Labor reallocation during booms: The role of duration uncertainty*

Marcos Sorá
University of Chicago
soramarcos@uchicago.edu

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Abstract

Booms are recurrent and affect sectors as varied as commodities, construction and tech. I study workers decision to enter booming sectors and the role of uncertainty about how long the boom will last in shaping labor supply. I build a model with sector-specific on-the-job human capital accumulation and show conditions under which increasing uncertainty about duration can induce more entry. The option value is crucial: if duration ends up being short workers will switch out and cut losses, while payoffs are high if duration is long because of human capital accumulation. To study the effects of duration uncertainty empirically I exploit the boom in world prices of mineral products of 2011-2018. Using novel administrative data from Australia, an exporter of those products, I build and estimate a general equilibrium model accounting for duration uncertainty in the estimation stage. I use the estimated model to study a perfect foresight economy in which the duration of the mining boom had been known and find that employment in mining would have been 13% higher on average.

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

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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.

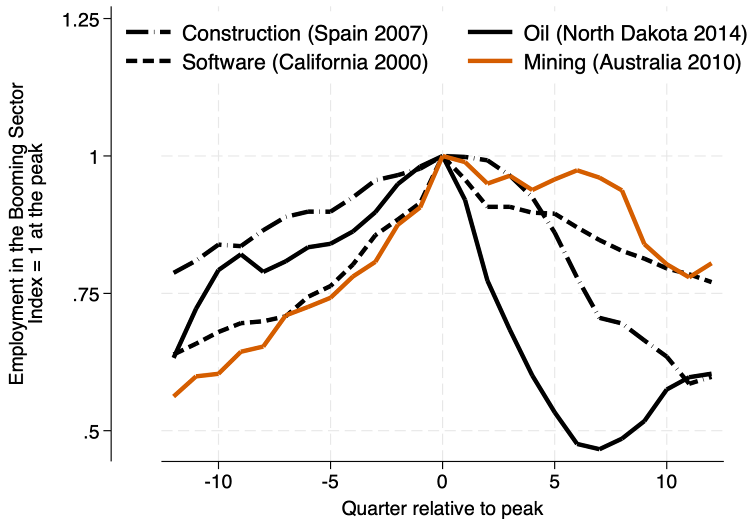
In this paper I focus on how uncertainty about duration of the boom phase shapes workers decision to enter into booming sectors. Workers rush into booming sectors likely knowing that, when the boom ends, these sectors will contract sharply. Figure 1 below shows the evolution of sectoral employment around the peak for some well-known examples of booms, normalized to take value 1 in the peak of the series. 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 episodes? Does it necessarily discourage workers from entering booming sectors? Using a model that relies on sector-specific human capital I find 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 that boom? 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 duration was known and 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 will focus on throughout. The economy has two sectors: wages in one sector are exposed to a boom and 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. In a world where the hazard rate for the end of the boom is constant, these elements are enough to make the discounted value of lifetime earnings of the worker who sorts into the booming sector convex in terms of the duration of the boom, which is the only random variable in the economy. The intuition for the convexity is the following. If duration ends up being short workers will decide to switch out of the booming sector when the bust happens, cutting losses. If duration is long, however, they will optimally decide to stay because they have 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]

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

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 main job* from Australian Bureau of Statistics for Australia.

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 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. To understand 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 for exporters across the world 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 were 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, specially 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

[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.

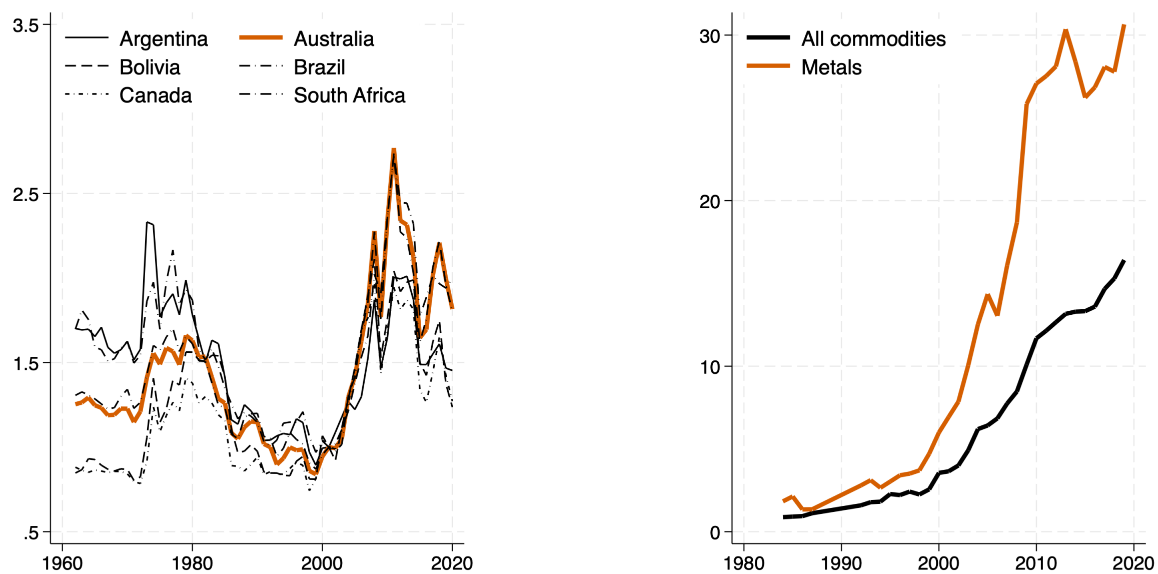
[3]In 2018, commodities represented more than 60% of exports in more than 100 countries (UNCTAD, 2021).

[4]This view can be found in several central bank reports from the period, specially when discussing the evolution

Section ?? 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.

Figure 2: Commodity boom driven by growth in China

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



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

To answer how much of 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 an increase an 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 costs of switching sectors that are independent of the opportunity cost channel which is the focus of this paper but have 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 understand 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 covers 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 sector. I can construct such a

of metal prices (Rayner and Bishop, 2013; Kruger et al., 2016).

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. To estimate switching costs between sectors the method relies on matching transition shares between sectors for workers with different characteristics. Intuitively, high switching costs between a pair of sectors are estimated if workers don't migrate between them despite high expected wage differences.[5] Under some extra assumptions on idiosyncratic shocks which are standard in the literature one can write an estimated equation which links current and expected one-period-ahead transition rates to migration costs and the gap in expected values between sectors. Traiberman (2019) assumes that the difference between the expected one-period-ahead transition rates and the data, the expectation error, is uncorrelated across periods. In my setting, given that I have data during the boom years, this expectation error includes the probability that the boom ends multiplied by the difference between transition rates if the boom finishes or continues and is therefore correlated across periods.[6] To deal with this issue I make a different set of assumptions about expectations and write down an equation in which expectations conditional on each future state of the boom appear separately. This last step has important effects on my estimate of switching costs and sectoral amenities. Accounting for the possibility of future drops in value changes the estimates of amenities and switching costs, on average, by 25%. The effect is stronger for mining, where the non-pecuniary cost of switching into mining is estimate to be 55% lower once uncertainty is accounted for. This is intuitive: the reason why people are not moving into mining is not high switching costs or bad amenities only, but partly the likelihood of a future loss in value in that sector.

The estimation step described in the last paragraph requires a measure 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 looking to estimate this parameter, given that asset prices are essentially forward looking. Put options, in particular, gain in value when the expected value of the stock falls, which should make them particularly sensitive to movements in 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 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

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

[6] See Figure 2a for why I interpret the 2011-2019 as still being part of the mining boom.

in which the duration of the boom is fixed to its expected duration. My main finding is that, in this setting, duration uncertainty decreased entry into the booming sector by almost half. The share of the population working in mining is 6% in the counterfactual, compared to 3.3% on average in the data.

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 has 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). 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 a potential 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 eventually got 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 can only increase 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 both 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; 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 0 and the only random variable in the economy is τ which marks the end of the boom. It is convenient to define the aggregate state as $b_t = \mathbb{I}[\tau > t]$. The economy is 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 1 are high while the boom lasts and fall when the boom ends. Wages in sector 0, the outside sector, are normalized to 1 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 obtains from working 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 how much experience she has 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:

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

I further assume that human capital depreciates if some time is spent in other sectors. Tenure drops to 0 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:

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

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 1 in all periods, utility is linear and workers discount future consumption at rate β.[7] Her problem can be written recursively as follows:

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

Where the last argument in the value function is b_t. If the economy is booming 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 1 initially.

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

- **$\ell_t = 1$ if $b_t = 1$.**
- **$\ell_t = 0 \rightarrow t = \tau$.**

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, relegated to the appendix, uses that as time goes by workers accumulate sector-specific human capital that they would lose if the changed sectors. If it was optimal to choose sector 1 initially, it has to be also optimal when the benefits of doing so go up.

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:

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

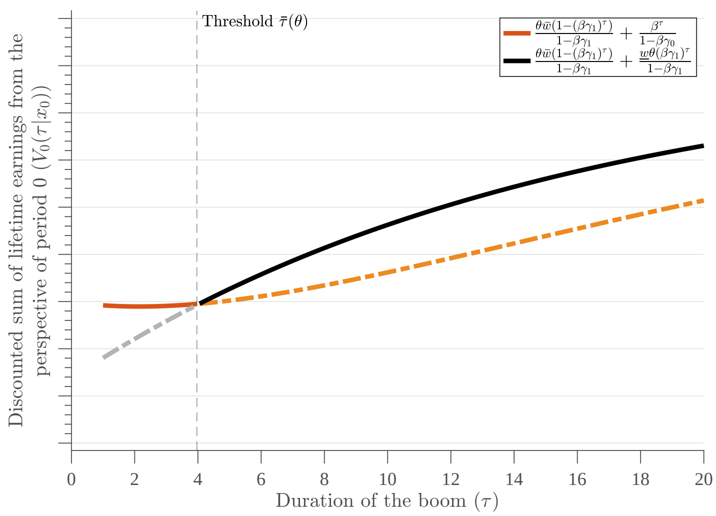
The worker would choose to stay in the booming sector if the left-hand side is greater than the right hand side, switch if it was smaller, and would be indifferent between sectors if both are equal. Because policy functions going forward follows such simple threshold rules, I can write the value from 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. They are given by:

[7] To complete the model, good 0 can be interpreted as the numeraire which is produced with linear technology so both wages and prices are 1. Good 1 could be a tradable good also produced with linear technology, which is exported in exchange of good 0. Under this interpretation, $\bar{w}$ could represent the world relative price of good 1.

$$V_0(\tau|\theta,\vec{0},0,1) = \begin{cases} \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\beta^\tau}{1-\beta\gamma_0} & \tau < \bar{\tau}(\theta) \\ \frac{\theta\bar{w}(1-(\beta\gamma_1)^\tau)}{1-\beta\gamma_1} + \frac{\underline{w}\theta(\beta\gamma_1)^\tau}{1-\beta\gamma_1} & \tau \geq \bar{\tau}(\theta) \end{cases} \tag{4}$$

The values in equation (4) 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 the worker 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 (4) as a function of τ for arbitrary values of the parameters.

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



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.

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:**

$$V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) \tag{5}$$

Proof. See Appendix Section A.2. The key difference between an extra period of 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. She will stay into a sector where he has $\bar{\tau}(\theta)$ periods of accumulated experience which, due to the functional form assumptions for human capital, increases the the returns to human capita accumulation going forward. The last requirement, $\frac{\bar{w}}{\underline{w}} \leq \left(\frac{1-\beta}{1-\beta\gamma_1}\right)^2$ is a technical requirement related to the model being in discrete time. The second difference between an extra period of 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 $t = 0$, 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 the human capital accumulation. This is an important difference which makes this setting different to 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).

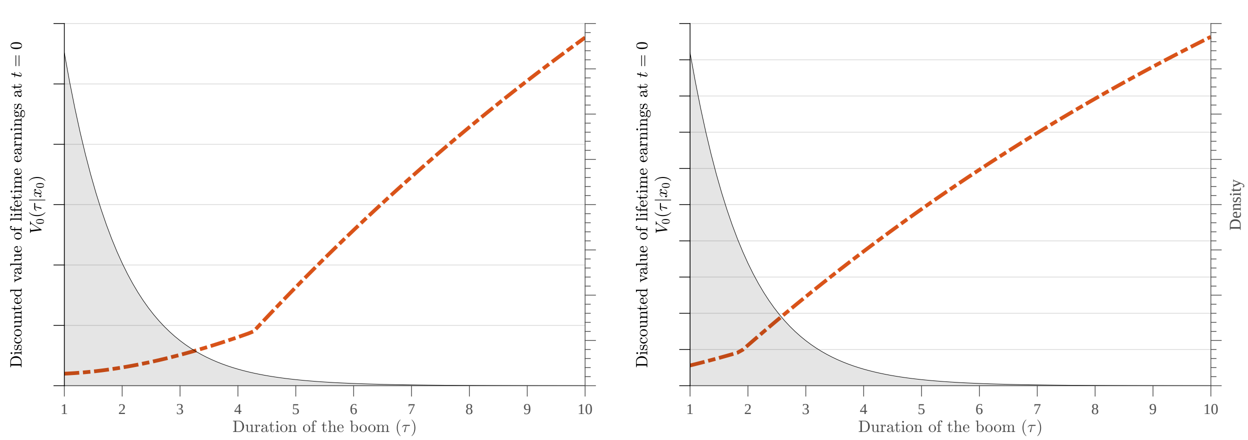
The kink is important because it implies that workers can have risk-loving attitudes towards duration around the kink $\bar{\tau}(\theta)$. If the process for the boom is such that durations close to the kink are very likely, duration uncertainty increases the ex-ante expected value for this worker.

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 (4) overlapped with the density for 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 to which sector to go initially. The value at birth of sorting into the booming sector is equal to the expected value of equation (4), where the expectation is taken over duration τ. The value of sorting into sector 0 is equal to the discounted value of lifetime earnings if staying in sector 0 forever.[8] Then, a worker of type θ sorts into sector 1 if the following inequality holds:

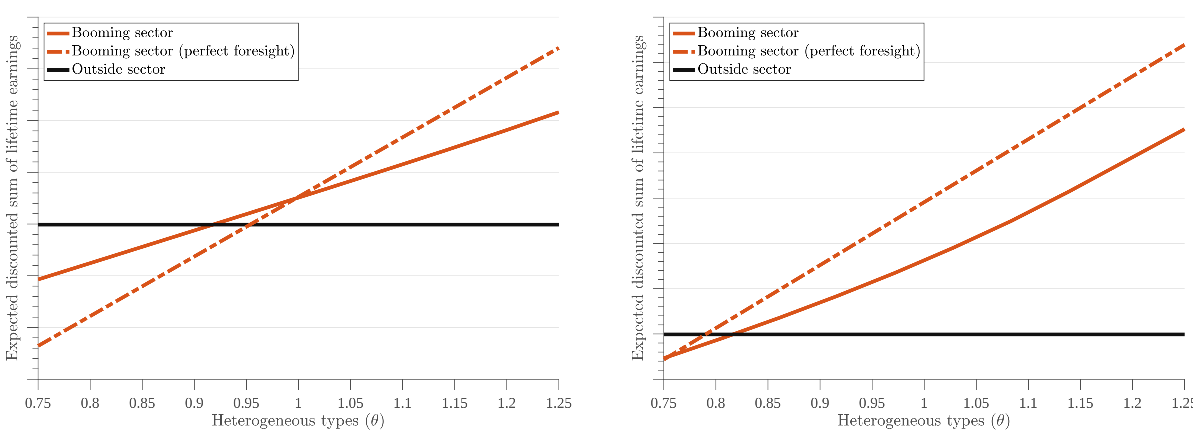
$$\ell_0(\theta, \vec{0}, 0, 1) = 1 \iff \mathbb{E}_\tau(V(\tau)) \geq \frac{1}{1-\beta\gamma_0}$$

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 into the booming sector ex-ante, which is intuitive.

I now turn to the key counterfactual question I'm interested in which isolates the role of duration uncertainty. I compare the economy just described with a perfect foresight economy in which the duration of the boom is fixed and set to $\tau^{pf} = \frac{1}{\mu}$, which is the expected duration 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

[8]The argument of why a worker never switches out of 0 is analogous to the one for sector 1 but simpler because the sector is not affected directly by the end of the boom.

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 into 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 duration is fixed, 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 don'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 1, 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 have started with this alternative definitions of wages, types and rates of human capital accumulation (which would never fall below 1 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.

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3 Appendix

A Mathematical appendix

A.1 Proof of Theorem 1

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

$$\bar{w}\theta + \beta\Big[\mu V(\theta, [0,1], 1, 0) + (1-\mu)V(\theta, [0,1], 1, 1)\Big] \geq 1 + \beta\Big[\mu V(\theta, [1,0], 0, 1) + (1-\mu)V(\theta, [1,0], 0, 1)\Big] \tag{6}$$

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

$$\bar{\theta} w \gamma_1^{t'} + \beta\Big[\mu V(\theta, [0, t'+1], 1, 0) + (1-\mu)V(\theta, [0, t'+1], 1, 1)\Big] < 1 + \beta\Big[\mu V(\theta, [1,0], 0, 1) + (1-\mu)V(\theta, [1,0], 0, 1)\Big] \tag{7}$$

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 (6) and equation (7) 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:

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tau}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{8}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tau}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^{\tilde{t}}(1-(\beta\gamma_1)^{\tilde{t}-\tau+1})}{1-\beta\gamma_1} + \frac{\beta^{\tilde{t}-\tau+1}}{1-\beta\gamma_0} \tag{9}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau(1-(\beta\gamma_1)^{2(\tilde{t}-\tau)+1})}{1-\beta\gamma_1} + \frac{\beta^{2(\tilde{t}-\tau)+1}}{1-\beta\gamma_0} \tag{10}$$

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

$$\frac{1}{1-\beta\gamma_0} < \frac{\underline{w}\theta\gamma_1^\tau}{1-\beta\gamma_1} \tag{11}$$

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

A.2 Proof of Lemma 1

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

$$\begin{aligned}
V_0(\bar{\tau}(\theta)) - V_0(\bar{\tau}(\theta)-1) \geq & V_0(\bar{\tau}(\theta)-1) - V_0(\bar{\tau}(\theta)-2) && (12)\\
\bar{w}\theta(\beta\gamma_1)^{T-1} + \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} - \frac{\beta^{T-1}}{1-\beta\gamma_0} \geq & \bar{w}\theta(\beta\gamma_1)^{T-2} + \frac{\beta^{T-1}}{1-\beta\gamma_0} - \frac{\beta^{T-2}}{1-\beta\gamma_0} && (13)\\
\bar{w}\theta(\beta\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{(\beta\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq & \frac{\beta^{T-2}(1-2\beta)}{1-\beta\gamma_0} && (14)\\
\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) - \frac{\beta^2(\gamma_1)^T\underline{w}\theta}{1-\beta\gamma_1} \leq & \frac{(1-2\beta)}{1-\beta\gamma_0} && (15)\\
& && (16)
\end{aligned}$$

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

$$\begin{aligned}
\bar{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq & \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} && (17)\\
\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq & \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} && (18)
\end{aligned}$$

Where in the last step I multiplied and divided by $\underline{w}$. For $\tau - 2$ the following inequality holds $\frac{\underline{w}\theta\gamma^{T-2}}{1-\beta\gamma_1} < \frac{1}{1-\gamma\beta_0}$. Then, it's enough for equation (18) to hold that the following holds:

$$\begin{aligned}
\frac{\bar{w}}{\underline{w}}\underline{w}\theta(\gamma_1)^{T-2}(1-\beta\gamma_1) \leq & \frac{1-2\beta+\beta^2}{1-\beta\gamma_0} && (19)\\
\frac{\bar{w}}{\underline{w}} \leq & \frac{1-2\beta+\beta^2}{(1-\beta\gamma_1)^2} = \left(\frac{1-\beta}{1-\beta\gamma_1}\right)^2 && (20)
\end{aligned}$$

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 (??)

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

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} + \frac{\beta}{\rho}\Big[\mu_t\mathbb{E}_t\tilde{V}_{t+1}(s',\omega') + (1-\mu_t)\mathbb{E}_t V_{t+1}(s',\omega')\Big] - \log(\pi_t(\omega,s,s')) \tag{21}$$

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

$$\begin{aligned}\frac{V_{t+1}(s',\omega')}{\rho} &= \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \\ &\quad \frac{\beta}{\rho}\Big[\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})V_{t+1}(s'',\omega''))\Big] - \log(\pi_{t+1}(\omega',s',s''))\end{aligned} \tag{22}$$

$$\frac{\tilde{V}_{t+1}(s',\omega')}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\omega',s',s'')) \tag{23}$$

Plugging equation (22) and equation (23) into equation (21):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{s't}\mathbb{E}_\zeta H_{s'}(\omega,\zeta_{s't}) + \eta_{s'} - f(\omega)C(s,s')}{\rho} - \log(\pi_t(\omega,s,s')) \tag{24}$$

$$+\beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{25}$$

$$+\frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{26}$$

$$-\beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\omega',s',s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\omega',s',s''))]\Big] \tag{27}$$

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.

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} + \frac{\beta}{\rho}\Big[\mu_t \mathbb{E}_t \tilde{V}_{t+1}(s,\hat{\omega}) + (1-\mu_t)\mathbb{E}_t V_{t+1}(s,\hat{\omega})\Big] - \log(\pi_t(\omega,s,s)) \tag{28}$$

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

$$\frac{V_{t+1}(s,\hat{\omega})}{\rho} = \gamma + \frac{w_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \tag{29}$$
$$\frac{\beta}{\rho}\Big[\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})V_{t+1}(s'',\omega'')\Big] - \log(\pi_{t+1}(\hat{\omega},s',s''))$$
$$\frac{\tilde{V}_{t+1}(s',\hat{\omega})}{\rho} = \gamma + \frac{\tilde{w}_{s''t+1}\mathbb{E}_\zeta H_{s''}(\hat{\omega},\zeta_{s''t+1}) + \eta_{s''} - f(\hat{\omega})C(s',s'')}{\rho} + \frac{\beta}{\rho}\Big[\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'')\Big] - \log(\tilde{\pi}_{t+1}(\hat{\omega},s',s'')) \tag{30}$$

Plugging equation (29) and equation (30) into equation (28):

$$\frac{V_t(s,\omega)}{\rho} = \gamma + \frac{w_{st}\mathbb{E}_\zeta H_s(\omega,\zeta_{st}) + \eta_s - f(\omega)C(s,s)}{\rho} - \log(\pi_t(\omega,s,s)) \tag{31}$$
$$+ \beta\Big[\gamma + \frac{(\mu_t\mathbb{E}_t\tilde{w}_{s''t+1} + (1-\mu_t)\mathbb{E}_t w_{s''t+1})\mathbb{E}_\zeta H_{s''}(\omega',\zeta_{s''t+1}) + \eta_{s''} - f(\omega')C(s',s'')}{\rho}\Big] \tag{32}$$
$$+ \frac{\beta^2}{\rho}\Big[\mu_t\mathbb{E}_{t+1}\tilde{V}_{t+2}(s'',\omega'') + (1-\mu_t)\Big(\mu_{t+1}\mathbb{E}_{t+1}\tilde{\tilde{V}}_{t+2}(s'',\omega'') + (1-\mu_{t+1})\mathbb{E}_{t+1}V_{t+2}(s'',\omega'')\Big)\Big] \tag{33}$$
$$- \beta\Big[\mu_t\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s''))] + (1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega}',s,s''))]\Big] \tag{34}$$

I can use the two expression for $V_t(s,\omega)$ in equation (24)-equation (31) to get rid of $V_t(s,\omega)$. Notice as well that equation (33) and equation (26) 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:

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right) + \beta\Big[\mu_t(\mathbb{E}_t[\log(\tilde{\pi}_{t+1}(\hat{\omega},s,s'')) - \log(\tilde{\pi}_{t+1}(\omega',s',s''))]) + \tag{35}$$
$$(1-\mu_t)\mathbb{E}_t[\log(\pi_{t+1}(\hat{\omega},s,s'')) - \log(\pi_{t+1}(\omega',s',s''))]]\Big] = Y^\omega_{s,s',t} - Y^\omega_{s,s,t} + \frac{\beta}{\rho}[f(\omega')C(s',s'') - f(\hat{\omega})C(s,s'')] \tag{36}$$

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 **??**, this becomes:

$$\log\left(\frac{\pi_t(\omega,s,s)}{\pi_t(\omega,s,s')}\right)+\beta(1-\mu_t)\log\left(\frac{\pi_{t+1}(\hat{\omega},s,s'')}{\pi_{t+1}(\omega',s',s'')}\right)= \tag{37}$$

$$Y^{\omega}_{s,s,t}-Y^{\omega}_{s,s',t}+\frac{\beta}{\rho}\left[f(\omega')C(s',s'')-f(\hat{\omega})C(s,s'')\right]-\beta\mu_t\Big[p(\hat{\omega},t+1,s,s'')-p(\omega',t+1,s',s'')\Big] \tag{38}$$

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[9]. 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 1 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 1 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

[9] Accessed September 23, 2022.

Table 1: Export prices in Australia and economic activity in China 2001-2019 (all variables in logs).

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

Standard errors in parentheses

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

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

C.3 Informality

These numbers come from the series *Share of employment outside formal sector - Annual*, downloaded fromhttps://ilostat.ilo.org/topics/informality/ in June 2023. Figure 7 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. [10] 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.

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

Figure 6: New residential housing in China in Squared Meters (Millions)

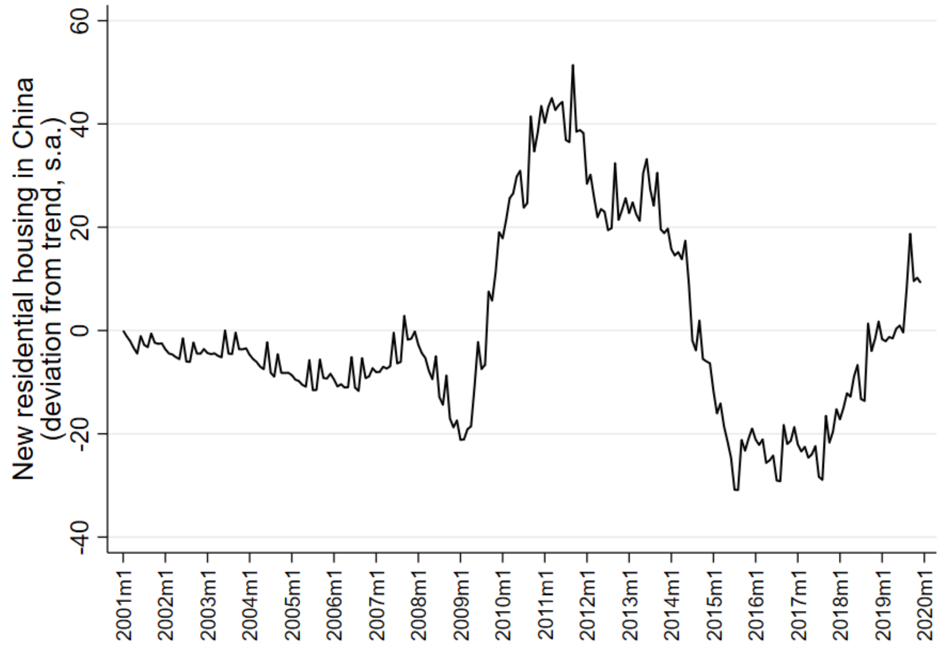
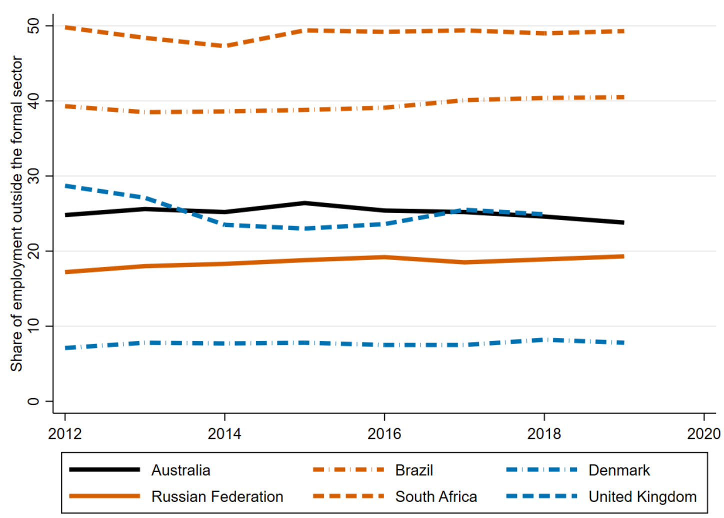


Figure 7: Share of employment outside formal sector



C.5 Panel of workers: details and descriptive statistics

Definition of education levels.

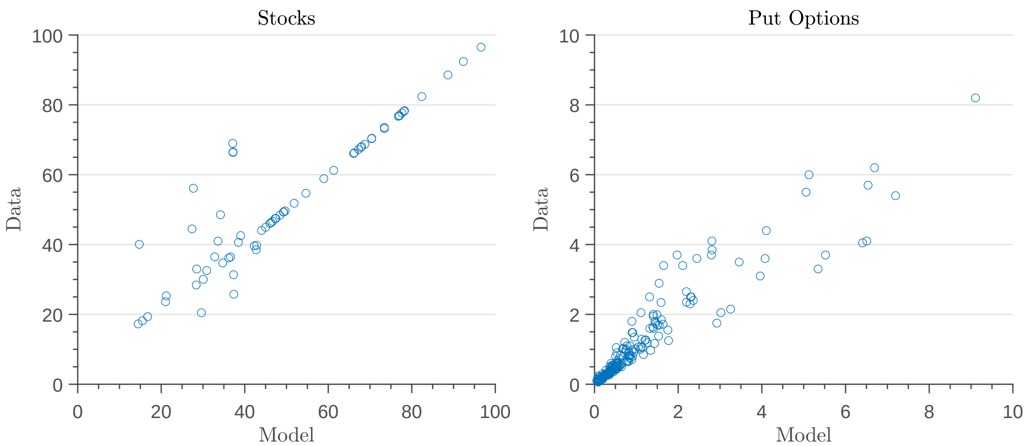
Group	Percentage of workers 2011-2019	Degrees
Group 1	41%	High school completed or less
Group 2	23%	Advanced Diploma
		Associate Degree
		Diploma
		Certificate I, II, III and IV Level
Group 3	36%	Higher Doctorate
		Doctorate by Research or Coursework
		Master Degree by Research or Coursework
		Graduate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

Joint distribution across sectors and education levels.

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

education sector obs2 1 1 44323 2 1 18332 3 1 16462 1 2 24964 2 2 9702 3 2 7611 1 3 11308 2 3 2959 3 3 2412 1 4 42529 2 4 22509 3 4 9134 1 5 393199 2 5 230403 3 5 426847

Figure 8: Model fit



D Estimation appendix

D.1 Model fit for stocks and put options on the stock of firm ζ in Section ??

The inputs to the model are a time series at the quarterly frequency for the value of the stock and three put options between the first quarter of 2004 and the last quarter of 2019. The free parameters of the model are $\bar{p}, \{\bar{Q}_t, \underline{Q}_t, \mu_t\}_{t=2004Q1}^{2019Q4}$. However, I need to specify beliefs about the evolution of $\mu, \bar{Q}, \underline{Q}$ beyond 2019Q4, as they enter into the value of stocks and options. I assume that μ will increase monotonically from its value at $2019Q4$ to reach a value of 1 in $2029Q4$. This aims at capturing that the shock is temporary.[11] I assume that both $\bar{Q}$ and $\underline{Q}$ stay constant at their mean value during the 2004Q1-2019Q4 period after 2019Q4. All thing considered, I'm trying to fit 256 observations with 193 parameters. Figure 8 below shows the model derived values against data.

[11]See Section **??** for a review of the duration of the shock that was mentioned in the literature during this period.