Labor reallocation during booms: The role of duration uncertainty*

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Abstract

Temporary booms affect sectors as varied as commodities, construction, and tech. I study how uncertainty about the length of the boom shapes labor mobility across sectors during the boom phase. I build a model of sector-specific on-the-job human capital accumulation and show that workers can exhibit risk-loving attitudes towards the boom's duration. These arise because there is an option value attached to working in booming sectors: if the boom is short the worker can switch out, while payoffs are high if the boom is long because of human capital accumulation. Uncertainty about duration can incentivize labor supply into the booming sectors on the margin. 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 known. I find that the share of employment in mining in Australia would have increased from 3.7% to 4.4% and the relative wage in the sector would have been substantially lower, indicating that duration uncertainty deterred labor supply and contributed to the rise in wage inequality following the shock.

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

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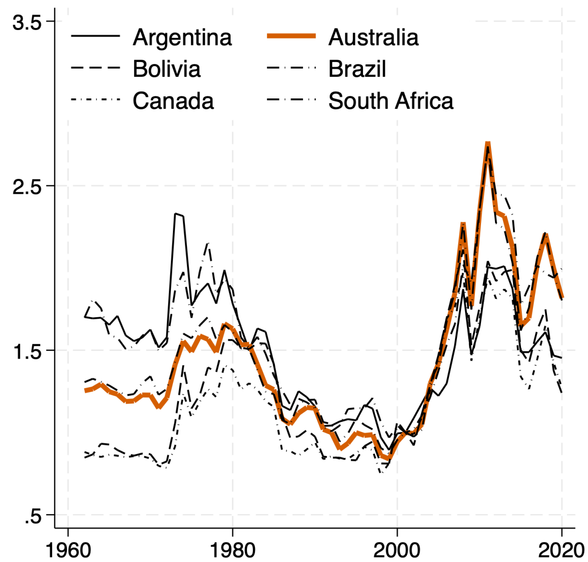
1 Introduction

Regime changes are pervasive in the economic and policy landscape: construction and tech booms end, protectionist trade policy turns liberal, and commodity prices shift from booms to busts. In all these cases, agents face considerable uncertainty about how long their current regime will last and this can, by itself, economic outcomes. In the international context, uncertainty about the future trade policy regime has been shown to affect firms' entry and exporting decisions in different countries (Handley and Limão 2015; Pierce and Schott 2016; Handley and Limão 2022). The literature on trade and labor, on the other hand, has focused on how workers sort across sectors abstracting from the role of uncertainty about future regime changes (Artuç et al. 2010; Dix-Carneiro 2014; Dix-Carneiro and Kovak 2017, 2019; Caliendo et al. 2019; Traiberman 2019). This paper fills this gap by studying the role of uncertainty about regime duration on labor supply, with a focus on regimes in world prices that disproportionately affect specific ('booming') sectors.

The main goal of the paper is to understand how labor supply across sectors is affected by uncertainty about the boom's length. First, I tackle the question theoretically by developing a model of sector-specific human capital accumulation. The main insight is that workers in the booming sector can have risk-loving attitudes towards duration; these arise because they have the option to switch out if the boom is short, but, if the duration is long enough, they will choose to stay to avoid losing the accumulated human capital. This generates a kink around which the value function is convex, implying that uncertainty about duration can incentivize labor supply into the booming sectors on the margin. 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 world mining prices were booming yet expected to fall, and Australia specializes in mining (44% of its exports during the period were mineral products). I use the quantified version of the model to simulate a counterfactual perfect foresight economy in which the boom was temporary and duration known. I find that, during this boom, uncertainty acted as a friction and employment in mining would increase in the counterfactual economy.

The model in the first part of the paper isolates how the value of being employed in a booming sector (mining, from now on) depends on the duration of the boom, the random variable over which workers form expectations during the boom phase. The economy has two sectors, mining and an outside sector, and two possible regimes, which determine whether the relative wage in mining is above or below one. The mining sector is booming at time zero, and with a constant probability, the regime changes, and the relative wage falls below one forever. The model focuses uncertainty about the duration of the boom phase, arguably the most salient unknown during episodes characterized by boom-bust dynamics, rather than variation within regimes. Importantly, workers also accumulate sector-specific human capital in their sector of

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.

employment and lose it when they switch sectors. I show that the discounted value of lifetime earnings for workers who sort into mining is convex over a range of possible durations, leading to risk-loving attitudes. The intuition is the following. If the duration ends up being short, the worker will decide to switch to the outside sector when the boom ends. On the other hand, if the duration is long enough, she will optimally decide to stay in mining even after the boom ends to avoid losing the accumulated human capital.[1] Convexity arises precisely around the duration that induces a change in behavior from leaving to staying in mining upon the end of the boom, which will be different 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. Less productive workers would require longer careers before doing so.

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, the boom is assumed to be temporary, and its length is fixed to the expected duration of the economy with uncertainty. The model's insight is that because some workers exhibit risk-loving attitudes towards duration, their expected value in mining is lower in the perfect foresight economy. If the marginal workers sorting into mining are risk-lovers, labor

[1] An analogy that can be drawn is with call options, 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 increases. Their model does not incorporate dynamics. The focus on sector-specific human capital derives from recent studies that find it an important driver of labor reallocation during trade shocks (Dix-Carneiro 2014; Traiberman 2019).

supply into mining would decrease in the perfect foresight economy. If marginal workers are on the concave region of their value function, the result is the opposite. The main conclusion from the model is that this type of uncertainty doesn't necessarily act as a friction to labor reallocation into booming sectors. Theoretically, the effects 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 the 2011-2018 period. The continuity of the boom was not assured during the period, given the tendency of commodity prices to follow cycles with strong variation between the boom and bust phases (Erten and Ocampo 2013).[2] 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 contemporaneous construction boom in China had increased dramatically the demand for mineral products used as inputs but it was expected that construction would stabilize. For these reasons, the 2011-2018 period represents an ideal setting to study the effects of uncertainty about future regime changes (a commodity bust, in this case), 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.

To explore counterfactual described theoretically above in my 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 à la Traiberman (2019). The main new ingredient relative to Traiberman (2019) stems from workers observing the hazard rate for the end of the boom, and therefore including the bust scenario as a possibility when switching sectors. Relative to the simple model, the quantitative model incorporates several realistic features that interact with risk-loving attitudes toward duration in a meaningful way. First, agents live finite lives. Old workers are less sensitive to increased 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 simple model, the nature of outside options is crucial to understanding workers' sensitivity to duration uncertainty, since workers' payoffs if the boom is short are given by wages in sectors other than mining. With this in mind, the quantitative model incorporates tradable and non-tradable sectors. While the price of tradable goods is exogenous, the prices of non-

[2] Commodity cycles are important given their impact on many economies worldwide. In 2018, commodities represented more than 60% of exports in more than 100 countries (UNCTAD 2021).

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. Financial markets are a natural source to look at when estimating this parameter, given that asset prices are forward-looking. 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 can be linked to 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 cover the universe of Australian workers in the formal sector between 2011 and 2018.[3] 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 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, but 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.

I use the estimated model to simulate my counterfactual of interest: a perfect foresight economy in which the boom's duration is fixed to 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 increases 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

[3] 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 receiving a pension in Australia in 2005 (their latest observation) was 90.7%, similar to 92.2% in the US.

model implied kink in the value value function should happen in the early years of the boom. Other sectors that grow in the counterfactual economy are agriculture and construction, 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 after 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 going forward. In order to explain why labor reallocation can be slow and heterogeneous across workers following this type of shocks, recent studies have argued that sector-specific human capital accumulated on-the-job is key (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 as an incentive to enter into booming sectors and that the effects are likely to be heterogeneous across workers. I show that this 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 these products.

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 are focused on the responses by firms (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 problem of the firm is an irreversible investment problem, and uncertainty necessarily increases the value of waiting (Handley and Limão 2022). In the context I study, this is not necessarily so, as workers continually decide in which sector to work and accumulate human capital.

This paper also contributes to the varied literature on commodity cycles, particularly to studies focusing on the effects on workers, none of which studies the interaction between human capital accumulation and duration uncertainty (Kline 2008; Adao 2016; Benguria et al. 2021). 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 one of the elements that may be important to determine sectoral labor supply elasticities.

2 A Stylized Model

The effects of duration uncertainty will depend on the attitudes towards duration risk exhibited by workers sorting into each sector, which can be risk-loving or risk-averse. I first characterize this insight in a setting with learning on the job and boom-bust dynamics. Although marginal utility is constant in the baseline, the environment leads to risk-loving attitudes towards the duration of the boom for a subset of workers. This result is robust to workers having decreasing marginal utility. In Section 4 I extend the model for the quantitative analysis.

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 $g(\theta) : [\underline{\theta}, \bar{\theta}] \to \mathbb{R}$, whose problem, defined in detail below, is to decide in which sector to work. There are two sectors in the economy, $s = 0, 1$. If the economy is in the boom state, wages per unit of skill are high in sector one; they fall when the boom ends. Wages in sector zero, the outside sector, are normalized to one at all times and states of nature

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

The boom doesn't have any effects other than on relative wages of sector one. The economy is booming at period zero 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 $b_t = \mathbb{I}[\tau > t]$. 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 this model. I further assume that the hazard rate for the end of the boom, denoted by μ, is constant.

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 to s, which will depend on her type θ and her tenure in s. Using $\vec{\Delta}_t = [\Delta_{0t} \;\; \Delta_{1t}]$ to denote a vector of sector-specific tenure at time t, labor income is given by

$$y_{st}(\theta, \vec{\Delta}_t, b_t) \equiv w_{st}(b_t) H_{st}(\theta, \vec{\Delta}) = \begin{cases} \gamma_0^{\Delta_{0t}} & s = 0 \\ w_{1t}(b_t) \times \theta \times \gamma_1^{\Delta_{1t}} & s = 1 \end{cases} \quad \forall t. \tag{2}$$

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 zero whenever a worker switches sectors, even if for one 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 one in all periods, utility is linear, and the future is discounted by a factor β.[4] Her problem can be written recursively as follows:

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

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

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 state of the economy at $t+1$. With probability μ the economy will go from boom to bust.

At time zero workers are born 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 $\{\theta, \vec{0}, 0, 1\}$. The following proposition describes the optimal policies for a worker who decides to sort into sector one initially.

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

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

- **$\ell_t = 1$ if $b_t = 1$.**
- **$\ell_\tau \in \{0, 1\}$.**
- **$\ell_t = \ell_\tau \;\; \forall t > \tau$.**

Proof. See Appendix Section A.1.

Proposition 1 states that the optimal strategy for workers that start working in the booming is to stay until the boom ends, re-optimize when it does, and then never switch again. 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 sector one have spent τ consecutive periods in it. The economy is deterministic going forward, so they will choose sectors by comparing the discounted lifetime earnings in each of them, namely,

$$V(\theta, [0\ \tau], 1, 0) = \frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \lesseqgtr \frac{1}{1-\beta\gamma_0} = V(\theta, [0\ 0], 0, 0). \tag{4}$$

The worker will choose to stay in the booming 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. The accumulation of sector-specific human capital, which would be lost upon switching, implies that the opportunity cost of leaving the booming sector is increasing in the duration of the boom. I define

$$\bar{\tau}(\theta, \cdot) \equiv \min_{\tau} : \frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \geq \frac{1}{1-\beta\gamma_0} \tag{5}$$

as the minimum duration that induces a change of behavior upon the end of the boom. It does depend on θ but also, as discussed below, more broadly on parameters like $\beta, \gamma_0, \gamma_1, \underline{w}$.

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

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

and, for a given θ, depends on other parameters

$$\frac{\partial \bar{\tau}(\theta; \gamma_0, \gamma_1, \underline{w})}{\partial \gamma_0} > 0, \quad \frac{\partial \bar{\tau}(\theta; \gamma_0, \gamma_1, \underline{w})}{\partial \gamma_1} < 0, \quad \frac{\partial \bar{\tau}(\theta; \gamma_0, \gamma_1, \underline{w})}{\partial \underline{w}} < 0.$$

Proof. See Appendix Section A.2.

Lemma 1 becomes important at the end of this section, when I discuss how the effect of duration uncertainty will be different in different economies.

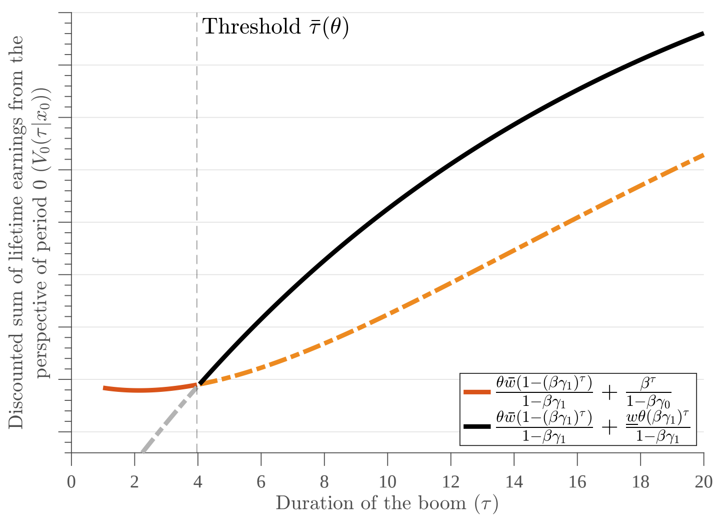
2.2 Attitudes towards Risk

Because policy functions in Proposition 1 follow such simple threshold rules I can write the discounted value of lifetime earnings for workers employed in sector one as a function of the duration of the boom, τ. This is a random variable, but workers at time zero can anticipate their lifetime earnings conditional on any duration τ. Values are then given by

$$\forall\theta : \ell_0(\theta,\cdot) = 1 \rightarrow V_0(\tau|\theta,\vec{0},0,1) = \begin{cases} \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\beta^\tau}{1-\beta\gamma_0} & \tau < \bar{\tau}(\theta) \\ \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\underline{w}\theta(\beta\gamma_1)^\tau}{1-\beta\gamma_1} & \tau \geq \bar{\tau}(\theta). \end{cases} \tag{6}$$

The values in equation (6) reflect that workers recognize that for short durations they will find it optimal to switch sectors, but for long durations they will not. The first term of the sum is the same in both cases, reflecting that she will stay in the booming sector earning wages $\bar{w}$ until the boom ends. Notice that, in the last term of the second line, the sum of human capital accumulated before the boom ended, γ_1^τ, appears, while it does not in the first line since human capital depreciates upon switching. For illustration, Figure 2 presents equation (6) as a function of τ.[5]

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

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

a relatively general feature of the environment. The following lemma states sufficient conditions for there to be convexity around the kink.

LEMMA 2. **If $\gamma_1 > 1$ and $\frac{\bar{w}}{\underline{w}} \leq \left(\frac{1-\beta}{1-\beta\gamma_1}\right)^2$ 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 of this worker.

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 by 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, 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 conditions 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.[6]

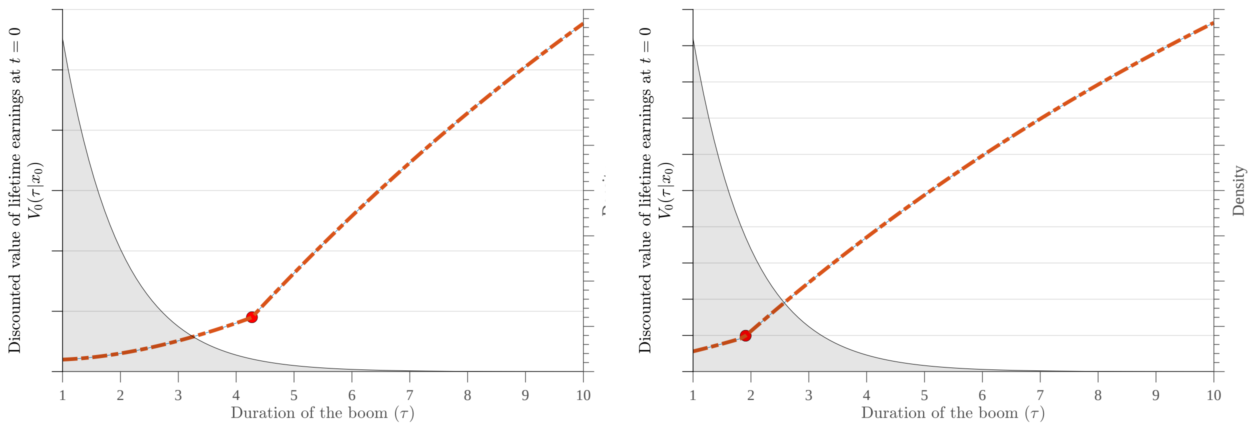
Because the position of the kink depends on θ but all workers face the same boom, the impact of duration uncertainty will be different for different workers. Figure 3a shows equation (6) overlapped with the density of the duration for a worker with low θ. Figure 3b shows the same graph for a worker with higher productivity in the booming sector. Because the second worker is more productive, the duration starting at which he decides to optimally stay in the booming 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

[6]To see that this is related to the model being in discrete time, consider fixing γ_1 and taking the limit as $\beta \to \frac{1}{\gamma_1}$, making workers as patient as possible while keeping the problem well-behaved. Then, the upper bound would increase to infinity.

worker that is more productive in the booming sector.

Figure 3: Heterogeneous risk-loving attitudes

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



2.3 Labor Supply: The Role of Duration Uncertainty

I now study how workers with different θ decide which sector to go to at time zero. The value at birth of sorting into the booming sector is equal to the expected value of equation (6), where the expectation is taken over duration τ. The value of sorting into sector zero is equal to the discounted value of lifetime earnings staying in sector zero forever.[7] Then, a worker of type θ sorts into sector one if the following inequality holds

$$\mathbb{E}_\tau(V(\tau)) \geq \frac{1}{1-\beta\gamma_0} \Rightarrow \ell_0(\theta, \vec{0}, 0, 1) = 1.$$

Figure 4 shows how different types θ sort across sectors in economies with low and high rates of human capital accumulation in the booming sector γ_1. The orange solid lines in each panel show the expected value of sorting into the booming sector at time zero. These lines are increasing in θ, as higher θ types have higher productivity. Workers at the right of the intersection between the solid lines sort into sector one. 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 and a higher labor supply in the booming sector at time zero.

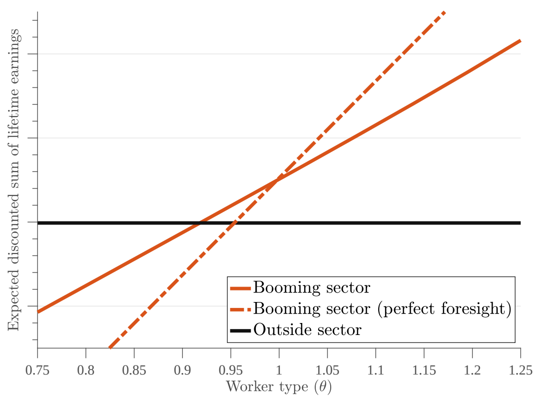
This environment serves as a laboratory for the following thought experiment, where I isolate the role of duration uncertainty. I compare the economy just described with a perfect foresight economy in which the duration of the boom is fixed and set to $\tau^{pf} = \frac{1}{\mu}$, which is the expected

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

duration in the baseline economy. The dashed lines in both panels of Figure 4 show how the ex-ante value of sorting into the booming 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 second and main aspect to note is that labor supply in the booming 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_1, that the effects of duration uncertainty on labor supply in this economy flip. In this economy, duration uncertainty discourages labor supply on the margin.

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 sector one, now interpreted as utility, would become: $u_{1t} = (w_{1t}\theta\gamma_1^{\Delta_{1t}})^{\sigma} = w_{1t}^{\sigma}\theta^{\sigma}(\gamma_1^{\sigma})^{\Delta_{1t}}$. 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 simple model is that, if there is sector-specific human capital accumulation, both the qualitative and quantitative answers about the effects of duration uncertainty on labor supply will depend on the context. It is crucial to know whether marginal workers exhibit risk-loving attitudes towards duration or not, as the comparison in Figure 4 show. I now turn to describe the context I focus on for the rest of the paper.

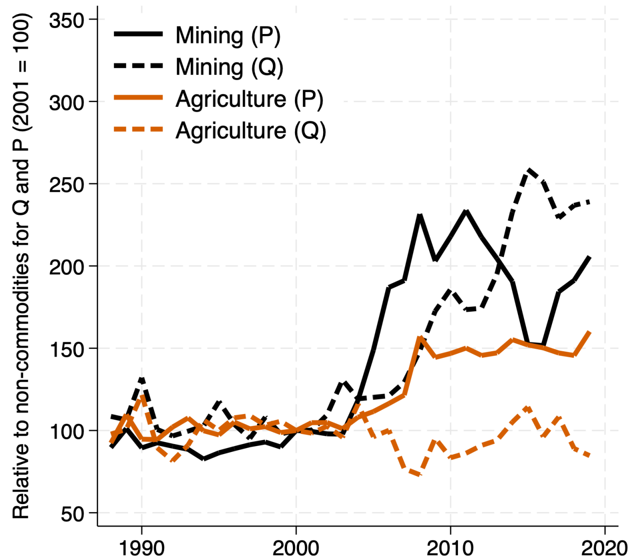
3 The Mining Boom in Australia

Rapid growth and urbanization in China in the early years of the century pushed up demand for commodities, which led to the highest commodity prices in decades and affecting countries around the world (see Figure 1). 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). Chinese imports of ores and metals, in particular, increased from being close to 5% of the global imports of these products in 2000 to 30% by the end of the 2010s.[8] These commodities were used as inputs in construction as the country urbanized and shifted to a more liberal real estate market. 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 which are used for steel production, an input to construction (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.

[8] 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 that the increase in export prices experienced by Australia is driven by construction in China, I collected data on construction activity in China and test how well it helps 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 3 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.[9] 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 for the prices of coal and iron ore, key products in Australia, between 2010 and 2018. These

[9]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 essentially temporary.

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 model I describe next introduces several sectors to capture these effects.

4 Quantitative Model

I extend the baseline model in Section 2 by introducing additional features in order to take it to the data from Australia between 2011 and 2018. The first difference is that I model boom-bust dynamics in world mining prices instead of wages, which are now endogenous. I borrow from Traiberman (2019) to build model of a small open economy with rich heterogeneity, sector-specific human capital accumulation and forward-looking workers where the process of prices is taken as given.

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 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.

This assumption is analogous to the process for wages in equation (1) in the baseline model. I allow now for variation in prices between periods conditional on the state being a boom. 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 over they fluctuate around a lower mean. The parameter ρ_1 measures persistence of deviations of the price around the state-specific mean. These assumptions will play a role in the estimation of the hazard rate for the process, not for the estimation of the labor side of the model. For the latter, the key is going to be that there are two regimes and the economy switches between them.

As in the simple model, I assume that the bust state is absorbing and the hazard rate μ_t can be 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 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 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

Time is discrete and there is 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. The newborn agents are born unattached to any particular sector.

There are five sectors, three of which are tradable goods (manufacturing, mining, and agriculture) and two of which are 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 need not finish when the mining boom ends. Second, as argued above, changes in terms of trade should also impact the demand for non-tradable goods so it is important to have a distinction between the two. I treat construction separately from other services because, during the period I study, there was a large spike in construction investment and I want to be able to capture the dynamics of this investment process separately. I discuss this further below.

Labor supply. 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 in period $t-1$. Finally, e and θ capture time-invariant characteristics: $e \in \{low, medium, high\}$ denotes the maximum education level attained. Θ is defined as the set of possible types and is assumed to be finite, and $\theta \in \Theta$ captures unobserved heterogeneity. I classify workers with at most high school as low education, some vocational training as medium, and college or more as high education.

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 booming sector, which could depend on their education and unobservable characteristics. Since correctly estimating the returns to human capital accumulation on-the-job is crucial, controlling for for selection in the type of workers who decide to stay for longer in a sector is essential. This is a second reason to allow for other determinants of income.

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 function H_s, the number of efficiency units of human capital that the worker is able to supply to a sector which depends on characteristics like 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.

I now turn to specifying worker preferences. Expected utility, shown in equation (13), is the combination of real income y_{it}, an amenity value η_s, and migration costs $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$, both of which are modeled in terms of utility. A worker with characteristics ω_{it} that switches from $s_{i,t-1}$ to s_t pays utility cost $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$. The flow utility of a worker with characteristics ω_{it} who sorts into s at period t can then 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 will be a function of the history of shocks and not only the current state. After the boom ends, equilibrium wages will move slowly towards the new steady state in a way that depends on the state of the economy when the boom ends, so 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, she makes her decision of where to work. The value of a worker 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. It takes ω', the future characteristics of the worker, as an argument. Age evolves mechanically by one, while education and unobserved type are constant.[10] 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, the fact that human capital depreciates upon switching is at the heart of the economic mechanism by which workers may have risk-loving attitudes towards the duration of the boom. 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.

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

[10] An interesting extension of the model would be to study how expectations about the duration of the shock affect education decisions, something which has been important in other contexts (Atkin 2016)

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

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.[11] Note that wages are sector-specific.

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, so I_t enters as demand for the construction sector at t, on top of construction for residential purposes from consumers. I discuss the implications of my 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 $\{w_t^s(h^t)\}_{t=0}^{\infty}$ 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:

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

- 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,

$$H^d_{st} = H^s_{st} \quad \forall s \in \mathcal{S}, \tag{21}$$

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

- The market for capital clears,

$$\sum_{s \in \mathcal{S}} K^d_{st} = K_t \tag{22}$$

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,

$$\sum_{s \in \mathcal{S}^T} p^s_t(h^t)\ C^s_t(h^t) = \sum_{s \in \mathcal{S}^T} p^s_t(h^t) Y^s_t(h^t).$$

Most of the elements in the model of labor supply are standard and build on Dix-Carneiro (2014) and Traiberman (2019). Compared to the baseline model, a key new ingredient is the fixed utility cost of moving sectors, $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$, which has been highlighted by the literature as drivers of labor reallocation on top of the opportunity cost which I underscore here. Since the work of Topalova (2010) and Autor et al. (2013), 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 migration costs $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$ are reduced substantially.

The main new ingredient in my model of labor supply is in the expectation term in equation (14). 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

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

Equation (23) will have important implications when estimating the costs of switching sectors using data only from a booming period. 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 manageable, 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 data on one firm which is among the biggest mining firms in Australia and in the world. From now on I call this firm φ. From OptionMetrics, a large provider of data on financial instruments traded in US markets, I have data on stocks and put options on the stock of this firm. Data on dividends is publicly available.

In the OptionMetrics data 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 of firm φ. 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. Clearly, these instruments gain in value whenever the expectations of the market price of the stock go down, particularly when they are expected to fall below K. This should make them sensitive to changes in the probability of big events, like the end of a commodity boom, which is why I choose to focus on them. 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 current 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 want to capture the probability that the boom is over 'one year ahead'. 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 data made public by the firm, I observe the value of dividends per share at a semi-annual frequency. These values are also expressed in current 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 2010 and 2018, where both the worker and the plant of employment are identified with a code. 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 demand 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 use the series of aggregate stock of capital from this source. To be consistent with the model, I use the series of non-dwelling construction at constant prices for 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 just described. To estimate the parameters of labor supply I will follow the approach in Traiberman (2019), who in turn follows a rich literature from industrial organization and labor economics (Rust 1987; Lee and Wolpin 2006; Arcidiacono and Miller 2011).

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 will describe how, under some assumptions about dividends, the theoretical value of stocks and options depends indirectly on μ. Then I explain the estimation and conclude by discussing my results.

6.1.1 The financial value of the mining firm and the aggregate state

I assume that the dividends the firm 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 from the half-yearly data for dividends and the price index of mining products from Figure 5.[12] 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,

[12]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.

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

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

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 dividends - the value of different financial instruments ex-ante. The value of the stock 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, the American put options allow the holder to sell the stock at some strike price K at any period before the termination date T. Their value when investors are risk neutral is 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.

6.1.2 Estimation

First I estimate $\delta_0, \delta_1, \rho_0$ and ρ_1 from half-yearly data on mining price indices and dividends using OLS. I obtain $\hat{\rho}_0 = 0.54, \hat{\rho}_1 = 0.68$, $\hat{\delta}_0 = 2.43, \hat{\delta}_1 = 2.33$. The standard deviation of the residuals in equation (24), which matters for equation (28), is $\hat{\sigma} = 0.3$.

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 can be interpreted as the estimated annual 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 the IMF forecasts for the prices of iron ore and coal shown in Figure 10a, which were negative throughout the decade. The large estimated values for the hazard rate suggest that the probability of an end to the boom 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.[13] Moreover, as shown in the Appendix Section B.2, new residential 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.

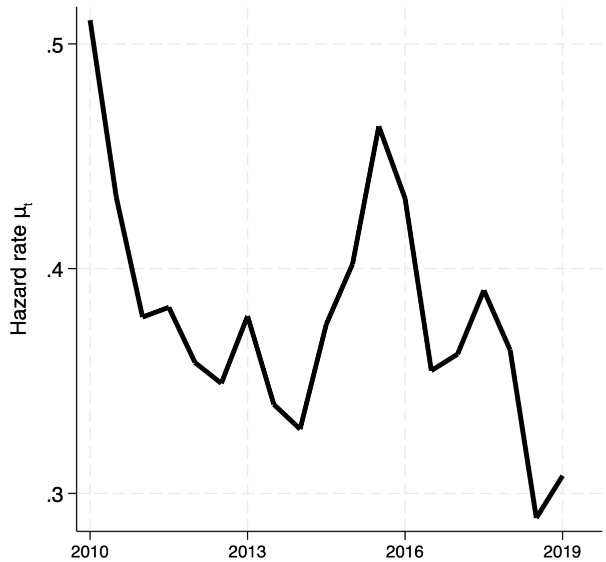
This estimate is obtained from asset prices, in some way distant from the agents in labor markets in Australia. To check whether this measure of μ correlates with labor markets outcomes in Australia I consider the following equation,

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

where $Y_{i,t}$ takes value one if worker i is employed in mining in year t and p_{t-1}^M 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 4 in Appendix Section C shows that the estimate of α_3 is negative and

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

Figure 6: Estimated hazard rate



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.

6.2 The real economy

6.2.1 Sectoral human capital accumulation

The relationship between human capital 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 also 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) I follow the expectation maximization approach (Arcidiacono and Miller 2011; Scott 2014; Traiberman 2019). The main idea 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

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

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

$$\begin{tikzcd}
& \omega'_t, s' \arrow[dr] & \\
\omega_{t-1}, s \arrow[ur] \arrow[dr] & & \omega''_{t+1}, s'' \\
& \hat{\omega}_t, s \arrow[ur] &
\end{tikzcd}$$

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.[14]

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 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 1 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 1 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.

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.

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

Table 1: 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

Labor shares and consumer preferences. Table 2 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 2: 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

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

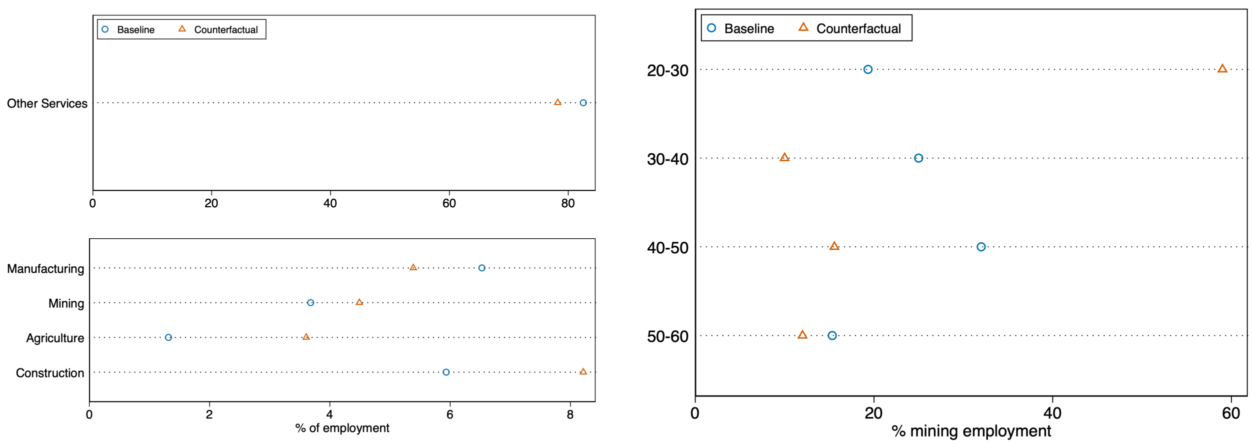
The end of the boom is dated in 2014, the expected duration derived from the calibrated hazard rate. Comparing the allocation of workers across sectors and relative wages in this economy to the data determines whether stripping out uncertainty about duration increases or reduces labor supply into the 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.[15]

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%.

Figure 8: Employment

(a) Changes in sectoral allocation

(b) Mining becomes younger



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 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.

[15] 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.

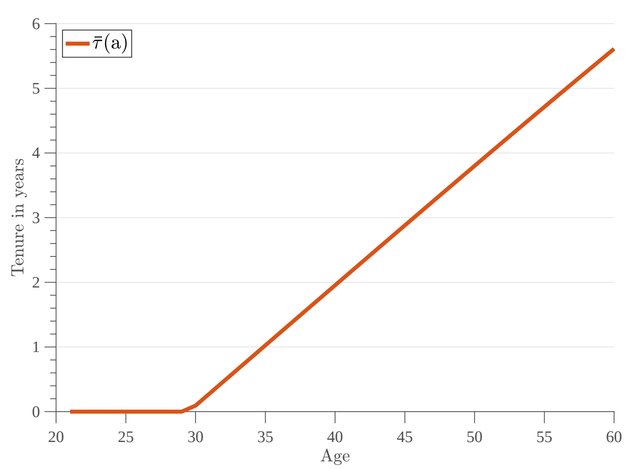
The simple model in Section 2 provides a lens to interpret these differential results by age. To see this, consider the following back-of-the-envelope calculation where I look for the value of $\bar{\tau}$ around which the value function would be convex. The only new ingredient is the effect of age, 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 $\bar{\tau}(\cdot)$



8 Concluding Remarks

Regime changes in which specific sectors go from booms to bust are recurrent. In this paper I have focused on one particular aspect that is arguably salient during a boom: uncertainty about when the regime will change, and how that impacts on labor mobility across sectors. Although the effects of this type of uncertainty on firms' have been studied, the effects on labor supply remain poorly understood.

In the first part of the paper I build a model of sector-specific on-the-job human capital accumulation, an ingredient found empirically relevant in other contexts (Dix-Carneiro 2014; Traiberman 2019). Through the lens of the model, I show that some entrants into the booming sectors will have risk-loving attitudes towards the duration of the boom, and these are heterogeneous across workers. Hence, whether this type of uncertainty incentivizes or deter labor supply into a booming sector is ambiguous, and likely to depend on the empirical context.

In the second part 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 estimated version of the model I found that in this particular case duration uncertainty decreases aggregate labor supply into mining. These labor supply responses are heterogeneous across ages, and for a group of middle-aged workers, duration uncertainty incentivized mobility into booming sectors. 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.

By 2018 more than 60% of the countries in the world specialized in commodities (UNCTAD 2021). Boom and bust dynamics are, therefore, a central part of how these economies are affected by globalization. The results in this paper suggest than in order to understand how inequality responds to trade shocks in these economies we need to consider uncertainty about the length of the boom phase as a determinant of sectoral labor supply elasticities.

The framework could be used to study normative questions, left for future research. For example, what's the effectiveness of subsidies to reallocation into booming sectors in a context in which duration uncertainty plays a role? Or more broadly, how does uncertainty about the duration of certain sectoral policies, like industrial policy, influence workers' decision to enter into the subsidized industries?

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9 Appendix

A Mathematical appendix

A.1 Proof of Proposition 1

Because $\ell_0 = 1$, the following inequality holds:

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

Assume there was $t' > 0$ such that $\ell_{t'} = 0$ and $\ell_t = 1 \forall t < t'$:

$$\bar{\theta} w \gamma_1^{t'} + \beta\Big[\mu V(\theta, [0, t'+1], 1, 0) + (1-\mu)V(\theta, [0, t'+1], 1, 1)\Big] < 1 + \beta\Big[\mu V(\theta, [1,0], 0, 1) + (1-\mu)V(\theta, [1,0], 0, 1)\Big] \tag{37}$$

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:

$$\bar{\theta} w \gamma_1^{t'} + \beta\Big[\mu V(\theta, [0, t'+1], 1, 0) + (1-\mu)V(\theta, [0, t'+1], 1, 1)\Big] < \bar{w}\theta + \beta\Big[\mu V(\theta, [0,1], 1, 0) + (1-\mu)V(\theta, [0,1], 1, 1)\Big]$$

Which is a contradiction if $\gamma_1 > 1$. 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's 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:

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tau}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{38}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tilde{t}}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{39}$$

Then, waiting until $\bar{t} + (\bar{t} - \tau)$ has to be preferred than switching at $t = 0$:

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau(1-(\beta\gamma_1)^{2(\tilde{t}-\tau)+1})}{1-\beta\gamma_1} + \frac{\beta^{2(\tilde{t}-\tau)+1}}{1-\beta\gamma_0} \tag{40}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \tag{41}$$

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

A.2 Proof of Lemma 1

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

$$\bar{\tau}(\theta;\gamma_0,\gamma_1,\underline{w}) = \frac{1}{\log(\gamma_1)}\Big[\log(\frac{1-\beta\gamma_1}{1-\beta\gamma_0}) - \log(\underline{w}\theta)\Big] \tag{42}$$

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:

$$\begin{aligned}
V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq & V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) && (43)\\
\bar{w}\theta(\beta\gamma_1)^{T-1} + \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} - \frac{\beta^{T-1}}{1-\beta\gamma_0} \geq & \bar{w}\theta(\beta\gamma_1)^{T-2} + \frac{\beta^{T-1}}{1-\beta\gamma_0} - \frac{\beta^{T-2}}{1-\beta\gamma_0} && (44)\\
\bar{w}\theta(\beta\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq & \frac{\beta^{T-2}(1-2\beta)}{1-\beta\gamma_0} && (45)\\
\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{\beta^2(\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq & \frac{(1-2\beta)}{1-\beta\gamma_0} && (46)\\
& && (47)
\end{aligned}$$

Because I'm looking at the kink $\tau = \bar{\tau}$, $\frac{\underline{w}\theta\gamma^{\tau}}{1-\beta\gamma_1} = \frac{1}{1-\beta\gamma_0}$ and the inequality becomes:

$$\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} \tag{48}$$

$$\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} \tag{49}$$

Where in the last step I multiplied and divided by $\underline{w}$. For $\tau - 2$ the following inequality holds $\frac{\underline{w}\theta\gamma^{T-2}}{1-\beta\gamma_1} < \frac{1}{1-\gamma\beta_0}$. Then, it's enough for equation (49) to hold that the following holds:

$$\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} \tag{50}$$

$$\frac{\bar{w}}{\underline{w}} \leq \frac{1-2\beta+\beta^2}{(1-\beta\gamma_1)^2} = \left(\frac{1-\beta}{1-\beta\gamma_1}\right)^2 \tag{51}$$

Using that $\gamma_1 > 1$, the right-hand side is greater than one as long as $2 > \beta\gamma_1$. This last condition always holds, as $\beta\gamma_1 < 1$ 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 (77)

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:

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

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

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.

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

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.

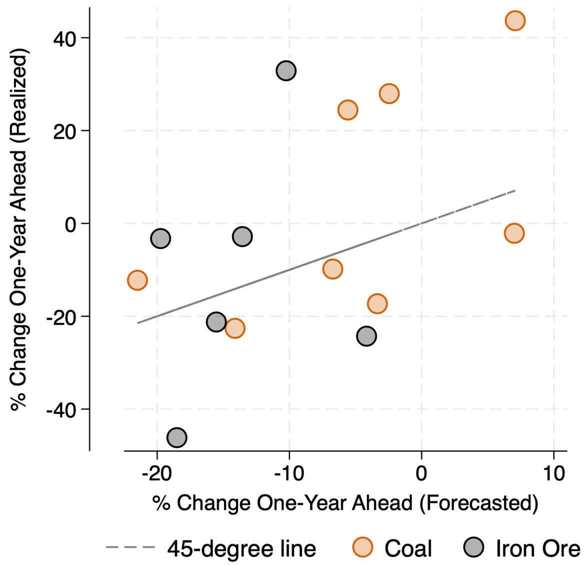
B Background and data appendix

In Section 3 I discuss how forecasts about future forecast evolved during the period and the broad evolution of labor allocation across sector during the period, making referrence to Figure 10 below.[16]

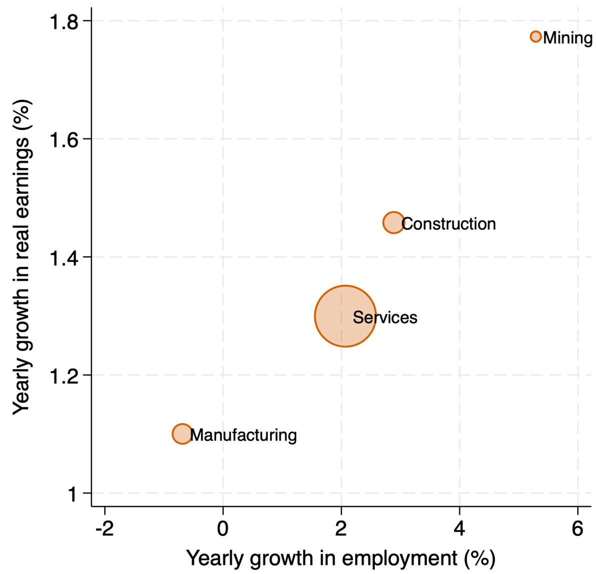
[16] Figure 10b draws from public data from ABS, which does not include wage data for Agriculture. Employment in services is likely to grow also for secular reasons common to all developed economies, but it is notable that earnings also increase fast in the sector.

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 ramped up 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 helps 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[17]. 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 these two series at the quarterly level.

I first 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 of Table 3 show that lagged construction floor space sold in China, which I take as a proxy for current construction levels, has a positive effect on future export prices. All variables are in logs, so the effect is quantitatively important. I include lagged retail sales in China as a control, which is not significant, to make sure I'm not picking up economic growth in China more generally.

[17]Accessed September 23, 2022.

Table 3: 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.*

The second and third columns of Table 3 repeat the exercise but keeping goods which are not usually 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 also suggests 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

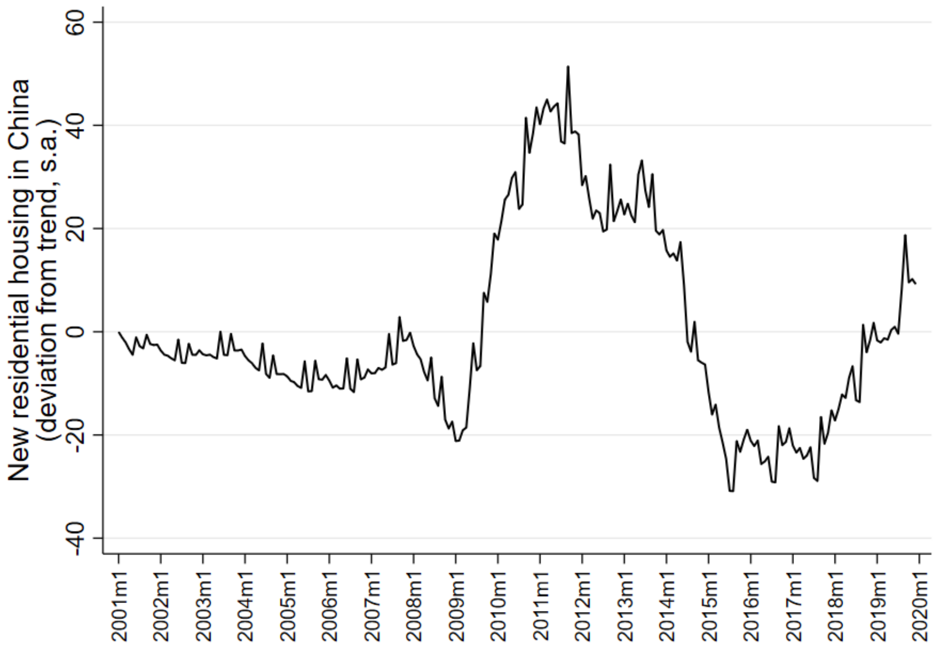
Using the same data as in the subsection above, Figure 11 plots the deviation of new residential buildings started in China from a linear trend. To smooth out seasonal variations I first calculated a moving average of the original series using 6 lags and 6 future values of the series. The key takeaway from this figure is that new building comes to a halt around the time of the financial crisis and around 2014.

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. [18] 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

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

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



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.

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 4 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 4 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 can't be mapped directly with the counterfactual I'm interested in.

C.2 Expectation maximization

In this subsection I am interested in estimating the parameters in the equation for human capital equation (12). The estimates $\{\hat{\gamma}_s^{ML}\}, \hat{q}_{i\theta}$ maximize the following likelihood, 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 conditional likelihood $\mathcal{L}_{i\theta}$ 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. Using equation (30) and that $\zeta \sim N(0,1)$, the first of these terms has a closed form. The second term is estimated from the data by regressing the probability of workers transitioning between sector pairs conditioning on observables through OLS. Formally:

Table 4: 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

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

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

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:[19]

$$\begin{aligned} \frac{V_t(s, \omega, h^t)}{\rho} =& \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega, \zeta_{s't}) - C(\omega, s, s')}{\rho} \\ &+ \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 0\}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 1\})\Big] - log(\pi_t(\omega, s, s')) \end{aligned} \tag{73}$$

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

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

$t+1$ 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

$$
\begin{tikzcd}
& \omega', s', t \arrow[dr] & \\
\omega, s, t-1 \arrow[ur] \arrow[dr] & & \omega'', s'', t+1 \\
& \hat{\omega}, s, t \arrow[ur] &
\end{tikzcd}
$$

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 (73) 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:

$$
\log\left(\frac{\pi_t(\omega, s, s)}{\pi_t(\omega, s, s')}\right) + \beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega}, s, s'')) - \log(\tilde{\pi}_{t+1}(\omega', s', s''))]) + \tag{74}
$$
$$
(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega}, s, s'')) - \log(\pi_{t+1}(\omega', s', s''))]]\Big] = Y^{\omega}_{s,s,t} - Y^{\omega}_{s,s',t} + \frac{\beta}{\rho}\left[f(\omega')C(s', s'') - f(\hat{\omega})C(s, s'')\right]
$$

Where $Y^{\omega}_{s,s',t}$ is the flow payoff of switching from s to s' at t for a worker with characteristics ω.[20] 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 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.[21] For this reason, I make the following assumptions.

Using Assumption 3, equation (74) becomes:

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

[21] To see this:

$$
\mathbb{E}_t[\pi_{t+1}] - \pi_{t+1} = \mu_t\tilde{\pi}_{t+1} + (1-\mu)\pi_{t+1} - \pi_{t+1} = \mu_t(\tilde{\pi}_{t+1} - \pi_{t+1}). \tag{75}
$$

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

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right)= \tag{76}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')\Big]+\tilde{u}_{s,s',t} \tag{77}$$

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.