Labor reallocation during booms: The role of duration uncertainty*

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Abstract

Temporary booms are recurrent in 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 have risk-loving attitudes towards the duration of the boom. These can arise because there is an option value attached to working in these 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. I use the model to study the effects of duration uncertainty during the boom in prices of mineral products during 2011-2018 in Australia, an exporter of mining products. I use the quantitative model to study a counterfactual perfect foresight economy in which the mining boom was temporary and duration known. I find that employment in mining would have been 8% higher and the relative wage in the sector significantly lower, indicating that labor supply was deterred by duration uncertainty in this case.

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, commodity prices shift from booms to busts. Uncertainty around when the regime will change can, by itself, affect economic outcomes. In the international context uncertainty about the trade policy regime has been shown to affect firms' entry and exporting decisions (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 on labor supply with a focus on uncertainty about the length of a commodity boom.

The main goal of this paper is to understand how labor supply across sectors is affected by uncertainty about the boom's length. First, I tackle the question theoretically using a model of sector-specific human capital accumulation. The main insight is that workers can have risk-loving attitudes towards the boom's duration over a range of possible durations. Convexity arises because workers continually optimize and can decide to switch out of the booming sectors if the boom is short. If the duration is long enough, however, they will not switch out as this would imply losing the already accumulated human capital. This generates a kink around which the value function is convex. The value of the booming sectors in the economy without uncertainty would be lower than the expected value if the durations around the kink are very likely. When this is true for the marginal workers switching into the booming sector, labor supply decreases in the economy without uncertainty.

Given that the effects of duration uncertainty are ambiguous, I proceed to study a particular boom. I estimate the model using novel data from Australia during the recent global commodity boom (shown in Figure 1a). An advantage of focusing on a boom driven by external forces is that there is potentially more domestic uncertainty over its duration than during sectoral booms caused by domestic policies. Then, I simulate a counterfactual perfect foresight economy in which the boom was temporary and duration known. I find that aggregate labor supply into the mining sector, the most affected by the boom in Australia, increases if there is no uncertainty. As suggested by the simple model, the responses are heterogeneous across workers: employment in mining decreases for middle-aged workers.

The simple model in the first part of the paper isolates how the value of being employed in a booming sector depends on the duration of the boom, the random variable over which workers form expectations when deciding where to work. The economy has two sectors, and the relative wage in one of them is booming at time zero. Relative wages in the sector will fall when the boom ends. Importantly, workers accumulate sector-specific human capital on-the-job in their sector of employment and lose it when they switch sectors. Under some conditions, I show that the discounted value of lifetime earnings for workers who sort into the booming sector is convex as a function of the boom's duration, leading to risk-loving attitudes. The intuition is the following. If the duration 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.[1] Convexity arises precisely around the duration that induces a change in behavior from leaving to staying in the sector upon the end of the boom, which will be different for different workers. For workers who are very productive in the booming sector, 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 for the following thought experiment. If the boom was temporary but the duration is known from the outset, who would sort into the booming sector? How is the labor allocation different compared to the economy with duration uncertainty? The model's insight is that some workers in the economy 'bet on the boom', and their expected value in the sector is higher than if they had been assured that the boom would have a certain length. If these workers are the marginal workers, the economy without uncertainty would have a lower labor supply into the booming sector.

To study the question empirically, I focus on the commodity boom that started in the early 2000s and on its impact on the Australian labor market.[2] As shown in Figure 1a, starting in the early years of the century commodity prices increased and peaked around 2010. The boom in Australia, highlighted in orange, has been strong and long-lasting, still ongoing by 2019. It is generally agreed upon that one of the main drivers of this boom was growth and urbanization in China (IMF 2016; WB 2015). As shown in Figure 1b, the participation of China in global commodity imports increased dramatically during the period, especially for ores and metals. Australia is a key supplier of the latter, used intensively in construction as China urbanized and converged to a higher level of housing per capita. Crucially, during this period there was considerable uncertainty about when demand from China would stabilize and the boom in metal prices come to an end.[3] In Section 3, I provide more details on the context and how labor markets in Australia evolved broadly during the period. For the goal of this paper, this setting is an example of a large boom, driven by temporary forces, whose duration was unknown.

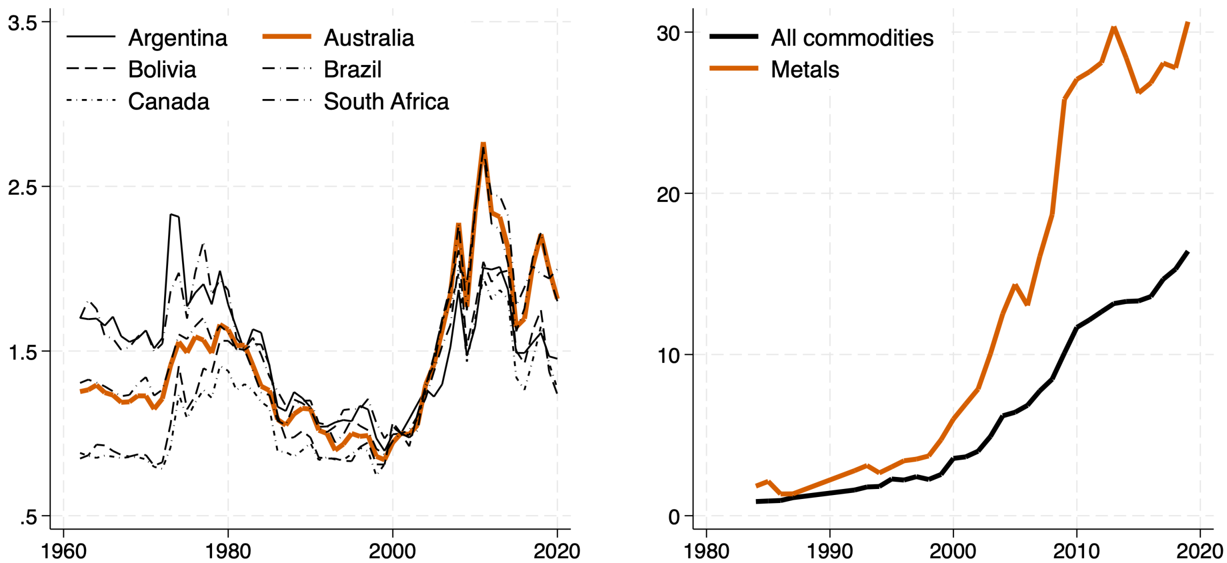
[1] An analogy that can be drawn is with call options, where the value goes up when volatility increases (Dixit and Pindyck 1994). Mulligan and Rubinstein (2008) use a similar analogy when explaining how selection patterns across women change when labor market inequality increases. Their model does not incorporate dynamics.

[2] These episodes are important both for their cyclical recurrence and their impact on many economies around the world. In 2018, commodities represented more than 60% of exports in more than 100 countries (UNCTAD 2021).

[3] This view can be found in several central bank reports from the period, especially when discussing the evolution of metal prices (Rayner and Bishop 2013; Kruger et al. 2016).

Figure 1: Commodity boom driven by growth in China

(a) Commodity export prices (Index 2001 = 100) (b) Imports from China (% World Imports)



Sources: *Historical Commodity Export Price Index (Weighted by Ratio of Exports to Total Commodity Exports, Fixed Weights)* from the IMF for Figure 1a and *World Bank Open Data* for 1b.

I build a quantitative model of sectoral choice à la Traiberman (2019) suited to the Australian context that I can use for my counterfactual analysis.[4] 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.[5] For example, if I did not allow for unobserved heterogeneity, part of the estimated returns to tenure would reflect selection of the type of workers that decide to spend longer periods in a sector. I aggregate sectors in the economy to a total of five: three of them tradable and two of them non-tradable. As I underscored in the discussion of the simple model, the nature of outside options when the boom ends is crucial to understanding workers' sensitivity to duration uncertainty. Other tradable goods may not bust when mining does, while non-tradable goods may be impacted by the end of the boom through a decrease in demand (Corden and Neary 1982).

[4]I mostly borrow from the model of human capital accumulation in Traiberman (2019). I do not include the occupation choice margin.

[5]This parameter is key for risk-loving attitudes to arise. See Lemma 1 in Section 2.

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. 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 on 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.[6] I construct a panel of workers between 2011 and 2018 by linking data from tax returns across years and to the 2016 census.[7] 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 labor side of the model mostly following the approach in Traiberman (2019), who 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 when making their decisions. The challenge then becomes how to disentangle between pure switching costs and counterfactual values in a sector if the boom ends. I tackle this issue by parameterizing the counterfactual changes in value in each sector. This last function appears, interacted with the hazard rate for the end of the boom, in the equation linking transition rates between sectors to pure switching costs.[8]

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 (its expected duration). The share of the population working in mining is 4% in the counterfactual, compared to 3.7% on average in the data. However, responses are heterogeneous by age. Young workers increase labor supply into mining the most, while middle-aged workers decrease theirs. Through the lens of the simple model, these workers could have been 'betting on the boom' and the expected value of the sector became lower once high durations were ruled out. In general equilibrium, of course, other variables also change. 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. Other sectors that grow in the counterfactual economy are agriculture and construction, while manufacturing shrinks.

[6] 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. This is important to measure outside options correctly.

[7] The panel can be constructed starting in 2002, which I use to construct my variable of sector-specific experience. The rest of the analysis focuses on 2011-2018.

[8] This is discussed in detail in Section 6. See Scott (2014) for a discussion.

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 that describes risk-loving attitudes towards duration and how it affects 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. 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 shocks to import competition (Topalova 2010; Artuç et al. 2010; Autor et al. 2013; Dix-Carneiro and Kovak 2017, 2019; Caliendo et al. 2019). Recent studies have argued that sector-specific human capital accumulated on-the-job is key to explain why labor reallocation can be slow and heterogeneous across workers (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. My contribution is to study a very different setting, the mining boom in Australia, in which boom-bust dynamics are salient and duration uncertainty arises as an additional driver of labor supply decisions. More broadly, as human capital is sector-specific in the model this paper relates to the study of specific-factor models of trade (Jones 1971; Mussa 1974; Matsuyama 1992).

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. A series of papers focused on how Chinese firms' entry and exporting decisions during the 1990s were affected by uncertainty about how long the low-tariff regime in the US would last (Handley and Limão 2015, 2017). Pierce and Schott (2016) study how the resolution of uncertainty about trade policy affected manufacturing employment through changes in labor demand. Other studies focus on other settings with trade policy uncertainty (Graziano et al. 2020). My contribution is to focus on how uncertainty matters for labor supply directly. At the conceptual level, a key difference is that in the settings just mentioned, the firm's problem is an irreversible investment problem, and uncertainty necessarily increases the value of waiting (Handley and Limão 2022). In the context I study this is not necessarily so, as workers continually decide in which sector to work and accumulate human capital. The results in this paper indicate that the reduced-form results in Pierce and Schott (2016) reflect a mix of changes in labor demand and labor supply.

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 have a negative effect on 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 simple model

I present first a simple model to discuss the core mechanisms. I expand the model to perform the quantitative analysis in Section 4. The economy is populated by a continuum of heterogeneous infinitely-lived agents indexed by their type θ, distributed according to density $g(\theta) : [\underline{\theta}, \bar{\theta}] \to \mathbb{R}$. Time is discrete. 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 $b_t = 0$. 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.

There are two sectors in the economy, $s = 0, 1$. Wages per unit of skill in sector one are high while the boom lasts and 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 labor income that a worker earns in sector s at t depends on wages per unit of skill and the human capital she is able to supply to that sector, which will depend on her type θ and her tenure in that sector. Using $\vec{\Delta}_t = [\Delta_{0t} \;\; \Delta_{1t}]$ to denote a vector of sector-specific tenure at time t, labor income is given by

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

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

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

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. Worker cannot save, the price of the consumption good is normalized to one in all periods, utility is linear, and workers discount the future using discount factor β.[9] 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 of the worker 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 must 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 1 initially.

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

- $\ell_t = 1$ **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 in Sector 1 is to stay in the booming sector 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.

[9] 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.

When the boom ends at $t = \tau$, workers that start in Sector 1 have spent there τ consecutive periods. The economy is deterministic going forward, so they will choose sectors by comparing the discounted lifetime earnings in each of them, namely,

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

The worker chooses 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. I define $\bar{\tau}(\theta)$ as the lowest value of τ such that $\frac{\underline{w}\theta\gamma_1^{\tau}}{1-\beta\gamma_1} \geq \frac{1}{1-\beta\gamma_0}$.

Because policy functions going forward follow such simple threshold rules, I can write the value from the perspective of period 0 as a function of the duration of the boom, τ. This is a random variable, but workers can anticipate their lifetime earnings conditional on any duration τ. Values are then given by

$$V_0(\tau|\theta, \vec{0}, 0, 1) = \begin{cases} \frac{\theta\bar{w}(1-(\beta\gamma_1)^{\tau})}{1-\beta\gamma_1} + \frac{\beta^{\tau}}{1-\beta\gamma_0} & \tau < \bar{\tau}(\theta) \\ \frac{\theta\bar{w}(1-(\beta\gamma_1)^{\tau})}{1-\beta\gamma_1} + \frac{\underline{w}\theta(\beta\gamma_1)^{\tau}}{1-\beta\gamma_1} & \tau \geq \bar{\tau}(\theta). \end{cases} \tag{5}$$

The values in equation (5) 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 (5) as a function of τ.[10]

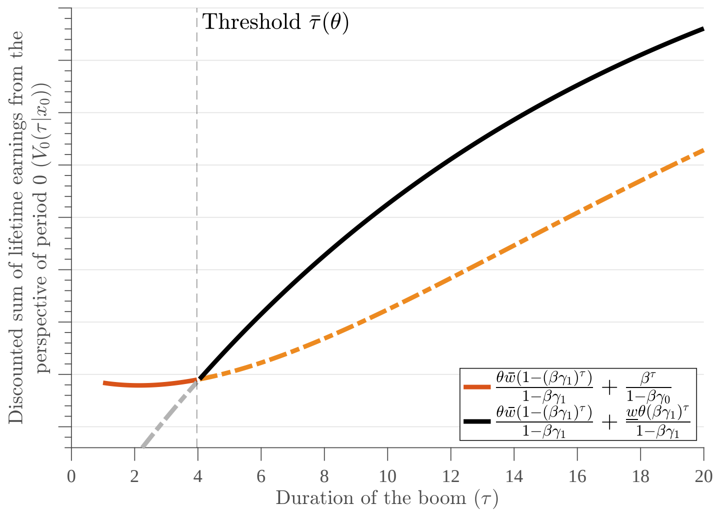
Importantly, there is convexity around the kink $\bar{\tau}(\theta)$. The intuition is the following. If the duration of the boom ends up being short, the worker will decide to switch out when the bust happens, cutting losses. If she was constrained to stay in the booming sector, her value would be given by the dashed gray line, and there would be no kink. On the other hand, if the duration is long enough she will optimally decide to stay even when the boom ends to avoid losing the accumulated human capital. This is a relatively general feature of the environment. The following lemma states sufficient conditions for there to be convexity around the kink.

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

$$V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta) - 1) \geq V_0(\bar{\tau}(\theta) - 1) - V_0(\bar{\tau}(\theta) - 2). \tag{6}$$

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

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



Which implies that the value function is convex at $\bar{\tau}(\theta)$.
Proof. See Appendix Section A.2.

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. There, firms have to pay a cost of entry or exporting but being an older firm doesn't carry any additional benefits (Pierce and Schott 2016; Handley and Limão 2017). It is also important that she can switch out when durations are short. If she was constrained to be in the booming sector, her value would be given by the dashed gray line in Figure 2 and there would be no kink. 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.[11]

[11] 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

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 (5) 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 worker that is more productive in the booming sector. The following lemma summarize this comparative static.

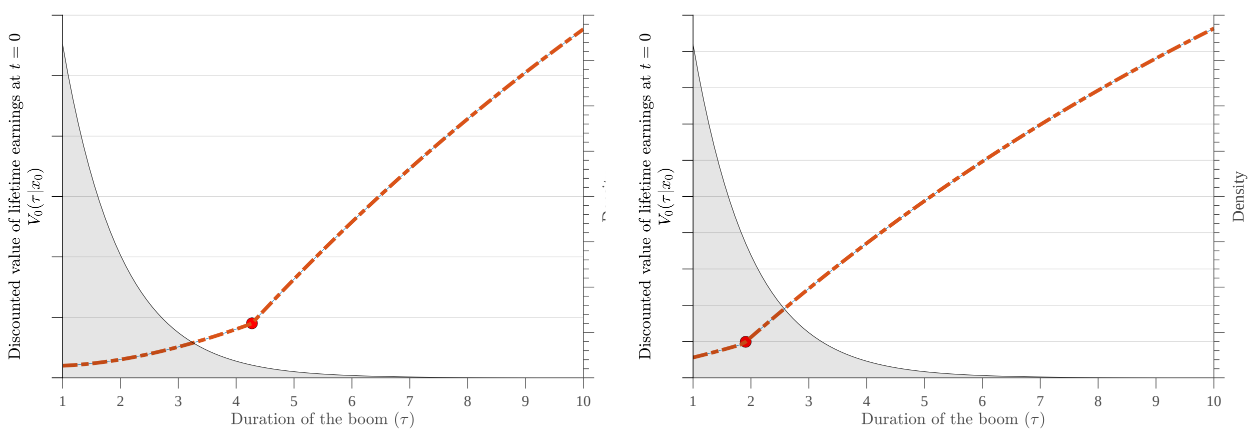
Lemma 2. **The kink in the value function happens at shorter durations for more productive workers**

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

Proof. See Appendix Section A.3.

Figure 3: Heterogeneous risk-loving attitudes for different workers

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



Lemma 2 compares workers with different productivities taking as given the rest of the parameters in the economy. The following lemma summarizes how the kink for a worker with the same productivity θ changes in economies with different parameters. This becomes important at the end of this section, when I discuss how the effect of duration uncertainty will be different in different economies.

Lemma 3. **The kink in the value function depends on the parameters of the**

would increase to infinity.

economy

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

Proof. See Appendix Section A.3.

I now study how workers with different θ decide which sector to go to initially. The value at birth of sorting into the booming sector is equal to the expected value of equation (5), where the expectation is taken over duration τ. The value of sorting into Sector 0 is equal to the discounted value of lifetime earnings staying in Sector 0 forever.[12] Then, a worker of type θ sorts into sector one if the following inequality holds:

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

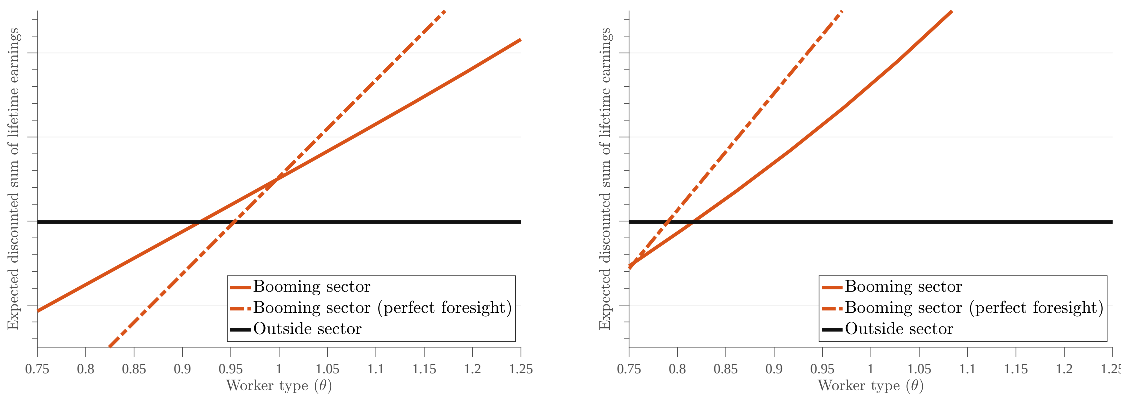
Figure 4 shows how different types θ sort across sectors in economies with low and high rates of human capital accumulation in the booming sector γ_1. The orange solid lines in each panel show the expected value of sorting into the booming sector at time zero. These lines are increasing in θ, as higher θ types have higher productivity. Workers at the right of the intersection between the solid lines sort into Sector 1. The solid orange line is also higher in the right panel, with higher rates of human capital accumulation. This translates into higher labor supply in the booming sector at time zero.

I now turn to the main counterfactual, where I isolate the role of duration uncertainty. I compare the economy just described with a perfect foresight economy in which the duration of the boom is fixed and set to $\tau^{pf} = \frac{1}{\mu}$, which is the expected duration in the baseline economy. The dashed lines in both panels of Figure 4 show how the ex-ante value of sorting into the booming sector changes.

[12] 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.

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. Figure 4b shows, how keeping all parameters the same except for a higher γ_1, the effects of duration uncertainty on labor supply flip. Duration uncertainty now discourages workers entry into the sector.

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 1 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 answer to the importance of duration uncertainty will depend on the context. That is, the economy could be in a situation illustrated by the left or the right panels in Figure 4. I now turn to describe the context I focus on for the rest of the paper.

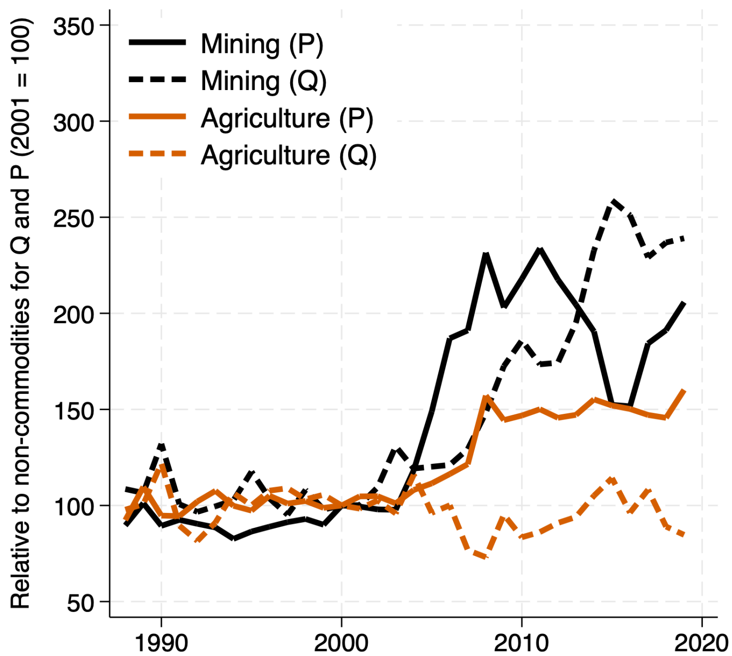
3 The mining boom in Australia

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 (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). From Figure 1a it is clear that the latest boom started in the early 2000s and affected commodity exporters across the globe. The country in which I will focus, Australia, experienced a relatively strong boom compared to the other commodity exporters. In the quantitative model below I will focus on the years 2011-2018, when the boom was still ongoing.[13]

The boom in Australia 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. Put together, these two figures show that 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.

[13]This is partly because Australia exports primarily metals. In other commodities, the boom ended in the mid-2010s.

Figure 5: Relative export prices and quantitities



What drove the strong increase in Chinese demand for ores and metals from around 5% of global imports of these products in 2000 to 30% by the end of the 2010s? A common view points to urbanization. Urban population in China increased from 26% of the total population in 1990 to 36% in 2000 and 49% in 2010.[14] 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.

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. See Table 4 in the Appendix, Section C.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

[14] World Bank data accessed online.

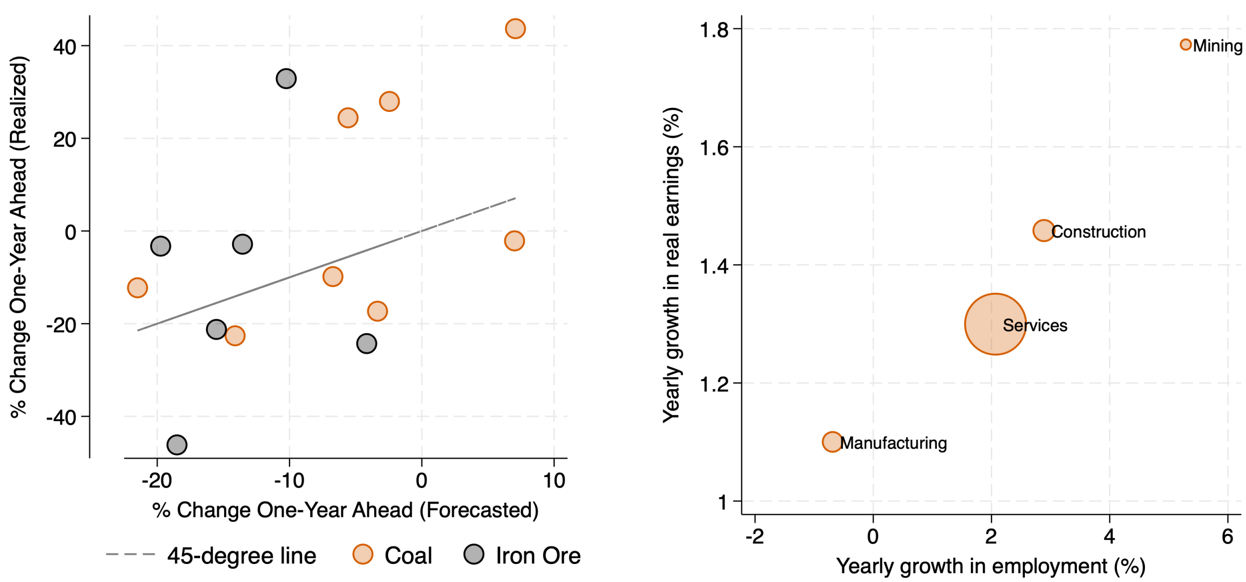
about how sustainable the boom would be.[15] Consider the following quote from Rayner and Bishop (2013), two researchers from the Reserve Bank of Australia:

> *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 6a shows IMF forecasts for the prices of coal and iron ore, key exports from Australia, between 2010 and 2018.[16] The horizontal axis shows, for each year, the forecasted change in the price of iron ore and coal one year ahead, in percentage terms. First, notice that most values are negative: it was expected that prices would fall. The vertical axis shows the realized variation in the price of the product one year ahead. The big gaps between forecasted and realized price changes suggest there was uncertainty about the evolution of prices.

Figure 6: 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 6b are proportional to the size of that sector between 2011 and 2018.

A potential caveat about studying this 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

[15] 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.

[16] All data come from the October World Economic Outlook.

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 6b shows that this is exactly what happened in Australia during the period.[17] 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 model a small open economy with rich heterogeneity 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, so**

$$p_t^M(b_t) = \begin{cases} \underline{p}^M & b_t = 0 \\ \bar{p}_t^M & b_t = 1 \end{cases} \quad \bar{p}_t^M > \underline{p}^M. \tag{7}$$

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. A potentially interesting extension of the model is to allow for uncertainty about prices beyond the boom-bust comparison on which I focus.

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.

[17] Figure 6b 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.

Erten and Ocampo (2013) calculate them to last 20 years. This assumption will become relevant when I calibrate the hazard rate for the end of the boom from financial data, as I highlight below.

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

$$\mathbb{P}_t[b_{t+1} = 0 | b_t] = \begin{cases} 1 & b_t = 0 \\ \mu_t & b_t = 1 \end{cases}. \tag{8}$$

The history of shocks up to period t, h^t, is given by a sequence $\{b_s\}_{s=0}^t$. 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 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. Θ is defined as the set of possible types and is assumed to be finite.

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.

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

$$y_{it}(h^t)|s \equiv \frac{w_s(h^t)}{P_t(h^t)} H_s(\overbrace{\omega_{it}}^{\text{Age, tenure, type}}, \overbrace{\zeta_{ist}}^{\text{Shock}}), \tag{9}$$

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 (10), is the combination of real income y_{it}, an amenity value η_s, and migration costs $\tilde{C}$, 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

$$U(\omega_{it}, s_{i,t-1}, s, h^t) = \mathbb{E}_\zeta[y_{it(h^t)|s}] + \overbrace{\eta_s}^{Amenity} + \overbrace{\tilde{C}(\omega_{it}, s_{it-1}, s_{it})}^{\text{Switching cost}}. \tag{10}$$

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 before and after idiosyncratic shocks are realized is given by

$$v(s_{i,t-1}, \omega_{it}, h^t, \epsilon_{it}) = \max_{s' \in \mathcal{S}} \left\{ U(\omega_{it}, s_{i,t-1}, s', h^t) + \rho \epsilon_{s'it} + \beta \mathbb{E}_t V_{t+1}(s', \omega', h^{t+1}) \right\} \tag{11}$$

$$\text{and } V(s, \omega, h^t) = \int v_t(s, \omega, h^t, \epsilon) dG(\epsilon) \tag{12}$$

respectively. In equation (11) 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 (11) 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. [18]. Tenure evolves as in the baseline model, namely,

$$\Delta_{i,t+1} = \begin{cases} \Delta_{it} + 1 & \text{if } s_{i,t-1} = s_{it} \\ 0 & \text{if } s_{i,t-1} \neq s_{it} \end{cases}. \tag{13}$$

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,

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

The price index, which already appeared in equation (9), will then be

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

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

[18] 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)

$$Y_{st} = A_{st} K_{st}^{1-\alpha_S} H_{st}^{\alpha_s}, \tag{14}$$

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

$$\frac{H_{st}^d(h^t)}{K_{st}^d(h^t)} = \frac{r\alpha_s}{w(1-\alpha_s)} \tag{15}$$

$$p_{st}(h^t) = \frac{\chi^s r_t(h^t)^{\alpha_s} w_{st}(h^t)^{1-\alpha_s}}{A_{st}}, \tag{16}$$

where χ^s is a constant and super-script d denotes demand.[19]

Capital. The aggregate stock of physical capital evolves according to:

$$K_{t+1} = (1-\delta)K_t + I_t \tag{17}$$

Capital is perfectly mobile between 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 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 s in $\mathcal{S}$ and h^t:

- Workers sectoral labor supply solves the problem in equation (11).
- Firms maximize profits. Namely, equation (15) and equation (16) hold.
- Labor markets clear,

$$H_{st}^d = H_{st}^s \quad \forall s \in \mathcal{S}, \tag{18}$$

  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 $H_s(\omega, \zeta)$.

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

- The market for capital clears,

$$\sum_{s \in \mathcal{S}} K^d_{st} = K_t \tag{19}$$

with capital supply in the right-hand side given by K_0 and equation (17).

- Markets for non-tradable sectors clear. Namely,

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

- Trade is balanced,

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

Most of the elements in the model of labor supply are standard and build on Dix-Carneiro (2014) and Traiberman (2019). Compared to the baseline model, a key new ingredient is the fixed utility cost of moving sectors, $\tilde{C}$, which have 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 $\tilde{C}$ are reduced substantially.

The main new ingredient in my model of labor supply is in the expectation term in equation (11). 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

$$\mathbb{E}_t V_{t+1}(s', \omega', h^{t+1}) = \mu_t \mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 0\}) + (1 - \mu_t)\mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 1\}). \tag{20}$$

Equation (20) 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. Of course, investment could also be responding to duration uncertainty in interesting ways. Other types of frictions in labor demand, such as labor adjustment costs as in Kline (2008) could also interact with duration uncertainty. 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 and calibration: 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 public data, 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.

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 C.5 shows the joint distribution of workers across education-sector pairs.

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. To be consistent with the model, I use the series of non-dwelling construction at constant prices for capital.

6 Estimation

I calibrate 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 Process for prices

The object of interest in this subsection is the hazard rate for the end of the boom, μ_t in equation (8). 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 calibration and conclude by discussing my results.

6.1.1 The financial value of firm φ 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:

$$\tilde{d}_t^{\varphi} = \delta_0 + \delta_1 \tilde{p}_{t-1}^M + u_t \tag{21}$$

This reduced-form equation is intended to capture 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 normally distributed with standard deviation σ.

Conditional on a boom, $\tilde{p}^M$ is assumed to follow an AR(1) process:

$$\tilde{p}_t^M = \rho_0 + \rho_1(\tilde{p}_{t-1}^M - \rho_0) + \nu_t \tag{22}$$

Where ν_t shocks are i.i.d with mean 0. The parameter ρ_1 measures persistence in deviation of prices around the mean for boom periods ρ_0. If there is no boom, the price of mining products will be $\tilde{p}^b$, the log of $\underline{p}$ in equation (7).

I estimate $\delta_0, \delta_1, \rho_0$ and ρ_1 from the half-yearly data for dividends and the price index of mining products from Figure 5.[20] The forecast of future dividends (in levels) can be calculated by exploiting the fact that from equation (21), future dividends will be log-normally distributed.

$$\mathbb{E}_t[d_{t+1}|b_t = 1] = e^{\delta_0 + \delta_1 \tilde{p}_t^M + \frac{\sigma^2}{2}} \tag{23}$$

$$\mathbb{E}_t[d_{t+j}|b_t = 1] = \mathbb{P}[b_{t+j} = 1] e^{\delta_0 + \delta_1 [(\rho_0 + \rho_1^j (p_{t-1} - \rho_0) p_t^M + \frac{\sigma^2}{2}} + (1 - \mathbb{P}[b_{t+j} = 1]) e^{\delta_0 + \delta_1 \tilde{p}^b + \frac{\sigma^2}{2}} \tag{24}$$

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

$$\mathbb{P}[b_{t+j} = 1] = \prod_{s=0}^{j-1} (1 - \mu_{t+s}) \tag{25}$$

[20] 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.

I now turn to how the perspective of future commodity prices affects - through dividends - the value of different financial instruments ex-ante. The value of the stock S_t^{φ} equals the expected discounted sum of dividends:[21]

$$S_t^{\varphi}(b_t) = \mathbb{E}_t\Big[\sum_{s=t+1}^{\infty} M_{t,s}(b_s) d_s^{\varphi}\Big] \tag{26}$$

Where $M_{t,s}$ is the stochastic discount factor between future state s and current t.

I now turn to American put options on the stock of this firm. As mentioned in Section 5, these instruments 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:[22]

$$F_t^{\varphi}(S_t(b)^{\varphi}, T, K) = \begin{cases} \max\{\frac{(1-\mu_t)F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=1),T,K)+\mu_t F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=0),T,K)}{(1+r_t)}, K - S_t^{\varphi}, 0\} & t < T, b_t = 1 \\ \max\{\frac{F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=0),T,K)}{(1+r_t)}, K - S_t^{\varphi}, 0\} & t < T, b_t = 0 \\ \max\{K - S_T, 0\} & t = T \end{cases} \tag{27}$$

Equation (27) reflects investors' optimal stopping time decision. The primitives μ will affect the evolution of F in a non-linear way.

6.1.2 Calibration

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 (21), which matters for equation (26), is $\hat{\sigma} = 0.3$.

I assume that stochastic discount factors can be parametrized as $M_{t,s} = \frac{\beta^{s-t} m_s(b_s)}{m_t(b_t)}$, with the interpretation that $m_s(b_s)$ 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 calibrate the values of $\{m_t(b_t = 1), m_t(b_t = 0), \mu_t\}_{t=2010\text{H1}}^{T}$ so as to minimize the distance between the time series and the model predicted values for these instruments, given by equation (26) and equation (27). Notice that I need to look for values up to a period T later than 2019H2.

[21] See, for example, Cochrane (2005).

[22] See, for example, Dixit and Pindyck (1994).

6.1.3 Discussion

Figure 7a below shows the annualized results for μ_t. This can be interpreted as the calibrated probability that the boom ends in the following two semesters from the perspective of t.[23] The spike in late 2015 coincides with a stock market crash in China, which raised doubts about whether the whole Chinese economy was about to enter into a recession.[24] Moreover, as shown in the Appendix Section C.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.

6.1.4 Validation

Is this the right measure for workers? The quote, references and Figure 6a 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 this estimate captures something that workers were aware of, as I will assume when I estimate the labor parameters of the model in the next sub-section. 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 (28), 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.

$$Y_{i,t} = \alpha_0 + \alpha_1 p^M_{t-1} + \alpha_2 p^M_{t-2} + \alpha_3 \mu_{t-1} + \bar{\alpha} X_{it} + \epsilon_{it} \tag{28}$$

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 7b 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.

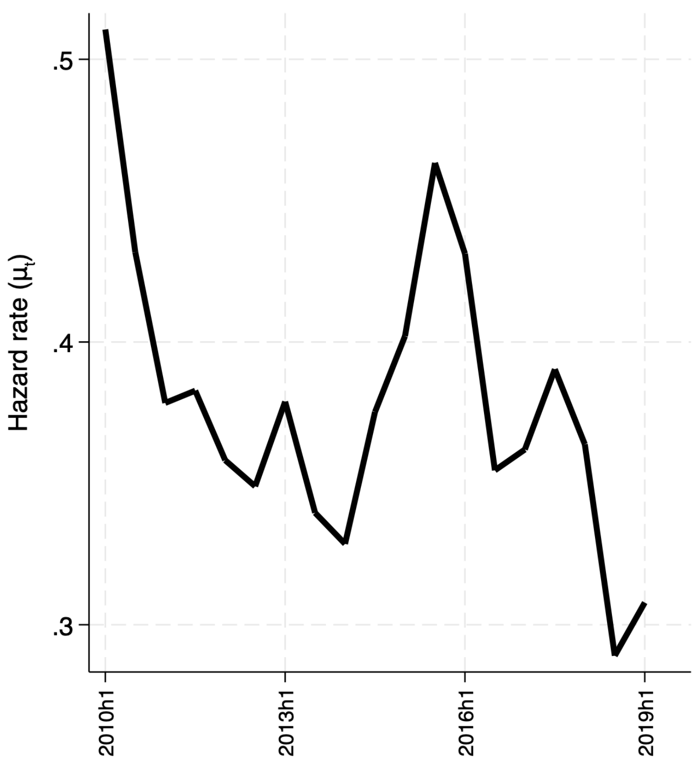
[23] $\mu_t^{annual} = \mu_t + (1-\mu_t)\mu_{t+1}$.

[24] 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.

The second column in Table 7b shows the results of estimating equation (28) 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.

Figure 7: Hazard rate: estimate and validation

(a) Hazard rate for the end of the boom



(b) 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

6.2 Small open economy

6.2.1 Estimation

I make the following functional form assumptions about the determinants of human capital and the structure of migration costs between sectors, following Traiberman (2019).

Determinants of human capital. The relationship between human capital and individual characteristics is given by:

$$log(H_s(\omega_{it},\zeta_{it})) = \beta_1^s \times a_{it} + \beta_2^s \times a_{it}^2 + \beta_3^s \times \Delta_{it} + \beta_4^s \mathbb{I}[e = med] + \beta_5^s \mathbb{I}[e = high] + log(\theta_{si}) + \zeta_{ist} \quad (29)$$

Notice that 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.

If there was no unobservable heterogeneity (and given the timing assumption on ζ) equation (29) could be estimated by regressing log income on observables. As already discussed, allowing for some degree of unobserved heterogeneity alleviates the concern that the returns to tenure I will estimate reflect the selection of the workers that decide to stay in a sector. Following Traiberman (2019) I assume two types θ per education level.

To estimate the parameters in equation (29) I follow the expectation maximization approach (Arcidiacono and Miller 2011; Scott 2014). The main idea is to estimate jointly the parameters of interest, β, as well as the probability that each worker i belongs to unobserved type $\theta \in \{1, ..., 6\}$, $q_{i\theta}$. The estimates $\hat{\beta}^{ML}, \hat{q}_{i\theta}$ maximize the following likelihood, where the contribution of each agent i if she was of type θ, $\mathcal{L}_{i|\theta}$, are weighted by their individual $q_{i\theta}$. 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 (29) 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:

$$\hat{\beta}^{ML}, \hat{q}_{i\theta} = argmax \prod_{i=1}^{N} \prod_{\theta=1}^{6} \hat{q}_{i\theta} \mathcal{L}_{i|\theta} \quad (30)$$

$$\mathcal{L}_{i|\theta} = \prod_{t=2011}^{2019} f(y_{it}(\omega_{it})|\beta,\theta)\pi(s_{it}|s_{i,t-1},\theta) \quad (31)$$

Switching costs. I assume the cost of switching from sector s to s' for a worker with characteristics ω can be parametrized as follows:

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

Where:

$$log(f(\omega_{it})) = \alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 \qquad log(C(s,s')) = \Gamma_o^s + \Gamma_d^s \tag{32}$$

The first component captures that it may be 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 sector of origin (destination). Assuming this, instead of flexible $\Gamma_{ss'}$ for all pairs, reduces the number of parameters to be estimated.

I assume that idiosyncratic shocks ϵ_{sit} are drawn from a Gumbel distribution. 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:[25]

$$\begin{aligned}\frac{V_t(s,\omega,h^t)}{\rho} =& \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) - C(\omega,s,s')}{\rho} \\ &+ \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t V_{t+1}(s',\omega',\{h^t,0\}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega',\{h^t,1\})\Big] - log(\pi_t(\omega,s,s'))\end{aligned} \tag{33}$$

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

Figure 8: 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 (13), 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 (33) 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:

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

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))-\log(\tilde{\pi}_{t+1}(\omega',s',s''))]])+ \tag{34}$$
$$(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s''))-\log(\pi_{t+1}(\omega',s',s''))]]\Big]=Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]$$

Where $Y^{\omega}_{s,s',t}$ is the flow payoff of switching from s to s' at t for a worker with characteristics ω.[26] 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.[27] For this reason, I make the following assumptions.

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, interacted with sectors. See Appendix Section A.4 for a complete specification of the polynomial.

The first item in Assumption 3 is equivalent to the assumption in Traiberman (2019) but for the conditional instead of the unconditional expectation. The second item states that to make expectations about how things would look 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 is stronger in the sense that I'm imposing a functional form assumption on expectations in the bust state. I make this assumption to be able to deal with the problem computationally.

Using Assumption 3, equation (34) becomes:

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

[27] To see this:

$$\mathbb{E}_t[\pi_{t+1}]-\pi_{t+1}=\mu_t\tilde{\pi}_{t+1}+(1-\mu)\pi_{t+1}-\pi_{t+1}=\mu_t(\tilde{\pi}_{t+1}-\pi_{t+1}). \tag{35}$$

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

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right)= \tag{36}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')\Big]+\tilde{u}_{s,s',t} \tag{37}$$

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.

Labor shares and preferences. I calibrate labor and expenditure shares as follows:

$$\alpha_s=\frac{w_sH_s}{Y_s}\qquad\qquad \gamma_s=\frac{Y_s+M_s-X_s}{\sum_{j\in\mathcal{S}}Y_j+M_j-X_j} \tag{38}$$

Where w_sH_s and Y_s are labor compensation and gross value added by sector. M_s and X_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. This procedure is similar to the one in Caliendo et al. (2018), except that I don't account for input-output linkages.

Productivities. The last parameters I need to calibrate are productivity parameters, A_{st} in equation (14). I use the structure of the model to back them out from the first-order condition of firms equation (**??**) 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 (9). 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 (9). For the observed allocation to be an equilibrium it has to be that the market for the two non-tradable goods and capital clear internally and that trade is balanced. I further assume that productivity is the same in all three tradable sectors. I calibrate the three productivity parameters and the rental cost of capital, r, such that the observed allocation is an equilibrium, as seen through the lens of the model.

6.2.2 Results

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 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, the estimates would have been higher as they partly capture differential selection across workers who decide to stay in a sector.

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

Switching costs and amenities. The elements in the switching cost function equation (32) and amenities are hard to interpret as standalone objects. Following the literature, I calculate the non-pecuniary payoff that a worker with characteristics ω moving from s to s' would face and divide that by the income of that same worker upon switching:

$$\frac{C(\omega, s, s') + \eta_{s'}}{w_{s't} H_{s'}(\omega)}$$

Then I sum across workers using transition shares $\pi_t(\omega, s, s')$ to weight the costs of moving for different workers. I do the calculations for year 2012, but results are similar for different years.

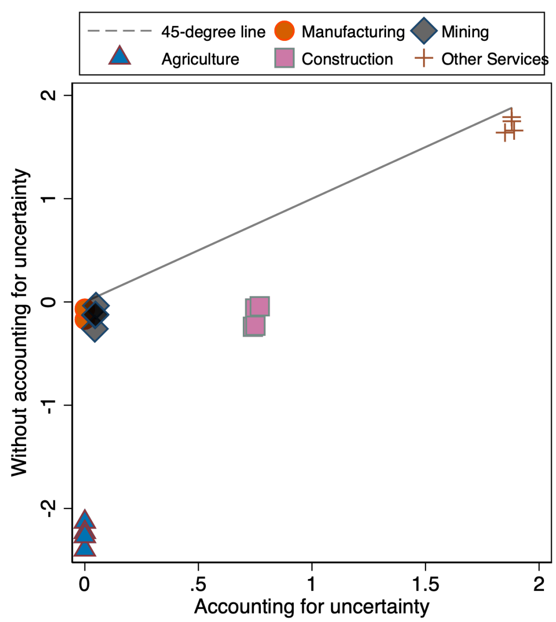
Table 2: Switching costs as a share of yearly income (weighted average)

Origin	Destination				
	Manufacturing	Mining	Agriculture	Construction	Other Services
Manufacturing	0	0.045	5×10^{-7}	0.75	1.87
Mining	0	0.037	5.2×10^{-7}	0.74	1.89
Agriculture	0	0.044	4.01×10^{-7}	0.75	1.85
Construction	0	0.045	5.11×10^{-7}	0.54	1.88
Other Services	0	0.047	5.24×10^{-7}	0.77	1.26

The estimated costs are relatively low but in the ballpark of the estimates in Traiberman (2019) who estimates switching costs between occupations close to one year of income. Both the amenities and the cost of switching into manufacturing are normalized to zero, which is why the first column of 2 are zeros.

To capture the importance of accounting for uncertainty at the estimation stage I re-estimate equation (37) ignoring the last term on the right-hand side. Figure 9 below compares the estimates in Table 2 with what I would have obtained if I had ignored the uncertainty term.

Figure 9: Accounting for uncertainty matters for estimates of switching costs



The estimates of non-pecuniary costs and amenities of working in different sectors get substantially reduced. Interestingly, the effect is particularly strong for agriculture and construction.

Labor shares and preferences.

Table 3: Calibration

Sector	Labor share α	Expenditure share γ
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

These results are intuitive. 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 directly spent on agriculture and mining. This has to do with not incorporating input-output linkages in the model directly. Some agricultural inputs would be used to produce manufacturing products, for example.

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:

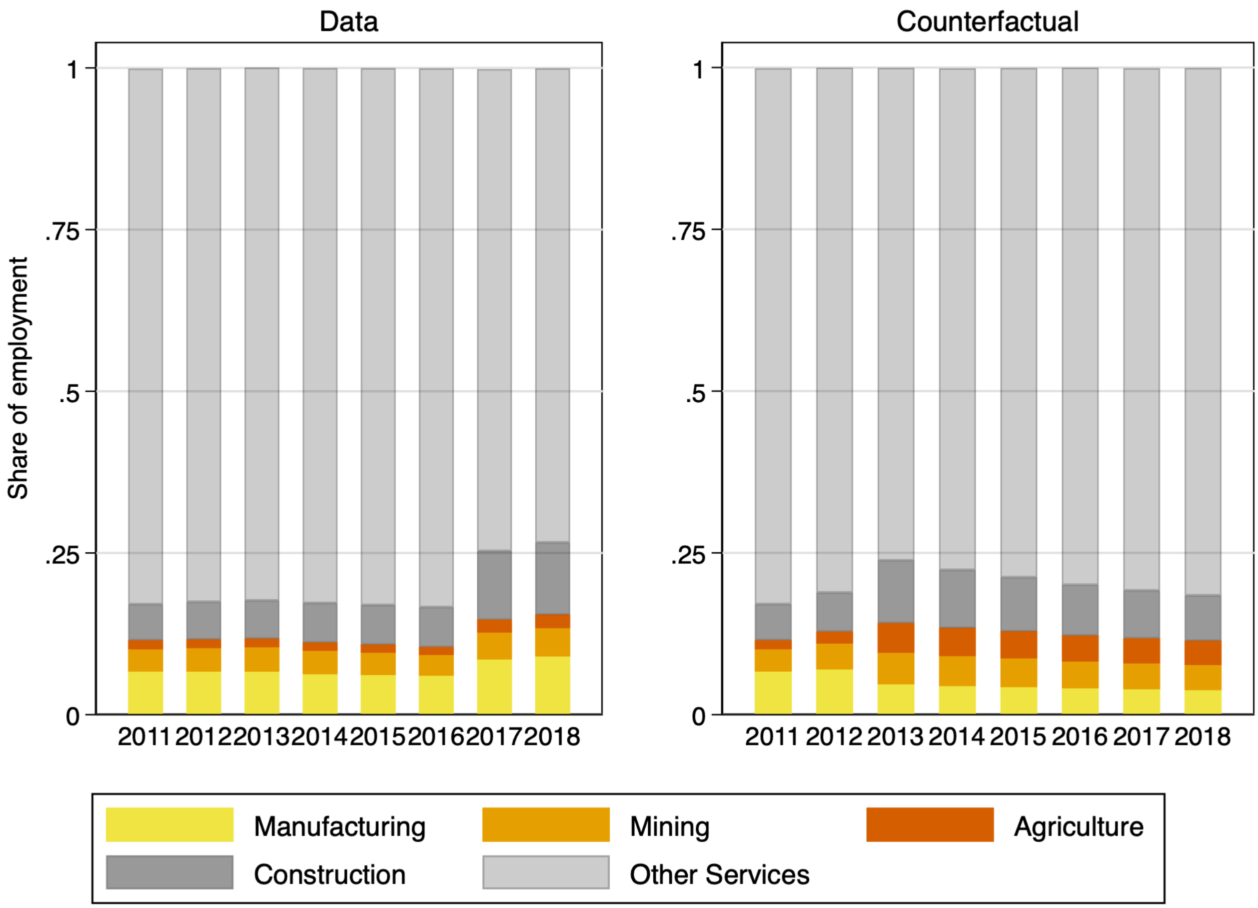
$$p_t^{M,cf} = \begin{cases} p_t^M & t < 2015 \\ \underline{p} & t \geq 2015 \end{cases}. \tag{39}$$

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 indicates 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 in Figure 4 in the baseline model of Section 2. Fan et al. (2023) consider a similar exercise, which they call analyzing the effects of uncertainty ex-post. Alessandria et al. (2023) do a similar analysis when estimating the effect of uncertainty about trade policy for the intra-year dynamics of firms' imports from China before China's WTO accession.

Figure 10 below compares employment across sectors in counterfactual without uncertainty to the data. Mining and agriculture grow substantially. The average share of workers employed in mining goes up to 4.0% compared to 3.7% in the baseline, an increase of 8.1%. The share of employment in agriculture goes up from 1.4% to 3.6%, more than doubling. The two sectors that lose employment are manufacturing, which drops from 6.9% to 4.4% and services, which drops marginally.

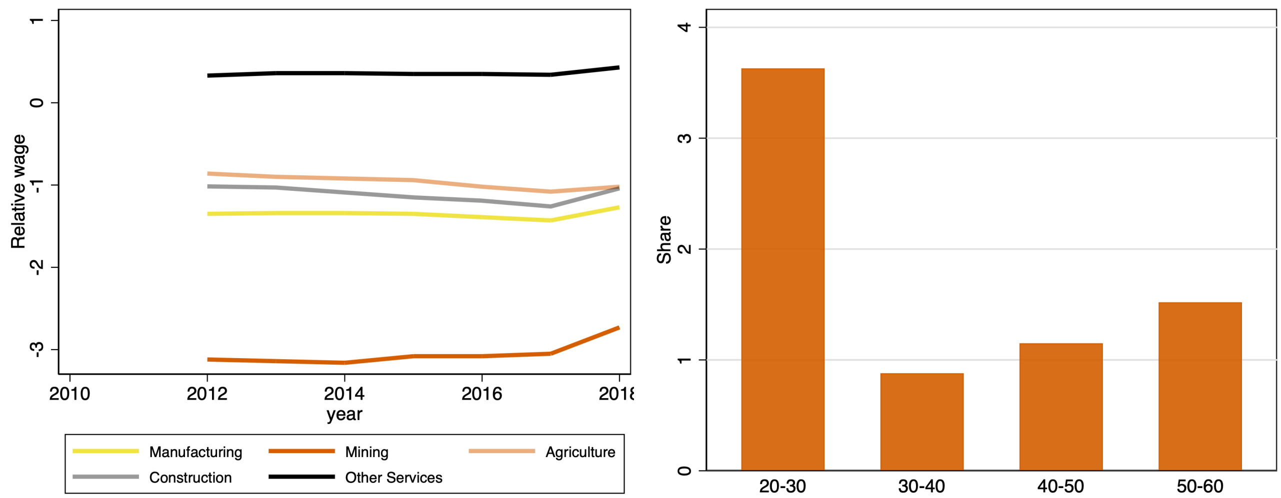
Figure 10: Difference between counterfactual and the data



To tell whether the driver of these changes in employment are changes in labor supply I now look at the wage in each sector, relative to a weighted average across sectors. The results are shown in Figure 11a below. The relative wage in mining is estimated to be three times the average wage in the data, while it's lower than the average wage in the counterfactual economy. From here I conclude that aggregate labor supply into mining increases in the counterfactual economy. Figure 11a shows how relative wages in the counterfactual economy compare to relative wages in the data for all sectors.

Figure 11: Counterfactual results

(a) Changes in relative wages (b) Heterogeneous effects



Heterogeneous effects. One main conclusion from the baseline model is that the effects of uncertainty about duration are different for different workers. One interesting dimension of heterogeneity is age. To study heterogeneity in general equilibrium I compare the number of workers sorting into mining in the counterfactual, relative to the data, by age groups. The results are shown in Figure 11b. Shutting off uncertainty about duration has a stronger effect on young workers: the number of them sorting into the sector more than triples. The smallest effects happen for middle-aged workers. For those in the $30-40$ group labor supply into mining even declines. The model in Section 2 provides a lens to understand this differential effect for middle-aged workers.

8 Concluding remarks

Substantial attention has been paid to labor reallocation following persistent changes in sectoral labor demand coming, for example, from trade liberalization reforms or technological change. In this paper, I study labor reallocation during temporary booms focusing on a novel element that arises in this environment: uncertainty about how long the boom phase will last.

In the first part of the paper, I show that duration uncertainty interacts with labor supply decisions in an interesting way. I build a model with 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 entrants into the booming sectors can have risk-loving attitudes towards the duration of the boom, and these are heterogeneous across workers.

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 that affected many economies (IMF 2016; WB 2015). Using the estimated version of the model I found that in this case the results go in the intuitive direction: duration uncertainty decreases aggregate labor supply into mining. However, the labor supply responses to uncertainty are heterogeneous across ages, and for a group of middle-aged workers, duration uncertainty had the opposite effect.

In this paper I tackled a positive question about the drivers of labor supply decisions during booms and, in the quantitative exercise, found support for the general framework from the first section. These results motivate normative questions. 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 policies - e.g: 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:

$$\bar{w}\theta + \beta\Big[\mu V(\theta,[0,1],1,0) + (1-\mu)V(\theta,[0,1],1,1)\Big] \geq 1 + \beta\Big[\mu V(\theta,[1,0],0,1) + (1-\mu)V(\theta,[1,0],0,1)\Big] \tag{40}$$

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

$$\bar{\theta}w\gamma_1^{t'} + \beta\Big[\mu V(\theta,[0,t'+1],1,0) + (1-\mu)V(\theta,[0,t'+1],1,1)\Big] < 1 + \beta\Big[\mu V(\theta,[1,0],0,1) + (1-\mu)V(\theta,[1,0],0,1)\Big] \tag{41}$$

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 (40) and equation (41) 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:

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tau}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{42}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tilde{t}}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{43}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau(1-(\beta\gamma_1)^{2(\tilde{t}-\tau)+1})}{1-\beta\gamma_1} + \frac{\beta^{2(\tilde{t}-\tau)+1}}{1-\beta\gamma_0} \tag{44}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \tag{45}$$

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

A.2 Proof of Lemma 1

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

$$\begin{aligned}
V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq& V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) && (46)\\
\bar{w}\theta(\beta\gamma_1)^{T-1} + \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} - \frac{\beta^{T-1}}{1-\beta\gamma_0} \geq& \bar{w}\theta(\beta\gamma_1)^{T-2} + \frac{\beta^{T-1}}{1-\beta\gamma_0} - \frac{\beta^{T-2}}{1-\beta\gamma_0} && (47)\\
\bar{w}\theta(\beta\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq& \frac{\beta^{T-2}(1-2\beta)}{1-\beta\gamma_0} && (48)\\
\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{\beta^2(\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq& \frac{(1-2\beta)}{1-\beta\gamma_0} && (49)\\
& && (50)
\end{aligned}$$

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:

$$\begin{aligned}
\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq& \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} && (51)\\
\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq& \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} && (52)
\end{aligned}$$

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 (52) to hold that the following holds:

$$\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} \tag{53}$$

$$\frac{\bar{w}}{\underline{w}} \leq \frac{1-2\beta+\beta^2}{(1-\beta\gamma_1)^2} = \Big(\frac{1-\beta}{1-\beta\gamma_1}\Big)^2 \tag{54}$$

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.3 Proof of Lemmas 2 and 3

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

$$\bar{\tau}(\theta;\gamma_0,\gamma_1,\underline{w}) = \frac{1}{\gamma_1}\Big[\log(\frac{1-\beta\gamma_1}{1-\beta\gamma_0}) - \log(\underline{w}\theta)\Big] \tag{55}$$

From where all partial derivatives follow directly.

A.4 Derivation of equation (37)

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 $s \to s' \to s''$:

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} + \frac{\beta}{\rho}\Big[\mu_t\mathbb{E}_t\tilde{V}_{t+1}(s',\omega') + (1-\mu_t)\mathbb{E}_tV_{t+1}(s',\omega')\Big] - \log(\pi_t(\omega,s,s')) \tag{56}$$

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

$$\begin{aligned}\frac{V_{t+1}(s',\omega')}{\rho} &= \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \\ &\frac{\beta}{\rho}\Big[\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})V_{t+1}(s'',\omega''))\Big] - \log(\pi_{t+1}(\omega',s',s''))\end{aligned} \tag{57}$$

$$\frac{\tilde{V}_{t+1}(s',\omega')}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\omega',s',s'')) \tag{58}$$

Plugging equation (57) and equation (58) into equation (56):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} - \log(\pi_t(\omega,s,s')) \tag{59}$$

$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{60}$$

$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{61}$$

$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\omega',s',s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\omega',s',s''))]\Big] \tag{62}$$

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

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

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} + \frac{\beta}{\rho}\Big[\mu_t\mathbb{E}_t\tilde{V}_{t+1}(s,\hat{\omega}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s,\hat{\omega})\Big] - \log(\pi_t(\omega,s,s)) \tag{63}$$

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

$$\frac{V_{t+1}(s,\hat{\omega})}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \tag{64}$$

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

$$\frac{\tilde{V}_{t+1}(s',\hat{\omega})}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\hat{\omega},s',s'')) \tag{65}$$

Plugging equation (64) and equation (65) into equation (63):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} - \log(\pi_t(\omega,s,s)) \tag{66}$$

$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{67}$$

$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{68}$$

$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega}',s,s''))]\Big] \tag{69}$$

I can use the two expression for $V_t(s,\omega)$ in equation (59)-equation (66) to get rid of $V_t(s,\omega)$. Notice as well that equation (68) and equation (61) 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:

$$\log\Big(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\Big)+\beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))-\log(\tilde{\pi}_{t+1}(\omega',s',s''))])+ \tag{70}$$

$$(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s''))-\log(\pi_{t+1}(\omega',s',s''))]]\Big]=Y^{\omega}_{s,s',t}-Y^{\omega}_{s,s,t}+\frac{\beta}{\rho}\big[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\big] \tag{71}$$

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:

$$\log\Big(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\Big)+\beta(1-\mu_t)\log\Big(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\Big)= \tag{72}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\big[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\big]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')\big] \tag{73}$$

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 Computational appendix

B.1 Implementing the expectation maximization approach

I start with

C Background and data appendix

C.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

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

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

Standard errors in parentheses

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

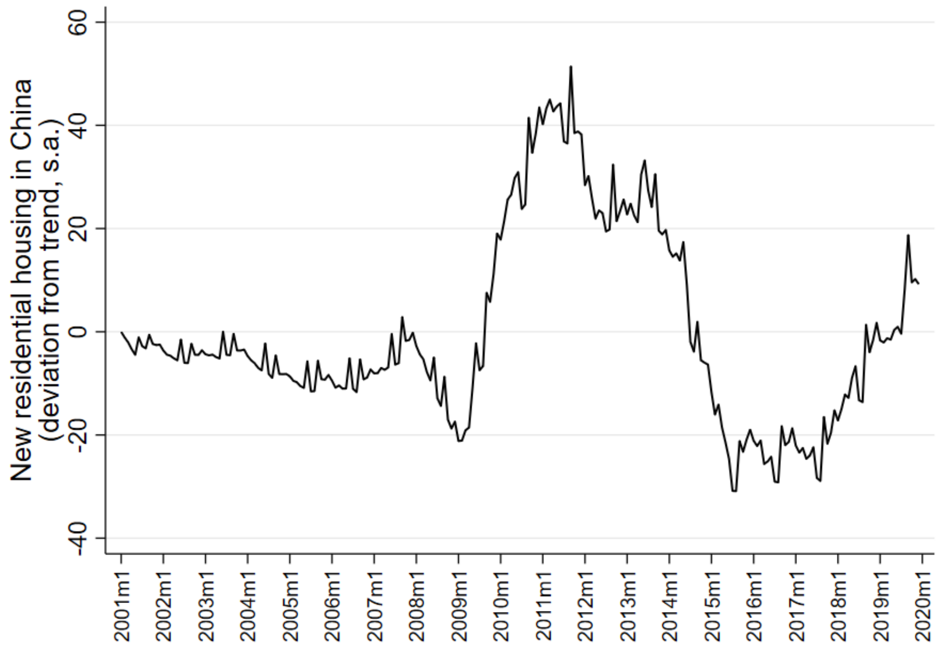
Australian Bureau of Statistics price index series. I retrieve data on Chinese economic activity from the website of the National Bureau of Statistics of China[28]. As a proxy for future construction, I create a series of new construction started each month from the series *Flor space of real estate 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 4 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.

The second and third columns of Table 4 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.

[28] Accessed September 23, 2022.

Figure 12: New residential housing in China in Squared Meters (Millions)



C.2 Time series of new residential housing in China

Using the same data as in the subsection above, Figure 12 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.

C.3 Informality

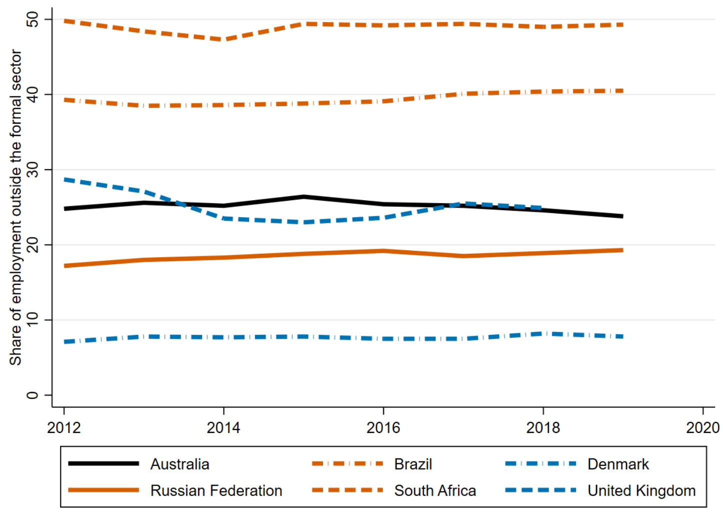
These numbers come from the series *Share of employment outside formal sector - Annual*, downloaded fromhttps://ilostat.ilo.org/topics/informality/ in June 2023. Figure 13 below shows the national time series.

C.4 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. [29] I merge this with the value of the stock at that particular day. Within each month-strike price group I keep only the daily observation with the median value for the option in month-strike price. Finally, I merge this with data on the

[29] 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 13: Share of employment outside formal sector



zero-coupon rate.

C.5 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.

Education	**Sector**	**Number of workers**
1	1	44,323
2	1	18,332
3	1	16,462
1	2	24,964
2	2	9,702
3	2	7,611
1	3	11,308
2	3	2,959
3	3	2,412
1	4	42,529
2	4	22,509
3	4	9,134
1	5	393,199
2	5	230,403
3	5	426,847