Labor reallocation during booms: The role of duration uncertainty*

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October 23, 2023

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Abstract

Booms are recurrent and occur in sectors as varied as commodities, construction, and tech. I study how uncertainty about how long the boom will be shapes labor supply into booming sectors. I build a model with sector-specific on-the-job human capital accumulation and find that uncertainty about duration can induce or deter entry. To study the effects of duration uncertainty empirically, I exploit the boom in world prices of mineral products during 2011-2018. I build a quantitative version of the baseline model and estimate it using novel administrative data from Australia, an exporter of mineral products. I use the estimated 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 substantially lower, indicating that labor supply was deterred by duration uncertainty in this case.

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

*I am grateful to Esteban Rossi-Hansberg, Rodrigo Adão, Greg Kaplan and Fernando Álvarez for their guidance and support. I benefited from insightful comments and helpful suggestions from Ufuk Akcigit, Olivia Bordeu, Jonathan Dingel, Santiago Franco, Agustín Gutiérrez, Erik Hurst, Aleksei Oskolkov, Jeremy Pearce, Daniela Puggioni, Robert Shimer, Felix Tintelnot, Harald Uhlig and seminar participants at the University of Chicago and Banco de Mexico. I am indebted to the staff at the Australian Bureau of Statistics for their patience and availability. All errors are my own.

1 Introduction

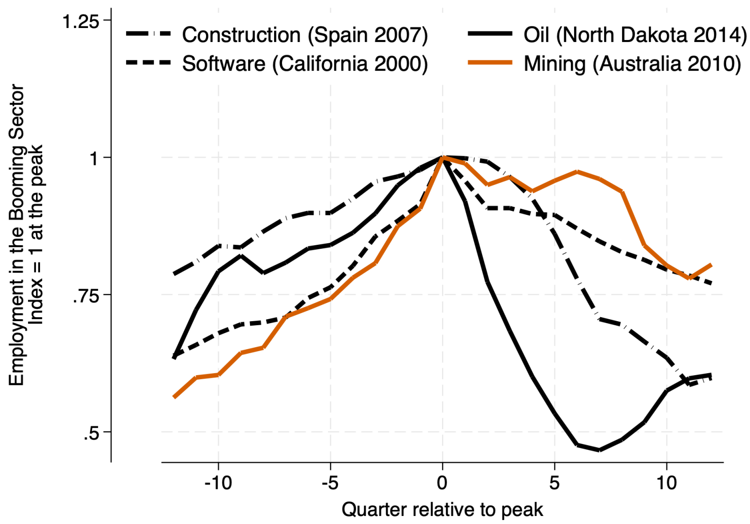
From the gold rush in nineteenth-century California to the oil boom in North Dakota or agricultural booms in developing countries every couple of decades; from construction booms to the dot-com bubble in the tech industry, booms and busts have been recurrent and affected all kinds of sectors and workers, low-skilled and high-skilled. The specific causes and features of the boom differ between settings, but there is something that they all have in common for agents making decisions during the boom: the saliency of the boom's end and uncertainty about when that end will come.

In this paper, I focus on how uncertainty about the duration of the boom phase shapes workers' decision to enter into booming sectors. Workers rush into booming sectors likely knowing that, when the boom ends, these sectors will contract sharply. Figure 1 below shows the evolution of sectoral employment around the peak for some well-known examples of booms, normalized to take value 1 in the series' peak. Sectors contract sharply and fast when booms end: in the case of North Dakota, for example, employment in the oil industry dropped by more than half in a matter of quarters.

The questions I tackle in this paper are two. First, how to think theoretically about the role of uncertainty about whether the boom is going to be short or long in this type of episode? Does uncertainty necessarily discourage workers from entering booming sectors? Using a model that relies on sector-specific human capital I show that the answer is theoretically ambiguous and depends on parameters that will likely differ between booms. Given that the answer to the first question is ambiguous my second question is: focusing on one particular boom, what's the role of uncertainty about duration in explaining labor supply in the booming sector? To answer it, I build a quantitative version of my model and estimate it using data from Australia during the years of the recent mining boom. I use the estimated model to simulate a counterfactual perfect foresight economy in which the boom was temporary and duration known. I find that, in this case, duration uncertainty decreased labor supply into mining.

In the first part of the paper I build a model that isolates the key economic mechanism I

Figure 1: Sectoral employment dynamics during booms



Sources: *All employees: Mining and logging in North Dakota* and *All Employees: Information: Software Publishers in California* from FRED for both US series. *Empleo por ramas de actividad* from the Spanish statistical institute for Spain. *Employed persons by Industry division of the main job* from Australian Bureau of Statistics for Australia.

will focus on throughout. The economy has two sectors and wages in one sector are exposed to a boom. They will fall the moment the boom ends, while wages in the other sector are always the same at some intermediate level between the boom and bust wages for the booming sector. Workers accumulate sector-specific human capital on-the-job in their sector of employment. Under some conditions, the discounted value of lifetime earnings of workers who sort into the booming sector is convex as a function of the boom's duration.

The intuition for the convexity is the following. If the duration ends up being short workers will decide to switch out of the booming sector when the bust happens, cutting losses. If the duration is long, however, they will optimally decide to stay to avoid losing the accumulated sector-specific human capital. This convexity leads to risk-loving attitudes towards the duration of the boom around a certain range of durations the boom could have, but not all.[1]

The key conclusion from the model is that moving from an economy in which the duration of the boom could be long or short, but is uncertain, to a comparable perfect foresight economy in which duration is known can either increase or decrease labor supply into the booming

[1] An analogy that can be drawn is with call options (Dixit and Pindyck, 1994).

sector.[2] The answer will depend in a complicated way on the rates of on-the-job human capital accumulation, wages in both sectors and the hazard rate of the end of the boom. Understanding the effects of duration uncertainty, even qualitatively, requires focusing on a context, estimating the relevant parameters, and using the estimated model to study a counterfactual without duration uncertainty. This is what I do next.

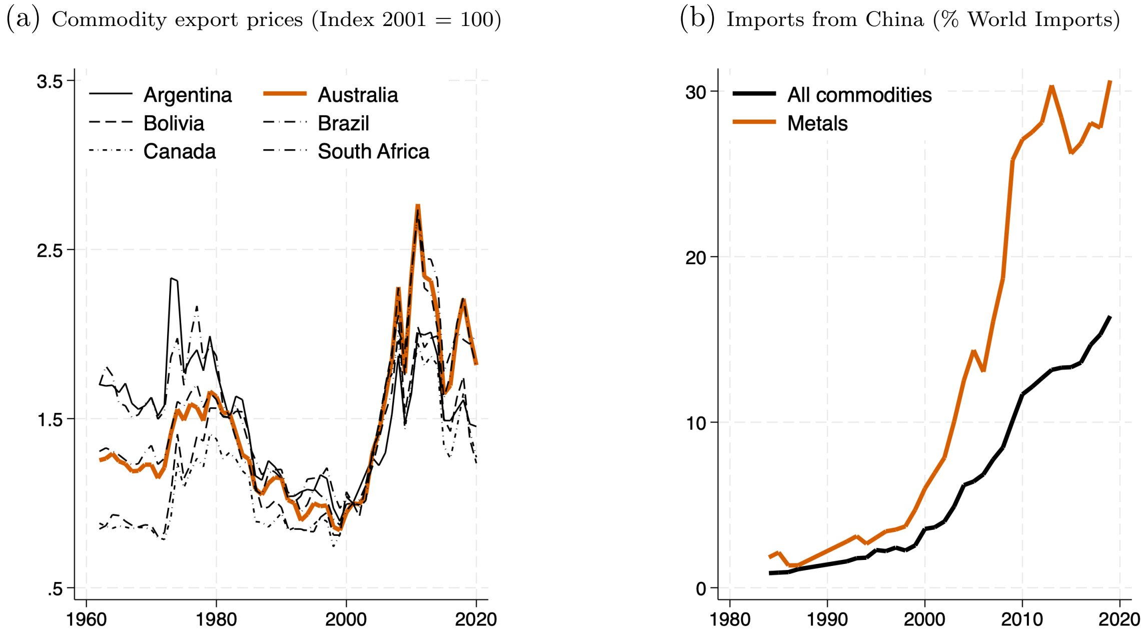
I focus on the commodity boom that kicked off in the early 2000s and its impact on the Australian labor market. Commodity booms are important both for their cyclical recurrence and their impact on many economies around the world.[3] As shown in Figure 2a, starting in the early years of the century commodity prices increased and peaked around 2010. The boom in Australia was relatively strong and long-lasting. It is understood that one of the main drivers of this boom was growth and urbanization in China (IMF, 2016; WB, 2015). As shown in Figure 2b, the participation of China in global commodity imports increased dramatically during the period, especially for ores and metals. Australia was a key supplier of the latter, used intensively in construction as China urbanized and converged to a higher housing steady state. Crucially, demand from China would eventually stabilize and the boom in metal prices would come to an end.[4] 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 strong boom, driven by temporary forces and whose duration was unknown.

[2]By comparable I mean that in the perfect foresight economy duration is set to be exactly equal to the expected duration from the economy with uncertainty.

[3]In 2018, commodities represented more than 60% of exports in more than 100 countries (UNCTAD, 2021).

[4]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 2: Commodity boom driven by growth in China



Sources: *Historical Commodity Export Price Index (Weighted by Ratio of Exports to Total Commodity Exports, Fixed Weights)* from the IMF for Figure 2a and *World Bank Open Data* for 2b.

To answer how much labor reallocation towards mining can be explained by risk-loving attitudes towards duration during this episode, I build a quantitative version of the baseline model that I can take to the data and use for my counterfactual of interest. Several features need to be added. First I incorporate finitely lived agents. Old workers could be less sensitive to increased uncertainty as they wouldn't be able to benefit from long durations, which is key for risk-loving attitudes to arise. I incorporate other determinants of labor income like age, education, and unobserved heterogeneity. I also model the costs of switching sectors that are independent of the opportunity cost channel which is the focus of this paper but has been highlighted in the literature. Finally, as stems from the discussion of the model in the first paragraphs, the nature of outside options in the event of an end of the boom is crucial to understanding workers' sensitivity to duration uncertainty. To that end, I include 5 sectors in the model and specify a structure for labor demand, with non-tradable wages determined endogenously.

For estimation, I exploit novel data from administrative sources that cover the universe of Australian workers in the formal sector between 2011 and 2018. To estimate key parameters of the model, like returns to tenure, one needs to follow workers across years and sectors. I construct such a panel by linking tax returns across years and to the 2016 census, from which I observe education levels. An added advantage of focusing this study on Australia, among all commodity exporters, is that because labor informality is low the coverage of such a dataset is relatively high. This is important in light of the initial discussion about getting workers outside options right.

I estimate the labor side of the model 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). The estimation method in Traiberman (2019) can be applied almost step-by-step in my setting, except for the following. High switching costs between a pair of sectors are estimated if workers don't migrate between them despite high expected wage differences.[5] In my setting, given that I have data during the boom years, unobservable costs could also reflect the probability that the boom ends interacted with the drop in value of the sector.[6] To deal with this issue I make a different set of assumptions about expectations than Traiberman (2019). Accounting for the possibility of future drops in value impacts the estimates of amenities and switching costs that rationalize switching patterns.

The estimation step described in the last paragraph requires an estimate of the hazard rate for the end of the boom. To construct it I collect data on the value of stocks and put options on one of the biggest mining firms in Australia. Financial markets are a natural source to look at when estimating this parameter, given that asset prices are forward-looking. Put options, in particular, gain in value when the expected value of the stock falls, which should make them particularly sensitive to the probability of a bust. The calibrated hazard rate varies between years, with a clear peak in 2015. This can be linked to the crash in the Chinese stock market

[5]It could also be because of differences in future values. By choosing the right sector pairs and assuming the existence of renewal actions, future values can be net out. This is discussed in detail in Section 6. See Scott (2014)

[6]See Figure 2a for why I interpret 2011-2018 as still being part of the mining boom.

which, in this context, cast doubts about the continuity of the real estate boom and should impact on future price of mining products.

I use the estimated model to simulate my counterfactual of interest: a perfect foresight economy in which the boom's duration is fixed to 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. There are heterogeneous responses by age. Young workers increase labor supply into mining the most, while middle-aged workers decrease theirs. The baseline model provides a lens to interpret heterogeneity in responses, which would be hard to interpret in the general equilibrium model. The wage in the mining sector, which is almost three times the average wage in the data, drop to being below the average wage in the counterfactual economy.

Related literature. A huge literature has studied labor reallocation after shocks to labor demand that are localized in some sectors or regions. An important strand of this literature studied labor reallocation following shocks to import competition (Topalova, 2010; Autor et al., 2013; Dix-Carneiro and Kovak, 2017, 2019; Caliendo et al., 2019). Recent papers have argued that sector-specific human capital accumulated on-the-job helps explain why labor reallocation following these shocks can be slow and the heterogeneous responses across workers (Dix-Carneiro, 2014; Traiberman, 2019). An important ingredient in these models is that human capital is not perfectly transferable across sectors, which links them to specific-factor models of trade (Jones, 1971; Mussa, 1974; Matsuyama, 1992). I build directly on these papers by assuming sector-specific human capital acquired on-the-job. My contribution is to study a very different setting in which boom-bust dynamics are salient and duration uncertainty arises as an additional driver of labor supply decisions.

A key element in this paper is uncertainty about duration. A strand of the literature in trade has studied a similar problem for firms in the US and China during the 1990s when China's access to low tariffs when exporting to the US had to be renewed yearly by Congress. This uncertainty, which was eventually resolved in 2001 when China entered the WTO, can be seen as uncertainty about how long the low-tariff regime would last. Studies have focused on how uncertainty affected the entry and exporting decisions in China and, indirectly, on US labor markets (Handley and Limão, 2017; Pierce and Schott, 2016). At the conceptual level, a key difference is that in the settings they study uncertainty increases the value of waiting. In the context I study this isn't necessarily so, for reasons discussed in Section 2. The results in this paper indicate that the reduced-form results in Pierce and Schott (2016) are potentially a mix of changes in labor demand and labor supply.

Given my empirical focus on the mining boom in Australia, this paper also contributes to the varied literature on commodity cycles. This paper is more closely related 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, a key ingredient is that factors can reallocate between tradable sectors. I focus precisely on that reallocation and highlight duration uncertainty as one of the elements that may be salient in these episodes.

In terms of estimation I follow closely the approach in Traiberman (2019), who builds on a huge literature in industrial organization and labor (Rust, 1987; Lee and Wolpin, 2006; Artuç et al., 2010; Arcidiacono and Miller, 2011; Scott, 2014). Lastly, this paper builds on the time series literature on commodity super-cycles, which has documented low-frequency cycles which can be very big in magnitude, making them an interesting setting in which to study boom-busty dynamics with uncertainty about duration (Erten and Ocampo, 2013).

2 Model

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 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:

$$w_{0t} = 1 \ \ \forall t, b_t \qquad w_{1t}(b_t) = \begin{cases} \bar{w} & b_t = 1 \\ \underline{w} & b_t = 0 \end{cases} \tag{1}$$

With $\bar{w} > 1 > \underline{w}$. The labor income that a worker earns in sector s at t depends on wages 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 with sector-specific tenure at time t, labor income is given by:

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

The parameter γ_s measures the rate of human capital accumulation in sector s. I further assume that human capital depreciates if some time is spent in other sectors. 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:

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

Timing works as follows. 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. They can't save, the price of consumption good is normalized to one in all periods, utility is linear and workers discount future consumption at rate β.[7] 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 $t = 0$ 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 $\{\theta, \vec{0}, 0, 1\}$ without loss of generality. The following theorem describes the optimal policies going forward for a worker who decides to sort into sector one initially.

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

- $\ell_t = 1$ **if** $b_t = 1$**.**
- $\ell_t = \ell_\tau \;\; \forall t \geq \tau$**.**

Proof. See Appendix Section A.1. Theorem 1 states that the optimal strategy for these workers is to stay in the booming sector until the boom ends, re-optimize when it does, and then never switch again. The proof uses that as time goes by workers accumulate sector-specific human capital that they would lose if they changed sectors. If it was optimal to choose sector one initially, it has to be optimal when the benefits of doing so go up.

[7] 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, $\bar{w}$ could represent the world relative price of good one.

At $t = \tau$, these workers have spent τ consecutive periods in sector 1. The economy is deterministic going forward, so they will choose sectors by comparing the discounted lifetime earnings in each of them:

$$\frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \lesseqgtr \frac{1}{1-\beta\gamma_0} \tag{4}$$

The worker would choose to stay in the booming sector if the left-hand side is greater than the right-hand side, switch if it was smaller, and would be indifferent between sectors if both are equal. 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 given by:

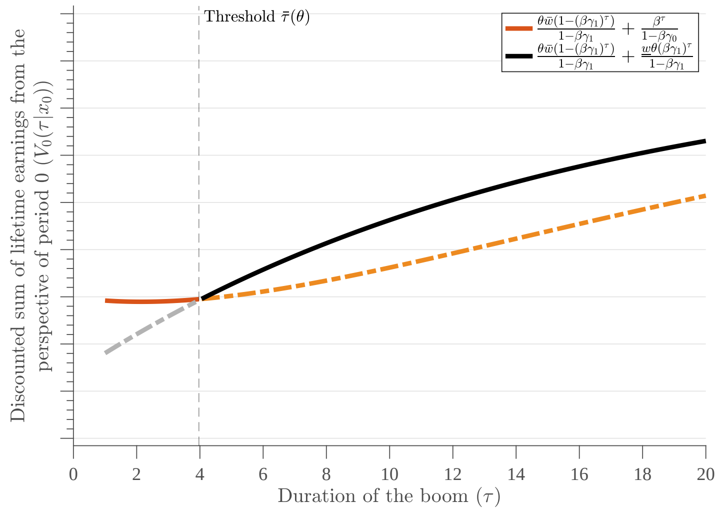
$$V_0(\tau|\theta,\vec{0},0,1) = \begin{cases} \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\beta^\tau}{1-\beta\gamma_0} & \tau < \bar{\tau}(\theta) \\ \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\underline{w}\theta(\beta\gamma_1)^\tau}{1-\beta\gamma_1}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

The values in equation (5) are a piece-wise function because for short durations the worker will find it optimal to switch, but for long durations, she won't. 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 in particular that in the last term of the second line γ_1^τ, the sum of human capital accumulated before the boom ended, appears, while it doesn't in the first line because human capital depreciates upon switching. For illustration, Figure 3 shows equation (5) as a function of τ for arbitrary values of the parameters.[8]

The key thing to notice is that there is a kink around $\bar{\tau}(\theta)$. This is not a feature of the particular calibration. The following lemma states sufficient assumptions for the kink to exist.

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

Figure 3: Risk-loving attitudes towards duration around the kink $\bar{\tau}(\theta)$



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

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

Proof. See Appendix Section A.2. 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 in fact increase the ex-ante expected value for this worker.

Why does the kink arise? 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 second case, 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 for life. This experience, due to the functional form assumptions for human capital, increases the level and the returns to human capital accumulation going forward. At $\bar{\tau}(\theta) - 2$ an extra year of the boom doesn't induce this change in behavior.

The last requirement in the lemma, $\frac{\bar{w}}{\underline{w}} \leq \left(\frac{1-\beta}{1-\beta\gamma_1}\right)^2$ is a technical requirement related to the model being in discrete time. The second difference between an extra period of the boom at $\bar{\tau}(\theta)-2$ and at $\bar{\tau}(\theta)-1$ is that in the first case, the worker enjoys an extra period of high wages $\bar{w}$ closer to the initial period, when they are discounted less.

The convexity at the kink arises because the worker can switch out when durations are short. 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. As Lemma 1 states, another important ingredient for convexity to arise is human capital accumulation. This is an important difference that makes this setting different from the one studied by the literature on trade policy uncertainty in which firms have to pay a cost of entry or exporting but being an older firm doesn't carry any extra benefits (Pierce and Schott, 2016; Handley and Limão, 2017).

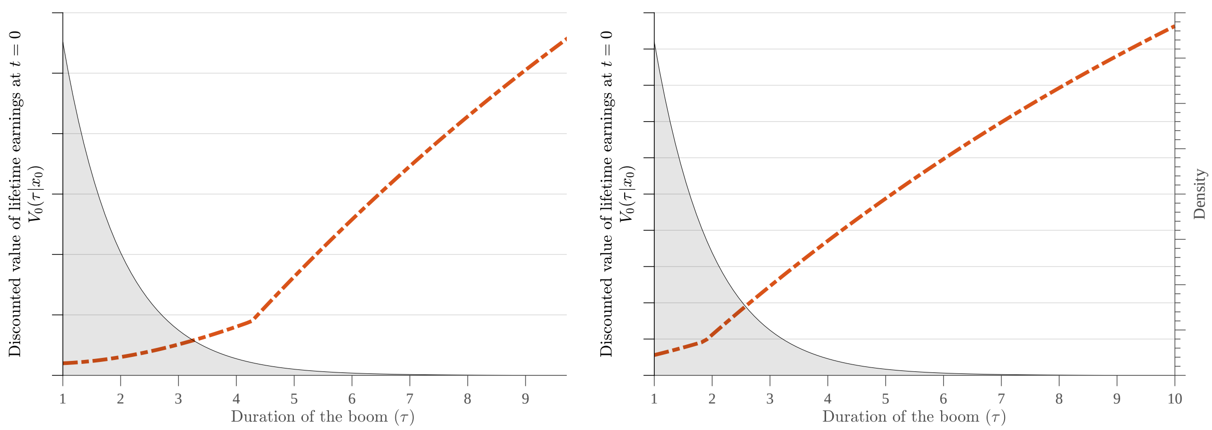
Because the position of the kink depends on θ but all workers face the same boom, the effects of duration uncertainty will be different for different workers. Figure 4a shows equation (5) overlapped with the density for the duration for a worker with low θ. Figure 4b shows the same graph for a worker with higher productivity in the booming sector, $\theta = 1.15$. Because the second worker is more productive in the booming sector, 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 this worker than for the first worker.

The point at which the kink $\bar{\tau}$ happens depends not only on θ but also more generally on the rates of human capital accumulation, β and wages $\underline{w}, \bar{w}$.

Figure 4: Heterogeneous risk-loving attitudes for different workers

(a) Low relative productivity in booming sector
($\theta = 1$)

(b) High relative productivity in booming sector
($\theta = 1.15$)



I now look at 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 zero is equal to the discounted value of lifetime earnings if staying in sector zero forever.[9] Then, a worker of type θ sorts into sector one if the following inequality holds:

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

The solid lines in both panels of Figure 5 show how different types θ sort across sectors in economies with low and high rates of human capital accumulation in the booming sector γ_1. These lines are increasing in θ, as higher θ types have higher productivity in the booming sector. The solid line is also higher in the right panel, with higher rates of human capital accumulation in the booming sector than in the left panel. This translates into a higher labor supply in the booming sector at time-zero which is intuitive.

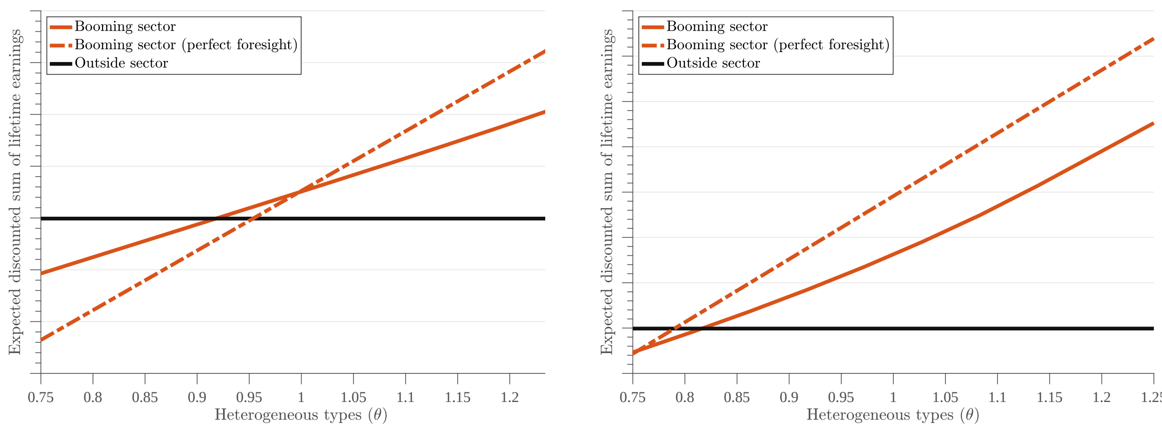
I now turn to the key counterfactual question I'm interested in which isolates the role of

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

duration 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 from the baseline economy. The dashed lines in both panels of Figure 5 show how the ex-ante value of sorting into the booming sector changes.

Figure 5: Aggregate effects of duration uncertainty on labor supply

(a) Low rate of human capital accumulation ($\gamma_1 = 1.02$) (b) High rate of human capital accumulation ($\gamma_1 = 1.04$)



The first thing to notice is that the new curve rotates and can be below or above the solid line for different values of θ. This echoes the idea from Figure 4 that the kink will happen at different points for different workers, leading their expected value to react to duration uncertainty differently. In other words, the density of duration will fall on convex and concave areas of V for different workers. The second and main thing to notice is that labor supply in the booming sector can either increase or decrease once the economy has no uncertainty about duration. In the case shown in Figure 5a, 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 in the outside sector. Figure 5b shows how keeping all parameters the same except for a higher γ_1, the effects of duration uncertainty on labor supply flip and become, in some sense, more intuitive. Duration uncertainty discourages entry in this case.

Importantly, the emergence of risk-loving attitudes towards duration doesn't hinge on the assumption of linear utility, as long as the conditions in lemma 1 hold. To see this, consider that utility had been 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 this 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 parameters, which will depend on the context. The economy could be in the left or the right panels in Figure 5. Now, I turn to describing the context I will 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 2 in the introduction). The literature studying commodity super-cycles, which has identified historical periods of booms and busts, puts this episode at par with the industrial revolution in the UK, the US and post-war reconstruction in Europe in terms of its impact on commodity prices (Erten and Ocampo, 2013). From Figure 2a in the introduction 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.[10]

Although Australia produces many commodities, the boom was concentrated in the mining sector. Figure 6a below 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

[10]This is partly because the country focuses on metals. In other commodities, the boom ended in the mid-2010s.

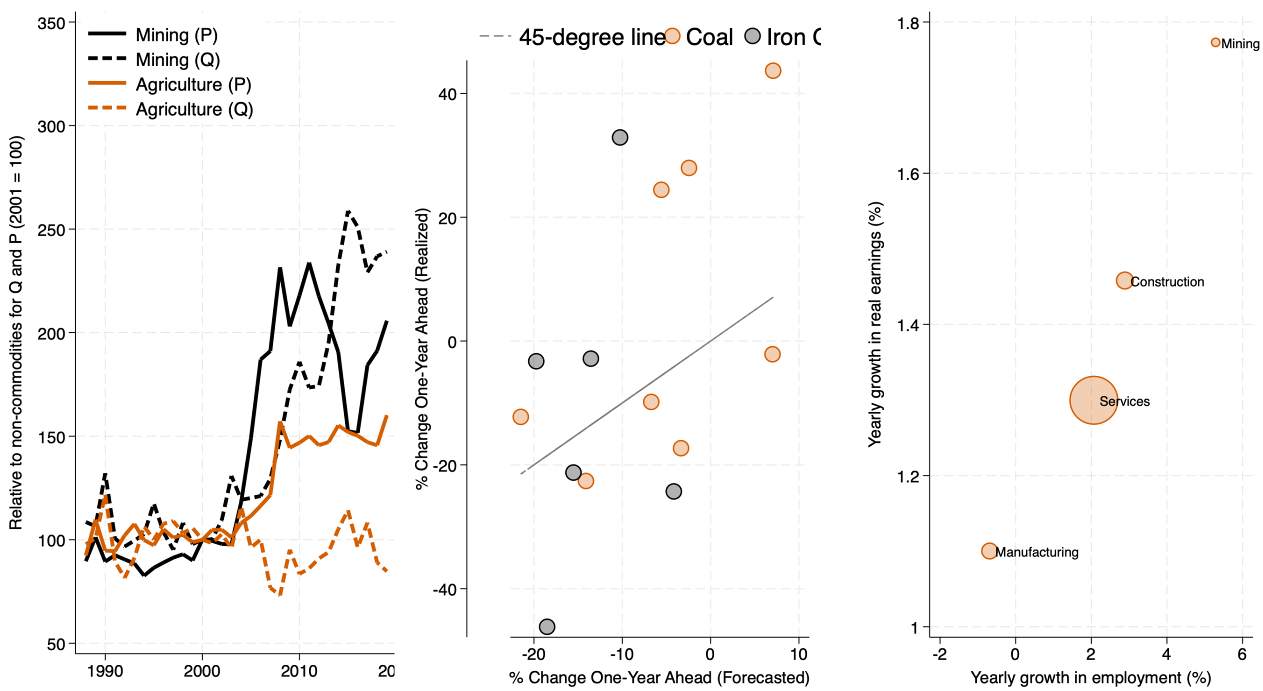
lines, the same panel shows the growth in exported quantities of both types of commodities during the period, relative to non-commodity exports. Relative exports of mineral commodities from Australia increased substantially during this period, especially after 2005. Put together, these two figures show that the economy responded to an increase in the relative price of mining products as expected, by producing more of the tradable goods whose price went up. Given that the increase in exported quantities was focused on mining products, from now on I will refer to mining as the booming sector.

Figure 6: Exports, forecasts, and labor markets during the boom

(a) Relative export prices and relative exports

(b) Evolution of commodity prices and IMF forecasts (2011-2019)

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



Sources: Australian Bureau of Statistics (ABS) and IMF. The size of the bubbles in Figure 6c are proportional to the size of that sector between 2011 and 2018.

What drove the strong increase in Chinese demand for ores and metals, shown in Figure, 2b, and the subsequent increase in the price of mining products that Australia exported? A common answer is urbanization. Urban population in China increased from 26% of the total population in 1990 to 36% in 2000 and 49% in 2010.[11] 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 its reserves, Australia became a key exporter of mineral products like iron ore and coal which are used for steel, an input to construction, during these years (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 for Australia is driven by construction in China I collect 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 constructed floor space started 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 about how sustainable the boom would be.[12] 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 6b shows IMF forecasts for the prices of coal and iron ore, key exports from Australia, between 2010 and 2018.[13] The horizontal axis shows, for each year, the forecasted change in the price of iron ore and coal one year ahead, in percentage terms. The first thing to notice is that most values are negative: it was consistently expected that prices would fall. The vertical axis

[11] World Bank data accessed online.

[12] 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.

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

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. Kulish and Rees (2017) study the evolution of the terms of trade in Australia and conclude that most of the increase was temporary.

A potential caveat about studying this boom is that mining is capital-intensive, and doesn't employ many workers directly. However, it is important to consider that booms in the terms of trade translate to booms in demand for non-tradable goods. The textbook response in a small open economy when terms of trade increase are for both the booming sector and non-tradables to expand, while other tradable sectors shrink (Corden and Neary, 1982). Figure 6c shows that this is exactly what happened in Australia during the period.[14] Employment and earnings in mining expanded jointly with services and construction while the other tradable sector, manufacturing, shrank in relative terms.

4 Quantitative model

I extend the baseline model in Section 2 by including realistic features so I can take it to the data from Australia between 2011 and 2018, which I describe in detail in the next section. The first difference is that I model boom-bust dynamics in world mining prices, instead of wages which are now endogenous. I will explain this first and, next, a small open economy environment 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:

[14] This Figure draws from public data from ABS, which doesn't 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.

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

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

Where $\bar{p}_t^M > \underline{p}^M$. This assumption is analogous to the process for wages in equation (1) in the baseline model. Now, I allow for variation in prices between periods conditional on the state being a boom. An interesting extension of the model would be 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. 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 bust state is absorbing and 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 of $\{b_s\}_{s=0}^t$. 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 $b_t = 1, 0$ 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). The reasons to incorporate more than two sectors are twofold. First, modeling outside options of workers in the event of the mining bust 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's important to have a distinction between the two. I treat construction separately from other services because, during the period I study, there was a huge 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. This part of the model builds directly on Traiberman (2019), except for the important difference that I don't incorporate occupations in the model. At the beginning of period t the state for worker i is $\omega_{it} = \{a_{it}, s_{it-1}, \Delta_{it}, e_i, \theta_i\}$, where a_{it} denotes their 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.

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 unobservables. Then, as explained with the help of the baseline model, correctly estimating the returns to human capital accumulation on-the-job is crucial. Allowing for other controls is important to attempt to control for selection in the type of workers who decide to stay for longer in a sector, which is why I allow for unobserved heterogeneity.

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

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

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, H_s, is the number of efficiency units of human capital that the worker is able to supply to a sector. The shock ζ is specific to s and is unobserved before the worker decides to sort into sector s. The role of this shock is to rationalize differences in income across workers conditioning on ω, s and will not play an important role in the analysis.

I now turn to specifying worker preferences. Utility, shown in equation (10), is the combination of real income y_{it}, an amenity value η_s and migration costs, 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 $\tilde{C}(\omega_{it}, s_{it-1}, s_{it})$. All things considered, the flow utility of a worker with characteristics ω_{it} who sorts into s at period t can be written as:

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

Timing works as follows. At the beginning of period t, worker i observes the aggregate 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's important to keep track of when the boom ended. As is standard in quantitative models, I also allow for sector-time-specific idiosyncratic shocks $\{\epsilon_{sit}\}$ that individual workers observe at the beginning of each period. After observing all of these, she makes her decision of where to work. Denoting by V_t and v_t her value before and after idiosyncratic shocks are realized:

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

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

The first thing to notice in equation (11) is that 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 is taken with respect to b_{t+1}, as I discuss in detail below. The expected continuation value in equation (11) takes ω', the future characteristics of the worker, as an argument. Age evolves mechanically by one, while education and unobserved type are constant. 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). Regarding the evolution of tenure, I make exactly the same assumption as in the baseline model:

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

Whenever a worker switches sectors her tenure gets reset. The content of this assumption is twofold. 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. This particular functional form will prove useful in the estimation where, as discussed by Traiberman (2019), assuming that one period is enough for tenure to be reset is not crucial; 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 that possibility.

Preferences. Workers have Cobb-Douglass preferences over all goods in the economy:

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

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

$$P_t = \prod_{s=1}^{S} (\frac{p_t^s}{\gamma_s})^{\gamma_s}$$

Labor demand. Good s is produced by a representative firm with access to Cobb-Douglass technology:

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

Where A and K capture productivity and capital in each sector and H is the sum of efficiency units of human capital across workers who sort into sector s at period t.

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

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

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 in the discussion section below.

Equilibrium. The path of $\{\mu_t\}_{t=0}^{\infty}$ and tradable prices $\bar{p}_t, \underline{p}_t$ are exogenous. An equilibrium is given by a path of non-tradable prices $\{p_t^s(h^t)\}_{t=0}^{\infty}$ for $s =$ *Construction, Other services* and rental price of capital $\{r_t^k(h^t)\}_{t=0}^{\infty}$ such that:

- Workers migration decisions are given by maximizing equation (11) at all h^t.
- Wages per efficiency unit of human capital equal the value of marginal productivity of

human capital in all sectors:

$$w_t^s(h^t) = \left[\frac{p_t^s(h^t)A_s}{r_t^k(h^t)^{1-\alpha_s}}\Gamma^s\right]^{\frac{1}{\alpha_s}} \ \forall h^t \tag{15}$$

Where Γ^s is a constant.[15]

- Markets for non-tradable sectors clear:

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

- Trade is balanced nationally:

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

Discussion. 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 is the focus of the paper. 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 costs in a model without sector-specific human capital accumulation, while Dix-Carneiro (2014) and Traiberman (2019) incorporate human capital and find that estimate 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:

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

$$\mathbb{E}_t V_{t+1}(s', \omega', h^{t+1}) = \mu_t \mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 0\}) + (1 - \mu_t)\mathbb{E}_t V_{t+1}(s', \omega', \{h^t, 1\}) \tag{16}$$

Equation (16) will have important implications when estimating the costs of switching sectors using data only from a booming period. The key challenge becomes disentangling between 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. To keep the model manageable, I abstract from this in the model.

Labor market frictions are assumed away, which makes the labor demand decisions by firms static. Kline (2008) suggests that sluggish adjustments in labor demand are important in the context of labor reallocation after oil shocks; more generally, introducing firing or search costs could be an important direction in which to extend the analysis. Clearly, in such a model firms would also react to changes in the expected duration of the shock. Such a model would also have unemployment, which is absent from my 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.[16] If the option gets exercised the holder sells a unit of the underlying stock for a price K. Clearly, these instruments gain in value whenever the expectations of the market value of the stock go down, especially when they are expected to fall below K. This should make them particularly 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 dollars and traded in US markets.

I keep put options with a horizon of T close to one year. As 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'. Given the frequency at which I observe dividends, I keep the median half-yearly value across options with the same K. 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 dollars.

Using F to denote the best offer for the options, S the value of the stock, and d the dividends per share, my data consists of observations of $\{d_t^\varphi, S_t^\varphi, \{F_t^\varphi(S_t^\varphi, T, K_i)\}_{i=1}^3\}$ for each semester between 2010h1 and 2019h2.

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 Lon-

[16]In comparison, European options can only be exercised at T.

gitudinal 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 5 sectors following as closely as possible the classification in Dix-Carneiro (2014): agriculture and forestry (1.3% of the workers in my panel), mining (3.3%), manufacturing (6.2%), construction (5.9%) and other services (83%).[17] The main difference in my classification is that I distinguish between agriculture and mining, given that the boom was focused on mining.[18]

This panel can then be linked to the 2016 census, from which I recovered the education that each worker reported to have in 2016. This means that I can't 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 public sources. I aggregate them at the level of the same 5 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.

[17]The percentages represent my 2011-2018 sample.

[18]See Section 3.

6 Calibration and 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:

$$\tilde{d}_t^{\varphi} = \delta_0 + \delta_1 \tilde{p}_{t-1}^M + u_t \tag{17}$$

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:

$$\tilde{p}_t^M = \rho_0 + \rho_1(\tilde{p}_{t-1}^M - \rho_0) + \nu_t \tag{18}$$

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 6a.[19] The forecast of future dividends (in levels) can be calculated by exploiting the fact that from equation (17), future dividends will be log-normally distributed.

$$\mathbb{E}_t[d_{t+1}|b_t = 1] = e^{\delta_0+\delta_1\tilde{p}_t^M+\frac{\sigma^2}{2}} \tag{19}$$

$$\mathbb{E}_t[d_{t+j}|b_t = 1] = \mathbb{P}[b_{t+j} = 1]e^{\delta_0+\delta_1[(\rho_0+\rho_1^j(p_{t-1}-\rho_0)p_t^M+\frac{\sigma^2}{2}} + (1 - \mathbb{P}[b_{t+j} = 1])e^{\delta_0+\delta_1\tilde{p}^b+\frac{\sigma^2}{2}} \tag{20}$$

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

$$\mathbb{P}[b_{t+j} = 1] = \prod_{s=0}^{j-1}(1 - \mu_{t+s}) \tag{21}$$

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:[20]

$$S_t^{\varphi}(b_t) = \mathbb{E}_t\Big[\sum_{s=t+1}^{\infty} M_{t,s}(b_s)d_s^{\varphi}\Big] \tag{22}$$

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:[21]

[19] Figure 6a plots the aggregate price index relative to non-commodities. For this calculation, I use the absolute level of the index for mining products.

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

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

$$F_t^{\varphi}(S_t(b)^{\varphi},T,K)=\begin{cases}\max\{\frac{(1-\mu_t)F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=1),T,K)+\mu_t F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=0),T,K)}{(1+r_t)},K-S_t^{\varphi},0\} & t<T,b_t=1\\ \max\{\frac{F_{t+1}^{\varphi}(S_{t+1}^{\varphi}(b=0),T,K)}{(1+r_t)},K-S_t^{\varphi},0\} & t<T,b_t=0\\ \max\{K-S_T,0\} & t=T\end{cases}\tag{23}$$

Equation (23) 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 δ_0,δ_1,ρ_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 (17), which matters for equation (22), 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 (22) and equation (23). Notice that I need to look for values up to a period T later than 2019H2.

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.[22] The spike in late 2015 coincides with a stock market crash in China, which raised doubts about

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

whether the whole Chinese economy was about to enter into a recession.[23] 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 6b 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 (24), 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.

$$Y_{i,t} = \alpha_0 + \alpha_1 p^M_{t-1} + \alpha_2 p^M_{t-2} + \alpha_3 \mu_{t-1} + \bar{\alpha} X_{it} + \epsilon_{it} \tag{24}$$

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

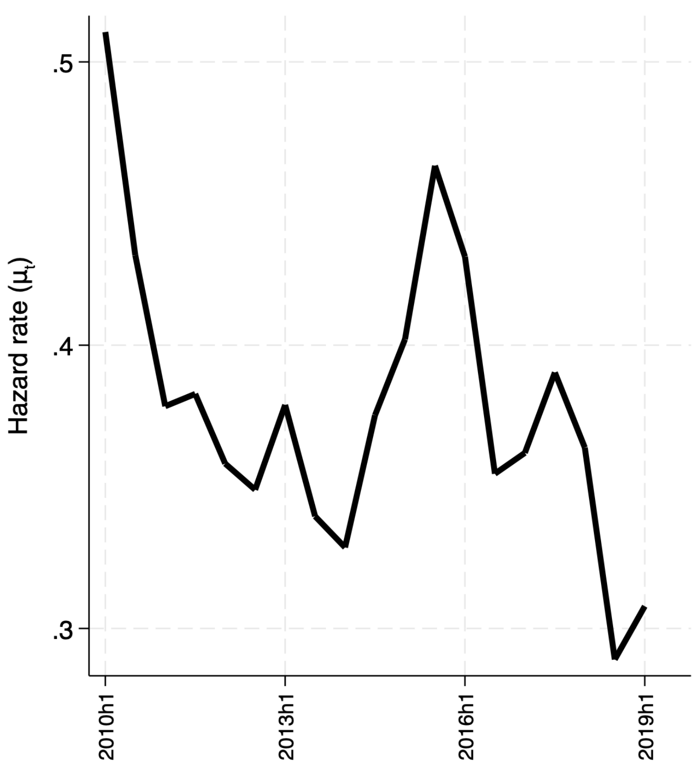
[23] The following piece of news from July 2015 in CNN is eloquent: *Fears of a downturn in China have already hammered the price of commodities like iron ore and copper this week. In the longer term, this could also hurt places like Australia, which supplies a lot of China's raw materials.* Link: https://www.cnn.com/2015/07/08/asia/china-stocks-explainer/index.html, accessed in August 2023.

the baseline share of workers employed in mining is low, 3.7% on average between 2011 and 2018, the estimated effect is large.

The second column in Table 7b shows the results of estimating equation (24) 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 × μ_t		-0.00911
		(0.00878)
College × μ_t		0.00804
		(0.00761)
Age 31-40× μ_t		-0.0297***
		(0.0105)
Age 41-50 × μ_t		-0.0214**
		(0.00976)
Age 51-60 × 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:

$$log(H_s(\omega_{it}, \zeta_{it})) = \beta_1^s \times a_{it} + \beta_2^s \times a_{it}^2 + \beta_3^s \times \Delta_{it} + \beta_4^s \mathbb{I}[e = med] + \beta_5^s \mathbb{I}[e = high] + log(\theta_{si}) + \zeta_{ist} \quad (25)$$

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 (25) 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 (25) 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 (25) 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:

$$\hat{\beta}^{ML}, \hat{q}_{i\theta} = argmax \prod_{i=1}^{N} \prod_{\theta=1}^{6} \hat{q}_{i\theta} \mathcal{L}_{i|\theta} \tag{26}$$

$$\mathcal{L}_{i|\theta} = \prod_{t=2011}^{2019} f(y_{it}(\omega_{it})|\beta, \theta)\pi(s_{it}|s_{i,t-1}, \theta) \tag{27}$$

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:

$$log(f(\omega_{it})) = \alpha_1 \times age_{it} + \alpha_2 \times age_{it}^2 \qquad log(C(s, s')) = \Gamma_o^s + \Gamma_d^s \tag{28}$$

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:[24]

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

$$
\begin{aligned}
\frac{V_t(s,\omega,h^t)}{\rho} =& \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) - C(\omega,s,s')}{\rho} \\
&+ \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t V_{t+1}(s',\omega',\{h^t,0\}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega',\{h^t,1\})\Big] - log(\pi_t(\omega,s,s'))
\end{aligned} \tag{29}
$$

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 (29) 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.3 in the Appendix, I end up with the following equation:

$$
\begin{aligned}
&\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right) + \beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s'')) - \log(\tilde{\pi}_{t+1}(\omega',s',s''))]) + \\
&(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s'')) - \log(\pi_{t+1}(\omega',s',s''))]]\Big] = Y^\omega_{s,s,t} - Y^\omega_{s,s',t} + \frac{\beta}{\rho}\left[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')\right]
\end{aligned} \tag{30}
$$

Where $Y^\omega_{s,s',t}$ is the flow payoff of switching from s to s' at t for a worker with characteristics ω.[25] Transitions $\pi_{t+1}(\omega,s,s')$ and $\tilde{\pi}_{t+1}(\omega,s,s')$ represent transition rates between sector pairs

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

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.[26] 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.3 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 (30) becomes:

[26] To see this:

$$\mathbb{E}_t[\pi_{t+1}] - \pi_{t+1} = \mu_t \tilde{\pi}_{t+1} + (1 - \mu)\pi_{t+1} - \pi_{t+1} = \mu_t(\tilde{\pi}_{t+1} - \pi_{t+1}). \tag{31}$$

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

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right)= \tag{32}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')\big]+\tilde{u}_{s,s',t} \tag{33}$$

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:

$$\alpha_s=\frac{w_sH_s}{Y_s}\qquad\quad \gamma_s=\frac{Y_s+M_s-X_s}{\sum_{j\in\mathcal{S}}Y_j+M_j-X_j} \tag{34}$$

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 (15) 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 (28) 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 (33) 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.

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.

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

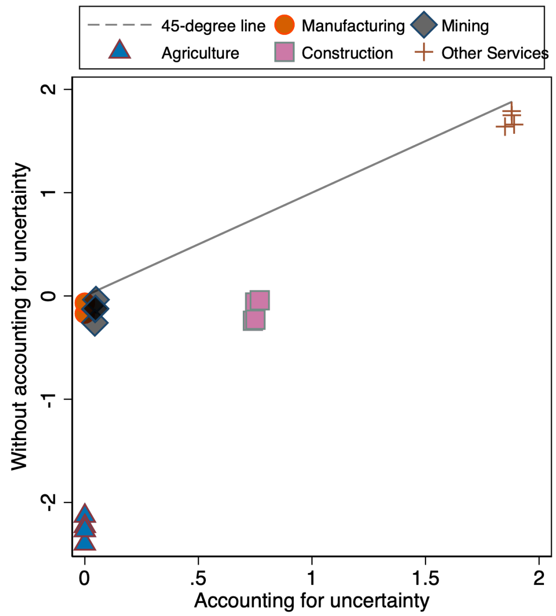


Table 3: Calibration

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 Counterfactual analysis

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:

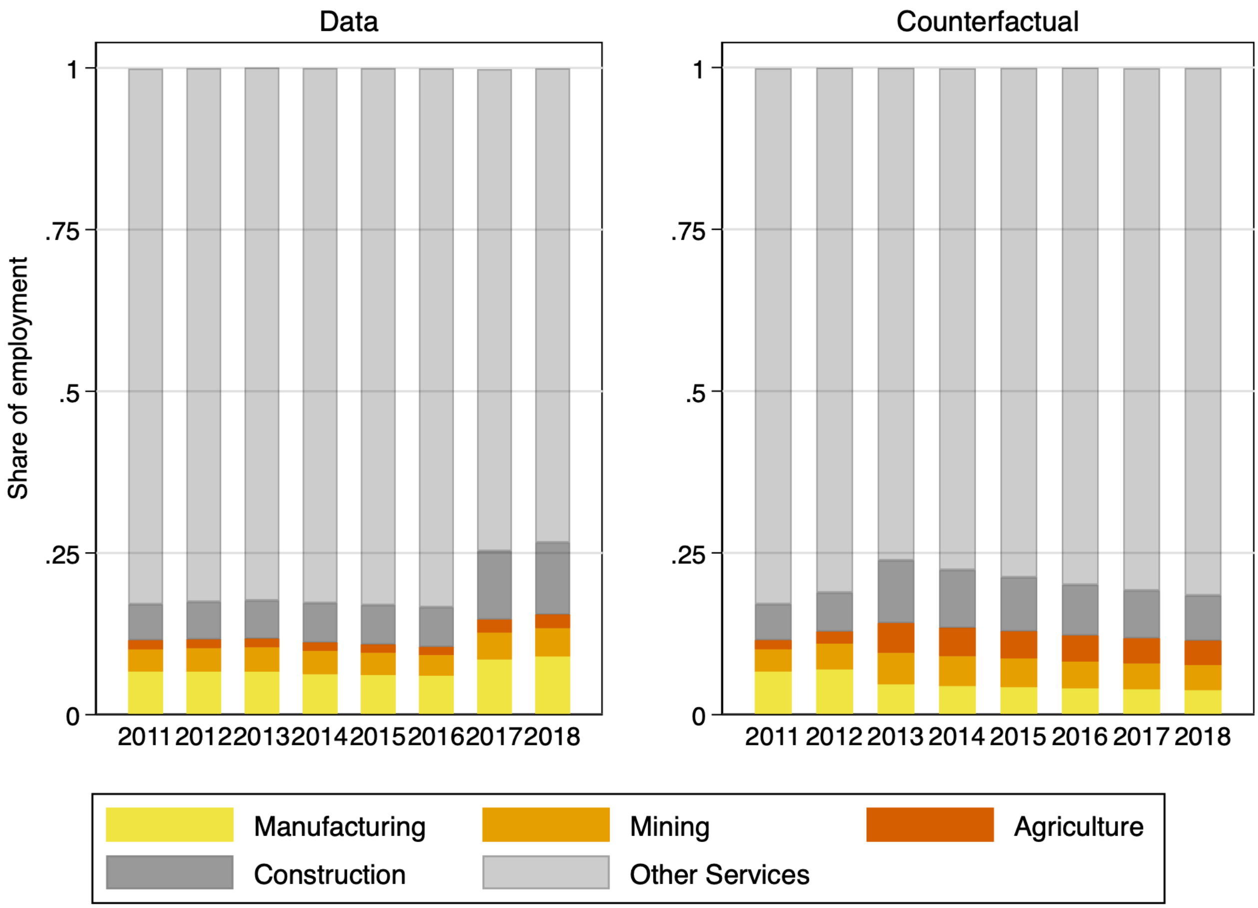
$$p_t^{M,cf} = \begin{cases} p_t^M & t < 2014 \\ \underline{p} & t \geq 2014 \end{cases}. \tag{35}$$

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 5 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.

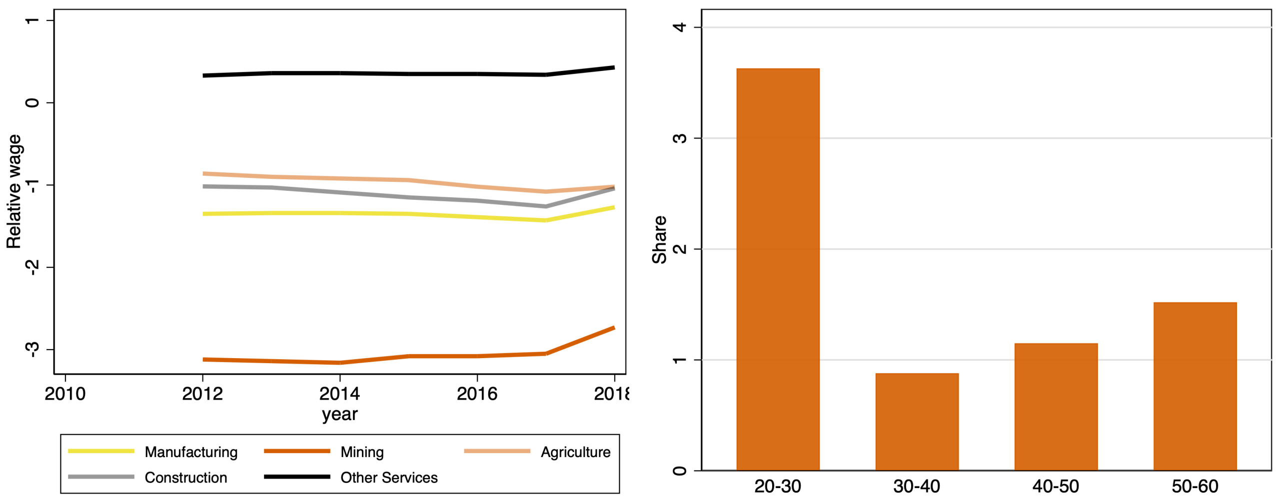
Figure 10: Difference between counterfactual and the data



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 Theorem 1

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

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

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

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

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

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

Which is a contradiction if $\gamma_1 > 1$. As $\frac{\partial V}{\partial \Delta} \geq 0$, both elements on the sum on the left-hand side would be bigger than their counterparts on the right-hand side. This proves that it's never optimal to leave sector 1 if the boom is ongoing.

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

If at $\tau < \bar{t}$ it is optimal to wait until $\bar{t}$ to switch the following inequality holds:

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

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

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

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

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

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

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

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

A.2 Proof of Lemma 1

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

$$V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) \tag{42}$$

$$\bar{w}\theta(\beta\gamma_1)^{T-1} + \frac{(\beta\gamma_1)^T \underline{w}\theta}{1-\beta\gamma_1} - \frac{\beta^{T-1}}{1-\beta\gamma_0} \geq \bar{w}\theta(\beta\gamma_1)^{T-2} + \frac{\beta^{T-1}}{1-\beta\gamma_0} - \frac{\beta^{T-2}}{1-\beta\gamma_0} \tag{43}$$

$$\bar{w}\theta(\beta\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{(\beta\gamma_1)^T \underline{w}\theta}{1-\beta\gamma_1} \leq \frac{\beta^{T-2}(1-2\beta)}{1-\beta\gamma_0} \tag{44}$$

$$\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{\beta^2(\gamma_1)^T \underline{w}\theta}{1-\beta\gamma_1} \leq \frac{(1-2\beta)}{1-\beta\gamma_0} \tag{45}$$

$$\tag{46}$$

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

$$\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} \tag{47}$$

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

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 (48) to hold that the following holds:

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

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

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 Derivation of equation (33)

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

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

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} + \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t \tilde{V}_{t+1}(s',\omega') + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega')\Big] - \log(\pi_t(\omega,s,s') \tag{51}$$

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

$$\frac{V_{t+1}(s',\omega')}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \tag{52}$$

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

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

Plugging equation (52) and equation (53) into equation (51):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} - \log(\pi_t(\omega,s,s')) \tag{54}$$

$$+\beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{55}$$

$$+\frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{56}$$

$$-\beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\omega',s',s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\omega',s',s''))]\Big] \tag{57}$$

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.

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} + \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t \tilde{V}_{t+1}(s,\hat{\omega}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s,\hat{\omega})\Big] - \log(\pi_t(\omega,s,s)) \tag{58}$$

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

$$\frac{V_{t+1}(s,\hat{\omega})}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \tag{59}$$

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

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

Plugging equation (59) and equation (60) into equation (58):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} - \log(\pi_t(\omega,s,s)) \tag{61}$$

$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{62}$$

$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{63}$$

$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega}',s,s''))]\Big] \tag{64}$$

I can use the two expression for $V_t(s,\omega)$ in equation (54)-equation (61) to get rid of $V_t(s,\omega)$. Notice as well that equation (63) and equation (56) 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:

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

$$(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s''))-\log(\pi_{t+1}(\omega',s',s''))]]\Big]=Y^{\omega}_{s,s',t}-Y^{\omega}_{s,s,t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right] \tag{66}$$

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:

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right)= \tag{67}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')] \tag{68}$$

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 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[27]. 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.

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.

[27]Accessed September 23, 2022.

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

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

Standard errors in parentheses

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

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

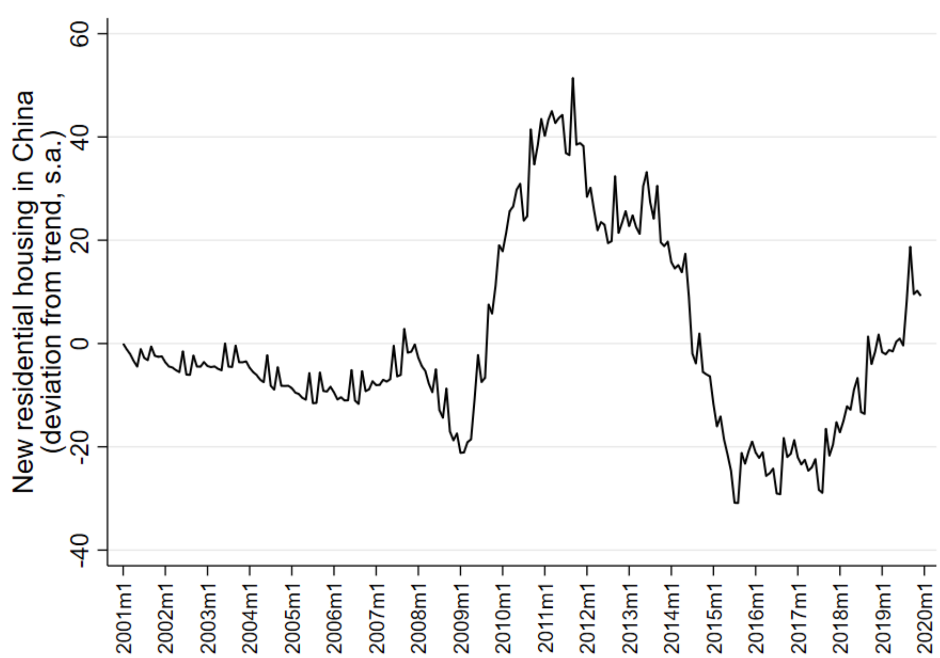
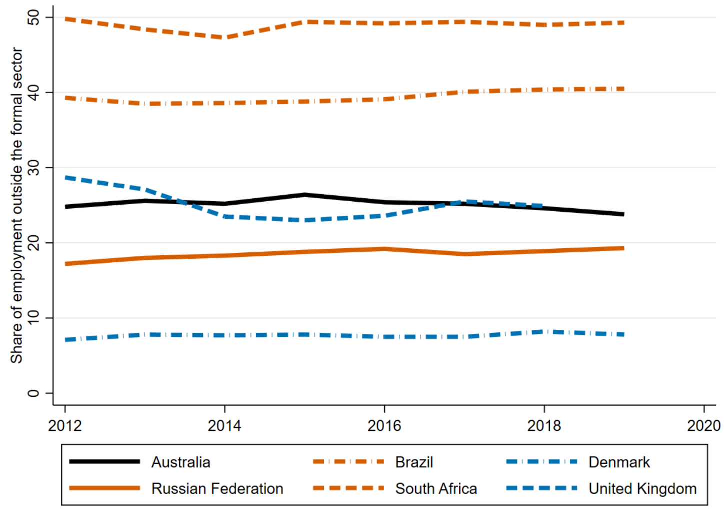


Figure 13: Share of employment outside formal sector



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

C.5 Panel of workers: details and descriptive statistics

Definition of education levels.

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

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

Joint distribution across sectors and education levels.

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