

A potential caveat about studying a mining boom is that mining is capital-intensive, and employs relatively few workers directly. However, it is important to consider that booms in the terms of trade translate into booms in demand for non-tradable goods. The textbook response in a small open economy when terms of trade increase is for both the booming sector and the non-tradable sector to expand, while other tradable sectors shrink (Corden and Neary 1982). Figure 10b in the Appendix Section B shows that this is exactly what happened in Australia during the period. Employment and earnings in mining expanded jointly with services and construction while the other tradable sector, manufacturing, shrank in relative terms. The quantitative general equilibrium model I describe next introduces several sectors to capture these effects. The mining boom in Australia has several features that make it an ideal setting to study the effects of uncertainty about duration: it consisted of a large boom, driven by temporary forces, and its duration was unknown.

4 Quantitative Model

I extend the baseline model in Section 2 in order to take it to the data from Australia between 2011 and 2018. The first new feature is to model boom-bust dynamics in world mining prices instead of wages, which are now endogenous. Secondly, I borrow from Traiberman (2019) to build a small open economy model with rich worker heterogeneity. The key assumption remains that workers accumulate sector-specific human capital in the sector where they work.

4.1 World prices

There are three tradable goods in the world economy: agriculture, manufacturing, and mining. The prices of the mining good, p_t^M, can be written as a function of the underlying state $b_t \in \{0, 1\}$ and time, where $b_t = 1$ means that the mining boom is still ongoing,

Assumption 1. **Mining prices are a function of the state b_t and time**

$$p_t^M(b_t) = \begin{cases} \bar{p}_t^M & b_t = 1 \\ \underline{p}_t^M & b_t = 0 \end{cases}. \tag{8}$$

Using tilde to denote logs,

$$\tilde{\bar{p}}_t^M = \bar{\rho}_0 + \rho_1(\tilde{\bar{p}}_{t-1}^M - \bar{\rho}_0) + \bar{\nu}_t \tag{9}$$

$$\tilde{\underline{p}}_t^M = \underline{\rho}_0 + \underline{\nu}_t \tag{10}$$

with $\bar{\rho}_0 > \underline{\rho}_0$. Shocks $\bar{\nu}_t, \underline{\nu}_t$, are independent across periods and normally distributed.

Assumption 1 is analogous to the process for wages in equation (1) in the baseline model. I allow for variation in prices between periods and conditional on the state. I further assume that, conditional on the state, prices in logs follow an an AR(1) with mean $\bar{\rho}_0$, while if the boom is prices are assumed to fluctuate around a lower mean $\underline{\rho}_0$. The parameter ρ_1 measures persistence of deviations in the price around the state-specific mean. These assumptions play a role in the estimation of the hazard rate for the stochastic process for the boom, not for the estimation of the labor side of the model.

As in the simple model, I assume that the bust state is an absorbing state and the hazard rate μ_t is time-varying, as summarized in Assumption 2 below. This strong absorbing property is intended as an approximation to the fact that bust periods, especially for metals, have been long on average. Erten and Ocampo (2013) calculate them to last 20 years.

Assumption 2. **The hazard rate for the end of the boom is given by**

$$\mathbb{P}_t[b_{t+1} = 0 | b_t] = \begin{cases} \mu_t & b_t = 1 \\ 1 & b_t = 0 \end{cases}. \tag{11}$$

The history of aggregate shocks up to period t, h^t, is given by a sequence $\{b_s\}_{s=0}^t$ and realized prices. I assume that there is no uncertainty about the prices of other tradable prices in the economy, manufacturing and agricultural goods, but their prices may still vary between years. I use $\bar{p}_t, \underline{p}_t$ to refer to the vector of all tradable prices at time t if $b_t = 1$ or 0 respectively.

4.2 Small open economy

The economy consists of five sectors, three tradable goods (manufacturing, mining, and agriculture) and two non-tradable (construction and other services). I denote the set of all goods by $\mathcal{S}$, tradable goods by $\mathcal{S}^T$ and non-tradable goods by $\mathcal{S}^N$. The reasons to incorporate more than two sectors are twofold. First, modeling the outside options of workers is crucial, and the boom in agricultural goods (shown in Figure 5) need not finish when the mining boom ends. Second, as argued above, it is important to have a distinction between tradable and non-tradable goods since changes in the terms of trade should impact the demand for the latter. I treat construction separately from other services because, during the period I study, there was a spike in construction investment.

Labor supply. The economy is populated by a constant mass of $\bar{L}$ finitely lived workers who live up to age $\bar{A}$. When a generation dies, a new generation of equal size is born unattached to any sector. Workers are heterogeneous in terms of their education and unobserved type, as defined below. Newborns have the same characteristics as the dying generation along these dimensions.

At the beginning of period t the state of worker i is $\omega_{it} = \{a_{it}, s_{it-1}, \Delta_{it}, e_i, \theta_i\}$, where a_{it} denotes her age, s_{it-1} the sector in which she worked in the previous period, and Δ_{it} tenure defined as the number of consecutive years of employment in the sector in which she was employed at $t-1$. Finally, e and θ capture time-invariant characteristics: $e \in \{low, medium, high\}$ denotes the maximum education level attained. I classify workers who have not studied beyond high school as low education, some vocational training as medium, and college or more as high education. Θ is defined as the set of possible types and is assumed to be finite, and $\theta \in \Theta$ captures unobserved heterogeneity.

There are several reasons to account for a broader set of determinants of human capital than in the baseline model. First, as explained in Section 2, the effects of duration uncertainty will be different for workers depending on their productivity in the mining sector, which could depend on their education and unobservable characteristics. A second reason is to control for selection in the type of workers who decide to spend longer spells in a sector. This is crucial for estimating the returns to human capital accumulation.

The characteristics of a worker determine her income in every sector. The real labor income of worker i, if she sorts into sector s after a history of aggregate shocks h^t, is given by

$$y_{it}(h^t)|s \equiv \frac{w_s(h^t)}{P_t(h^t)} H_s(\overbrace{\omega_{it}}^{\text{Age, tenure, type}}, \overbrace{\zeta_{ist}}^{\text{Shock}}), \tag{12}$$

where w_s is the sector-specific wage per efficiency unit of human capital and P_t denotes the price level, defined below. The second term includes the function H_s, the number of efficiency units of human capital that the worker is able to supply to a sector. H_s depends on age, tenure and unobserved type. The shock ζ_{ist} is specific to s and is observed *after* the worker decides to sort into sector s. The role of this shock is to rationalize differences in income across workers conditioning on ω and will not play an important role in the analysis. I assume it is normally distributed with mean zero and unit variance.

The flow utility of a worker with characteristics ω_{it} who sorts into s, shown in equation (13), is the combination of real income y_{it}, an amenity value η_s, and switching costs $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$, both of which are modeled in terms of utility. It can be written as

$$U(\omega_{it}, s_{i,t-1}, s, h^t) = \mathbb{E}_\zeta[y_{it(h^t)|s}] + \overbrace{\eta_s}^{Amenity} + \overbrace{\tilde{C}(\omega_{it}, s_{it-1}, s_{it})}^{\text{Switching cost}}. \tag{13}$$

At the beginning of period t, worker i observes the history of aggregate shocks up to t, h^t. In this setting, and contrary to the baseline model, wages are a function of the history of shocks and not only the current state. The reason is that after the boom ends and $p_t = \underline{p}_t$, equilibrium wages move slowly towards the new steady state in a way that depends on the state of the economy when the boom ends. Therefore, it is important to keep track of when the boom ended. As is standard in quantitative models, I also allow for sector-time-specific idiosyncratic shocks $\{\epsilon_{sit}\}$. These shocks are independently and identically distributed across sectors, individuals, and time according to a Gumbel distribution. After observing all of these, the worker makes her decision of where to work. Her value after idiosyncratic shocks are realized, and the expected value ex-ante, are given by

$$v(s_{i,t-1}, \omega_{it}, h^t, \epsilon_{it}) = \max_{s' \in \mathcal{S}} \left\{ U(\omega_{it}, s_{i,t-1}, s', h^t) + \rho\epsilon_{s'it} + \beta\mathbb{E}_t V_{t+1}(s', \omega', h^{t+1}) \right\} \tag{14}$$

$$\text{and } V(s, \omega, h^t) = \int v_t(s, \omega, h^t, \epsilon) dG(\epsilon) \tag{15}$$

respectively. In equation (14) idiosyncratic shocks are scaled by parameter ρ, which measures the importance of idiosyncratic factors relative to the fundamental reasons for moving between sectors. The expectation in equation (14) is taken with respect to b_{t+1}, as I discuss in detail below. The continuation value V_{t+1} takes ω', the future characteristics of the worker, as an argument. Age evolves mechanically by one, while education and unobserved type are constant.[9] Tenure evolves as in the baseline model, namely,

$$\Delta_{i,t+1} = \begin{cases} \Delta_{it} + 1 & \text{if } s_{i,t-1} = s_{it} \\ 0 & \text{if } s_{i,t-1} \neq s_{it} \end{cases}. \tag{16}$$

Whenever a worker switches sectors her tenure gets reset. As discussed in Section 2, human capital depreciation upon switching is at the heart of the economic mechanism underlying risk-loving attitudes. This assumption is important for estimation as well. In that context, assuming that one period is enough for tenure to be reset is not crucial, however; what matters is that there are different decision paths that two identical workers can take after which their state variables are identical. Dix-Carneiro (2014) allows for human capital accumulated in one sector to be imperfectly transferred to other sectors as well. I exclude this possibility.

[9] An interesting extension of the model would be to allow for expectations about the duration of the shock to affect education decisions, a margin which has been important in other contexts (Atkin 2016).

Consumer problem. Workers have Cobb-Douglass preferences over all goods in the economy. Hence,

$$u(C_1, ..., C_S) = \prod_{s=1}^{S} C_s^{\kappa_s} \text{ with } \sum_{s}^{S} \kappa_s = 1.$$

The price index, which already appeared in equation (12), will then be

$$P_t(h^t) = \prod_{s=1}^{S} (\tfrac{p_t^s(h^t)}{\kappa_s})^{\kappa_s},$$

where $p_t^s(h^t)$ is the price of good s after history of shocks h^t. The price of the tradable goods will be exogenous while the price of non-tradable goods will be endogenous, as discussed below.

Technology. Good s is produced competitively by a representative firm with access to Cobb-Douglass technology given by

$$Y_{st} = A_{st} K_{st}^{1-\alpha_S} H_{st}^{\alpha_s}, \tag{17}$$

where A_{st} and K_{st} capture productivity and physical capital in each sector and H is the sum of efficiency units of human capital. From the profit maximization and zero profit conditions for the firm,

$$\frac{H_{st}^d(h^t)}{K_{st}^d(h^t)} = \frac{r_t(h^t)\alpha_s}{w_s(h^t)(1-\alpha_s)} \tag{18}$$

$$p_{st}(h^t) = \frac{\chi^s r_t(h^t)^{1-\alpha_s} w_s(h^t)^{\alpha_s}}{A_{st}}, \tag{19}$$

where χ^s is a constant and super-script d denotes demand.[10] Note that wages are sector-specific.

Physical capital. The aggregate stock of physical capital evolves according to

$$K_{t+1} = (1-\delta)K_t + I_t \tag{20}$$

and physical capital is perfectly mobile across sectors. I take the path of $\{I_t\}$ as exogenous and assume it consists of buildings only. Then, I_t enters as demand for the construction sector at t, on top of construction for residential purposes coming from consumers. I discuss the implications of this assumption about the evolution of investment below.

Equilibrium. Given K_0 and paths of $\{\mu_t\}_{t=0}^{\infty}$ and a process for tradable prices $\{\bar{p}_t, \underline{p}_t\}$, an equilibrium is given by a path of non-tradable prices $\{p_t^s(h^t)\}_{t=0}^{\infty}$ for $s \in \mathcal{S}^N$, wages $\{w_t^s(h^t)\}_{t=0}^{\infty}$

[10] $\chi^s = \frac{\alpha_s}{(1-\alpha_s)}^{1-\alpha_s} + \frac{(1-\alpha_s)}{\alpha_s}^{\alpha_s}$.

for $s \in \mathcal{S}$, rental prices of capital $\{r_t(h^t)\}_{t=0}^{\infty}$, and quantities $\{K_{st}(h^t), H_{st}(h^t), C_{st}(h^t), Y_{st}(h^t)\}$ such that for all h^t:

- Workers sectoral labor supply solves the problem in equation (14).
- Firms maximize profits . Namely, equation (18) and equation (19) hold for all s in $\mathcal{S}$.
- Labor markets clear,

$$H_{st}^d = H_{st}^s \quad \forall s \in \mathcal{S}, \tag{21}$$

  where human capital supply in the right-hand side is given by the sum across characteristics ω_{it} of all workers who find it optimal to sort into sector s and the function $H_s(\omega, \zeta)$.

- The market for physical capital clears,

$$\sum_{s \in \mathcal{S}} K_{st}^d = K_t \tag{22}$$

  with capital supply in the right-hand side given by K_0 and equation (20).

- Markets for non-tradable sectors clear. Namely,

$$C_t^{other\ services}(h^t) = Y_t^{other\ services}(h^t)$$
$$C_t^{const}(h^t) + I_t = Y_t^{const}(h^t).$$

- Trade is balanced,

$$\sum_{s \in \mathcal{S}^T} p_t^s(h^t)\ C_t^s(h^t) = \sum_{s \in \mathcal{S}^T} p_t^s(h^t) Y_t^s(h^t).$$

Most of the elements in the model of labor supply are standard and build on Dix-Carneiro (2014) and Traiberman (2019). A key ingredient is the fixed utility cost of switching sectors, $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$, which has been highlighted by the literature as a driver of labor reallocation on top of the opportunity cost which I underscore here. Since the work of Topalova (2010) and Autor et al. (2013), the costs of switching industries or regions have played a central role in our understanding of labor responses to shocks to labor demand like trade liberalizations. Artuç et al. (2010) estimated large costs of switching in a model without sector-specific human capital accumulation, while Dix-Carneiro (2014) and Traiberman (2019) incorporate human capital and find that estimates of pure switching costs $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$ are reduced substantially.

The main new ingredient in my model of labor supply, compared to the ones in the literature, lies in the expectation term in equation (14), which can be expanded as follows. By the law of iterated expectations, the continuation value for a worker with characteristics ω' who was employed in s' at t can be written as

$$\mathbb{E}_t V_{t+1}(s', \omega', h^{t+1}) = \mu_t \mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 0\}) + (1 - \mu_t)\mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 1\}). \qquad (23)$$

Equation (23) has important implications at the moment of estimating the costs of switching sectors using data only from a booming period, as I will do in the next section. The key challenge is to disentangle the pure switching costs from unobserved changes in future value in the event of a bust (which are not observed).

Investment in physical capital is assumed to be exogenous. The reason to incorporate this element, despite its simplistic form, is the empirical relevance in the context. Investment was large, particularly in the early stages of the boom, which introduced a temporary increase in labor demand as mines and roads to the mines had to be built. This and other types of frictions in labor demand, such as labor adjustment costs as in Kline (2008) could interact with duration uncertainty in meaningful ways. To keep the model tractable, I abstract from these two elements in the model.

5 Data Sources

I rely on three types of data for the estimation: financial data, matched employer-employee data, and aggregate sectoral data from national accounts.

5.1 Financial data

I use financial data from the firm BHP, which is among the biggest mining firms in Australia and in the world. The data on the values of stocks and put options on the stock of this firm come from OptionMetrics, a large provider of data on financial instruments traded in US markets. Data on dividends is publicly available.

I observe, at a daily frequency between March 2004 and December 2019, the best offer for put options of different horizons (T) and strike prices (K) on the stock. These are American options, which means that the holder of the instrument can exercise the option at *any* time before time T. If the option is exercised, the holder sells a unit of the underlying stock for the strike price K. I focus on these instruments since, as their value goes up whenever expected stock prices drop — especially when they drop below K —, the values of these instruments are particularly sensitive to extreme events, like the end of a commodity boom. In OptionMetrics I also observe the value of the stock of the firm underlying the option just described. Both put and stock values are denominated in dollars and traded in US markets.

I use put options with a horizon of T close to one year, since the rest of the model will be estimated at an annual frequency. I keep the median value per instrument-semester pair. The number of observations with different strike prices in a particular semester varies. To have a stable number of observations per semester I keep three instruments with different strike prices per semester.

From public data I also observe the value of dividends per share at a semi-annual frequency, also expressed in dollars. Using F to denote the best offer for the options, S the price of the stock, and d the dividends per share, my data consists of observations of $\{d_t, S_t, \{F_t(S_t, T, K_i)\}_{i=1}^3\}$ for each semester between 2010 and 2019.

5.2 Labor data

My main source of data is a novel and rich collection of administrative datasets from Australia which combines the Multi-Agency Data Integration Project (MADIP) and the Business Longitudinal Data Environment (BLADE), both compiled and held by the Australian Bureau of Statistics (ABS). The first one has information on workers and the second on firms.

From MADIP I observe tax returns filed between 2002 and 2018, where both the worker and the plant of employment are identified with a code. I use the first years of data to construct sector-specific employment histories for each worker and focus on 2011-2018. Plants can be linked to firms using information from BLADE. Workers are identified with the same code across years and the different tax returns they may file in a given year. I use this identifier to construct a panel of workers where I keep the highest-paying job a worker had each year. I deflate labor incomes using the consumer price index.

Firms in the data are classified into sectors according to the ANZSIC classifications, which are original to ABS. I aggregate sectors into five, as discussed in the setup of the model: agriculture and forestry (1.3% of the workers in my panel), mining (3.3%), manufacturing (6.2%), construction (5.9%) and other services (83%).

This panel can then be linked to the 2016 census, from which I recovered the education that each worker had in 2016. This means that I can not observe changes in education status. I classify workers into three education groups. The first group includes people with at most high school completed (41% of the workers in my panel); the second encompasses workers who have done courses shorter than two years above high school, which includes vocational training (23%); the third group encompasses everyone with a bachelor degree or higher (36%). Appendix Section B.4 shows the joint distribution of workers across education-sector pairs. One thing to note is that mining demands a significant share of workers from all three education categories: 22% of the workers employed in mining had some vocational training and 18% had a college degree or higher.

5.3 National accounts

I collect data on value-added, exports, wage bills, and imports by sector from the series of national accounts and international goods and services accessed on-line from the ABS website. I aggregated variables at the level of the same five sectors used in the rest of the paper. I also retrieve the series of aggregate stock of capital from this source. To be consistent with the model, I keep the series of non-dwelling construction at constant prices as my measure of capital.

6 Estimation

I estimate the series of μ_t by matching the theoretical value of financial instruments, using standard formulas, to the financial data described above. To estimate the parameters determining labor supply I follow the approach in Traiberman (2019), who builds on a rich literature from industrial organization and labor economics (Rust 1987; Lee and Wolpin 2006; Arcidiacono and Miller 2011). The remaining parameters that characterize the real economy — like parameters of the production functions — are estimated by matching aggregate moments.

6.1 Hazard rate

The object of interest in this subsection is the hazard rate for the end of the boom, μ_t in equation (11). First I describe how, under some assumptions on how BHP decides to distribute dividends, the theoretical value of stocks and options depends indirectly on μ. Then, I present the estimation procedure and conclude by discussing results.

6.1.1 Financial values in mining and the aggregate state

I assume that the dividends that BHP pays in period t (in logs) are a linear function of the aggregate price index of mining products in period $t-1$ (in logs) and an error term. Using a tilde to indicate that variables are in logs,

$$\tilde{d}_t = \delta_0 + \delta_1 \tilde{p}^M_{t-1} + u_t. \tag{24}$$

This reduced-form equation captures both how the profits of the firm react to the aggregate level of mining prices and the firm's decision to distribute part of those profits as dividends. The error term u_t is assumed to be independent and identically normally distributed with standard deviation σ.

I estimate $\delta_0, \delta_1, \bar{\rho}_0$ and ρ_1 in equations equation (9) and equation (24) from the half-yearly data for dividends and the price index of mining products (described in Figure 5).[11] The forecast of future dividends (in levels) can be calculated by exploiting the fact that, by equation (24), future dividends will be log-normally distributed. Hence,

$$\mathbb{E}_t[d_{t+1}|b_t = 1] = e^{\delta_0+\delta_1\tilde{p}_t^M+\frac{\sigma^2}{2}} \tag{25}$$

$$\text{and } \mathbb{E}_t[d_{t+j}|b_t = 1] = \mathbb{P}[b_{t+j} = 1]e^{\delta_0+\delta_1[(\bar{\rho}_0+\rho_1^j(p_{t-1}-\bar{\rho}_0)p_t^M+\frac{\sigma^2}{2}} + (1 - \mathbb{P}[b_{t+j} = 1])e^{\delta_0+\delta_1\underline{\rho}_0+\frac{\sigma^2}{2}} \tag{26}$$

Notice that the probability that the boom is ongoing at $t + j$ is itself a function of the path of μ. Namely,

$$\mathbb{P}[b_{t+j} = 1] = \prod_{s=0}^{j-1}(1 - \mu_{t+s}). \tag{27}$$

The perspective of future commodity prices affects, through the impact on dividends, the theoretical value of different financial instruments ex-ante. The theoretical value of the stock, denoted by S_t, equals the expected discounted sum of dividends

$$S_t(b_t) = \mathbb{E}_t\Big[\sum_{s=t+1}^{\infty} M_{t,s}(b_s)d_s\Big], \tag{28}$$

where $M_{t,s}$ is the stochastic discount factor between future state s and current t (Cochrane 2005). As mentioned in Section 5, American put options allow the holder to sell the stock at strike price K at any period before termination date T. The value of these options when investors are risk neutral is then given by

$$F_t(S_t(b), T, K) = \begin{cases} \max\{\frac{(1-\mu_t)F_{t+1}(S_{t+1}(b=1),T,K)+\mu_t F_{t+1}(S_{t+1}(b=0),T,K)}{(1+r_t)}, K - S_t, 0\} & t < T, b_t = 1 \\ \max\{\frac{F_{t+1}(S_{t+1}(b=0),T,K)}{(1+r_t)}, K - S_t, 0\} & t < T, b_t = 0 \\ \max\{K - S_T, 0\} & t = T \end{cases} \tag{29}$$

(Dixit and Pindyck 1994). Equation (29) reflects investors' optimal stopping time decision. The hazard rate μ affects the evolution of F in a non-linear way.

[11] Figure 5 plots the aggregate price index relative to non-commodities. For this calculation, I use the absolute level of the index for mining products.

6.1.2 Estimation

I estimate $\delta_0, \delta_1, \rho_0$ and ρ_1 in equations equation (9) and equation (24) from half-yearly data on mining price indices and dividends using OLS. Results are shown in Table 1 below. The standard deviation of the residuals in equation (24), which enters equation (28), is $\hat{\sigma} = 0.29$.

Table 1: Auto-regressive processes for dividends and prices

	Mining prices	Dividends
Constant	0.567***	-2.215***
	(0.019)	(0.32)
Deviation in mining prices (lagged)	0.687***	2.541***
	(0.11)	(0.532)

Standard errors in parentheses

The results in Table 1 indicate that there is persistence in the process for world prices. In addition to this, movements in the world prices translate into higher dividends paid by the firm one semester later. Results, not shown, are robust to incorporating contemporaneous level of prices in the equation for dividends.

I assume that stochastic discount factors can be parametrized as $M_{t,s} = \frac{\beta^{s-t} m_s(b_s)}{m_t(b_t)}$, where β is the discount factor and $m_s(b_s)$ is the marginal utility in period s if the state is b_s (Cochrane 2005). I set $\beta = 0.96$, a standard value for the parameter. I estimate the values of $\{m_t(b_t = 1), m_t(b_t = 0), \mu_t\}_{t=2010}^{T}$ so as to minimize the distance between the time series and the model predicted values for these instruments, given by equation (28) and equation (29). Note that I estimate values up to a period T beyond the end of 2019.

6.1.3 Discussion

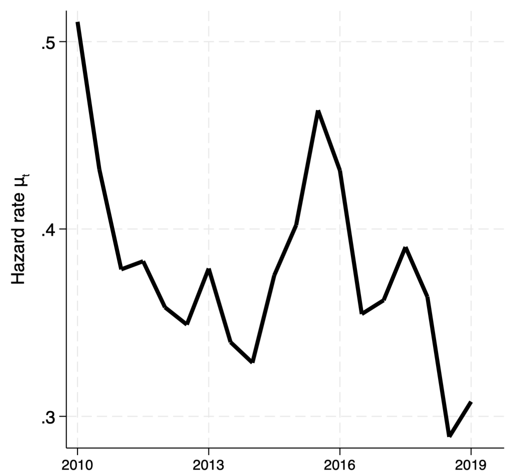
Figure 6 below shows the annualized results for μ_t. This series can be interpreted as the estimated probability that the boom ends in the following two semesters from the perspective of semester t. The estimates for the probability for to the end of the boom are large. This is consistent with both the qualitative evidence from policy reports quoted in Section 3 and the IMF forecasts for the prices of iron ore and coal shown in Figure 10a in the Appendix, which were negative throughout the decade. The large estimated values for the hazard rate suggest that the bust scenario was also salient to workers sorting across sectors during the period.

The hazard rate varied substantially between periods. The spike in late 2015 coincides with a stock market crash in China, which raised doubts about the prospects of the Chinese economy falling into a recession.[12] Moreover, as shown in the Appendix Section B.2, new residential

[12] The following piece of news from July 2015 in CNN is eloquent: *Fears of a downturn in China have already hammered the price of commodities like iron ore and copper this week. In the longer term, this could also hurt places like Australia, which supplies a lot of China's raw materials.* Link:

housing started to grow below trend in late 2014, and by 2016 Kruger et al. (2016) suggested that the housing boom was over. However, construction quickly picked up by mid-2017 as the government in China provided stimulus to the real estate sector. This is reflected in the series for μ_t, which quickly goes back to its pre-2015 level.

Figure 6: Estimated hazard rate



The estimate of μ_t reflects information from asset prices, and does not necessarily reflect what agents in labor markets in Australia believe. To test whether my measure of μ_t captures information that is relevant for labor markets, I estimate the following equation,

$$Y_{i,t} = \alpha_0 + \alpha_1 p^M_{t-1} + \alpha_2 p^M_{t-2} + \alpha_3 \mu_{t-1} + \bar{\alpha} X_{it} + \epsilon_{it},$$

where $Y_{i,t}$ takes value one if worker i is employed in mining in year t and p^M_{t-1} and μ_{t-1} denote the lagged levels of mining prices and the hazard rate for the end of the boom. I lag these as, naturally, it takes time to switch sectors. The last term includes controls like age, education, and the previous sector of employment. I estimate this equation through OLS. The first column in Table 5 in Appendix Section C shows that the estimate of α_3 is negative and both statistically significant and economically large. I also study the interaction of μ_{t-1} with age and find that the effect of an increase in μ_{t-1} is particularly strong for middle-aged workers, suggesting that the decrease in employment reflects an impact on labor supply which is heterogeneous across workers.

https://www.cnn.com/2015/07/08/asia/china-stocks-explainer/index.html, accessed in August 2023.

6.2 The real economy

6.2.1 Human capital

The relationship between human capital, which determines labor incomes in equation (12), and individual characteristics is given by

$$log(H_s(\omega_{it}, \zeta_{it})) = \gamma_1^s \times a_{it} + \gamma_2^s \times a_{it}^2 + \gamma_3^s \times \Delta_{it} + \gamma_4^s \mathbb{I}[e = med] + \gamma_5^s \mathbb{I}[e = high] + log(\theta_{si}) + \zeta_{ist}. \quad (30)$$

The coefficients on age, tenure, education group, and unobserved heterogeneity are allowed to vary by sector. This functional from relating log income linearly to experience is standard and is analogous to the one in the baseline model since the rate of human capital accumulation is constant. Here, I allow for a richer set of determinants of human capital.

If there was no unobservable heterogeneity (and given the timing assumption on ζ) equation (30) could be estimated by regressing log income on observables. As already discussed, allowing for some degree of unobserved heterogeneity alleviates the concern that the estimated returns to tenure reflect the selection of the workers that decide to stay in a sector. I assume two types θ per education level.

To estimate the parameters in equation (30) in the presence of unobserved heterogeneity I follow the expectation maximization approach (Arcidiacono and Miller 2011; Scott 2014; Traiberman 2019). The main idea of the procedure is to estimate jointly the parameters of interest, $\{\gamma^s\}$, and the probability that each worker i belongs to unobserved type $\theta \in \{1, ..., 6\}$. Section C.2 in the Appendix formalizes the likelihood being maximized and discusses my implementation of the expectation maximization algorithm.

6.2.2 Switching costs

I assume the cost of switching from sector s to s' for a worker with characteristics ω_{it} can be parametrized as

$$\tilde{C}(\omega_{it}, s, s') = f(\omega_{it}) C(s, s'),$$

where

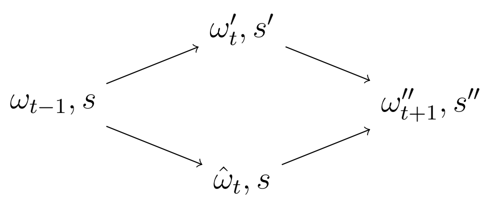
$$log(f(\omega_{it})) = \alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 \quad \text{and} \quad log(C(s, s')) = \Gamma_o^s + \Gamma_d^s \quad (31)$$

The first component captures that it is differentially costly for workers of different ages to switch sectors, as this involves learning new skills. The second function captures flexible ways in which it may be costly to both leave and enter a sector. Γ_o^s (Γ_d^s) indexes the utility cost paid by a worker when s is the sector of origin (destination). Assuming this, instead of flexible $\Gamma_{ss'}$ for all pairs, reduces the number of parameters to be estimated.

The presence of idiosyncratic shocks in equation (13) leads to transition shares between sectors that are somewhere between zero and one, and increase when the payoff associated with switching between a pair of sectors is higher. In particular, assuming these are drawn from a Gumbel distribution allows me to write down in closed-form an equation linking transition probabilities as a function of the following parameters: $\rho, \eta_s, \alpha_1, \alpha_2, \{\Gamma_o^s, \Gamma_d^s\}$, where ρ scales the importance of idiosyncratic shocks, η_s is the amenity value of sector s, and the rest are the parameters in equation (31).

It is particularly useful to write down a closed-form equation involving the two trajectories illustrated in Figure 7. For workers with the same characteristics ω_{it} the first trajectory is $s \to s' \to s''$ and the second, $s \to s \to s''$ with $s'' \neq s \neq s'$.

Figure 7: Trajectories for worker with characteristics ω at t in estimated equation



The fact that, by equation (16) both workers are identical at $t+1$ means that the probability of observing the first trajectory, relative to the second one, will only be a function of flow parameters. After some steps, which are standard in the literature and I relegate to the Appendix Section A.4, I end up with an equation that links the relative probability of trajectory one to the income that the worker would earn in sector s' relative to her income in s, the relative cost of switching, and the relative probability that she goes from s' to s'' in the event of a bust at period $t+1$. This last term is multiplied by the hazard rate μ_t. Illustratively,

$$(1-\mu_t) \times \begin{array}{c}\text{Relative probability}\\ \text{of trajectory 1}\end{array} + \ \mu_t \times \begin{array}{c}\text{'Bust' relative probability}\\ \text{of trajectory 1}\end{array} = \begin{array}{c}\text{Income}\\ \text{differences}\end{array} + \begin{array}{c}\text{Switching}\\ \text{costs}\end{array}. \tag{32}$$

Given the steps are standard and well-known, I relegate the precise statement of all terms in the equation to the Appendix Section A.4. Setting $\mu_t = 0$ leads to the standard equation in conditional choice probability estimation from other contexts, where the saliency of a regime change is lower and workers don't know μ_t. In my setting, the challenge becomes disentangling between the pure switching costs, the last term on the right-hand side, and the unobserved drops in value as alternative reasons why certain observed transitions are more or less likely, the last term on the left-hand side. Calculating the equilibrium counterfactual bust probabilities for each guess of the parameters becomes computationally unfeasible. Therefore, I make the following assumption about expectations

Assumption 3. **Conditional expectations for transition probabilities are given by**

- $\mathbb{E}_t[\pi_{t+1}(\omega, s, s')|b_{t+1} = 1] = \pi_{t+1}(\omega, s, s') + u_{\omega,s,s',t}$, **with u uncorrelated across periods.**
- $\mathbb{E}_t[\pi_{t+1}(\omega, s, s')|b_{t+1} = 0] = p(\omega, t, s, s')$**.**

Where $p(\omega, t, s, s')$ is a polynomial of second order in age, tenure, year, with coefficients that vary by sector. See Appendix Section A.4 for a complete specification of the polynomial.

The first assumption in Assumption 3 is equivalent to the assumption in Traiberman (2019) but for the conditional instead of the unconditional expectation. The second assumption states that to construct expectations in the event of the boom ending at $t + 1$ workers are less sophisticated and form expectations using a polynomial on age, sector pairs, and time. My assumptions are weaker in the sense that uncorrelated expectation errors are assumed only conditional on the boom. My assumptions are stricter in the sense that I am imposing a functional form on expectations in the bust state. Having made this assumption, I estimate parameters $\rho, \eta_s, \alpha_1, \alpha_2, \{\Gamma^s_o, \Gamma^s_d\}$ by minimizing the gap between both sides of equation (32). Appendix Section C.3 discusses the implementation.

6.2.3 Preferences and production function parameters

I calibrate labor and expenditure shares as follows:

$$\alpha_s = \frac{w_s H_s}{VA_s} \text{ and } \kappa_s = \frac{VA_s + M_s - X_s}{\sum_{j \in \mathcal{S}} VA_j + M_j - X_j} \tag{33}$$

Where $w_s H_s$ and VA_s are labor compensation and gross value added by sector. X_s and M_s are exports and imports respectively. For these parameters I use aggregated data by industry from national accounts, which I then aggregate using my industry classifications.[13]

Productivities. The last parameters I need to calibrate are the productivity parameters, A_{st} in equation (17). I use the structure of the model to back them out from the profit maximization conditions for firms, equation (18)-equation (19), and the market clearing conditions.

First I recover the wages per efficiency unit of human capital, w_{st}, from the sector-year fixed effects in the estimation of equation (12). I can also calculate the effective units of human capital that sort into each sector H_{st}, as I know the characteristics of all workers and have estimated the parameters in equation (12). For the observed allocation to be an equilibrium in the model described in Section 4 the market for the two non-tradable goods and capital clear internally

[13] This procedure is similar to the one in Caliendo et al. (2018), except that I don't account for input-output linkages.

and trade is balanced. I further assume that productivity is the same in all three tradable sectors in order to have the same number of equations and free parameters. I obtain the three productivity parameters and the rental cost of capital, r_t, such that the observed allocation is an equilibrium of the model.

6.2.4 Estimated parameters

As underscored in Section 2 the main parameter behind risk-loving attitudes towards duration is the rate of human capital accumulation.

Returns to tenure. The first column of Table 2 below shows the estimates of the returns to tenure. These estimates indicate that there is substantial on-the-job sector-specific human capital accumulation, and that the rate at which it is accumulated differs between sectors. The second column of Table 2 shows the returns to tenure estimated through OLS, without accounting for unobserved heterogeneity. Intuitively, these estimates tend to be higher since they partly capture differential selection across workers who decide to stay in a sector.

Table 2: Returns to tenure in each sector

	β^{ten}	
	Expectation Maximization	OLS
Manufacturing	0.0774***	0.0865***
	(0.001)	(0.002)
Mining	0.0836***	0.0719***
	(0.002)	(0.003
Agriculture	0.0358***	0.119***
	(0.003)	(0.004)
Construction	0.0713***	0.0849***
	(0.001)	(0.002)
Other services	0.086***	0.1095***
	(0.000)	(0.001)

Standard errors in parentheses

The results suggest that workers accumulate substantial human capital on the job in their sector of employment. This is particularly strong in mining, where the estimated semi-elasticity indicates that real labor income increases at approximately 8% per year.

Labor shares and consumer preferences. Table 3 shows the results. Manufacturing and services are the most labor-intensive sectors, and agriculture and mining are the least. In terms of expenditure shares, most of the income goes to services and very little gets spent on agriculture and mining directly.

Table 3: Labor shares and consumer preferences

Sector	Labor share (α_s)	Expenditure share (κ_s)
Manufacturing	0.60	0.20
Mining	0.22	0.03
Agriculture	0.21	0.02
Construction	0.52	0.09
Other Services	0.72	0.66

7 The Role of Duration Uncertainty

I use the estimated model to simulate an economy in which there is no uncertainty about the path of prices, but there is still a temporary boom in mining. Mining prices are given by

$$p_t^{M,cf} = \begin{cases} p_t^M & t \leq 2014 \\ \underline{p} & t > 2014 \end{cases}. \tag{34}$$

The end of the boom is dated in 2014, the expected duration derived from the calibrated hazard rate. Comparing the allocation of workers across sectors and relative wages in this economy to the data determines whether stripping out uncertainty about duration increases or reduces labor supply into the booming sector in general equilibrium. The nature of the counterfactual exercise is the same as the one illustrated in Figure 4 in the baseline model of Section 2.[14]

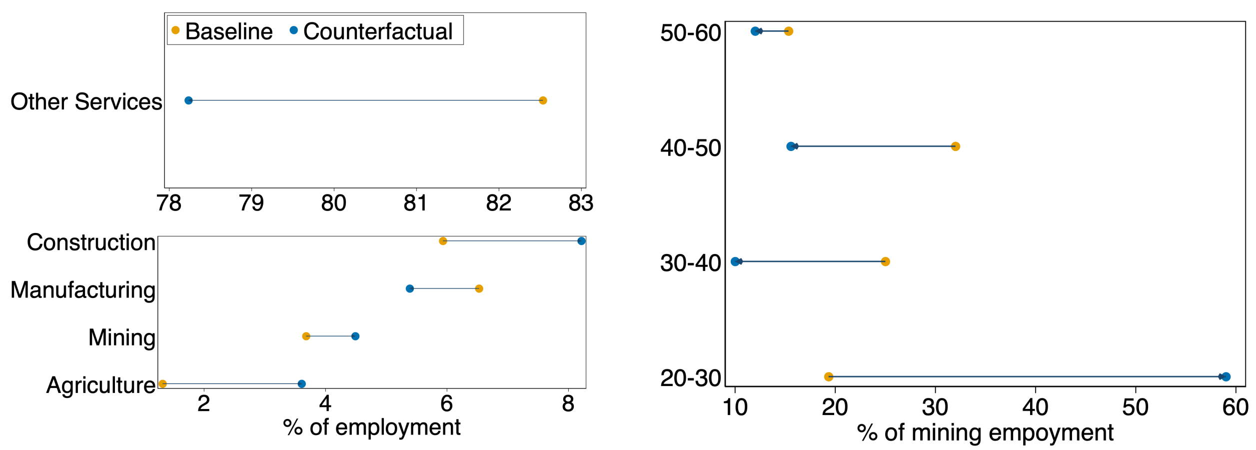
Changes in labor supply. I focus on outcomes during 2012-2014, the pre-boom period in this case. Figure 8a compares employment in each sector in the counterfactual versus the baseline. The top panel shows that the share of employment in the biggest sector, services other than construction, shrinks from 82.5% to 78.2%. This employment reallocates towards other tradable sectors. Agriculture is the sector that grows the most, and mining increases. The share of workers employed in mining goes up from 3.7% to 4.4%, an increase of 22.0%. The share of employment in agriculture goes up from 1.3% to 3.6%, more than doubling. Manufacturing shrinks from 6.5% to 5.3%.

One of the main conclusions from the baseline model in Section 2 is that the effects of uncertainty about duration are likely heterogeneous across workers. One interesting dimension

[14] Fan et al. (2023) consider an analogous exercise in which uncertainty is shut down, which they call analyzing the effects of uncertainty ex-post. In their model the interpretation of uncertainty differs. Similarly, Alessandria et al. (2023) do a similar analysis after estimating the effect of trade policy uncertainty on the intra-year dynamics of US firms' imports from China.

Figure 8: Counterfactual results

(a) Employment across sectors (b) Employment in mining by age group (in years)



of heterogeneity is age. Figure 8b shows the age composition of mining in the counterfactual relative to he baseline. Shutting off uncertainty about duration has a stronger effect on young workers: the share of young workers in the sector approximately triples. The labor supply in the $30-40$ and $40-50$ group declines in absolute terms, and this is reflected in a sharp reduction in their share of mining employment.

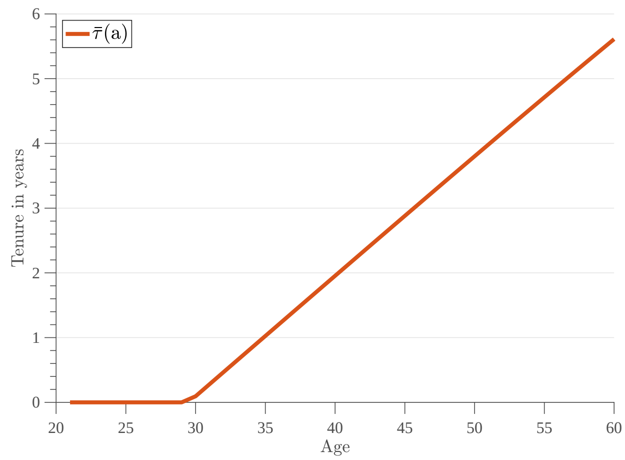
The simple model in Section 2 provides a lens to interpret these differential results by age. To see this, consider the following back-of-the-envelope calculation where I look for the value of $\bar{\tau}$ around which the value function would be convex. The only new ingredient is the effect of age, which was not present in the baseline model:

$$\frac{(\gamma_1^{Min})^{a+\bar{\tau}} \times (\gamma_3^{Min})^{\bar{\tau}} \times (1-(\beta\gamma_1^{Min}\gamma_3^{Min})^{60-a-\bar{\tau}})}{1-\beta\gamma_1^{Min}\gamma_3^{Min}} = \frac{(\gamma_1^{Mf})^{a+\bar{\tau}} \times (1-(\beta\gamma_1^{Mf}\gamma_3^{Mf})^{60-a-\bar{\tau}})}{1-\beta\gamma_1^{Mf}\gamma_3^{Mf}} \tag{35}$$

The idea is to find, for each level of age a, the tenure that would make the worker indifferent between staying in mining if the boom ended at $\bar{\tau}$ or switching to manufacturing when the boom ends. I am setting $\theta, \underline{w}$ both equal to one, as an approximation. I also set $\beta = 0.96$, what I use in the estimation, and the values of γ_1^s, the coefficient on age, and γ_3^s, the coefficient on tenure, that I estimated above. The final new ingredient is that workers live up to age 60, so this new term appears in the numerator on both sides.

Figure 9 shows $\bar{\tau}(a)$ from equation (35), where negative values imply that workers would always switch, so are set to zero As this figure shows, a worker aged 40 that spend approximately two years before the boom ends finds it optimal to stay in mining in order to avoid losing the sector-specific human capital. Young workers will always switch upon the end of the boom so, through the lens of simple model, would never have the convexity associated with the kink in the value function. This partly explains why they react so positively in the counterfactual without duration uncertainty.

Figure 9: Back-of-the-enveope calculation of $\bar{\tau}(\cdot)$



The aggregate responses in labor supply have an impact on wages and inequality. The wage in the mining sector, which is almost three times as large as the average wage in the data, drops to below the average wage in the counterfactual economy, reducing wage inequality in the economy.

8 Concluding Remarks

By 2018, more than half of the countries in the world specialized in commodities, whose prices follow low frequency cycles with strong variation between peaks and troughs (Erten and Ocampo 2013; UNCTAD 2021). Boom and bust dynamics are, therefore, central to how these countries have been affected by globalization. In this paper I focused on one aspect that is inseparable from boom-bust dynamics yet had not been incorporated into analyses of the labor impact of trade shocks: uncertainty about when the regime will change. I borrow from studies of the effects of uncertainty on firms and find that, at a conceptual level, uncertainty's effects on workers differ. Human capital accumulation and option values change the structure of workers' problem, relative to firms', in such a way that uncertainty can either deter or incentivize labor mobility towards booming sectors.

In the second part of the paper, I build and estimate a quantitative version of the baseline model and use it to study the importance of duration uncertainty during the recent mining boom in Australia, which was part of a broader boom in the prices of commodities (IMF 2016; WB 2015). Using the quantified version of the model I found that in this particular case duration uncertainty acted as a friction and decreased aggregate labor supply into mining. The effects on labor supply are heterogeneous across workers and matter for labor income inequality.

The framework could be used to study normative questions, left for future research, regarding the effectiveness of sectoral policies when duration uncertainty plays a role. More broadly, it leads to an alternative view of how uncertainty about the duration of a regime can shape decisions once dynamic aspects like learning by doing or human capital accumulation are taken into account.

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9 Appendix

A Mathematical appendix

A.1 Proof of Proposition 1

Because $\ell_0 = c$, the following inequality holds:

$$\bar{w}\theta + \beta\Big[\mu V(\theta, [0,1], c, 0) + (1-\mu)V(\theta, [0,1], c, 1)\Big] \geq 1 + \beta\Big[\mu V(\theta, [1,0], o, 1) + (1-\mu)V(\theta, [1,0], o, 1)\Big] \tag{36}$$

Assume there was $t' > 0, t' < \tau$ such that $\ell_{t'} = o$ and $\ell_t = c \; \forall t < t'$:

$$\bar{\theta}w\gamma_c^{t'} + \beta\Big[\mu V(\theta, [0,t'+1], c, 0) + (1-\mu)V(\theta, [0,t'+1], c, 1)\Big] < 1 + \beta\Big[\mu V(\theta, [1,0], o, 1) + (1-\mu)V(\theta, [1,0], o, 1)\Big] \tag{37}$$

Where the state inside the value function is $x_t = (\theta, [\Delta_0, \Delta_1], s_{t-1}, b_t)$. Because the right-hand side is the same, from equation (36) and equation (37) it follows that:

$$\bar{\theta}w\gamma_c^{t'} + \beta\Big[\mu V(\theta, [0,t'+1], c, 0) + (1-\mu)V(\theta, [0,t'+1], c, 1)\Big] < \bar{w}\theta + \beta\Big[\mu V(\theta, [0,1], c, 0) + (1-\mu)V(\theta, [0,1], c, 1)\Big]$$

Which is a contradiction if $\gamma_c > 1$. As $\frac{\partial V}{\partial \Delta} \geq 0$, both elements on the sum on the left-hand side would be bigger than their counterparts on the right-hand side. This proves that it is never optimal to leave sector 1 if the boom is ongoing.

The last part of the proposition states that it's never optimal to wait until period $\tilde{t} > \tau$ before switching to sector 0. The only case which needs to be considered is one in which $\tilde{t} < \bar{\tau}$. In all cases with $\tilde{t} > \bar{\tau}$, by definition of $\bar{\tau}$, it will never be optimal to switch. If at $\tau < \bar{t}$ it is optimal to wait until $\bar{t}$ to switch, the following inequality holds:

$$\frac{1}{1-\beta\gamma_o} < \frac{\underline{w}\theta\gamma_c^{\tau}(1-(\beta\gamma_c)^{\tilde{t}-\tau+1})}{1-\beta\gamma_c} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_o} \tag{38}$$

From here it follows that at $\tilde{t}$ it will also be optimal to wait $\tilde{t} - \tau$ periods more since

$$\frac{1}{1-\beta\gamma_o} < \frac{\underline{w}\theta\gamma_c^{\tau}(1-(\beta\gamma_c)^{\tilde{t}-\tau+1})}{1-\beta\gamma_c} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_o} < \frac{\underline{w}\theta\gamma_c^{\tilde{t}}(1-(\beta\gamma_c)^{\tilde{t}-\tau+1})}{1-\beta\gamma_c} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_o} \tag{39}$$

where it is crucial that the worker has accumulated more human capital by period $\bar{t}$. Then, waiting until $\bar{t}+(\bar{t}-\tau)$ has to be preferred than switching at $t=0$:

$$\frac{1}{1-\beta\gamma_o} < \frac{\underline{w}\theta\gamma_c^{\tau}(1-(\beta\gamma_c)^{2(\tilde{t}-\tau)+1})}{1-\beta\gamma_c} + \frac{\beta^{2(\tilde{t}-\tau)+1}}{1-\beta\gamma_o} \tag{40}$$

The argument could be repeated infinitely until obtaining that it's preferred to wait indefinitely before switching:

$$\frac{1}{1-\beta\gamma_o} < \frac{\underline{w}\theta\gamma_c^{\tau}}{1-\beta\gamma_c} \tag{41}$$

Which contradicts that $\tau < \bar{\tau}$.

A.2 Proof of Lemma 1

From the definition of $\bar{\tau}(\theta)$:

$$\bar{\tau}(\theta;\gamma_o,\gamma_c,\underline{w}) = \frac{1}{\log(\gamma_c)}\Big[\log(\frac{1-\beta\gamma_c}{1-\beta\gamma_o}) - \log(\underline{w}\theta)\Big] \tag{42}$$

From where all partial derivatives follow directly.

A.3 Proof of Lemma 2

There is a kink around $\bar{\tau}$ if the following inequality holds:

$$V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) \tag{43}$$

$$\bar{w}\theta(\beta\gamma_c)^{T-1} + \frac{(\beta\gamma_c)^T \underline{w}\theta}{1-\beta\gamma_c} - \frac{\beta^{T-1}}{1-\beta\gamma_o} \geq \bar{w}\theta(\beta\gamma_c)^{T-2} + \frac{\beta^{T-1}}{1-\beta\gamma_o} - \frac{\beta^{T-2}}{1-\beta\gamma_o} \tag{44}$$

$$\bar{w}\theta(\beta\gamma_1 c)^{T-2}(1-\beta\gamma_c) - \frac{(\beta\gamma_c)^T \underline{w}\theta}{1-\beta\gamma_c} \leq \frac{\beta^{T-2}(1-2\beta)}{1-\beta\gamma_o} \tag{45}$$

$$\bar{w}\theta(\gamma_c)^{T-2}(1-\beta\gamma_c) - \frac{\beta^2(\gamma_c)^T \underline{w}\theta}{1-\beta\gamma_c} \leq \frac{(1-2\beta)}{1-\beta\gamma_o} \tag{46}$$

$$\tag{47}$$

Because $\tau = \bar{\tau}$, $\frac{\underline{w}\theta\gamma_c^{\tau}}{1-\beta\gamma_c} = \frac{1}{1-\beta\gamma_o}$ and the inequality becomes:

$$\bar{w}\theta(\gamma_c)^{T-2}(1-\beta\gamma_c) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_o} \tag{48}$$

$$\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_c)^{T-2}(1-\beta\gamma_c) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_o} \tag{49}$$

Where in the last step I multiplied and divided by $\underline{w}$. For $\tau - 2$ the following inequality holds $\frac{\underline{w}\theta\gamma_c^{T-2}}{1-\beta\gamma_c} < \frac{1}{1-\gamma_o\beta}$. Then, it's enough for equation (49) to hold that the following holds:

$$\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_c)^{T-2}(1-\beta\gamma_c) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_o} \tag{50}$$

$$\frac{\bar{w}}{\underline{w}} \leq \frac{1-2\beta+\beta^2}{(1-\beta\gamma_c)^2} = \Big(\frac{1-\beta}{1-\beta\gamma_c}\Big)^2 \tag{51}$$

Using that $\gamma_c > 1$, the right-hand side is greater than one as long as $2 > \beta\gamma_c$. This last condition always holds, as $\beta\gamma_c < 1$ for the problem to be well-defined. The right-hand side is the equation is the upper bound ω referred to in the main text.

A.4 Derivation of equation (80)

Variables with tilde indicate they correspond to the economy in which the boom ends at $t+1$ and variables with double tilde correspond to the economy in which the boom ends at $t+2$.

First trajectory. Start by the worker whose trajectory is $s \to s' \to s''$:

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} + \frac{\beta}{\rho}\Big[\mu_t\mathbb{E}_t\tilde{V}_{t+1}(s',\omega') + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega')\Big] - \log(\pi_t(\omega,s,s') \tag{52}$$

Now I re-write V_{t+1} and $\tilde{V}_{t+1}$ conditioning on the worker choosing s'' in both cases:

$$\frac{V_{t+1}(s',\omega')}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \tag{53}$$
$$\frac{\beta}{\rho}\Big[\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})V_{t+1}(s'',\omega''))\Big] - \log(\pi_{t+1}(\omega',s',s''))$$

$$\frac{\tilde{V}_{t+1}(s',\omega')}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\omega',s',s'')) \tag{54}$$

Plugging equation (53) and equation (54) into equation (52):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} - \log(\pi_t(\omega,s,s')) \tag{55}$$
$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{56}$$
$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{57}$$
$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\omega',s',s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\omega',s',s''))]\Big] \tag{58}$$

From the perspective of period t, both future wages in s' and s'' as well as future values and transition rates are unknown, therefore have expectations. However, the future hazard rate μ_{t+1} is known. Also notice that terms like $\mathbb{E}_t[\tilde{\pi}]$ are a conditional expectation, as the future transition will be $\tilde{\pi}$ if the boom ends at $t+1$.

Second trajectory. Consider the worker whose trajectory is $s \to s \to s''$. Let $\hat{\omega}$ denote the characteristics of this workers once she is at s at $t+1$, which includes tenure going up by 1.

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} + \frac{\beta}{\rho}\Big[\mu_t\mathbb{E}_t\tilde{V}_{t+1}(s,\hat{\omega}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s,\hat{\omega})\Big] - \log(\pi_t(\omega,s,s)) \tag{59}$$

Again, now I re-write V_{t+1} and $\tilde{V}_{t+1}$ conditioning on the worker choosing s'' in both cases:

$$\frac{V_{t+1}(s,\hat{\omega})}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \tag{60}$$
$$\frac{\beta}{\rho}\Big[\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})V_{t+1}(s'',\omega''))\Big] - \log(\pi_{t+1}(\hat{\omega},s',s''))$$

$$\frac{\tilde{V}_{t+1}(s',\hat{\omega})}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\hat{\omega},s',s'')) \tag{61}$$

Plugging equation (60) and equation (61) into equation (59):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} - \log(\pi_t(\omega,s,s)) \tag{62}$$

$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{63}$$

$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{64}$$

$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega}',s,s''))]\Big] \tag{65}$$

I can use the two expression for $V_t(s,\omega)$ in equation (55)-equation (62) to get rid of $V_t(s,\omega)$. Notice as well that equation (64) and equation (57) are identical, given that entering s'' is a renewal action and both workers lose tenure upon entering. This is the key step to get ride of future values from $t+2$ onwards (Scott 2014; Traiberman 2019).

This equation can be re-arranged to get:

$$\log\Big(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\Big) + \beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s'')) - \log(\tilde{\pi}_{t+1}(\omega',s',s''))]) + \tag{66}$$

$$(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s'')) - \log(\pi_{t+1}(\omega',s',s''))]]\Big] = Y^{\omega}_{s,s',t} - Y^{\omega}_{s,s,t} + \frac{\beta}{\rho}\big[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')\big] \tag{67}$$

Where $Y^{\omega}_{s,s,t}$ is the flow payoff of switching from s to s at t for a worker with characteristics ω. Using Assumption 3, this becomes:

$$\log\Big(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\Big) + \beta(1-\mu_t)\log\Big(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\Big) = \tag{68}$$

$$Y^{\omega}_{s,s,t} - Y^{\omega}_{s,s',t} + \frac{\beta}{\rho}\big[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')\big] - \beta\mu_t\Big[p(\hat{\omega},t+1,s,s'') - p(\omega',t+1,s',s'')\Big] \tag{69}$$

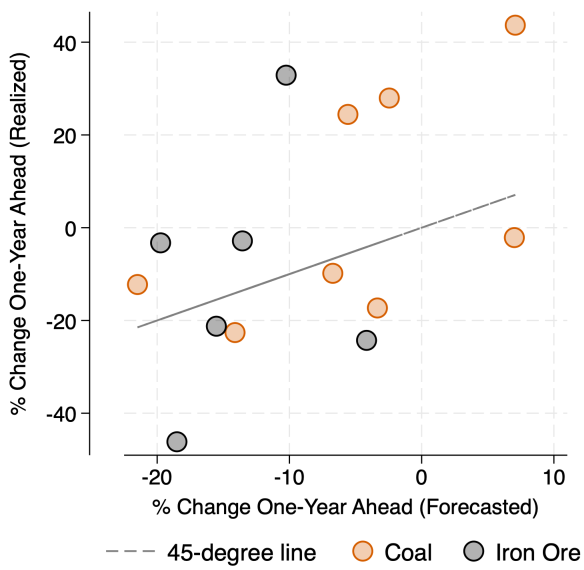
For the main text I use that $f(\omega') = f(\hat{\omega})$ so this term can be factored out. Then $C(s',s'') - C(s,s'') = \Gamma^{s'}_o - \Gamma^s_o$. The left-hand side of this equation is data, while the right-hand side combines μ, which I have already estimated at this stage, the predicted income for workers with characteristics as they affect the terms in Y, which I have also estimated at this stage and migration costs and p, which I estimate by minimizing the distance between both sides in this equation.

B Background and data appendix

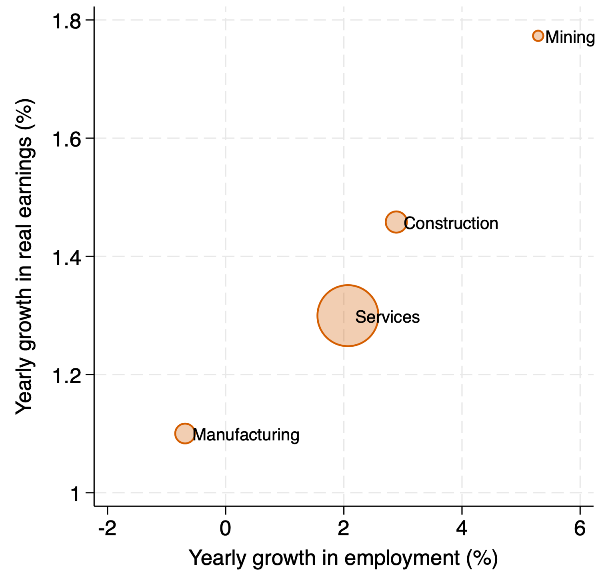
In Section 3 I discuss how forecasts about future commodity prices and realized prices evolved during the period, making reference to Figure 10a below. I also refer to the broad evolution of employment across sectors during the period, making reference to Figure 10b below. This figure draws from public data from ABS, which does not include wage data for Agriculture. Although employment in services is likely to have grown for secular reasons common to all developed economies, it is notable that earnings increased fast in the sector in Australia.

Figure 10: Forecasts and labor markets during the boom

(a) IMF forecasts vs. realizations (2011-2019)



(b) Changes between 1990-99 and 2010-19



Sources: Australian Bureau of Statistics (ABS) and IMF. The size of the bubbles in Figure 10b are proportional to the size of that sector between 2011 and 2018.

B.1 Construction in China and export prices in Australia

The rise in the export prices of the main mineral products in Australia during 2001-2010 is usually attributed to the surge in demand from China for construction purposes.

In order to test the common view I collect data on construction activity in China and test how well it can predict commodity prices of different goods. I retrieve quarterly export prices from the Australian Bureau of Statistics price index series. I retrieve data on Chinese economic activity from the website of the National Bureau of Statistics of China[15]. As a proxy for future construction, I create a series of new construction started each month from the series *Flor space of real estate started this year accumulated*. In order to have another control of economic activity in China, I create a series of monthly retails sales from the series *Total retail sales of consumer goods*. I aggregate each of these two series at the quarterly level.

First, I construct a panel with the quarterly export prices of mineral and metals and the two proxies for different aspects of economic activity in China. The panel regressions results in column 1

[15] Accessed September 23, 2022.

Table 4: Export prices in Australia and economic activity in China 2001-2019 (all variables in logs).

	(1) Minerals and Metals	(2) Agriculture	(3) Manufactures
Retail sales in China (lagged 1 year)	0.217	-0.00151	-0.0816
	(0.383)	(0.161)	(0.319)
Construction started in China (lagged 1 year)	0.455	0.0317	-0.116
	(0.108)	(0.111)	(0.0450)
Commodity-Year Observations	288	288	288
Within-R2	0.724	0.640	0.269
Commodity Yearly Trend	Yes	Yes	Yes
Commodity-Quarter FE	Yes	Yes	Yes

Standard errors in parentheses

For each column I keep 4 industries and run separate panel regressions. The industries are: *(1): Coal, coke and briquettes; Petroleum, petroleum products and related materials; Gas, natural and manufactures; Gold, non-monetary*, *(2): Meat and meat preparations; Dairy products and birds' eggs; Fish, crustaceans, molluscs and acquatic invertabrates and preparations thereof; Cereals and cereals preparations*, *(3): Leather, leather manufactures; Rubber manufactures; Paper, paperboard, and articles of paper pulp; Non-metallic mineral manufactures.*

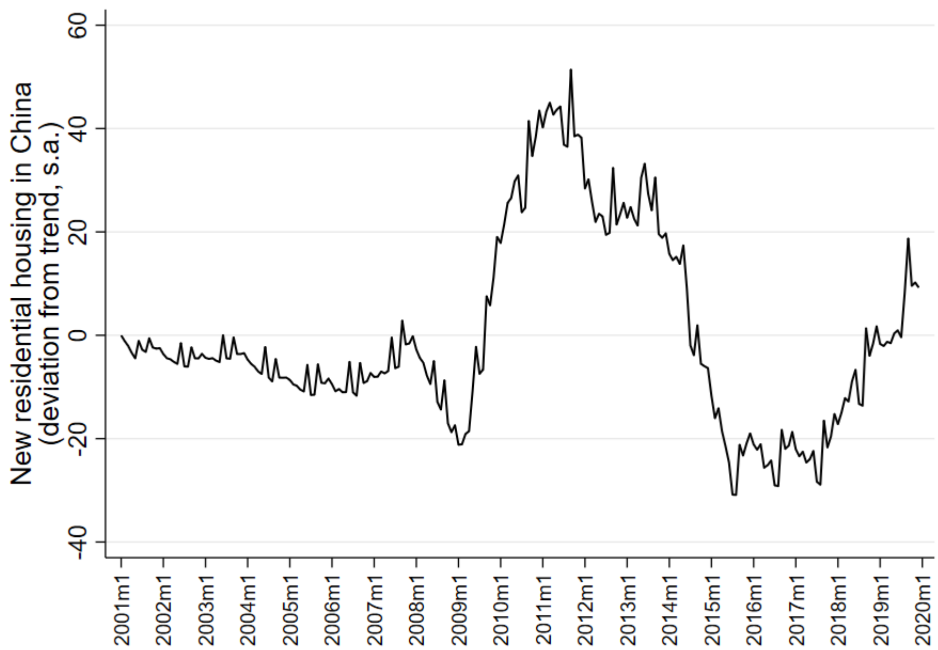
of Table 4 show that lagged construction floor space sold in China, which I take as a proxy for current construction levels, has a positive and statistically significant effect on export prices. All variables are in logs, so the effect can be interpreted as an elasticity and is quantitatively important. I include lagged retail sales in China as a control, which is not significant, to confirm that the effect is not coming from economic growth in China more generally.

The second and third columns of Table 4 repeat the exercise but replacing the outcome variable with the prices of goods which are not associated with construction activity in China. Consistent with the common view, I find that construction in China doesn't impact agricultural prices and has a negative effect on manufacturing prices. Comparing the within R-squares between the three regressions reaffirms the view that construction in China is a driver of metals and mineral prices, but not of other goods.

B.2 Time series of new residential housing in China

Using the same data as in subsection B.1, Figure 11 plots the deviation from a linear trend of the series of new construction in China, adjusted for seasonality. The key takeaway from this figure is that construction came to a halt twice: around the time of the financial crisis and around 2014.

Figure 11: New residential housing in China in Squared Meters (Millions)



B.3 Options data: details and descriptive statistics

I start with a dataset where I observe, at a daily frequency, the best offer for put options of a horizon of approximately one year and three strike prices K per horizon. [16] I merge this with the value of the stock at that particular day. Within each month-strike price group I keep only the daily observation with the median value for the option in month-strike price. Finally, I merge this with data on the zero-coupon rate.

B.4 Panel of workers: details and descriptive statistics

Definition of education levels.

[16]The median difference between the horizons in my data and 365 is 76. The 10th percentile is 11 and the 90th percentile is 139.

Group	Percentage of workers 2011-2019	Degrees
Group 1	41%	High school completed or less
Group 2	23%	Advanced Diploma
		Associate Degree
		Diploma
		Certificate I, II, III and IV Level
Group 3	36%	Higher Doctorate
		Doctorate by Research or Coursework
		Master Degree by Research or Coursework
		Graduate Diploma
		Graduate Qualifying or Preliminary
		Professional Specialist Qualification at Graduate Diploma Level
		Graduate Certificate
		Professional Specialist Qualification at Graduate Certificate Level
		Bachelor Degree

Joint distribution across sectors and education levels.

Sector	Education	Number of workers
Manufacturing	1	44,323
	2	18,332
	3	16,462
Mining	1	24,964
	2	9,702
	3	7,611
Agriculture	1	11,308
	2	2,959
	3	2,412
Construction	1	42,529
	2	22,509
	3	9,134
Other Services	1	393,199
	2	230,403
	3	426,847

C Estimation appendix

C.1 Validation

The quote, references and Figure 10a from Section 3 indicate that informed observers were aware of the temporary nature of the boom and consistently forecast prices to drop. A natural question is whether the estimate of μ_t from financial data captures something that workers were aware of, as I assume when I estimate the labor parameters of the model. At the aggregate level, is there evidence of this? Do labor markets indeed respond to changes in the expected duration of the boom measured by μ?

To address this, I compare how transition rates into mining react to changes in μ. Consider equation (70), where $Y_{i,t}$ takes value one if worker i is employed in mining in year t. In X I include controls like age, education, and the previous sector of employment. The last control is important if switching costs depend on both sectors of origin and destination. Because μ may be related to the level of prices themselves, I also include the level of prices for mining products, p^M.

$$Y_{i,t} = \alpha_0 + \alpha_1 p^M_{t-1} + \alpha_2 p^M_{t-2} + \alpha_3 \mu_{t-1} + \bar{\alpha} X_{it} + \epsilon_{it} \tag{70}$$

I lag the values of p and μ as, naturally, it takes time to switch sectors. I estimate this equation through OLS in the panel of workers described in Section 5 for the years 2011-2018. The first column in Table 5 shows that the estimate of α_3 is negative, as expected. Given that the baseline share of workers employed in mining is low, 3.7% on average between 2011 and 2018, the estimated effect is large.

The second column in Table 5 shows the results of estimating equation (70) allowing for interactions between μ_{t-1} and characteristics like age and education. I find that middle-aged workers are the most responsive to increases in μ. The differential effect is consistent with the mechanism posited in the paper: as younger workers have longer horizons, they should be more sensitive to changes in the expected duration of the boom, which is inversely related to μ. Notice that changes in μ affect the expected duration of the boom, not its uncertainty, and therefore cannot be mapped directly with the counterfactual of interest.

Table 5: Reduced-form relation between hazard rate and labor market outcomes

	Mining	Mining
p^M_{t-1}	0.000448	0.000437
	(0.000321)	(0.000321)
p^M_{t-2}	-0.00185***	-0.00185***
	(0.000260)	(0.000260)
μ_{t-1}	-0.0133***	-0.00340
	(0.00370)	(0.00918)
Vocational $\times$ μ_t		-0.00911
		(0.00878)
College $\times$ μ_t		0.00804
		(0.00761)
Age 31-40$\times$ μ_t		-0.0297***
		(0.0105)
Age 41-50 $\times$ μ_t		-0.0214**
		(0.00976)
Age 51-60 $\times$ μ_t		0.000281
		(0.00932)
Observations	681218	681218
Previous sector FE	Yes	Yes
Region FE	Yes	Yes
Year Trend	Yes	Yes

Standard errors in parentheses

C.2 Expectation maximization

I focus on the basic elements of the method, as I am essentially following Traiberman (2019) and Arcidiacono and Miller (2011). I am interested in estimating the parameters in the equation for human capital equation (30). The key difficulty is the presence of unobserved heterogeneity. The likelihood to be maximized is described in equation (71), where the contribution of each agent i if she was of type θ, $\mathcal{L}_{i|\theta}$, are weighted by the probability that they belong to each type θ, $q_{i\theta}$. The product runs across all workers in the economy, $i = 1, ..., N$ and across all the possible unobserved types θ, which are assumed to be six.

$$\mathcal{L} = \prod_{i=1}^{N} \prod_{\theta=1}^{6} \hat{q}_{i\theta} \mathcal{L}_{i|\theta} \tag{71}$$

The conditional likelihood $\mathcal{L}_{i\theta}$ is the probability of observing a particular trajectory of sectors and earned income for worker i if she was of type θ. This is the product of the likelihood that worker i earns income y conditional on being of type θ, and the probability that she chooses to be in that sector in period t,

$$\mathcal{L}_{i|\theta} = \prod_{t=2011}^{2019} f(y_{it}(\omega_{it})|\gamma,\theta)\pi(s_{it}|s_{i,t-1},\theta). \tag{72}$$

Where ω captures all observable characteristics: age, education, and sector-specific tenure. Taking logs in equation (72), the estimators maximize the expected value of the log-likelihood:

$$\ell = ma\frac{1}{NT}\sum_{i=1}^{N}\sum_{\theta=1}^{6} q_{i\theta}[\log\pi(s_{i2011}|\omega_{i2011},\theta) + \sum_{t=2012}^{2019}\log f(y_{it}|\gamma,\omega_{it},s,\theta) + \log\pi(s_{it}|\gamma,s_{it-1},\omega_{it-1},\theta,)] \tag{73}$$

Implementation. Direct maximization of equation (75) is computationally unfeasible, given that it involves calculating the optimal transition probabilities for each guess of the parameters γ. The estimates maximize the value of the approximate likelihood,

$$\hat{\gamma}^{ML}, \hat{q}_{i\theta} = argmax\hat{\ell} \tag{74}$$

$$\hat{\ell} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{\theta=1}^{6} q_{i\theta}[\log\hat{\pi}(s_{i2011}|\omega_{i2011},\theta) + \sum_{t=2012}^{2019}\log f(y_{it}|\gamma,\omega_{it},s,\theta) + \log\hat{\pi}(s_{it}|\gamma,s_{it-1},\omega_{it-1},\theta,)] \tag{75}$$

The iterative maximization procedure is as follows. At each iteration k I start with some estimated $\{\hat{\gamma}^{k-1}\}, \{\hat{\pi}^{k-1}(s|s,\theta)\}, \{\hat{q}_{i\theta}^{k-1}\}$. The steps are:

- Update $\hat{q}^k$ through Bayes rule

$$q_{i\theta}^k = \Big[\frac{\prod_{t=2011}^{2019} f(y_{it}|\gamma^{k-1},\omega_{it},s_{it},\theta)\pi^{k-1}(s_{it}|s_{it-1},\omega_{it-1},\theta)\Big]\pi^{k-1}(\theta|s_{i2001},\omega_{i2011})}{\sum_{\theta'=1}^{6}\prod_{t=2011}^{2019} f(y_{it}|\gamma^{k-1},\omega_{it},s_{it},\theta')\pi^{k-1}(s_{it}|s_{it-1},\omega_{it-1},\theta')\Big]\pi^{k-1}(\theta'|s_{i2001},\omega_{i2011})}$$

- Update $\hat{\pi}^k(\theta|s_{i2011},\omega_{i2011})$ through OLS, where the outcome variable is $q_{i\theta}^k$.
- Update $\{\hat{\gamma}^k\}$ through a weighted least squares regression of equation (12) where $\hat{q}^k$ are the weights. Update $\hat{\pi}^k$ through OLS.
- Calculate the updated likelihood, $\hat{\ell}^k$.

This procedure is repeated until the likelihood converges. I initialize the procedure by estimating equation (12) ignoring unobserved heterogeneity and drawing q^0 from a uniform distribution for one of the two unobserved types that each worker can belong to, given their educational characteristics.

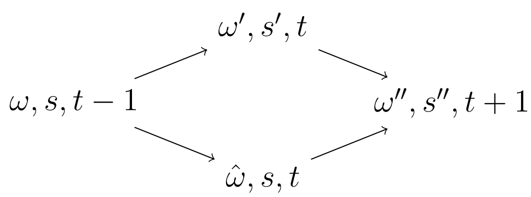
C.3 Conditional choice probabilities

Given the Gumbel assumption on idiosyncratic shocks, the value of a worker who was employed in s at $t-1$, if the boom is still ongoing at t can be written conditioning on any sector s' she could choose at t:[17]

$$\begin{aligned}\frac{V_t(s,\omega,h^t)}{\rho} =& \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) - C(\omega,s,s')}{\rho} \\ &+ \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t V_{t+1}(s',\omega',\{h^t,0\}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega',\{h^t,1\})\Big] - log(\pi_t(\omega,s,s'))\end{aligned} \tag{76}$$

Agents observe h^t before making decisions at t, so there is no expectation about current wages, only on the current ex-post shock ζ. On the right-hand side, I used the law of iterated expectations to write $\mathbb{E}_t[V_{t+1}]$ as the sum of the value conditional on the boom continuing at $t+1$ and finishing by then. I could now iterate again on V_{t+1} choosing any particular action s'' at $t+1$. It is particularly useful to consider the following trajectories:

Figure 12: Trajectories for worker with characteristics ω at t in estimated equation



For workers with the same characteristics ω I consider two trajectories: $s \to s' \to s''$ and $s \to s \to s''$ with $s'' \neq s \neq s'$. By equation (16), their human capital when they arrive at s'' will be the same, so their continuation value from $t+2$ onwards will be the same. This can be used, after writing down equation (76) conditioning on both trajectories and taking differences, to net out continuation values and wages at $t+2$ on both sides. After these steps, relegated to Section A.4 in the Appendix, I end up with the following equation:

$$\begin{aligned}&\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right) + \beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s'')) - \log(\tilde{\pi}_{t+1}(\omega',s',s''))]) + \\ &(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s'')) - \log(\pi_{t+1}(\omega',s',s''))]]\Big] = Y^\omega_{s,s,t} - Y^\omega_{s,s',t} + \frac{\beta}{\rho}\big[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')\big]\end{aligned} \tag{77}$$

Where $Y^\omega_{s,s',t}$ is the flow payoff of switching from s to s' at t for a worker with characteristics ω.[18] Transitions $\pi_{t+1}(\omega,s,s')$ and $\tilde{\pi}_{t+1}(\omega,s,s')$ represent transition rates between sector pairs s,s' for a worker with characteristics ω if the boom continues and ends at $t+1$, respectively. The

[17] These steps are standard. See Rust (1987); Arcidiacono and Miller (2011).

[18] $\rho Y^\omega_{s,s,t} = w_{s't}\mathbb{E}_\zeta[H_{s'}(\omega,\zeta)] + \eta_s - f(\omega)C(s,s')$.

analogous equation in Traiberman (2019) looks like this with $\mu_t = 0$. Traiberman (2019) replaces $\mathbb{E}_t[\pi_{t+1}]$ with the observed π_{t+1} and an expectation error. He makes the assumption, standard in the literature, that expectation errors are uncorrelated across periods. In my context, these assumptions on unconditional expectations are strong. As I only have data during the boom years, the expectation error involves μ_t and the gap between transition rates across regimes, on top of the error term.[19] For this reason, I make the following assumptions.

Using Assumption 3, equation (77) becomes:

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right) + \beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right) = \tag{79}$$

$$Y^{\omega}_{s,s,t} - Y^{\omega}_{s,s',t} + \frac{\beta}{\rho}\left[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')\right] - \beta\mu_t\Big[p(\hat{\omega},t+1,s,s'') - p(\omega',t+1,s',s'')\Big] + \tilde{u}_{s,s',t} \tag{80}$$

The left-hand side measures, appropriately weighting transition rates in both periods, how much more likely it is that a worker follows the s, s, s'' trajectory rather than s, s', s'' during two boom years. This gap depends on three terms: the flow utility in s versus s' at period t, which workers observe before deciding where to work; how much more costly it will be to leave s relative to leave s' in the future; and the drop in value in sector s relative to s' at $t+1$ in the event of an end of the boom. The key challenge is to tell apart this drop in value from pure migration costs. The left-hand side is data and the right-hand side is, at this stage, only a function of the cost parameters in $\tilde{C}$. I estimate them by minimizing the gap between the two.

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[19] To see this:

$$\mathbb{E}_t[\pi_{t+1}] - \pi_{t+1} = \mu_t\tilde{\pi}_{t+1} + (1-\mu)\pi_{t+1} - \pi_{t+1} = \mu_t(\tilde{\pi}_{t+1} - \pi_{t+1}). \tag{78}$$

. Where I've omitted arguments of π for simplicity.