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# Uncertainty, depreciation and industry growth

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ABSTRACT

When investment is irreversible, firms invest only when the mismatch between their productivity and their capital stock is large. This suggests that two factors should be related to the frequency of mismatch: volatility and capital depreciation. A canonical model of industry dynamics with investment irreversibility displays slow growth in times of high uncertainty, and decline is particularly pronounced in industries where capital depreciation is rapid. A differences-in-differences regression using industry growth data from a large sample of countries supports this result.



## 1. Introduction

An extensive literature studies the economic impact of second-moment shocks, often referred to as *uncertainty*. There is a general consensus that increased uncertainty leads to declines in aggregate economic activity. This applies even when economic uncertainty is measured net of any shocks to levels of fundamentals that might coincide with increases in uncertainty – see Baker and Bloom (2013).

However, there is less consensus regarding the key mechanisms behind this phenomenon. In particular, where decisions are of the $(s, S)$ form, key mechanisms include the *wait-and-see* or *real options* effect, whereby the irreversibility of investment induces caution in investment decisions when uncertainty is high, and the *volatility* effect, whereby greater uncertainty pushes more firms near the adjustment thresholds (i.e. further away from efficient scales of production).[1] Since much evidence points to investment decisions being of $(s, S)$ form, the impact of uncertainty on growth may depend on these two effects.

To see which of these effects is related to slower growth, we develop a parsimonious model of industry dynamics in the presence of investment irreversibilities. Firms have opportunities to grow or shrink based on their idiosyncratic productivity, which varies according to a Markov process as in Hopenhayn (1992). We show that investment irreversibilities have two effects on investment patterns in the model. First, they introduce a motive of caution. Firms will not wish to actively invest nor disinvest – since any current or future disinvestment will be costly – unless there is a significant mismatch between

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[1] See for example Vavra (2014) and Bachmann et al. (2019).

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their productivity and their existing capital stock. Second, when firms do invest, it is because this mismatch is large, so they are more likely to invest in "lumps." Thus, the model generates the (*s, S*) investment behavior that is required for the wait-and-see and volatility effects to operate, and that is consistent with empirical investment patterns.[2]

Into this environment we introduce uncertainty shocks, defined as periods when the productivity process is a mean-preserving spread of what is observed in normal times.[3] The calibrated model makes several predictions. First of all, uncertainty shocks of reasonable magnitude have little impact on investment behavior, in the sense that the range of capital-productivity combinations that result in "wait-and-see" behavior change little when uncertainty is high. This suggests that the *volatility* effect is more important for industry dynamics and for growth. Second, it predicts that investment lumps – defined as an increase in the capital stock of 30% or more as in Doms and Dunne (1998) – should be more prevalent in industries with rapid depreciation. This is because any firm that has capital that is neither too large to require disinvesting nor too small to require investment shrinks towards the investment threshold. Thus, firms in industries with higher depreciation will tend to be closer to the investment thresholds, where they are least efficient and where any increase in productivity could lead them to a spike in investment. Third, since firms tend to be closer to the adjustment thresholds in high-depreciation industries, they should experience disproportionately slow growth in the presence of uncertainty shocks. This is the case even though the calibrated extent of irreversibility is fairly low – about 12%.

Then, we test these predictions – that high-depreciation industries and high-lumpiness industries grow disproportionately slowly in times of high uncertainty – using data on manufacturing industries and uncertainty shocks from a large number of countries. We pool data for a large number of countries because not many uncertainty shocks will be found in the time series of any particular country. In addition, this allows us to use a differences-in-differences specification that ensures that our results are robust to all country-specific conditions at any date, industry-specific conditions at any date or industry-specific conditions in any country, giving our results considerable robustness.[4] We show that high depreciation industries are also high lumpiness industries, and that these industries grow disproportionately slowly in the presence of uncertainty shocks. We also study whether the *risk aversion* effect – whereby uncertainty discourages investment by raising the cost of capital – might be responsible for our results by seeing whether industries with high external finance dependence or low fixed-asset intensity display disproportionate sensitivity to uncertainty shocks, finding that they do not.

Finally, we use the model to generate a panel of pseudo-data similar to that used in the empirical exercise – where several industries operate in a number of countries that experience uncertainty shocks. We run the same regression specification on the artificial data, finding a negative regression coefficient on the interaction between depreciation and uncertainty shocks of about two-thirds the magnitude of the coefficient estimated using actual data. Interestingly, we find that the impact of the magnitude of uncertainty shocks is non-linear. There are significant growth interactions between uncertainty and depreciation even when the magnitude of uncertainty shocks is small – on the order of $5-10\%$ higher volatility of idiosyncratic shocks in periods of high uncertainty. This suggests that economic growth – particularly in high-depreciation industries – is vulnerable even to small increases in volatility.

Although empirical work tends to find that uncertainty slows growth, the theoretical literature contains mechanisms that could in principle lead uncertainty to *enhance* growth. In our model economy, as depreciation approaches 100%, we find that the misallocation effects disappear and uncertainty particularly *favors* growth, as in Oi (1961), Hartman (1972) and Abel (1983). This is because such rapid depreciation makes irreversibility costs irrelevant: the "range of inaction" where firms neither invest nor disinvest disappears and there is no room for misallocation of capital. Instead, higher volatility introduces the possibility of higher upside risk, that can be exploited by investing, whereas the negative impact of downside risk can be limited by allowing capital to depreciate. Thus, the model is able to accommodate parameterizations whereby uncertainty *increases* growth through these mechanisms. Nonetheless, in the calibrated model, we find that these effects are only important for depreciation rates above the empirically relevant range. We conclude that investment irreversibility is key to understanding the response of growth to uncertainty shocks, primarily through the volatility effect.

This study also relates to the capital misallocation literature, for example Hsieh and Klenow (2009) and Bartelsman et al. (2013). Eisfeldt and Rampini (2006) emphasize the importance of capital misallocation for understanding business cycles. In contrast, we discuss the increases in capital misallocation due to *uncertainty shocks* (as in Bloom, 2009), and argue that the source of such misallocation is linked to rapid capital depreciation.

Our findings also contribute to the long literature on real options and flexibility in manufacturing, including Kulatilaka and Marks (1988), McDonald and Siegel (1985), McDonald and Siegel (1986) and Dixit and Pindyck (1994). Flexibility in manufacturing can be interpreted as machine flexibility, material handling system flexibility or operational flexibility. Our model provides a parsimonious model of the irreversibilities which cause inflexibility in firm's investment decisions, as well as providing new evidence supporting the importance of flexibility in the manufacturing sector.

[2] It is well known that firm level investment patterns are "lumpy", in the sense that the distribution of investment includes both a significant frequency of zero investment and also large spikes in investment – see for instance Doms and Dunne (1998). This is evidence of firms often following an inertial investment policy as a result of partial investment irreversibilities. Ramey and Shapiro (2001) document the partial investment irreversibility in the aerospace industry. On the other hand, the fact that small investments are made suggests that it is irreversibilities rather than fixed costs that are responsible.

[3] The model can be interpreted in terms of common productivity shocks across firms, purely idiosyncratic productivity shocks or any combination thereof.

[4] We focus on manufacturing industry growth data because of the difficulty of identifying large cross-country data sets with service sector data: naturally a study using a broader set of industries would be a useful extension.

Finally, this paper contributes to the literature on industry dynamics over the business cycle. Braun and Larraín (2005) find that industries dependent on external finance grow disproportionately slowly in business cycles. Samaniego and Sun (2015) study a broad set of industry characteristics and show that growth in labor intensive industries is especially sensitive to contractions. This paper focuses on industry depreciation rates and lumpiness, and adds value to the literature by revealing more dimensions of industry technological features underlying aggregate fluctuations – in this case, fluctuations due to uncertainty shocks.

Section 2 describes the model economy. Section 3 provides a quantitative analysis of the model economy and derives empirical predictions. Section 4 outlines the estimation strategy and Section 5 describes the data to be used. Section 6 delivers the empirical results and replicates these using the model economy. Section 7 delivers concluding remarks.

## 2. Model economy

We first explore the interaction of depreciation and uncertainty in the context of a canonical model of firm dynamics with investment irreversibilities. We build on the model of Hopenhayn (1992), where firms experience productivity shocks that affect their optimal input use, and introduce partial investment irreversibilities.[5] Time is discrete and there is a [0, 1] continuum of firms in the industry.

The environment is subject to uncertainty shocks. Variable $v_t \in \{0, 1\}$ is a volatility variable, where $v_t = 1$ is referred to as an *uncertainty shock*. The volatility process evolves according to $v_{t+1}\ F_v(v_{t+1}|v_t)$. In what follows we will define an environment where firms experience idiosyncratic shocks that depend on the level of volatility, yet volatility itself has no effect on the *level* of fundamentals – in this case, expected productivity. Thus, there are no aggregate shocks other than volatility itself.

Firms are subject to idiosyncratic productivity shocks. The volatility variable $v$ affects the evolution of these shocks. Denote a firm's productivity in period $t$ as $z_t \in Z \subset \mathbb{R}$, where $Z$ is bounded and $z_{t+1}\ F_z(z_{t+1}|z_t, v_{t+1})$. Assume $F_z(z_{t+1}|z_t, 1)$ is a *mean-preserving spread* of $F_z(z_{t+1}|z_t, 0)$ for all $z_t \in Z$. Notice this implies that *expected* productivity conditional on $z_t$ does not depend on the realization of $v$. We maintain all other aspects of the environment constant so that uncertainty is characterized solely as a mean-preserving spread of productivity shocks: there are no shocks to levels of economic fundamentals nor other level variables in the system. Any impact on levels of economic activity will be due to changes in the optimal investment policies of firms under different uncertainty regimes.

Firms own their own capital, which they may purchase at price $p_k$ and which depreciates at rate $\delta$. New capital is created through investment of a final good as in a typical growth model, so we set the final good as the numeraire and set $p_k = 1$ accordingly. In order to *remove* capital, however, a share $\kappa \in (0, 1)$ of it is destroyed – so its resale price is only $1 - \kappa$. Parameter $\kappa$ represents the extent of partial investment irreversibility. The presence of $\kappa$ can be interpreted as being due to capital being customized upon installation – so that it does not transfer with full functionality when sold to other firms – or because capital is damaged in the removal process, or because of costs incurred when placing capital on a secondary market.

A given firm closes at the end of each period with probability $\lambda(z_t)$.[6] We assume that $\lambda(\cdot)' \leq 0$: productivity $z_t$ will turn out to be a key determinant of firm size, and it is well known that larger firms are less likely to close, see Evans (1987). Each period a number of entrants $e$ is born, drawing their initial productivity $z_t$ from a distribution $\psi(z_t)$.

Agents in this environment discount the future at rate $i$.

The firm produces a good at price $p$ which is set to one without loss of generality since it only has a level effect. It pays a wage $w$ for each unit of labor it hires.

**Remark 1.** Notice that we have set prices to be constant over time. An equivalent assumption would be to make the pricing process part of the productivity process.[7] One interpretation of our environment is that it describes a small open economy where prices are largely given by conditions in international markets, and where wages are rigid at a cyclical frequency as in for example Shimer (2012). Regardless, the main assumption we wish to ensure is that uncertainty shocks have no level effects, so as to isolate the impact of uncertainty on behavior net of any level effects. As mentioned, the empirical literature makes great effort to identify separately the impact of uncertainty shocks and of level shocks that might coincide with them, see for example Baker and Bloom (2013).

Each period firms observe values of $z_t$ and $v_t$, and choose capital $k_t$ and labor $n_t$ to produce output $y_t$ using the following production function:

$$y_t = z_t k_t^{\alpha} n_t^{\theta}.$$

[5] Bloom et al. (2018) show that uncertainty shocks can be thought of as shocks to the dispersion of innovations to idiosyncratic productivity. Our model builds on their results, adding the two key elements we need to be able to exploit industry variation: irreversible investment and industry differences in depreciation rates.

[6] We assume that when the firm shuts down its value is zero: in a different context (Samaniego, 2006a) argues this will likely be the case in practice as the owners' stake in a failing firm will be eaten up by other claims on the firm's assets.

[7] Note that since producivity $z_t$, wages and prices will enter the firm's investment decisions multiplicatively, it is without loss of generality to assume that any two of them are constant over time as long as their evolution is described by a Markov process.

Firms pay a wage $w$ for each unit of labor they hire, and purchase capital at price one. In the event that a firm decreases its capital holdings, however, it is only able to recover $1-\kappa$ from each unit of capital sold.

Given the stationarity of the economic environment, it lends itself to analysis using recursive optimization techniques. The firm's value function is[8]

$$V(z_t,k_{t-1};\nu_t)=\max_{n_t,k_t}\left\{z_t k_t^{\alpha} n_t^{\theta}-wn_t-(k_t-k_{t-1})-\kappa\max\{0,k_{t-1}-k_t\}+\frac{1-\lambda(z_t)}{1+i}EV(z_{t+1},k_t(1-\delta);\nu_{t+1})\right\},\quad (1)$$

where $k_{t-1}=0$ for newborn firms. The firm earns $z_t k_t^{\alpha} n_t^{\theta}$ but must pay $wn_t$ for labor and $(k_t-k_{t-1})$ for any increase in capital relative to what it had at the beginning of the period. If it decreases its capital it recovers only $(1-\kappa)(k_{t-1}-k_t)$, however. Then with probability $1-\lambda(z_t)$ it survives until the following period, which it begins with capital holdings of $k_t(1-\delta)$. Henceforth we suppress time subscripts for simplicity and use diacritics to indicate the value of a variable the following period, as is standard for recursive problems.

### 2.1. Solution of the firm's problem

Samaniego (2006b) shows in a continuous time context without uncertainty that this class of problems can be analyzed using standard recursive techniques by specifying two different control variables, investment $u\geq 0$ and disinvestment $h\geq 0$, and setting

$$k=k_{-1}+u-h. \quad (2)$$

Extending this insight to our environment, we are able to prove the following:

**Lemma 1.** *The solution to the problem in Eq. (1) is the same as the solution to one where $k$ is not a control variable and is instead determined by (2).*

**Proposition 1.** *Optimal capital $k^*(z,k_{-1};\nu)$ is characterized by two thresholds$\underline{k}^*(z,\nu)<\bar{k}^*(z,\nu)$ that do not depend on $k_{-1}$ such that:*[9]

$$k^*(z,k_{-1};\nu)=\begin{cases}\bar{k}^*(z,\nu) & \text{if } k_{-1}>\bar{k}^*(z,\nu)\\ \underline{k}^*(z,\nu) & \text{if } k_{-1}<\underline{k}^*(z,\nu)\\ k_{-1} & \text{if } k_{-1}\in\left[\underline{k}^*(z,\nu),\bar{k}^*(z,\nu)\right]\end{cases} \quad (3)$$

The proof of Proposition 1 hinges on the fact that the expected future value of the firm $\frac{1-\lambda(z)}{1+i}EV\left(z',k(1-\delta);\nu'\right)$ does not depend at all on $k_{-1}$. This means that, if firms choose to invest or disinvest, their choice of $k$ will not depend on $k_{-1}$, indicating the existence of the thresholds $\underline{k}^*(z,\nu)$ and $\bar{k}^*(z,\nu)$. Showing that $\underline{k}^*(z,\nu)<\bar{k}^*(z,\nu)$ then implies that firms whose value of $k_{-1}$ is below $\underline{k}^*(z,\nu)$ will invest up to $\underline{k}^*(z,\nu)$, and firms whose value of $k_{-1}$ is above $\bar{k}^*(z,\nu)$ will disinvest to $\bar{k}^*(z,\nu)$. Firms in between opt neither to invest nor to disinvest – waiting for further information on their production opportunities $z_t$ and volatility $\nu_t$. The optimal investment rules are characterized by a "range of inaction" $\left[\underline{k}^*(z,\nu),\bar{k}^*(z,\nu)\right]$, where neither investment nor active disinvestment occurs.

### 2.2. Depreciation and uncertainty

To understand how depreciation and uncertainty might interact, consider the following. From Proposition 1, it follows that:

**Corollary 1.** *There are two productivity thresholds $\underline{z}^*(k_{-1},\nu)$ and $\bar{z}^*(k_{-1},\nu)>\underline{z}^*(k_{-1},\nu)$ such that*

$$k^*(z,k_{-1};\nu)=\begin{cases}\bar{k}^*(z,\nu) & \text{if } z<\underline{z}^*(k_{-1},\nu)\\ \underline{k}^*(z,\nu) & \text{if } z>\bar{z}^*(k_{-1},\nu)\\ k_{-1} & \text{if } z_{-1}\in[\underline{z}^*(k_{-1},\nu),\bar{z}^*(k_{-1},\nu)]\end{cases}. \quad (4)$$

In other words, if a firm does not experience much change in productivity, it will likely not invest, so next period it will have the same level of capital minus depreciation – unless it depreciates to below $\underline{k}^*(z,\nu)$, in which case it invests just enough to stay there. If productivity rises above $\bar{z}^*(k_{-1},\nu)$, however, it will invest. Similarly, if productivity declines below $\underline{z}^*(k_{-1},\nu)$, it will disinvest.

Consider that, within the range $[\underline{z}^*(k_{-1},\nu),\bar{z}^*(k_{-1},\nu)]$ (or, equivalently, the range $\left[\underline{k}^*(z,\nu),\bar{k}^*(z,\nu)\right]$) the mismatch between productivity and capital is acceptable in that the firm does not feel it needs to adjust $k$. Near the edges of either of those ranges, however, the mismatch is more significant, so that labor productivity is lower.

[8] We could modify the firms problem so as introduce a price term $p$ in front of $z$ which itself follows a Markov process that depends on uncertainty. However, the value function would depend only on the process for the product $pz$. In the paper we normalize $p=1$ and allow $z$ to follow a Markov process: we could just as well have set $z=1$ and allowed $p$ to change, calibrating it in the same manner. As a result, our paper can be interpreted as one where firms experience price shocks, whether due to demand uncertainty or other factors.

[9] See Veracierto (2008) for a similar result in a context with asymmetric labor adjustment costs.

Suppose that the volatility effect dominates "wait and see" effects, so that the thresholds $[\underline{z}^*(k_{-1}, v), \bar{z}^*(k_{-1}, v)]$ and $\left[\underline{k}^*(z, v), \bar{k}^*(z, v)\right]$ are not sensitive to uncertainty: instead, firms fall outside the intervals more frequently when uncertainty is high. In a low-uncertainty environment, firms will not generally experience large productivity shocks, so from any level of $k$ within the bounds they depreciate gradually until they reach $\underline{k}^*(z, v)$. In a high uncertainty environment, however, large shocks are more likely. Firms with low $\delta$ face some probability that they may need to invest or disinvest. However, since they depreciate gradually, they are more likely to still be in the middle of the range $[\underline{z}^*(k_{-1}, v), \bar{z}^*(k_{-1}, v)]$, so their current value of $k$ will continue to be acceptable for some range of $z$. Firms with high $\delta$, however, shrink rapidly within their inaction bounds and rapidly reach the lower bound of acceptable capital values $\underline{k}^*(z, v)$. In that position, any increase in $z$ means their current capital is too small. If they invest, they will invest to the new threshold $\underline{k}^*(z, v)$, which is the boundary of the acceptable values of capital, i.e. a value far below the myopic optimum. Thus, firms in industries with rapid depreciation tend to be at the low end of the range of acceptable capital, i.e. the greatest acceptable distance from the myopic optimum. When there is higher uncertainty, they are more likely than firms in low $\delta$ industries to continue far from the myopic optimum.

The empirically relevant case is likely to be the one where the volatility effect dominates. The reason is that, while the distribution of idiosyncratic productivity varies with the value of $v_t$, the overall variance in $z_t$ likely swamps any *differences* in those variances across volatility regimes. We will study whether this is the case by calibrating the model in Section 3.

### 2.3. Equilibrium

Define the measure $\mu_t : Z \times \mathbb{R}^+$ to be the measure over firm types $(z_t, k_{t-1})$ at date $t$. Let $I(\cdot)$ be an indicator function that equals one if its argument is true and zero otherwise. The state of the economy evolves according to

$$\mu_{t+1}(\mathbf{z}, \mathbf{k}) = \int_{k \in \mathbb{R}^+} \int_{z' \in \mathbf{z}} \int_{z \in Z} I(k^*(z, k; v_t) \in \mathbf{k}) dF_z\left(z' | z, v_{t+1}\right) d\mu_t(z, k) \tag{5}$$

for all Borel sets $(\mathbf{z}, \mathbf{k}) \subset Z \times \mathbb{R}^+$. If $Z$ is discrete then (5) can be translated accordingly so that $\mathbf{z}$ is any number or subset of numbers in $Z$.

**Definition 1.** An equilibrium of the model economy is an initial condition $(\mu_0, v_0)$ and a sequence $\{\mu_t, v_t\}_{t=1}^{\infty}$ such that $v_t$ follows the Markov process $F_z$ and $\mu_t$ satisfies Eq. (5).

**Proposition 2.** *Suppose* $\sup\{z \in Z\} < \infty$. *An equilibrium of the model economy exists such that output at all firms is finite. Also there exists* $k^{\max} < \infty$ *such that* $\mu_t(\mathbf{z}, k : k > k^{\max}) = 0$ *for* $t \geq 1$.

**Proposition 3.** *Suppose Z has finite values. Then there is a finite set* $K \subset \mathbb{R}^+$ *and* $T < \infty$ *such that* $\mu_t(\mathbf{z}, k : k \notin K) = 0$ *for* $t \geq T$.[10]

Propositions 2 and 3 have the following useful implications. If the support of $z$ is bounded then, regardless of the initial condition $\mu_0$, above a certain date the capital stocks of all firms will be bounded. This is useful for computing the model economy, as we just need to identify the bounds on capital and focus on initial conditions that lie within those bounds. Notice that in our environment there is no notion of a steady state equilibrium unless $F_v$ equals the identity matrix, i.e. the uncertainty state of the economy does not change over time. This implies that our model economy cannot be calibrated by matching certain statistics from the data to those generated in a model steady state: instead, we will have to run large numbers of simulations of the model economy during the calibration process itself.

As well as calibrating the model economy to examine the decision rules, we will also be interested in performing simulations to see whether uncertainty is associated with higher or lower growth. To understand how growth might change depending on the volatility regime, consider that the economic environment is stationary. Moreover, if the realization of $v$ were constant over time, the economy would converge to a steady state. Thus, growth differences between high and low volatility regimes occur *in transition* after the value of $v_t$ has switched.[11] Formally:

**Proposition 4.** *Suppose the realization of* $v_t$ *is constant over time. For each value of v, there exists a unique measure* $\mu^*(v)$ *such that* $\mu_t \to \mu^*(v)$.

Proposition 4 implies that, once $v$ takes on a certain value, the economy converges to an ergodic distribution that corresponds to that value of $v$, where there is zero growth because the distribution of firm types is constant over time. If and when $v$ changes, there is a period of transition as the economy converges to a different ergodic distribution. Differences in growth between high- and low-uncertainty regimes occur during this transition.

Proposition 4 also suggests some reasons why, if the volatility effect dominates the wait-and-see effects as conjectured, industries with higher depreciation might experience disproportionately slow growth when an uncertainty shock arrives. First of all, assume that the low-uncertainty regime is the norm, so that the distribution of productivity $\mu_{t-1}$ would

[10] As with Proposition 1, see Veracierto (2008) for a similar result.

[11] The model could be extended to include a productivity trend, in which case these transitions would correspond to periods of higher or lower growth. However, the behavior of such a model would be the same as this one if it were to be detrended.

typically be close to $\mu^*(0)$ at the moment an uncertainty shock hits. Firms in low-$\delta$ industries are likely to be spread around $\left[\underline{k}^*(z_{t-1},0),\bar{k}^*(z_{t-1},0)\right]$. In contrast, those in high-$\delta$ industries will likely be concentrated around $\underline{k}^*(z_{t-1},0)$. Thus, if $\nu_t=1$, any of these firms getting positive productivity shocks $z_t > z_{t-1}$ (which are more likely than before) will have to invest up to $\underline{k}^*(z_t, 1)$ (a relatively inefficient level and now given more weight because of the high value of $z_t$) whereas in low depreciation industries more of the firms would still be in the interior of $\left[\underline{k}^*(z_t,1),\bar{k}^*(z_t,1)\right]$. In the case the wait-and-see effect dominates, the bands of inaction would widen so that regardless of the rate of depreciation firms that were near the lower threshold $\underline{k}^*(z_{t-1},0)$ would now be in the interior, and would be less likely to experience an investment jump to an inefficient level if $z_t > z_{t-1}$.

It is difficult to provide an analytical result concerning the interaction between depreciation and uncertainty because industry behavior depends on the entire distribution $\mu_t$, which is an endogenous variable. As a result, we turn to quantitative analysis to test whether the above intuition holds out in a calibrated version of our model economy.

## 3. Quantitative analysis

We now calibrate the model to match a typical industry according to US data. Then, we examine how industry growth depends on the presence or absence of volatility shocks.

Our calibration strategy will be somewhat unusual. Typically in a model of this type where there are counterfactual experiments one calibrates the model to match a hypothetical steady state, and then performs experiments. In our case, however, our model industry switches between volatility regimes. Thus we adopt a calibration strategy that does not assume a steady state at any given point in time. Instead, we assume values for certain parameters, and match the remainder by simulating the model economy for a large number of firms over a large number of periods, comparing the moments of the model economy with the statistics we wish to match.

Since we are not calibrating a steady state, our calibration requires the simulation of the model over several periods including both high and low volatility regimes. We simulate the behavior of 1000 firms, over 1400 periods, and discard the first 400 periods to ensure any assumptions on initial conditions are washed out.[12] The volatility process evolves according to $F_v$ and firm values of $z_t$ follow $F_z(\cdot)$. Firm investment and therefore industry growth result from the firms following the optimal investment and employment rules described above. When a firm exits it is replaced by an entrant with a value of $z$ drawn randomly from $\psi(\cdot)$. This is equivalent to setting the number of entrants $e=1000\lambda$.[13] Industry growth is defined as the log growth rate in the sum of output across all the firms.

Notice that this exercise has several interpretations. One is that it measures the difference in industry growth on average in an environment where uncertainty is purely idiosyncratic, i.e. there are no aggregate shocks other than the process $v_t$ itself. Another however is that we are looking at differences in industry growth when $z_t$ at different firms evolves due to common values of $v_t$. When taking averages over large numbers of simulations, these two will yield the same results, thus our results are informative about the impact of uncertainty purely through the idiosyncratic productivity, through aggregate productivity, or any combination of the two, net of any level shocks. This is important because in the data there are several approaches to measuring uncertainty: our simulation results should speak to all of them.

Before listing the calibration parameters, we need to parameterize the distributions $F_v$ and $F_z$ as well as the exit function $\lambda(\cdot)$ and the entry function $\psi(\cdot)$. $F_v$ is a matrix that describes the probability of switching between volatility regimes. We set it equal to:

$$F_v = \begin{bmatrix} 0.878 & 0.0122 \\ 0.4 & 0.6 \end{bmatrix}.$$

This matches the average duration of high and low uncertainty regimes in the data to be considered later.

To complete the calibration process we require values of the set of shocks $Z$. We select a large number of shocks so that inertia in firms' decisions is not mainly guided by inertia built into the calibrated model by simply having few $z$ values. By the same token, we also want the range of $z$ to be fairly spread out, both because we do not want to create excessive inertia and because dispersion in $z$ will result in dispersion in firm sizes in the model (measured using employment), and we wish this dispersion to be large as in the data. We choose 60 values[14] of $z$, log-distributed evenly between 0.5 and 2.

To determine whether this spread of productivity values is sufficiently large, we observe that productivity $z$ is a key determinant of firm size in the model economy. The optimal choice of labor is $n(z,k)=\left(\frac{\theta z k^{\alpha}}{w}\right)^{\frac{1}{1-\theta}}$: firms with higher values

[12] The initial conditions assume that the volatility is low and that firm productivities are random draws from the ergodic distribution of $F_z(\cdot, 0)$.

[13] We have two choices for simulating our model using a large number of discrete firms. One is to have a constant number of firms $e$ entering each period, with extant firms closing with probability $\lambda$, as the model stipilates. In this case, the number of firms in our simulation will change over time, and will add an additional complication to the (already complicated) simulation procedure. The other choice is to simply replace firms as they die randomly. If the number of firms is large enough it doesn't matter which approach we take (the behavior of the two procedures would converge), so we take the less compuatationally-intensive path.

[14] Relates studies typically use under 10 values of $z$ to conserve computational resources when there are many dimensions of heterogeneity as here. We found that working with 30 provided negligible differences to results.

of $z$ will be larger, conditional on the choice of capital $k$. In the US the largest employer is Walmart, with about 1 million US employees at the time of writing.[15] In the calibrated economy the largest firm is also about a million times larger than the smallest. This indicates that the range of productivity values in the model economy is adequately broad.

Then, we assume that $F_z(z'|z, 0)$ is a discretized version of $\log z_{t+1} = \log z_t + \varepsilon_{t+1}$, and we assume that the standard deviation of $\varepsilon_{t+1}$ equals a parameter $\sigma$. When volatility is high we assume that $F_z(z'|z, 1)$ is a discretized version of $\log z_{t+1} = \rho(z_t)\log z_t + \varepsilon_{t+1}$ and that the standard deviation of $\varepsilon_{t+1}$ is $\sigma(1+\omega)$, $\omega > 0$. The factor $\rho(z_t)$ is chosen for each $z$ to ensure that $\int z' dF_z\left(z'|z, 1\right) = \int z' dF_z\left(z'|z, 0\right) \forall z$: in other words, it is set so that $F_z(z'|z, 1)$ is a mean-preserving spread of $F_z(z'|z, 0)$.[16]

As for $\lambda(\cdot)$, we assume that $\lambda(z)$ declines exponentially from $\lambda^{\max}$ down to zero as $z$ rises. This captures the fact that larger firms tend to exit less often. The specific functional form is $\lambda(z) = \lambda^{\max} \frac{\log[\max(z)] - \log[z]}{\log[\max(z)] - \log[\min(z)]}$.

For $\psi(\cdot)$, we assume that $\psi(z)$ declines with $z$, matching the well known fact that entrants are typically smaller than incumbents.[17] The specific functional form is $\psi(z) = \frac{(\max(z) - z) + \bar{\psi}}{\sum_{z' \in Z} \psi(z')}$. As $\bar{\psi} \to \infty$, the distribution becomes uniform.

The following parameters remain to be calibrated: $\alpha$, $\theta$, $i$, $\delta$, $e$, $w$, $\bar{\psi}$, $\lambda^{\max}$, $\kappa$, $\sigma$ and $\omega$.

We set $e = w = 1$ without loss of generality. These are all essentially scale parameters and do not affect the response of the model economy to uncertainty.

We set $\alpha = 0.63$ and $\theta = 0.25$, as in Samaniego (2010). We set $i$ to equal 2%, a standard number in the business cycle literature.

As a benchmark we set $\delta = 0.0827$. This is the median value across the industries in the data to be presented in more detail later.[18] Later we consider $\delta \in [0.06, 0.11]$, which is the empirically relevant range in our data.

An important parameter is $\omega$, the extent to which the standard error of productivity shocks is larger when volatility is high ($\nu_t = 1$) than when it is low ($\nu_t = 0$). To calibrate $\omega$, we draw on Bloom et al. (2018). They estimate an AR(1) process for productivity and find that the variance of the error process is 76% higher during the Great Recession than in the years before. This is equivalent to their standard deviation rising by about 33%, suggesting that $\omega = 0.33$. However, given its severity, it is possible that the Great Recession was an unusually large uncertainty shock. Thus, we set the uncertainty shock $\omega = 0.22$ as a benchmark, two thirds of what the Great Recession suggests. Later we explore the impact of varying $\omega$.

It remains to calibrate the parameters $\sigma$, $\kappa$, $\bar{\psi}$ and $\lambda^{\max}$. We select these parameters using simulated annealing (Bertsimas and Tsitsiklis, 1993) so as to match some key moments of the data on industry dynamics:

1. The share of entrants that are "small", i.e. one third the size of the average firm or less in terms of employment – see Samaniego (2008).
2. The 5-year exit rate of new firms – see Evans (1987).
3. The average 5-year exit rate – see Evans (1987).
4. The share of firms experiencing a lump in investment – defined as in Doms and Dunne (1998) as an event when the growth in the capital stock exceeds 30%. They define growth in the capital stock as investment (excluding depreciation) divided by the average of the capital stock last period and the new capital stock. The number of firms in the data experiencing "lumps" is 6%.[19] For the model, define the "lumpiness" function $\Lambda : \mathbb{R}^2 \times \{0, 1\} \to \{0, 1\}$ as follows. If in period $t$ the firm chooses $k_t = k^*(z_t, k_{t-1}; \nu)$. since it started the period with $k_{t-1}$, its capital at the same stage previous period (i.e. before it depreciated) must have been $k_{t-1}/(1-\delta)$. Then, the proportional increase in capital is $g(z_t, k_{t-1}; \nu) \equiv \frac{k^*(z_t, k_{t-1}; \nu) - k_{t-1} \div (1-\delta)}{0.5 \times \left(k^*(z_t, k_{t-1}; \nu) + k_{t-1} \div (1-\delta)\right)}$. Notice that the denominator is the average of the capital stock at the two dates, as in Doms and Dunne (1998). Then, we define $\Lambda$ so that

$$\Lambda(z, k_{-1}; \nu_t) = \begin{cases} 0 & \text{if } g(z_t, k_{t-1}; \nu) < 0.3 \\ 1 & \text{if } g(z_t, k_{t-1}; \nu) \geq 0.3 \end{cases} \tag{6}$$

The share of firms experiencing a lump in investment at any date $t$ is then the share of firms for whom $\Lambda(z, k_{-1}; \nu_t) = 1$.

The model matches these statistics reasonably well in spite of its simplicity. We also find that the model reasonably matches the share of investment that occurs in lumps, which in the data is 25%. In the model it is a bit lower at 19%, not far off.

[15] See https://www.usatoday.com/story/money/business/2013/08/22/ten-largest-employers/2680249/, last checked 09/05/2019.

[16] Notice that for low uncertainty we approximate a random walk, and for high uncertainty we have persistence parameters that are set to ensure uncertainty is a mean preserving spread. The reason for the random walk assumption is that, given that we are using a bounded range for $z_t$, there will be mean reversion regardless. When we generated several thousand values of $z_t$ we found that the computed autocorrelation was about 0.72. This is similar to Samaniego (2010), which has lumpy investment due to an irreversible technology updating decision rather than a simple investment irreversibility as we have here.

[17] This follows from the following observations. First, as discussed above, $z$ is linked to firm size. Second, the distribution of productivity $z$ has an ergodic distribution which will necessarily be clustered towards the middle as the autocorrelation of idiosyncratic productivity in the calibrated model is less than one (see above).

[18] The data are based on US manufacturing industries, with depreciation measured by the US Bureau of Economic Analysis.

[19] The published version of Doms and Dunne (1998) reports a different number, but entrants and exiters are excluded from that sample. Six percent is the value in the panel that includes entry and exit. This is also the median industry value in Compustat.

**Table 1**
Calibrated parameter values.

| Parameter | Value | Source |
|---|---|---|
| $\alpha$ | 0.63 | Samaniego (2010) |
| $\theta$ | 0.25 | Samaniego (2010) |
| $i$ | 0.02 | Business cycle literature |
| $\delta$ | 0.0827 | UNIDO data |
| $\bar{\psi}$ | 4 | See text |
| $\lambda^{max}$ | 0.153 | See text |
| $\kappa$ | 0.1225 | See text |
| $\sigma$ | 0.0225 | See text |
| $\omega$ | 0.22 | See text |

**Table 2**
Model Statistics.

| Statistic | Model | Data | Source |
|---|---|---|---|
| Small entrants | 0.72 | 0.74 | Samaniego (2008) |
| Average exit | 0.24 | 0.22 | Evans (1987) |
| Entrant exit | 0.37 | 0.37 | Evans (1987) |
| Lumpy firms | 0.06 | 0.06 | Doms and Dunne (1998) |
| Lumpy investment | 0.19 | 0.25 | Doms and Dunne (1998) |

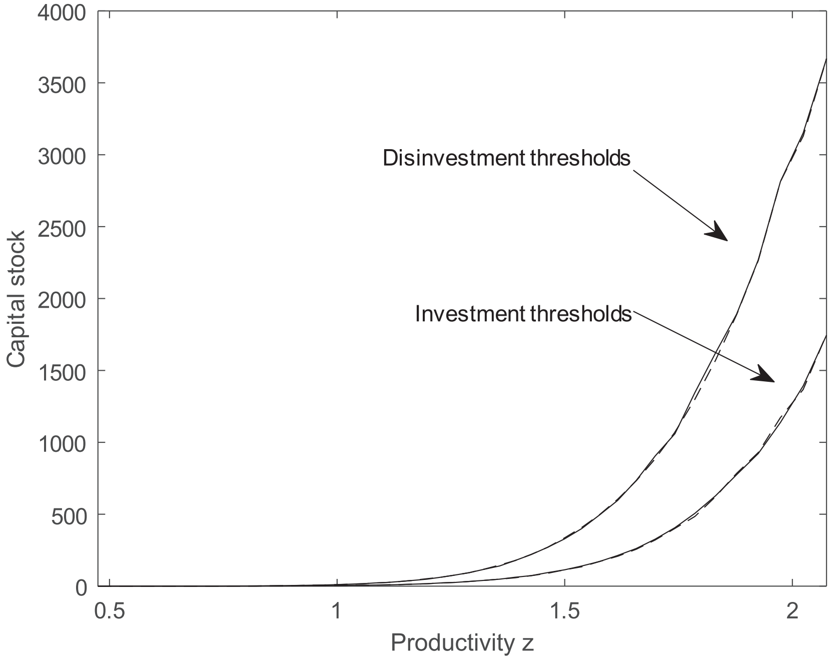


**Fig. 1.** Decision rules. The upper lines are the disinvestment thresholds $\bar{k}^*(z; v)$ for given values of $z$ and $v$. The lower lines are investment thresholds $\underline{k}^*(z; v)$ for given values of $z$ and $v$. The thick lines assume low volatility and the dashed lines represent high volatility.

Interestingly, the extent of irreversibility in the calibrated model is about 12%. This is fairly small: for example, Ramey and Shapiro (2001) find larger values in their study of the aerospace industry. Nonetheless we will find that an irreversibility cost of this magnitude has a significant impact on industry dynamics.

Fig. 1 displays the decision rules – i.e. the investment and disinvestment thresholds – for a firm in the calibrated economy. We find in the calibrated economy that, as proven, the disinvestment threshold $\bar{k}^*(z, v)$ is more than the investment threshold $\underline{k}^*(z, v)$ for any $z, v$. Comparing across different levels of volatility, we find that $\underline{k}^*(z, 0) > \underline{k}^*(z, 1)$ for most values of $z$: when volatility is higher, firms invest more conservatively. We also find that $\bar{k}^*(z, 0) < \bar{k}^*(z, 1)$ for most values of $z$: when volatility is higher, the threshold for firms to disinvest is higher. At the same time, Fig. 1 shows that the differences in these thresholds across different levels of volatility are quite small – at least for the benchmark parameterization. This suggests that the main impact of volatility in this environment is not to change the decisions variables regarding the conditions under which to invest or disinvest. Rather, its main impact is to affect the frequency with which firms hit one or other of the thresholds.

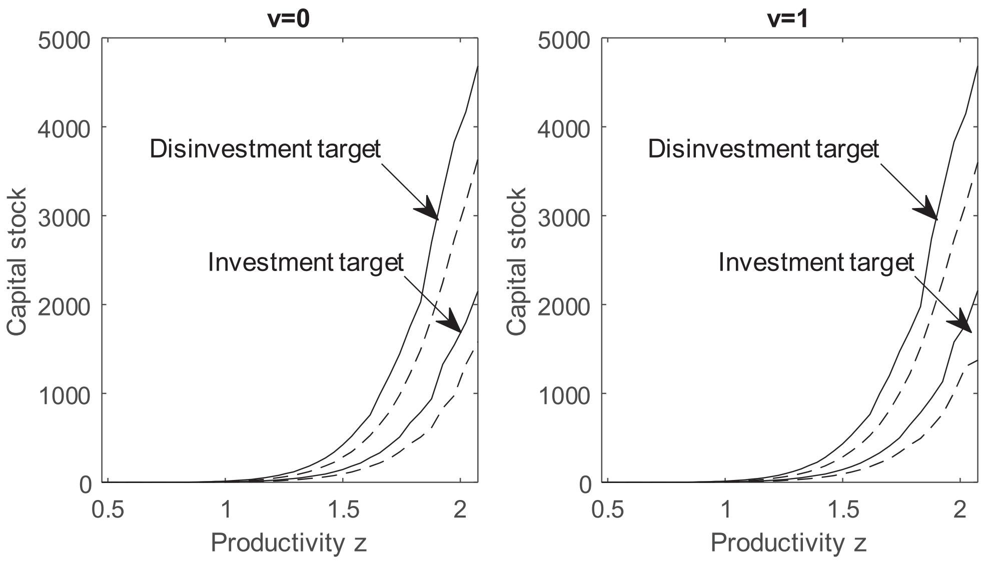


**Fig. 2.** Decision rules. The thick lines represent decision rules when $\delta$ equals 0:065, and the dashed lines when $\delta$ equals 0:095. In each panel, the upper lines are the disinvestment thresholds $\bar{k}^*(z; v)$ for given values of $z$ and $v$. The lower lines are investment thresholds $\underline{k}^*(z; v)$ for given values of $z$ and $v$. The left panel represents low volatility and the right panel represents high volatility.

In Fig. 2 we examine how these decision rules are affected by changes in $\delta$. Thick lines represent decision rules when $\delta = 0.065$, and dashed lines assume that $\delta = 0.095$, towards the low and high ends of the empirically relevant range, respectively. The first observation is that, while volatility appears to have very little impact on decision rules, depreciation leads both investment and disinvestment thresholds to decline significantly. The bands of inaction – the vertical distance between the investment and disinvestment thresholds for a particular productivity value – do not change much in size. Fig. 2 also shows that firms will tend to be *smaller* under high depreciation.

Consider a firm that has a value of $z$ and a capital stock $k \in \left[\underline{k}^*(z, v), \bar{k}^*(z, v)\right]$. When volatility is low, $z$ changes little so the firm's position in the figure moves south until it reaches the investment target $\underline{k}^*(z, v)$, and stays there until $z$ changes. When $\delta$ is low, this movement is slow, so the firm will spend a lot of time between the two bounds where it operates relatively efficiently. When $\delta$ is large, this movement is rapid, so the firm will spend a lot of time at the threshold $\underline{k}^*(z, v)$ where its scale is relatively inefficient.

When volatility is high, however, the firm instead is also moving side to side significantly, and is thus more likely to end up outside the bounds and having to invest or disinvest. For firms with low $\delta$, since they spend more time in between the bounds, there is a range of $z$ around them for which their capital remains a reasonably good match. Firms with high $\delta$, however, will be bunched up near the lower threshold $\underline{k}^*(z, v)$. If $z$ declines to any $z' < z$, its value of capital will likely end up in the middle of the bounds. On the other hand, if $z$ rises to any $z' > z$, it will have to invest to $\underline{k}^*(z', v)$ – not in the middle of the bounds and thus far from myopic efficiency. In other words, when $\delta$ is low a firm's $k$ is likely to be reasonably efficient for both high and low shocks, whereas when $\delta$ is high a firm responds inefficiently to positive shocks, leading to weaker performance.

### *3.1. Experiments*

Having calibrated these parameters, we measure industry growth in the simulated economy in high and low volatility regimes. We compute this separately for a variety of different values of $\delta$. We define the empirically relevant range of $\delta$ as that we observe in the data to be presented later, from about 6% to about 11%. We compute this by running simulations of a large number of firms as described earlier. It is worth underlining that, while our volatility process is described as being aggregate and having an impact on idiosyncratic productivity, the same statistics obtain if all firms have common shocks to $v$ and/or to $z$ over a large number of runs.

Fig. 3 displays how growth in the high and low uncertainty regimes varies on average depending on $\delta$. For each depreciation rate, the solid line represents average industry growth when uncertainty is low, and the dashed line represents industry growth when uncertainty is high. The two lines are more-or-less mirror images of each other. Recall that, according to Proposition 4, once $v$ takes on a certain value, the economy converges to an ergodic distribution that corresponds to that value of $v$, where there is zero growth because the distribution of firm types is constant over time. If and when $v$ changes, there is a period of transition as the economy converges to a different ergodic distribution. Differences in growth between high- and low-uncertainty regimes occur during this transition. Since the economic environment is stationary, over time there is no growth, so differences between regimes must be close to symmetric.

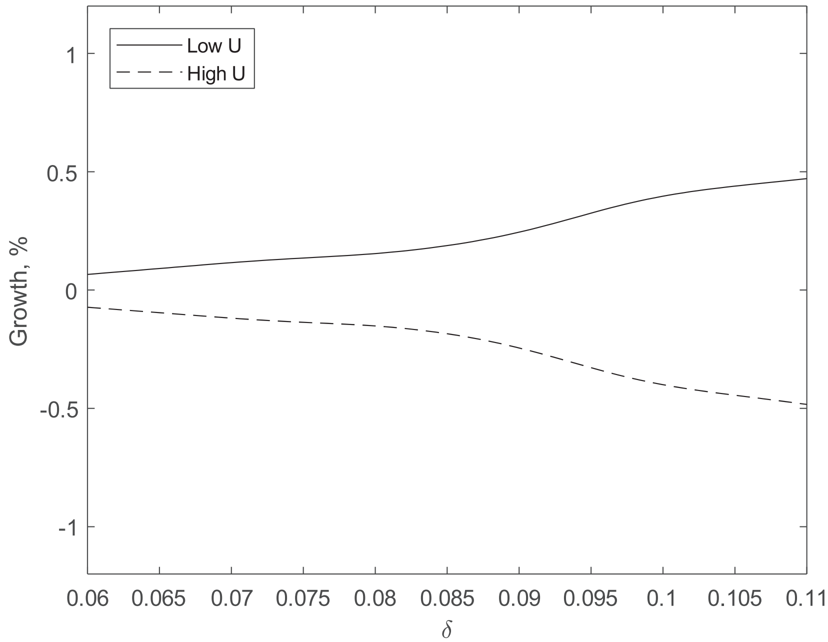


**Fig. 3.** Response surfaces for average growth when uncertainty is high and when uncertainty is low, as a function of $\delta$. The values were computed in simulations of the model economy for 100 values of $\delta$.

Several observations stand out from Fig. 3. First, when $\delta$ is low firms tend to grow slower when uncertainty is high than when uncertainty is low. However the difference is small. In contrast, as hypothesized, the difference in industry growth between uncertainty regimes is much larger when $\delta$ is high. Considering that the consensus in the literature is that high uncertainty depresses *aggregate* growth, this finding suggests that the aggregate impact of uncertainty must be mainly driven by the impact of uncertainty on high-depreciation industries. The model suggests that these industry differences are an important part of the impact of uncertainty on the aggregate economy.

Another implication is that the impact of uncertainty on different economies may depend on their *industry composition*. Countries which, for whatever reason, specialize in low-$\delta$ industries may be insensitive to uncertainty shocks, whereas countries which specialize in high-$\delta$ industries may be more sensitive to uncertainty.

As a result, Fig. 3 suggests an empirical test of the model: testing whether industries with high depreciation rates display grow disproportionately slowly compared to other industries in the presence of uncertainty shocks. A test of this kind can be used to test the real options channel of the impact of uncertainty shocks on economic growth.

Fig. 4 suggests why this may be happening: in industries with high $\delta$, labor productivity growth is slower when $v$ is high. Since labor is allocated efficiently (conditional on $k$ and $z$) this must be because capital is significantly mismatched relative to the myopic optimum as a result of inertial investment in those industries when uncertainty is high. When uncertainty is low, there is less mismatch simply because one factor of mismatch, the volatility of productivity, is less important.

Another prediction of our model is that high $\delta$ is related to more frequent lumps in investment, because it leads to more frequent mismatches between productivity and capital. Fig. 5 illustrates this prediction holds in the context of the model. This suggests that another way to test our mechanism would be to see whether in the data industries with higher $\delta$ also experience more frequent investment lumps, as in Fig. 4.

Finally, if high $\delta$ is related to high lumpiness, we have an additional prediction we might use to test the real options channel of the impact of uncertainty shocks on economic growth: seeing whether industries with high *investment lumpiness* grow disproportionately slowly compared to other industries in the presence of uncertainty shocks. Indeed, Fig. 6 shows that the calibrated economy displays this feature.

Finally, it is worth noting that these effects are for *empirically reasonable values* of depreciation rates. Suppose instead that $\delta = 1$. In this case, since capital depreciates fully every period, no firm every pays the irreversibility cost $\kappa$. Thus, there is no scope for misallocation (given that parameter value), and firms set capital $k$ to equal their optimal values (conditional on $\delta$) – i.e. there is no range of inaction. Substituting this into the production function, the production function will be a function of $z^{\frac{1}{1-\alpha}}$, i.e. a convex function of $z$. It is easy to show that the expected value of output under such circumstances is increasing in uncertainty. Thus firms will tend to grow faster in a high uncertainty regime relative to a low uncertainty regime.

**Example 1.** More formally, suppose that $\delta = 1$, and that the productivity process for $z_{t+1}$ does not depend on $z_t$. In this case $k$ will be chosen optimally so that $k^*(z, v) \propto z^{\frac{1}{1-\alpha}}$, and output will be $xz^{\frac{1}{1-\alpha}}$, where $x$ is a constant. As a result, average

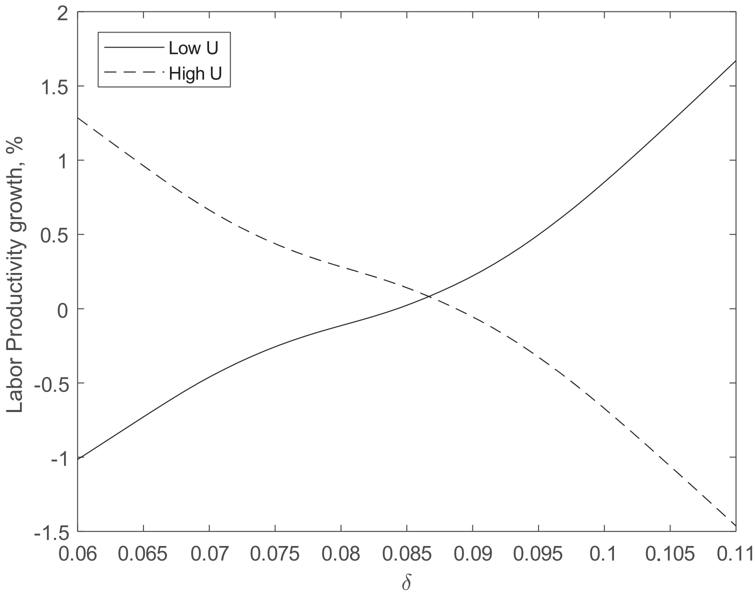


**Fig. 4.** Average labor productivity growth when uncertainty is high and when uncertainty is low as a function of $\delta$. The values were computed in simulations of the model economy for 100 values of $\delta$.

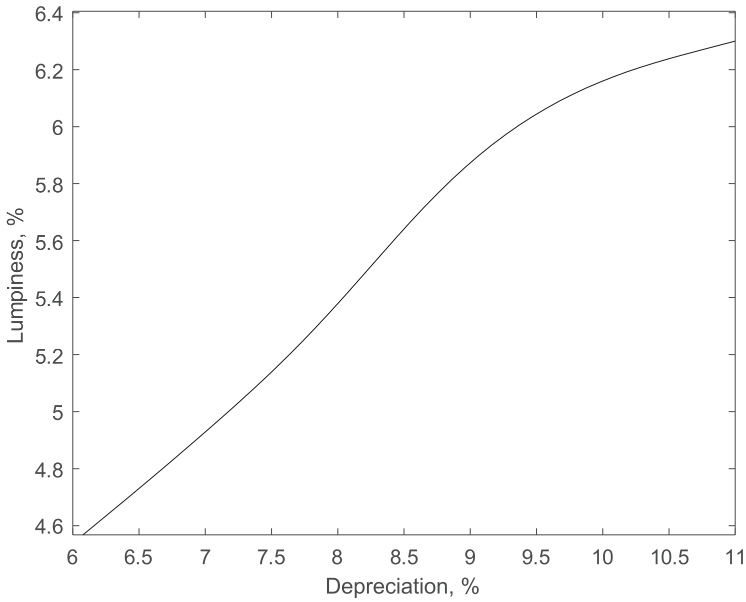


**Fig. 5.** Relationship between depreciation and the share of rms experiencing an investment lump on average in the calibrated economy.

output will be

$$Y(\nu) = \int xz^{\frac{1}{1-\alpha}} dF_z(z, \nu) = x \int z^{\frac{1}{1-\alpha}} dF_z(z, \nu)$$

We have that $\int zdF_z(z, 0) = \int zdF_z(z, 1)$ by assumption. Observe that $z^{\frac{1}{1-\alpha}}$ is a convex transformation of $z$: thus, $Y(0) < Y(1)$ and the economy will grow when volatility increases (and shrink when volatility decreases): uncertainty promotes growth. If we allow the productivity process for $z_{t+1}$ to depend on $z_t$, the economy would transit more slowly between the ergodic distributions of $F_z(\cdot|z, 0)$ and $F_z(\cdot|z, 1)$ (which will be a mean-preserving spread of $F_z(\cdot|z, 0)$) but the environment with $\nu = 1$ would experience faster growth than when $\nu = 0$ along this transition.

Indeed, Fig. 7 shows that this is the case: as $\delta$ approaches unity, uncertainty becomes *beneficial* to growth. This is consistent with Oi (1961), Hartman (1972) and Abel (1983), who find that when firms can adjust investment at low cost in the

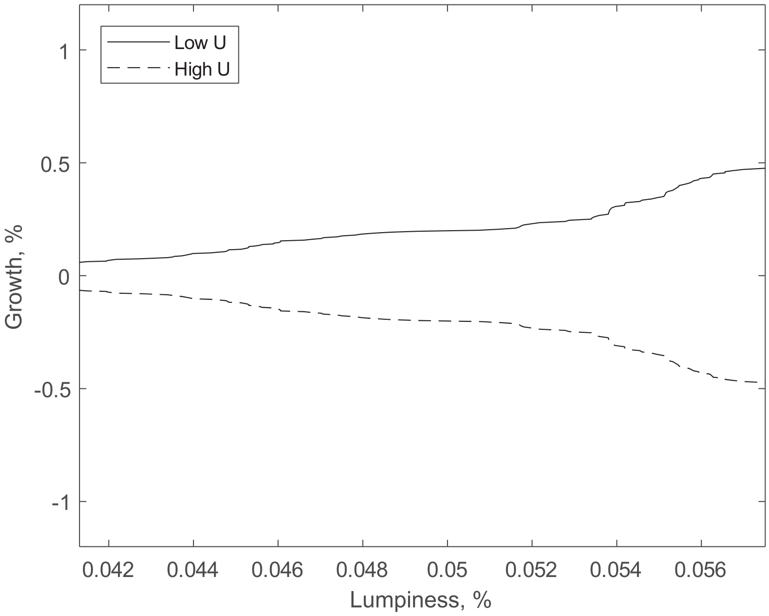


**Fig. 6.** Response surfaces for average growth when uncertainty is high and when uncertainty is low, as a function of lumpiness. The values were computed in simulations of the model economy for 100 values of $\delta$. The graph represents dierent combinations of observed lumpiness and industry growth.

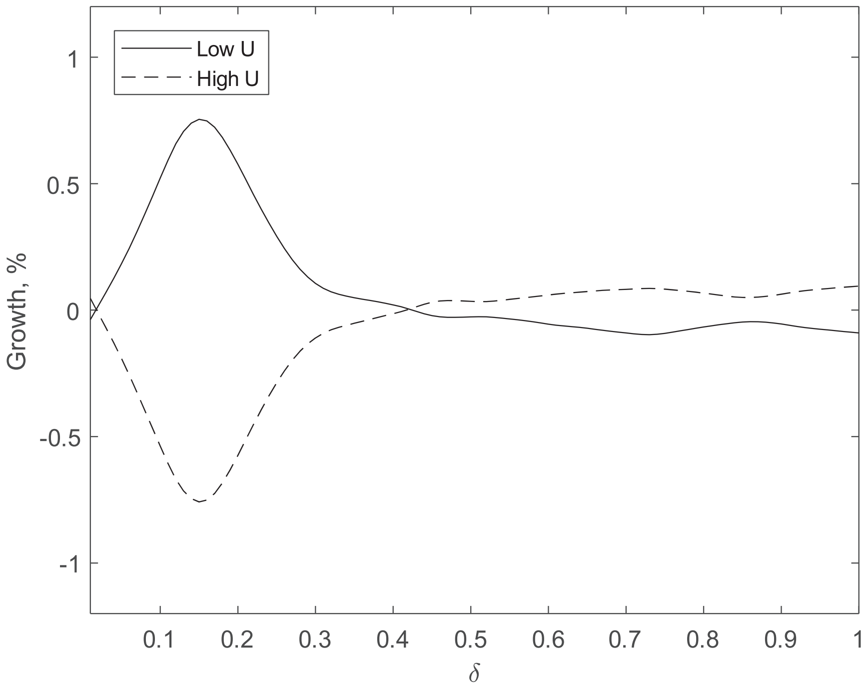


**Fig. 7.** Response surfaces for average growth when uncertainty is high and when uncertainty is low, as a function of $\delta$. The values were computed in simulations of the model economy for 100 values of $\delta$.

face of uncertainty, uncertainty may benefit investment and growth. What happens is that for empirically relevant ranges of $\delta$ the inflexibility induced by the adjustment cost $\kappa$ is significant, so the misallocation effect dominates. It is interesting that the value of $\delta$ above which Oi-Hartman-Abel effects dominate is about 0.4, well outside the empirically relevant range. In this paper the empirically relevant range is about 0.06 to 0.116, based on our manufacturing data. The turning point in Fig. 7 after which the negative interaction of uncertainty and growth starts to weaken is around 0.15, again outside the empirically relevant range.

In what follows, we will test what we see as the key predictions of our model of industry dynamics:

1. lumpiness and depreciation should be positively related across industries;
2. industries with high depreciation should grow disproportionately slowly in the presence of uncertainty shocks; and
3. industries with high lumpiness should grow disproportionately slowly in the presence of uncertainty shocks.

## 4. Empirical strategy

Our objective is to see whether certain industry technological characteristics – namely capital depreciation rates and lumpiness rates – lead industries to be more sensitive to uncertainty shocks. One approach to do this would be to use firm level data. However, that approach carries several challenges. Depreciation would depend on the mix of capital goods (since depreciation rates vary across types of capital) and could be endogenous, assuming it could be measured at the firm level. The same applies to the frequency of investment "lumps," since investment is clearly a decision variable of the firm. It is not clear what would be the correct way to adjust for such endogeneity even if an appropriate data set containing these variables at the firm level were to exist.

As a result, we use a different approach. We build on the extensive differences-in-differences literature that posits that technological factors – such as depreciation rates – vary across industries in a systematic manner.[20] If this variation is more-or-less preserved across countries, then an interaction of an industry technological variable (such as depreciation rates) with a country measure of uncertainty should indicate that the technological variable and uncertainty interact in a particular way. This approach avoids the complications of the firm level approach, and draws on easily obtainable data for purposes of replication and extension.

To be precise, we estimate the following equation:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta(UncertaintyShock_{c,t-1} \times X_i) + \alpha Controls_{i,c,t} + \epsilon_{c,i,t} \tag{7}$$

In Eq. (7), $Growth_{c,\,i,\,t}$ is a measure of growth in industry $i$ in country $c$ at date $t$. The dummy variables $\delta_{i,c} + \delta_{i,t} + \delta_{c,t}$ capture all date- or country-specific factors that might affect growth in industry $i$, or factors affecting overall growth in country $c$ at a particular date, including all economy-wide shocks. All that remains are factors that specifically affect growth in industry $i$ in country $c$ at date $t$.

$X_i$ is a technological factor of interest that characterizes the production function of industry $i$ (such as the depreciation rate), and which is hypothesized to interact with uncertainty. It appears in Eq. (7) interacted with $UncertaintyShock_{c,t-1}$, which is an uncertainty shock measured at date $t-1$. Thus the coefficient $\beta$ is the differential impact of industry characteristic $X_i$ on industry growth when uncertainty in the previous year is high. Pooling data for many industries, years and countries gives our estimation strategy more statistical power and gives our results more generality.

Since $\beta$ captures the difference in industry growth in uncertain times relative to normal times for industries with different levels of $X_i$, $\beta \neq 0$ indicates that growth in industries with high $X_i$ is more sensitive to uncertainty. For example, if $X_i$ measures the depreciation rate of capital, then $\beta < 0$ would indicate that industries that use rapidly depreciating capital grow particularly *slowly* when there is uncertainty. Conversely $\beta > 0$ would indicate that such industries grow particularly *fast* when there is uncertainty.

Our control variables $Controls_{i,c,t}$ include an interaction $(LevelShock_{c,t-1} \times X_i)$. The variable $LevelShock_{c,t-1}$ is a country- and year-specific measure of the level of economic activity at date $t-1$. We interact it with the technological variable $X_i$ also because, as is well known in the literature, increases in uncertainty may coincide with downturns in economic activity, and the level effects may interact with technological variables too. Thus we wish to condition on first moment measures of the level of economic activity. The overall level is already captured by the dummy $\delta_{c,t}$, so the coefficient $\beta$ captures any residual industry-specific impact of level shocks (including the impact of uncertainty shocks on levels of overall economic activity) on industry growth based on technological measure $X_i$.

The need to condition on level shocks raises the possibility of endogeneity: the level and uncertainty effects may be correlated and also endogenous. See Baker and Bloom (2013). One way we handle this is precisely by looking at industry growth rather than aggregate growth. Any omitted variables that cause both growth and uncertainty (as well as level shocks) should be picked up by the $\delta_{c,t}$ indicators. In addition, we condition on possible interactions of level effects and the technological variables. The potential endogeneity of uncertainty is already controlled for because specification (7) is based on *past* uncertainty, and current year growth cannot cause past uncertainty.

Since the number of group-specific effects in this estimation equation is very large,[21] the computational cost of estimating (7) is significant. Instead, we proceed by subtracting from all dependent and independent variables the mean value for each $(c,\,t)$, $(i,\,t)$ and $(c,\,i)$ pair so that the dummy variables $\delta_{i,c}$, $\delta_{i,t}$ and $\delta_{c,t}$ are removed from the estimation equation. We call these variables $\widehat{Growth}_{c,i,t}$, $\left(\widehat{UncertaintyShock}_{c,t-1} \times X_i\right)$ and $\widehat{Controls}_{c,i,t}$. Then, we estimate (7), using the de-meaned

[20] See Rajan and Zingales (1998), Dell'Ariccia et al. (2008) and Samaniego and Sun (2015) inter alia.

[21] Since there are about 60 countries, 28 industries and 42 years, we would have over 50,000 fixed effects in a balanced panel.

variables, and without $\delta_{i,c} + \delta_{i,t} + \delta_{c,t}$ among the regressors. Samaniego and Sun (2015) show that this is equivalent to estimating the following specification:

$$\widehat{Growth}_{c,i,t} = \beta(\widehat{UncertaintyShock}_{c,t-1} \times X_i) + \alpha\widehat{Controls}_{i,c,t} + \epsilon_{c,i,t} \tag{8}$$

The exact error structure for this procedure is not known so we use a variety of approaches, finding that the results are robust. These methods include bootstrapping, allowing for heteroskedasticity using the Huber-White method, clustering by industry, and allowing for autocorrelated errors.[22] The results reported use bootstrapped errors.

Country- or date-specific factors that affect a given industry will be absorbed by the indicator variables in Eq. (7) – including the impact of uncertainty on overall growth. Then, any interaction between uncertainty and $X_i$ indicates that characteristic $X_i$ is important for understanding how uncertainty shocks impact industry growth.

### 4.1. Discussion

Some further comments on our estimation strategy are in order. First, we seek industry technological indicators $X_i$ that are representative of the technology of production across countries. Suppose for example that $X_i$ represents the frequency of lumpy investment. The identification strategy does not require measures of the *observed* lumpiness at firms in industry $i$ in each country, nor at each date. Observed lumpiness is not a strictly technological variable, as it may be affected by current economic conditions such as the level of uncertainty at date $t$ in country $c$, or by country conditions including the frequency of uncertainty shocks in country $c$. Instead, we seek a benchmark measure of lumpiness that firms in industry $i$ would adopt in a relatively undistorted environment – which, when distorted by uncertainty in country $c$ at date $t$, might particularly impact firms in industry $i$. Following the related literature, we will measure the technological variables $X_i$ such as depreciation using US data and, where possible, using data on publicly traded firms in the US, whose technological choices are unlikely to be distorted by financing difficulties or by other frictions in normal times – see Rajan and Zingales (1998), Ilyina and Samaniego (2011) and Samaniego and Sun (2015) among others.[23]

We also explore whether our industry-based strategy finds evidence of any important role for financial markets in either the origination or propagation of uncertainty shocks, a key question in the literature.[24] This is important because of our focus on depreciation and on investment lumpiness. Theory suggests that industries with rapid depreciation and where capital is more likely to be firm-specific are also those where the ability to use capital as collateral to raise external funds is weakest – see Hart and Moore (1994). In addition, Ilyina and Samaniego (2011) find that investment lumpiness is linked to external finance dependence. As a result, the risk-aversion theory of uncertainty, whereby firms experience higher borrowing costs in uncertain times,[25] might also predict that these industry variables interact with uncertainty shocks. Thus, we need to verify that our results are due to real options considerations, and not due to financial channels that might also apply to these industry technological characteristics.

We verify that our results are not due to the risk-aversion theory in four ways. First, we include a measure of *external finance dependence* (Rajan and Zingales, 1998) in our list of technological variables. Second, we also look at R&D intensity, which Ilyina and Samaniego (2011) argue is the technological basis of external finance dependence. Third, we use asset fixity as additional technological variable that the literature finds to be sensitive to financial frictions. Fourth, we condition on an interaction of technology with financial crisis indicators (Laeven and Valencia, 2013). These might be expected to interact with depreciation and lumpiness too if financial channels are important.

## 5. Data

We require a measure of uncertainty that can be measured for many countries. Similar to much of the literature, we measure uncertainty using the average standard deviation of daily stock returns over the period, drawing from Baker and Bloom (2013). Stock market indices are available for each country from the Global Financial Database.

We measure industry growth $Growth_{c,\,i,\,t}$ using the log change in the Laspeyres production index. It is reported for 28 manufacturing industries based on the ISIC-revision 2 classification in INDSTAT3. We use only countries for which there are at least 10 years of observations. To avoid the influence of outliers, the 1st and 99th percentiles of $Growth_{c,\,i,\,t}$ are eliminated from the sample. We lose some countries as uncertainty data in Baker and Bloom (2013) are not available for the whole globe. This generates a sample of 56 countries from 1970 to 2012. The panel is unbalanced, and the sample sizes vary across countries and industries as some of the data were not reported by national statistical agencies. The Appendix lists

[22] Bertrand et al. (2004) argue that differences-in-differences specifications may suffer from problems with autocorrelated errors. However this relates to specifications where there is a persistent treatment vs. non-treatment variable. In our context there is no such problem because of the constellation of country-time and industry-time dummies. When we estimate the specification allowing for autocorrelated errors the estimated autocorrelation coefficient is small, around 0.01.

[23] Even so, we do find that our technical measures are correlated across time and space. Regarding time, Ilyina and Samaniego (2011) show that the rankings of industries according to most of our industry measures computed by decades persist over the period (1970–2000). Regarding country variation, the data simply do not exist to measure industry characteristics in each country separately.

[24] See for example Arellano et al. (2012) or Gilchrist et al. (2014).

[25] See Gilchrist et al. (2014), for example.

**Table 3**
Correlation Matrix of Industry Technological Characteristics.

| Industry variable | EFD | DEP | RND | FIX |
|---|---|---|---|---|
| DEP | 0.09 | – | – | – |
| RND | 0.79** | 0.09 | – | – |
| FIX | 0.09 | 0.19 | 0.39** | – |
| LMP | 0.50** | 0.39** | 0.61** | 0.73** |

*Note:* $EFD_i$ (external finance dependence), $DEP_i$ (depreciation), $LMP_i$ (investment lumpiness), $RND_i$(R&D intensity) and $FIX_i$ (fixity) are the average of 70 s, 80 s and 90 s from Ilyina and Samaniego (2011). ** significance level 5%

the country sample and the number of observations for each country. Data from 1970–2004 are from INDSTAT3, while data from 2005–2012 are from the successor dataset INDSTAT4. The United States is not included in the regressions because it is the benchmark economy for measuring industry technological variables.

Regarding industry variables, we follow the conventions of growth theory by defining "technology" in terms of the production function. We identify industry differences in the production technology using factor intensities, or using the qualitative attributes of factors of production, an approach that dates back to at least the seminal work of Cobb and Douglas (1928). For example, we assume that differences between the technology for producing plastic products (ISIC 356) and the technology for producing tobacco (ISIC 314) can be described in terms of the former experiencing higher depreciation rate of capital than the latter. Our technology indicators include measures of capital depreciation, the lumpiness of investment, external finance dependence, R&D intensity and asset fixity, as explained below.

The different technological measures are calculated using U.S. data and are assumed to represent real industry technological characteristics in a (relatively) unregulated and financially frictionless environment. Technological differences among industries are assumed to be persistent across countries, meaning that the rankings of these indices are stable across countries (or would be in the absence of uncertainty shocks), although index values in each country do not necessarily have to be assumed to be the same.[26] See Rajan and Zingales (1998), Ilyina and Samaniego (2011) and Samaniego and Sun (2015) for related discussions.

Our industry technological indicators are:

- *Capital depreciation*: we compute the industry rate of depreciation ($DEP_i$) using the BEA industry-level capital flow tables.
- *Investment lumpiness:* As in Ilyina and Samaniego (2011), lumpiness ($LMP_i$) is defined as the average number of investment spikes per firm during a decade in a given industry, computed using Compustat data. A spike is defined as an annual capital expenditure exceeding 30% of the firm's stock of fixed assets, as in Doms and Dunne (1998).

One concern with our estimation strategy is that the rate of capital depreciation might be related to a firm's (in)ability to raise external funds. In a classic paper, Kiyotaki and Moore (1997), argue that the depreciation is a key determinant of whether or not capital serves well as collateral. To the extent that this is the case, firms in industries that experience rapid depreciation might be more sensitive to financial conditions, so that our estimation might be detecting financial channels through which uncertainty affects industry growth, not the real options channels emphasized in our paper. We follow several approaches to showing that financial channels are not responsible for our findings, one of which is to use measures that have been widely used in the literature to proxy for the financial sensitivity of industries. These are:

- *External finance dependence*: Many studies such as Rajan and Zingales (1998) find that the industry tendency to draw on external funds is related to growth and/or the business cycle. As such, any interaction of this variable with uncertainty could indicate the importance of financial channels for the propagation of uncertainty shocks. We measure external finance dependence ($EFD_i$) as the share of capital expenditures not financed internally, see Rajan and Zingales (1998) for details.
- *R&D intensity*: R&D intensity is closely related to finance dependence (Ilyina and Samaniego, 2011;2012), so it too could interact with uncertainty if financial sources or channels are important. R&D intensity ($RND_i$) is measured as R&D expenditures over total capital expenditures, as reported in Compustat.
- *Asset fixity*: Braun and Larraín (2005) argue that asset fixity is a key determinant not of the need for external finance but of the *ability* to raise external funds, on the assumption that fixed assets serve as collateral better than intangibles. As a result, an interaction of fixity with uncertainty could be indicative of financial sources or channels for uncertainty. Asset fixity ($FIX_i$) is the ratio of fixed assets to total assets, computed using Compustat data following Braun and Larraín (2005).

Table 3 shows the matrix of correlations among the technological measures. Notably, $DEP_i$ and $LMP_i$ are positively correlated, as expected. Lumpiness is also correlated with EFD, however, so it is not ex-ante clear how to interpret an interaction of a particular technological variable with uncertainty – unless the interactions of its correlates are not significant or not robust.

[26] The measures below are drawn from Ilyina and Samaniego (2011) and Samaniego and Sun (2015), and represent averages over the period 1970–2000. Industry measures computed using the Compustat database are median firm values for each industry unless otherwise stated.

**Table 4**
Basic Results.
This table represents results from the following regression:

$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta(UncertaintyShock_{c,t-1} \times X_i) + \alpha Controls_{i,c,t} + \epsilon_{c,i,t}$

We only report $\beta$. Each cell represents one regression. The dependent variable is the industry output index growth rate. Independent variables are the following: $DEP_i$(depreciation) and $LMP_i$ (investment lumpiness), are the average of 70 s, 80 s and 90 s from Ilyina and Samaniego (2011). Standard errors in parentheses, *** p < 0.01, ** p < 0.05.

| $X_i \times stockuncertainty$ | OLS | | | IV |
|---|---|---|---|---|
| DEP | −0.458*** | | −0.301 | |
| | (0.173) | | (0.190) | |
| LMP | | −1.35*** | −1.04** | −3.07*** |
| | | (0.458) | (0.477) | (1.19) |
| Obs | 18,519 | | | |

### 5.1. Control variables

In the empirical literature on industry growth it is common to condition on the share of industry *i* in manufacturing in the previous period, to control for mean reversion, structural change, or other secular factors of industry growth. We do so as well.

Given the likely correlation between first and second moment shocks, we condition on interactions of the technological variables with first moment shocks as well. Since uncertainty is measured using stock market volatility, the first moment shock is the annual cumulative stock market return. In addition, Samaniego and Sun (2015) find that technological characteristics may interact with *contractions*, so we condition on interactions of contractions and the technological variables as well, as a non-linear control for business cycle effects. Contractions are defined using a standard peak-trough criterion as implemented by the NBER, see Samaniego and Sun (2015) for details. Our results concerning uncertainty turn out not to be sensitive to the presence of this control.

In order to ensure our results are not the result of financial channels through which uncertainty affects industry growth, in one of our robustness exercises we condition on whether or not the interactions of interest are robust to including an interaction of technology with a *financial crisis indicator*. We draw on the Systemic Banking Crises Database developed by Laeven and Valencia (2013), which covers the period 1970 to 2011. We define the variable $Crisis_{c,t}$ to equal one if the Database considers country *c* at date *t* to be experiencing a banking crisis, and zero otherwise. A year-country pair is determined to be in crisis if there are significant signs of financial distress in the banking system (bank runs, significant bank losses or bank liquidations, and if there is significant policy intervention in response to losses in the banking system). Then, we use $Crisis_{c,t} \times X_i$ as a control for each technological variable $X_i$, to see whether the results are driven by crises rather than uncertainty and to see whether there are financial channels for uncertainty.

## 6. Findings

### 6.1. Empirical results

We estimate the basic regression Eq. (7) using output index growth as the dependent variable and inserting the interaction terms of uncertainty with the technological variables one by one first. Results are in Table 4. Both depreciation $DEP_i$ and investment lumpiness $LMP_i$ interact with uncertainty – in the sense that there is a significant interaction. Then we run the basic regression with both interactions of $DEP_i$ and $LMP_i$ with uncertainty. The interaction with $LMP_i$ is still significant, while the interaction with $DEP_i$ is not – of course the two variables are correlated so it is not surprising that one of their interactions might become less significant when they are in the same regression. On the other hand, considering the structure of the model, it is possible that $DEP_i$ affects industry growth through its association with lumpy investment, i.e. with $LMP_i$. If so, this suggests that one could use the interaction term with $DEP_i$ as the instrument for the interaction with $LMP_i$ using the two stage least square regression. See the last column of the table. The coefficient for $LMP_i$ is more than double, and significance is higher, in the IV regression.

We also find that external finance dependence ($EFD_i$), R&D intensity ($RND_i$) and asset fixity ($FIX_i$) which are associated with financial frictions, do not interact with uncertainty shocks. See Table 5. We thus conclude that real options considerations – rather than financial frictions – are responsible for these results. The absence of evidence linking uncertainty with financial dependence is consistent with the findings of Caldara et al. (2016), who find that while uncertainty may sometimes have an impact on financial markets they are not the main source thereof.

Another way to see whether our findings regarding $LMP_i$ and of $DEP_i$ are related to financial constraints – as opposed to real options considerations such as the volatility effect – is to compare our uncertainty measures with the financial crisis indicator $Crisis_{c,t}$. We find that the correlation between $Crisis_{c,t}$ and uncertainty is quite high. The correlation is 9.29% and very highly statistically significant. The relationship remains highly statistically significant even when we condition on

**Table 5**
Regressions with financial variables.
This table represents results from the following regression:

$$Growth_{c,i,t}=\delta_{i,c}+\delta_{i,t}+\delta_{c,t}+\beta(UncertaintyShock_{c,t-1}\times X_i)+\alpha Controls_{i,c,t}+\epsilon_{c,i,t}$$

We only report $\beta$. Each column represents one regression. The dependent variable is the industry output index growth rate. Independent variables are $EFD_i$ (external finance dependence), $RND_i$(R&D intensity) and $FIX_i$ (fixity), are the average of 70s, 80s and 90s from Ilyina and Samaniego (2011)). Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$.

| | Industry variable $X_i$ | | |
|---|---|---|---|
| Interaction | EFD | RND | FIX |
| $UncertaintyShock_{c,t} \times X_i$ | −0.373 | −0.00381 | 0.0501 |
| | (0.636) | (0.00650) | (0.0257) |

**Table 6**
Controlling for Banking Crises.
This table represents results from the following regression:

$$Growth_{c,i,t}=\delta_{i,c}+\delta_{i,t}+\delta_{c,t}+\beta(UncertaintyShock_{c,t-1}\times X_i)+\beta_C(Crisis_{c,t}\times X_i)+\alpha Controls_{i,c,t}+\epsilon_{c,i,t}$$

We only report $\beta$ and $\beta_C$. Each cell represents one regression. The dependent variable is the industry output index growth rate. Independent variables are $DEP_i$ (depreciation) and $LMP_i$ (investment lumpiness). Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$.

| | Industry variable $X_i$ | |
|---|---|---|
| Interaction | DEP | LMP |
| $Crisis_{c,t} \times X_i$ | −0.275 | −1.46** |
| | (0.268) | (0.591) |
| $UncertaintyShock_{c,t} \times X_i$ | −0.428*** | −1.18** |
| | (0.190) | (0.551) |

country fixed effects. This suggests that there could be a finance-uncertainty link. Then, we introduce into our specification an additional control in the form of an interaction variable of the technological variables with the financial crisis indicator $Crisis_{c,t}$. The specification becomes:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta(UncertaintyShock_{c,t-1} \times X_i) + \beta_C(Crisis_{c,t} \times X_i) + \alpha Controls_{i,c,t} + \epsilon_{c,i,t}$$

If financial frictions, not the volatility effect, are the true cause of our observed interactions, we might expect these measures to interact with crises, or expect that adding the crisis interaction as a control variable might reduce the statistical significance of our coefficient of interest $\beta$.

We find that, first of all, the impact on industry growth of the interaction of $LMP_i$ and of $DEP_i$ with stock market uncertainty is robust to the inclusion of this control variable, indeed it remains statistically significant. See Table 6. In contrast, the interactions of $Crisis_{c,t}$ with $DEP_i$ is not significant. We notice that the interaction of $Crisis_{c,t}$ with $LMP_i$ is significant and negative. Thus, our findings are not affected by uncertainty coinciding with financial crises, nor are these interactions likely due to financial frictions.

### *6.2. Replicating the regression in the model*

We perform one final experiment. We use the model economy to generate an artificial panel data set with $N$ countries, $I$ industries and $T$ periods, roughly of the size of the data set we used in the empirical section. Then, we estimate the baseline specification using the model-generated data set.

The way we do this is as follows. First, we set $N = 55$ (the number of countries in our baseline regression). Then, for each country, we generate a volatility sequence of a certain length larger than $T$. We set $T = 42$, to match the number of years in our baseline regression which spans the period 1970 – 2012. Then, we set $I = 28$, and generate an industry growth sequence given the volatility sequence for each country for $I$ times, setting the depreciation rate to equal the depreciation rates of each industry in the data set in sequence. Also, for each industry we measure the degree of lumpiness in the same way as the data using model investment behavior – i.e. using the relationship between depreciation and lumpiness in Fig. 5. We measure industry growth by adding up the output of 500 firms, and drop the pseudodata for all but the last $T = 42$ years to eliminate the impact of initial conditions, which we set as before. The regression specification requires a measure of the level: we simply use the level of GDP in each country as measured using the sum of output in all industries.

See Table 7. We find that the coefficients are a bit smaller than those obtained in the empirical investigation, about 40 – 60% in magnitude. At the same time, the model-based estimates are well within the confidence bounds of the empirically derived coefficients.

**Table 7**
Basic Results with model-generated pseudodata.
This table represents results from the following regression estimated using model-generated pseudodata:

$$Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta(UncertaintyShock_{c,t-1} \times X_i) + \alpha Controls_{i,c,t} + \epsilon_{c,i,t}$$

We only report $\beta$. Each cell represents one regression. The dependent variable is the industry output index growth rate. Independent variables are $DEP_i$ (depreciation) and $LMP_i$ (investment lumpiness), the average of 70 s, 80 and 90 s from Ilyina and Samaniego (2011). Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$.

| | Industry growth measure $Growth_{c,\,i,\,t}$ | |
|---|---|---|
| $X_i$ | UNIDO data | Model Growth |
| DEP | $-0.458^{***}$ | $-0.282^{***}$ |
| | (0.173) | (0.006) |
| LMP | $-1.35^{***}$ | $-0.591^{***}$ |
| | (0.458) | (0.013) |
| Obs | 18,519 | 66,220 |

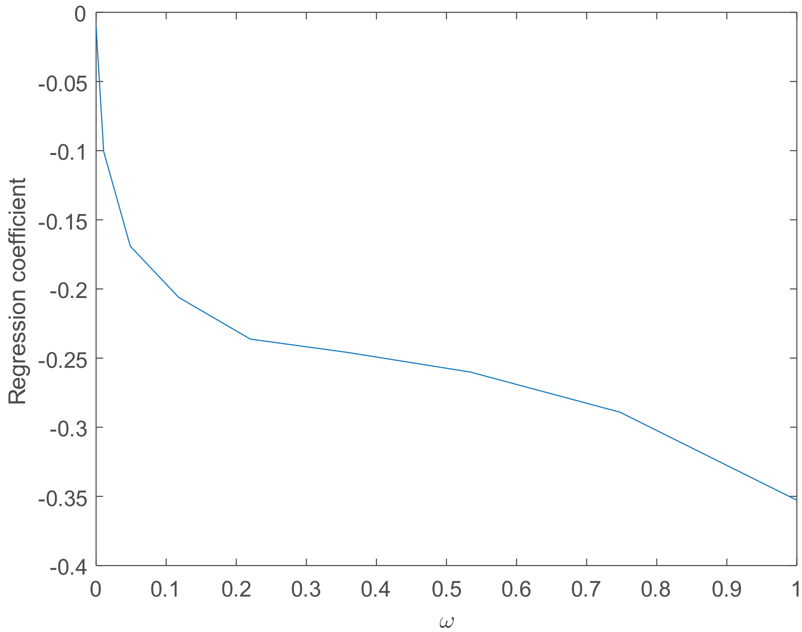


**Fig. 8.** Response surface for the relationship between $\omega$, the extent of uncertainty (the extent to which variance $\gamma$ increases) and the regression coe cient in the specification $Growth_{c,i,t} = \delta_{i,c} + \delta_{i,t} + \delta_{c,t} + \beta(UncertaintyShock_{c,t-1} \times X_i) + \alpha Controls_{i,c,t} + \epsilon_{c,i,t}$ estimated using model- generated pseudodata. All parameters other than $\omega$ are kept constant. The estimation procedure is similar to that used to generate Table 7.

Finally, Fig. 8 displays how the magnitude of the interaction coefficient varies with the magnitude of $\omega$, the relative increase in the variance of idiosyncratic shocks in times of high uncertainty. It is interesting that the impact of uncertainty $\omega$ on the interaction coefficient is non-linear: a small amount of uncertainty is capable of generating a significantly large coefficient, including values much smaller than our baseline value of $\omega = 0.22$, and also values that are significantly larger. We conclude that an economy with partially irreversible investment – where in this case the irreversibility is small, about 12 – is vulnerable to increased misallocation due to even relatively small uncertainty shocks, as seen through their significant interaction with depreciation. Indeed, for a large range of values of $\omega$ there is relatively little difference in the interaction coefficient. A scree test would suggest a value of $\omega = 0.05 - 0.1$ as being the inflection point above which increases in the magnitude of uncertainty shocks make relatively small contributions to the interaction coefficient.

## 7. Conclusion

We develop a canonical model of investment irreversibility, and argue that it is a natural consequence of such models for growth to be more sensitive to uncertainty shocks in industries where depreciation is rapid. In addition, in such industries we would expect investment to be more lumpy, so that measures of lumpiness should interact with uncertainty in the same way as depreciation. We then use a differences-in-differences specification to show that industry growth data from a large set of countries are consistent with these predictions. We conclude that the misallocation introduced by investment irreversibilities are an important mechanism through which uncertainty has an impact on economic outcomes, through the volatility effect.

A limitation of the study is that it is not clear how much changes in prices might offset (or exacerbate) the impact of uncertainty shocks on different industries. An interpretation of our work is then that we assume some degree of price rigidity at the horizon relevant for the frequency of uncertainty shocks, an assumption that is popular in the macroeconomics literature due to its necessity for monetary policy to have real effects. This assumption would be interesting to relax in future work. We also abstract from details of firm dynamics – for example, the extent to which firm productivity evolves due to innovations they produce, or potential strategic interaction among firms. As mentioned in the paper, our goal is parsimony and transparency, and including these features would necessarily complicate the analysis of the model, the calibration of which is already quite onerous, without necessarily adding much insight regarding the depreciation-uncertainty interaction. This would be interesting to explore in future studies.

Another extension would be to introduce financial frictions into our model. Financing frictions might interact with investment irreversibilities to lead to even more significant misallocation in times of high uncertainty, so that uncertainty shocks might have a more severe impact on growth in the presence of financing frictions, as found by Alfaro et al. (2016). We leave this extension for future work.

More broadly, our study provides an anatomy of how uncertainty affects different parts of the macroeconomy, in order to better understand the aggregate impact of economic uncertainty. The interaction of irreversibilities with depreciation and lumpiness is also something that could be useful in future studies trying to identify the impact of volatility, and the general strategy of looking at industry interactions to identify microeconomic features that are difficult to measure directly (such as irreversibilities) could be useful more broadly to explore topics other than the interaction of uncertainty and irreversibilities.

Finally, Veracierto (2002) finds that investment irreversibilities do not have an impact on business cycle fluctuations. It is not clear whether the same would be true of uncertainty shocks, but it is possible, since it is well known that in general equilibrium wages and other prices rather than quantities are mainly affected by microeconomic asymmetries. However, if there were many industries affected differently by uncertainty (or by the business cycle) wages would only partially ameliorate the impact of shocks on the most severely affected industries, possibly leading some residual impact of shocks to affect aggregates. This would be interesting to study in future work.

## Appendix A. Basic data

Table 8 reports an overview of the data by country. Table 9 reports the industry technological characteristics.

**Table 8**
Country Coverage and Number of Observations.

| Country | No. of observations | Country | No. of observations |
|---|---|---|---|
| Argentina | 961 | Kuwait | 907 |
| Australia | 999 | Luxembourg | 1013 |
| Austria | 1013 | Mexico | 961 |
| Belgium | 1009 | Morocco | 1039 |
| Bangladesh | 961 | Netherlands | 1013 |
| Canada | 961 | Nigeria | 934 |
| China | 772 | Norway | 985 |
| Chile | 1033 | New Zealand | 1065 |
| Colombia | 1013 | Pakistan | 961 |
| Czech Rep. | 715 | Peru | 1065 |
| Denmark | 1013 | Philippines | 799 |
| Ecuador | 1013 | Poland | 1013 |
| Egypt | 961 | Portugal | 1007 |
| Finland | 1013 | Romania | 1039 |
| France | 1013 | Russian Federation | 499 |
| United Kingdom | 1010 | South Africa | 1036 |
| Germany | 444 | Saudi Arabia | 934 |
| Greece | 986 | Singapore | 1025 |
| Hungary | 1013 | Spain | 1011 |
| India | 987 | Sweden | 1013 |
| Indonesia | 1013 | Switzerland | 961 |
| Ireland | 1004 | Thailand | 961 |
| Iran, Islamic Rep. of | 1013 | Tunisia | 961 |
| Israel | 957 | Turkey | 961 |
| Italy | 1011 | Ukraine | 445 |
| Japan | 1013 | venezuela | 961 |
| Kenya | 1018 | Vietnam | 202 |
| Korea, Rep. of | 1039 | | |

**Table 9**
Industry Technological Measures.

| Industry | ISIC | EFD | DEP | RND | FIX | LMP |
|---|---|---|---|---|---|---|
| Food products | 311 | −0.039 | 7.09 | 0.073 | 0.373 | 1.195 |
| Beverages | 313 | −0.048 | 7.09 | 0.039 | 0.372 | 1.29 |
| Tobacco | 314 | −0.801 | 5.248 | 0.222 | 0.189 | 0.815 |
| Textiles | 321 | 0.029 | 7.665 | 0.144 | 0.345 | 1.232 |
| Apparel | 322 | 0.075 | 6.437 | 0.02 | 0.134 | 1.998 |
| Leather | 323 | −0.959 | 9.266 | 0.198 | 0.135 | 1.927 |
| Footwear | 324 | −0.45 | 8.325 | 0.153 | 0.16 | 2.239 |
| Wood products | 331 | 0.052 | 9.525 | 0.032 | 0.305 | 1.72 |
| Furniture, except metal | 332 | 0.015 | 8.312 | 0.155 | 0.28 | 1.381 |
| Paper and products | 341 | −0.062 | 8.632 | 0.083 | 0.472 | 0.902 |
| Printing and publishing | 342 | −0.222 | 9.745 | 0.1 | 0.261 | 1.67 |
| Industrial chemicals | 351 | 0.028 | 9.646 | 0.269 | 0.381 | 1.34 |
| Other chemicals | 352 | 1.654 | 6.888 | 1.951 | 0.207 | 2.13 |
| Petroleum refineries | 353 | −0.055 | 6.776 | 0.057 | 0.591 | 0.763 |
| Misc. pet. and coal products | 354 | −0.059 | 6.776 | 0.186 | 0.372 | 1.042 |
| Rubber products | 355 | −0.064 | 10.072 | 0.187 | 0.322 | 1.098 |
| Plastic products | 356 | 0.088 | 10.072 | 0.171 | 0.374 | 1.557 |
| Pottery, china, earthenware | 361 | −0.107 | 8.234 | 0.503 | 0.4 | 1.292 |
| Glass and products | 362 | 0.289 | 7.554 | 0.115 | 0.4 | 1.755 |
| Other non-met. Min. prod. | 369 | 0.021 | 8.234 | 0.095 | 0.48 | 0.99 |
| Iron and steel | 371 | −0.004 | 6.578 | 0.066 | 0.427 | 0.951 |
| Non-ferrous metals | 372 | 0.037 | 5.393 | 0.101 | 0.364 | 1.245 |
| Fabricated metal products | 381 | −0.052 | 7.043 | 0.147 | 0.274 | 1.365 |
| Machinery, except electrical | 382 | 0.542 | 8.832 | 0.933 | 0.195 | 2.694 |
| Machinery, electric | 383 | 0.543 | 9.381 | 0.814 | 0.208 | 2.704 |
| Transport equipment | 384 | 0.041 | 10.559 | 0.316 | 0.264 | 1.614 |
| Prof. & sci. equipment | 385 | 0.942 | 9.21 | 1.194 | 0.181 | 2.79 |
| Other manufactured prod. | 390 | 0.404 | 10.07 | 0.302 | 0.186 | 2.006 |

*Note:* $EFD_i$ (external finance dependence), $DEP_i$ (depreciation), $LMP_i$ (investment lumpiness), $RND_i$(R&D intensity) and $FIX_i$ (fixity) are the average of 70 s, 80 s and 90 s from Ilyina and Samaniego (2011).; The manufacturing industry classification is 3 digit ISIC rev2.

## Appendix B. Proofs

First some derivations.

Given $z$ and $k$ it is simple to find the optimal value of $n(z,k) = \left(\frac{\theta z k^{\alpha}}{w}\right)^{\frac{1}{1-\theta}}$. Plugging that in we end up with a modified reduced form problem of the form:

$$V(z, k_{-1}; \nu_t) = \max_{k} \left\{ \tilde{z} k^{\tilde{\alpha}} - (k - k_{-1}) - \kappa \max\{0, k_{-1} - k\} + \frac{1-\lambda(z)}{1+i} EV\left(z', k(1-\delta); \nu'\right) \right\} \tag{9}$$

where $\tilde{\alpha} = \frac{\alpha}{1-\theta} < 1$ and $\tilde{z} = (\frac{z}{w^{-\theta}})^{\frac{1}{1-\theta}}[\theta^{\frac{\theta}{1-\theta}} - \theta^{\frac{1}{1-\theta}}]$.

**Proof of Lemma 1.** Consider the transformed problem

$$V(z, k_{-1}; \nu_t) = \max_{u,h} \left\{ \tilde{z} k^{\tilde{\alpha}} - u - (1-\kappa) h + \frac{1-\lambda(z)}{1+i} EV(z, k(1-\delta); \nu_t) \right\}$$
$$u \geq 0, h \geq 0$$
$$k = k_{-1} + u - h.$$

It is straightforward to show that when $h > 0$ is optimal, $u = 0$, since having $u > 0$ would imply incurring larger costs $\kappa$ to achieve a desired level of capital $k$. Similarly, when $u > 0$ is optimal, $h = 0$, since having $h > 0$ would imply incurring costs $\kappa$ to achieve a desired level of capital $k$ when this is not needed. □

**Proof of Proposition 1.** The recursive problem has also an infinite-horizon specification that has the same solution. We find it convenient to work with the infinite problem. This is

$$\max \left\{ E \sum_{t=0}^{\infty} \left( \frac{1-\lambda(z)}{1+i} \right)^{t} \left[ \tilde{z}_t k_t^{\tilde{\alpha}} - u_t - (1-\kappa) h_t \right] \right\}$$
$$u_t \geq 0, h_t \geq 0$$
$$k_t = k_{t-1}(1-\delta) + u_t - h_t$$

Writing down the Lagrangian for this problem we obtain:

$$E\sum_{t=0}^{\infty}\left(\frac{1-\lambda(z)}{1+i}\right)^{t}\left[\tilde{z}_t k_t^{\tilde{\alpha}} - u_t + (1-\kappa)h_t + \eta_t u_t + \lambda_t h_t + \gamma_t[k_t - k_{t-1}(1-\delta) - u_t + h_t]\right]$$

where $\eta_t$, $\lambda_t$ and $\gamma_t$ are the multipliers on $u_t$, $h_t$ and $k_t$ respectively. The Karush-Kuhn-Tucker (KKT) conditions for the multipliers are:

$$\eta_t u_t = 0,\ \lambda_t h_t = 0,\ \gamma_t[k_t - k_{t-1}(1-\delta) - u_t + h_t] = 0$$

The derivatives of the Lagrangian yield the following optimality conditions:

$$\begin{aligned}
&\tilde{z}_t k_t^{\tilde{\alpha}} - u_t + (1-\kappa)h_t + \eta_t u_t + \lambda_t h_t + \gamma_t[k_t - k_{t-1}(1-\delta) - u_t + h_t] + \left(\frac{1-\lambda(z)}{1+i}\right)\\
&\quad\times E\left[\tilde{z}_{t+1}k_{t+1}^{\tilde{\alpha}} - u_{t+1} + (1-\kappa)h_{t+1} + \eta_{t+1}u_{t+1} + \lambda_{t+1}h_{t+1} + \gamma_{t+1}[k_{t+1} - k_t(1-\delta) - u_{t+1} + h_{t+1}]\right]\\
&\tilde{\alpha}\tilde{z}_t k_t^{\tilde{\alpha}-1} + \gamma_t - \left(\frac{1-\lambda(z)}{1+i}\right)E[\gamma_{t+1}(1-\delta)] = 0\\
&\quad -1 + \eta_t - \gamma_t = 0,\ (1-\kappa) + \lambda_t + \gamma_t = 0
\end{aligned}$$

This yields three cases. First, if $u_t > 0$ (positive investment) then

$$\eta_t = 0, -1 = \gamma_t, \lambda_t = \kappa, h_t = 0$$

and

$$\tilde{\alpha}\tilde{z}_t k_t^{\tilde{\alpha}-1} - 1 = \left(\frac{1-\lambda(z)}{1+i}\right)E[\gamma_{t+1}(1-\delta)] \tag{10}$$

This implies that if firms *invest* they will invest up to the value of $k_t$ that satisfies this equation. Then, if $h_t > 0$ (negative investment) then

$$\lambda_t = 0, \gamma_t = -(1-\kappa), \eta_t = \kappa$$

and

$$\tilde{\alpha}\tilde{z}_t k_t^{\tilde{\alpha}-1} - (1-\kappa) = \left(\frac{1-\lambda(z)}{1+i}\right)E[\gamma_{t+1}(1-\delta)] \tag{11}$$

This implies that if firms *disinvest* they will do so down to the value of $k_t$ that satisfies this equation.

If both $h$ and $u$ are zero then

$$\eta_t \geq 0, \lambda_t \geq 0, \gamma_t \leq 0$$

and

$$k_t = k_{t-1}(1-\delta)$$

So that $\gamma_t$ satisfies:

$$\tilde{\alpha}\tilde{z}_t k_t^{\tilde{\alpha}-1} + \gamma_t - \left(\frac{1-\lambda(z)}{1+i}\right)E[\gamma_{t+1}(1-\delta)] = 0 \tag{12}$$

We also have that

$$\begin{aligned}
&-1 + \eta_t - \gamma_t = 0\\
&(1-\kappa) + \lambda_t + \gamma_t = 0\\
&\lambda_t + \eta_t = \kappa
\end{aligned}$$

Notice this implies that $\gamma_t \in [-1, -(1-\kappa)]$. The next stage in the proof is to return to the recursive problem and note that the fact that there is a recursive solution implies that $\gamma_t = \gamma(k_{-1}, z, \nu)$, $\eta_t = \eta(k_{-1}, z, \nu)$ and $\lambda_t = \lambda(k_{-1}, z, \nu)$. Our conditions then become

$$\begin{aligned}
&\eta(k_{-1}, z, \nu)u(k_{-1}, z, \nu) = 0\\
&\lambda(k_{-1}, z, \nu)h(k_{-1}, z, \nu) = 0\\
&\gamma(k_{-1}, z, \nu)[k(k_{-1}, z, \nu) - k_{t-1}(1-\delta) - u(k_{-1}, z, \nu) + h(k_{-1}, z, \nu)] = 0
\end{aligned}$$

$$\tilde{\alpha}\tilde{z}_t k(k_{-1},z,v)^{\tilde{\alpha}-1} + \gamma(k_{-1},z,v) - \left(\frac{1-\lambda(z)}{1+i}\right)E\left[\gamma\left(k,z',v'\right)(1-\delta)\right] = 0$$
$$-1 + \eta(k_{-1},z,v) - \gamma(k_{-1},z,v) = 0$$
$$(1-\kappa) + \lambda(k_{-1},z,v) + \gamma(k_{-1},z,v) = 0$$

For the case where either of $h$ or $u$ are non-zero, this implies that the chosen value of $k$ when there is investment or disinvestment depends only on $z$ and $v$, since $k_{-1}$ does not enter the relevant Eqs. (10) and (11). This defines the thresholds $\bar{k}^*(z,v)$ and $\underline{k}^*(z,v)$. In addition, (10) and (11) imply that

$$\underline{k}^*(z,v)^{\tilde{\alpha}-1} = \bar{k}^*(z,v)^{\tilde{\alpha}-1} + \frac{\kappa}{\tilde{\alpha}\tilde{z}_t} \tag{13}$$

which in turn implies that $\underline{k}^*(z,v) < \bar{k}^*(z,v)$. Then, for the case where both $h$ and $u$ are zero, Eq. (12) becomes

$$\tilde{\alpha}\tilde{z}_t k_{-1}^{\tilde{\alpha}-1} + \gamma(k_{-1},z,v) - \left(\frac{1-\lambda(z)}{1+i}\right)E\left[\gamma\left(k_{-1}(1-\delta),z',v'\right)(1-\delta)\right] = 0. \tag{14}$$

Rearranging this so that $\gamma(k_{-1},z,v)$ is a function of other arguments, standard recursive arguments apply to this problem so that the Bellman operator $B$ in the following equation is a contraction mapping:

$$B\gamma(k_{-1},z,v) = \min\left\{\kappa-1, \max\left\{-1, -\tilde{\alpha}\tilde{z}k_{-1}^{\tilde{\alpha}-1}(1-\delta)^{\tilde{\alpha}-1} + \left(\frac{1-\delta}{1+i}\right)(1-\lambda(z))\int\int\gamma\left(k_{-1}(1-\delta),z',v'\right)dF_z\left(z'|z,v\right)dF_v\left(v'|v\right)\right\}\right\}$$

Assuming that $\gamma$ is increasing and concave implies that $B\gamma$ is also increasing and concave (since the sum of concave functions is concave). This completes the proof. □

**Proof of** Proposition 2. The solution to the decision problem is found by construction in the proof of Proposition 1. The fact that, regardless of the original condition, all firms will immediately restrict their capital stocks to being below the supremum of $\bar{k}^*(z,v)$ means that the measure $\mu_t$ cannot explode. This is because firms above $\bar{k}^*(z,v)$ immediately shrink to $\bar{k}^*(z,v)$. □

**Proof of Proposition 3** Note that all firms either invest to $\bar{k}^*(z,v)$, disinvest to $\underline{k}^*(z,v)$ or depreciate by a factor of $1-\delta$. Thus, for any given value of $(z,v)$ firms are either at $\bar{k}^*(z,v)(1-\delta)^x$ or $\underline{k}^*(z,v)(1-\delta)^x$ for some $x \geq 0$. Or zero if they are newborn. However since incumbent firms cannot have capital below the lowest value of $\bar{k}^*(z,v)$ or $\underline{k}^*(z,v)$ that means that at some point they need to reinvest (or disinvest) back to $\bar{k}^*(z,v)$ or $\underline{k}^*(z,v)$. The exception of course is firms whose initial conditions were not on that grid: however as they depreciate and/or experience shocks at some point they will have to invest or disinvest to $\bar{k}^*(z,v)$ or $\underline{k}^*(z,v)$. □

**Proof of Proposition 4** It is readily verified that, for a given value of $v$, the process for $\mu_t$ described in Eq. (5) satisfies the assumptions of Theorem 2 in Hopenhayn and Prescott (1992). It follows that for a given value of $v$, $\exists!\mu^*(v)$: $\mu_t \to \mu^*(v)$, and that this occurs regardless of the value of $\mu_t$ at the moment when $v_t$ switches to value $v$. □

## Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2019.103314.

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