

# The Tail that Wags the Economy: Beliefs and Persistent Stagnation

Julian Kozlowski

NYU

Laura Veldkamp

NYU Stern, CEPR, NBER

Venky Venkateswaran\*

NYU Stern, NBER

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## Abstract

The Great Recession was a deep downturn with long-lasting effects on credit markets, labor markets and output. While narratives about what caused the recession abound, the persistence of GDP below its pre-crisis trend is puzzling. We propose a simple persistence mechanism that can be easily quantified and combined with existing models, even complex ones. Our solution rests on the premise that no one knows the true distribution of shocks to the economy. If agents use observed macro data to estimate this distribution non-parametrically, then transitory events, especially extreme events, generate persistent changes in beliefs and thus in macro outcomes. We apply our tool to an existing model, designed to explain the onset of the great recession, and find that adding belief updating endogenously generates the persistence of the downward shift in US output, colloquially known as “secular stagnation.”

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\*kozjuli@nyu.edu; lveldkam@stern.nyu.edu; vvenkate@stern.nyu.edu. We thank our four anonymous referees and our Editor, Harald Uhlig, as well as Mark Gertler, Mike Golosov, Mike Chernov, Francois Gourio, Christian Hellwig and participants at the Paris Conference on Economic Uncertainty, IMF Secular Stagnation conference, Einaudi, SED and NBER summer institute for helpful comments and Philippe Andrade, Jennifer La’O, Franck Portier and Robert Ulbricht for their insightful discussions. Veldkamp and Venkateswaran gratefully acknowledge financial support from the NYU Stern Center for Global Economy and Business.

The Great Recession was a deep downturn with long-lasting effects on credit markets, labor markets and output. Why did output remain below trend long after financial markets had calmed and uncertainty diminished? This recession missed the usual business cycle recovery. Such a persistent, downward shift in output (Figure 1) is not unique to the 2008 crisis. Financial crises, even in advanced economies, typically fail to produce the robust GDP rebound needed to restore output to its pre-crisis trend.<sup>1</sup>

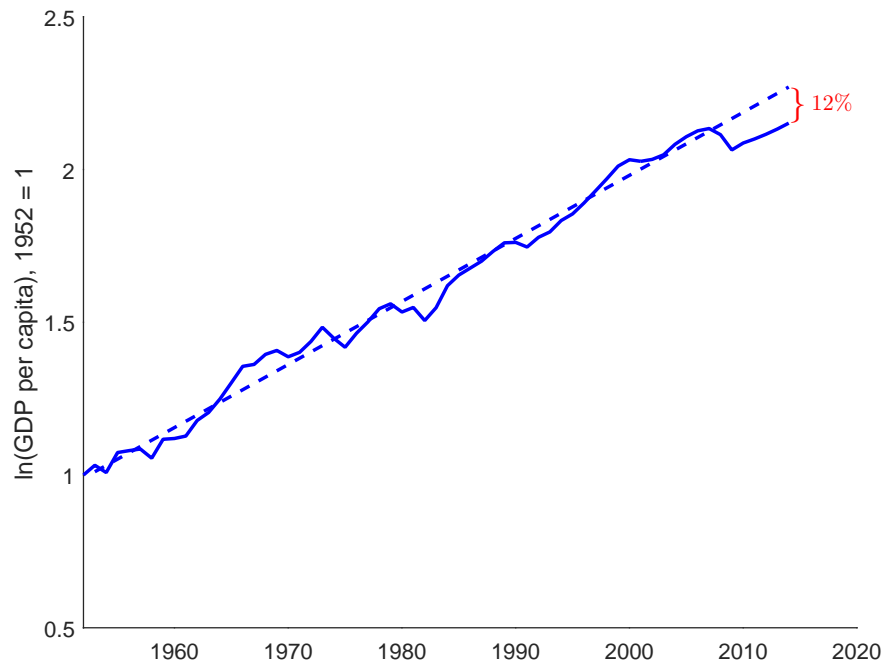


Figure 1: **Real GDP in the U.S. and its trend.**

*Dashed line is a linear trend that fits data from 1950-2007. In 2014, real GDP was 0.12 log points below trend.*

Our explanation is that crises produce persistent effects because they scar our beliefs. For example, in 2006, few people entertained the possibility of financial collapse. Today, the possibility of another run on the financial sector is raised frequently, even though the system today is probably much safer. Such persistent changes in the assessments of risk came from observing new data. We thought the U.S. financial system was stable. Economic outcomes taught us that the risks were greater than we thought. It is this new-found knowledge that is having long-lived effects on economic choices.

The contribution of the paper is a simple tool to capture and quantify this scarring effect, which produces more persistent responses from extreme shocks than from ordinary business cycle shocks. We start from a simple premise: No one knows the true distribution of shocks in the economy. Consciously or not, we all estimate the distribution using economic data, like an econometrician would. Tail events are those for which we have little data. Scarce data

<sup>1</sup>See Reinhart and Rogoff (2009), fig 10.4.

makes new tail event observations particularly informative. Therefore, tail events trigger larger belief revisions. Furthermore, because it will take many more observations of non-tail events to convince someone that the tail event really is unlikely, changes in tail risk beliefs are particularly persistent. To explore tail risk in a meaningful way, we need to use an estimation procedure that does not constrain the shape of the distribution's tail. Therefore, we allow our agents to learn about the distribution of aggregate shocks non-parametrically. Each period, they observe one more piece of data and update their estimates of the distribution. Section 1 shows that this process leads to long-lived responses of beliefs to transitory events, especially extreme, unlikely ones. The mathematical foundation for persistence is the martingale property of beliefs. The logic is that once observed, the event remains in agents' data set. Long after the direct effect of the shock has passed, the knowledge of that tail event affects their estimation. The belief that tail risks were higher than previously thought persists and restrains the economic recovery.

To illustrate the economic importance of these belief dynamics, Section 2 applies our belief updating tool to an existing model of the great recession. The model in [Gourio \(2012, 2013\)](#) is well-suited to our exploration of the persistent real effects of financial crises because the underlying assumptions are carefully chosen to link tail events to macro outcomes, in a quantitatively plausible way. It features firms that are subject to bankruptcy risk from idiosyncratic profit shocks and aggregate capital quality shocks. This set of economic assumptions is not our contribution. It is simply a laboratory we employ to illustrate the persistent economic effects from observing extreme events. Section 3 describes the data we feed into the model to discipline our belief estimates. Section 4 combines model and data and uses the resulting predictions to show how belief updating quantitatively explains the persistently low level of output colloquially known as "secular stagnation." We compare our results to those from the same economic model, but with agents who have full knowledge of the distribution, to pinpoint belief updating as the source of the persistence.

Our main insight about why tail events have persistent effects does not depend on the specific economic structure of the [Gourio \(2012\)](#) model, or on the use of a particular shock process as a driving force. To engage our persistence mechanism, three ingredients are needed. One is a shock process that captures the extreme, unusual aspects of the Great Recession. These were evident mainly in real estate and capital markets. Was this the first time we have ever seen such shocks? In our data set, which spans the post-WWII period in the US, yes. Total factor productivity, measured with or without adjustments, does not meet this criterion.<sup>2</sup> The capital quality shock specification is arguably the most direct one that does. Of course, similar extreme events have been observed before in global history – e.g. in other countries or

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<sup>2</sup>It begins to fall prior to the crisis and by an amount that was not particularly extreme. See Appendix C.5 for an analysis of TFP shocks.

during the Great Depression. Section 4.2 explores the effect of expanding the data set to include additional infrequent crises and shows that it does temper persistence, but only modestly.

The second ingredient is a belief updating process that uses new data to estimate the distribution of shocks, or more precisely, the probability of extreme events. It is not crucial that the estimation is frequentist.<sup>3</sup> It is important that the distribution does not impose thin tails.

The third necessary ingredient is an economic model that links the risk of extreme events to real output. The model in Gourio (2012, 2013) has the necessary curvature (non-linearity in policy functions) to deliver a sizeable output response from modest changes in disaster risk. The preference and bankruptcy assumptions that make Gourio’s model complex are there to deliver that curvature. This curvature also makes the economy more sensitive to disaster risk than extreme boom risk. Section 4.4 explores the role of these ingredients, by turning each on and off. That exercise shows that even though these assumptions deliver a large drop in output, they do not in any way guarantee the success of our objective, which is to generate persistent economic responses. In other words, when agents do not learn from new data, the same model succeeds in matching the size of the initial output drop, but fails to produce persistent stagnation.

We use data on the aggregate market value of capital to measure the driving shocks and quantify the changes in beliefs that took place around the Great Recession. Across a broad range of macroeconomic and financial variables, the model with belief changes outperforms the model without. Because of the economic environment, both models produces realistic initial drops in labor and output. However, belief revisions create persistence that is more consistent with data. While both models miss features of investment behavior, learning substantially improves these predictions. In addition, the number of tail-risk-related internet searches suggests continued concern about tail risk. Searches for terms like “economic crisis,” “financial crisis,” “tail risk,” or “systemic risk” all spike around 2008 and then fall, but return to a level that is permanently higher than the pre-crisis level.

Finally, data on asset prices and debt are also consistent with an increase in tail risk. At first pass, one might think that financial market data are at odds with our story. For instance, Hall (2015a) objects that stagnation must not come from tail risk because sustained high risk would show up as high credit spreads. In the data, credit spreads for 2015 – the difference between the return on a risky loan and a riskless one – are only a few basis points higher than what they were before 2007. Similarly, a rise in risk might suggest that equity prices should be persistently low, when in fact, they too have recovered. Our model teaches us that when tail risk rises, firms

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<sup>3</sup>For an example of Bayesian estimation of tail risks in a setting without an economic model, see Orlik and Veldkamp (2014).

borrow less to avoid the risk of bankruptcy. By deleveraging, they lower their credit risk and increase the value of their equity claims. Thus, low credit spreads and a rise in equity prices are not inconsistent with tail risk. Others point to low interest rates as a potential cause of stagnation. Our story complements this low interest rate trap narrative by demonstrating how heightened tail risk makes safe assets more attractive, depressing riskless rates in a persistent fashion. In sum, none of these patterns disproves our theory about elevated tail risk, though, in fairness, they also do not distinguish it from others.

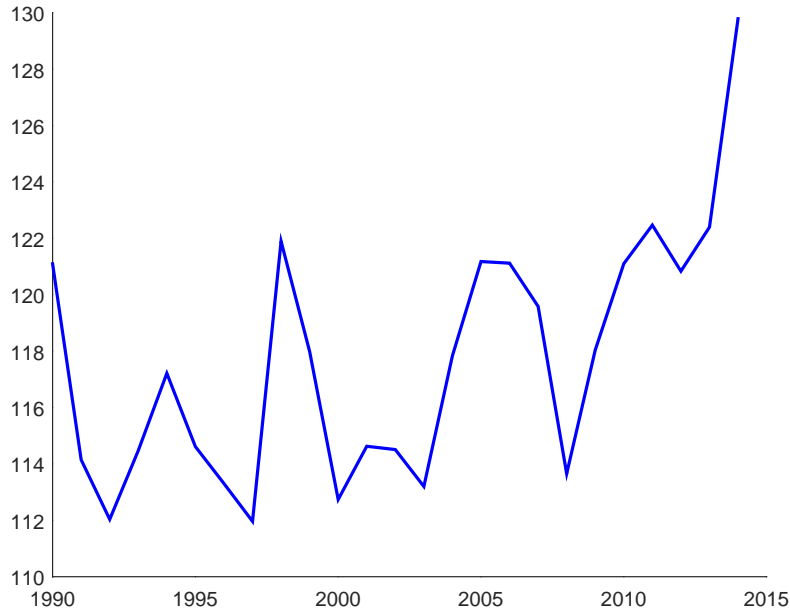


Figure 2: **The SKEW Index.**

*A measure of the market price of tail risk on the S&P 500, constructed using option prices. Source: Chicago Board Options Exchange (CBOE). 1990:2014.*

There are some asset prices which do speak directly to tail risk, in particular out-of-the-money put options on the S&P 500. The SKEW index uses these to back out the implied skewness measure or equivalently, probability of a negative tail event. Figure 2 shows that this option-implied tail risk went up in the aftermath of the crisis and has stayed high. Section 4.3 reviews the asset pricing evidence, explains its connection to the model and shows that the option-implied and model-implied changes in tail risks are similar.

**Comparison to the literature** There are many theories now of the financial crisis and its consequences, many of which provide a more detailed account of its mechanics (e.g., Gertler et al. (2010), Gertler and Karadi (2011), Brunnermeier and Sannikov (2014) and Gourio (2012, 2013)). Our goal is not to add a new explanation for why the crisis arose, or a new theory of business cycles. Rather, we offer a mechanism based on belief formation that complements

these theories by adding endogenous persistence. We explain why extreme events, like the recent crisis, lead to more persistent responses than milder downturns. In the process, we also develop a new tool for tying belief revisions firmly to data that is compatible with modern, quantitative macro models.

Of course, one could avoid all this complexity and simply assume that the persistence comes from serial correlation in the driving shock process. But this simpler explanation has two problems: First, it is inconsistent with our shock data, which shows little persistence. Second, it doesn't explain why some shocks deliver more persistent responses than others. What is it about financial crises that produces stagnation? Our answer is that such events are a rare opportunity to learn about tail risk and they invariably teach us that our investments are less safe than we thought.

A small number of uncertainty-based theories of business cycles also deliver persistent effects from transitory shocks. In [Straub and Ulbricht \(2013\)](#) and [Van Nieuwerburgh and Veldkamp \(2006\)](#), a negative shock to output raises uncertainty, which feeds back to lower output, which in turn creates more uncertainty. To get even more persistence, [Fajgelbaum et al. \(2014\)](#) combine this mechanism with an irreversible investment cost, a combination which can generate multiple steady-state investment levels. These uncertainty-based explanations leave two questions unanswered. First, why did the depressed level of economic activity continue long after the VIX and other measures of uncertainty had recovered? Our theory emphasizes tail risk. The SKEW index data in [Figure 2](#) reveal that tail risk has lingered, making it a better candidate for explaining continued depressed output. Second, why were credit markets hardest hit and credit volume most persistently impaired after the crisis? Rises in tail risk hit the volume of credit because default is particularly sensitive to tail events.

Our belief formation process is similar to the parameter learning models by [Johannes et al. \(2015\)](#), [Cogley and Sargent \(2005\)](#) and [Orlik and Veldkamp \(2014\)](#) and is advocated by [Hansen \(2007\)](#). However, these papers focus on endowment economies and do not analyze the potential for persistent effects in a setting with production. [Pintus and Suda \(2015\)](#) embed parameter learning in a production economy, but feed in persistent leverage shocks and explore the potential for amplification when agents hold erroneous initial beliefs about persistence. In [Moriera and Savov \(2015\)](#), learning changes demand for shadow banking (debt) assets. But, again, agents are learning about a hidden two-state Markov process, which has persistence built in.<sup>4</sup> We, on the other hand, have transitory shocks to capital and explore endogenous persistence. In addition, our non-parametric approach allows us to incorporate beliefs about tail risk.

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<sup>4</sup>Other learning papers in this vein include papers on news shocks, such as [Beaudry and Portier \(2004\)](#), [Lorenzoni \(2009\)](#), [Veldkamp and Wolfers \(2007\)](#), uncertainty shocks, such as [Jaimovich and Rebelo \(2006\)](#), [Bloom et al. \(2014\)](#), [Nimark \(2014\)](#) and higher-order belief shocks, such as [Angeletos and La'O \(2013\)](#) or [Huo and Takayama \(2015\)](#).

While this literature has taught us an enormous amount about the mechanisms that triggered declines in lending and output in the financial crisis, it assumes rather than explains their persistence.

Finally, our paper contributes to the recent literature on secular stagnation. [Eggertsson and Mehrotra \(2014\)](#) argue that a combination of low effective demand and the zero lower bound on nominal rates can generate a long-lived slump. In contrast, [Gordon \(2014\)](#), [Anzoategui et al. \(2015\)](#) and others attribute stagnation to a decline in productivity, education or shift in demographics. These are longer-run trends that may be suppressing growth. But they don't explain the level shift in output associated with the financial crisis. [Hall \(2015a\)](#) surveys these and other theories. While all these alternatives may well be part of the explanation, our simple idea, that no person could possibly know the true distribution of aggregate shocks, reconciles the recent stagnation with economic, financial and internet search evidence suggesting heightened tail risk.

The rest of the paper is organized as follows. Section 1 describes the belief-formation mechanism. Section 2 presents the economic model. Section 3 shows the measurement of shocks and calibration of the model. Section 4 analyzes the main results of the paper while Section 4.4 decomposes the principal economic forces driving the results. Finally, Section 5 concludes.

## 1 Belief Formation

A key contribution of this paper is to explain why tail risk fluctuates and why such fluctuations are persistent. Before laying out the underlying economic environment, we begin by explaining the novel part – belief formation and the persistence of belief revisions. These insights are more general than the results derived in the specific economic model in the following section, which is used primarily to quantify the effect of belief changes in the aftermath of the Great Recession on the US economy.

No one knows the true distribution of shocks to the economy. We estimate such distributions, updating our beliefs as new data arrives. The first step is to choose a particular estimation procedure. A common approach is to assume a normal distribution and estimate its parameters (namely, mean and variance). While tractable, this has the disadvantage that the normal distribution, with its thin tails, is unsuited to thinking about changes in tail risk. We could choose a distribution with more flexibility in higher moments. However, this will raise obvious concerns about the sensitivity of results to the specific distributional assumption used. To minimize such concerns, we take a non-parametric approach and let the data inform the shape of the distribution.

Specifically, we employ a kernel density estimation procedure, one of most common approaches in non-parametric estimation. Essentially, it approximates the true distribution function with a smoothed version of a histogram constructed from the observed data. By using the widely-used normal kernel, we impose a lot of discipline on our learning problem but also allow for considerable flexibility. We also experimented with a handful of other kernel and Bayesian specifications, which yielded similar results.<sup>5</sup>

**Setup** Consider a shock  $\phi_t$  whose true density  $g$  is unknown to agents in the economy. The agents do know that the shock  $\phi_t$  is i.i.d. Their information set at time  $t$ , denoted  $\mathcal{I}_t$ , includes the history of all shocks  $\phi_t$  observed up to and including  $t$ . They use this available data to construct an estimate  $\hat{g}_t$  of the true density  $g$ . Formally, at every date, agents construct the following normal kernel density estimator of the pdf  $g$

$$\hat{g}_t(\phi) = \frac{1}{n_t \kappa_t} \sum_{s=0}^{n_t-1} \Omega\left(\frac{\phi - \phi_{t-s}}{\kappa_t}\right)$$

where  $\Omega(\cdot)$  is the standard normal density function,  $\kappa_t$  is the smoothing or bandwidth parameter and  $n_t$  is the number of available observations of at date  $t$ . As new data arrives, agents add the new observation to their data set and update their estimates, generating a sequence of beliefs  $\{\hat{g}_t\}$ .

The key mechanism in the paper is the persistence of belief changes induced by transitory  $\phi_t$  shocks. This stems from the martingale property of beliefs - i.e. conditional on time- $t$  information ( $\mathcal{I}_t$ ), the estimated distribution is a martingale. Thus, on average, the agent expects her future belief to be the same as her current beliefs. This property holds exactly if the bandwidth parameter  $\kappa_t$  is set to zero.<sup>6</sup> In line with the literature on non-parametric

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<sup>5</sup>Specifically, we estimated our belief process using (i) a non-parametric Epinechnikov kernel, (ii) the Champownne transformation (which is designed to better capture tail risk), (iii) semi-parametric estimators, e.g. with Pareto tails and (iv) the g-and-h family of distributions which allows for a flexible specification of tail risk using various transformations of the normal distribution. These approaches yielded similar changes in tail probabilities and therefore, similar predictions for economic outcomes. A Bayesian approach is conceptually similar - posterior beliefs exhibit the martingale property, the key source of persistence. However, the departure from normality needed to capture tail risk, requires particle filtering techniques, making it difficult to integrate it into any but the simplest economic environments. For a detailed discussion of nonparametric estimation, see Hansen (2015).

<sup>6</sup>As  $\kappa_t \rightarrow 0$ , the CDF of the kernel converges to  $\hat{G}_t^0(\phi) = \frac{1}{n_t} \sum_{s=0}^{n_t-1} \mathbf{1}\{\phi_{t-s} \leq \phi\}$ . Then, for any  $\phi$ ,  $j \geq 1$

$$\mathbb{E}_t \left[ \hat{G}_{t+j}^0(\phi) \middle| \mathcal{I}_t \right] = \mathbb{E}_t \left[ \frac{1}{n_t + j} \sum_{s=0}^{n_t+j-1} \mathbf{1}\{\phi_{t+j-s} \leq \phi\} \middle| \mathcal{I}_t \right] = \frac{n_t}{n_t + j} \hat{G}_t^0(\phi) + \frac{j}{n_t + j} \mathbb{E}_t [\mathbf{1}\{\phi_{t+1} \leq \phi\} | \mathcal{I}_t]$$

Thus, future beliefs are, in expectation, a weighted average of two terms - the current belief and the distribution from which the new draws are made. Since our best estimate for the latter is the current belief, the two terms are exactly equal, implying  $\mathbb{E}_t \left[ \hat{G}_{t+j}^0(\phi) \middle| \mathcal{I}_t \right] = \hat{G}_t^0(\phi)$ .



assumption, we use the optimal bandwidth.<sup>7</sup> This smoothes the density but also means that the martingale property does not hold exactly. Numerically, deviations of beliefs from a martingale are minuscule, both for the illustrative example in this section and in our full model. In other words, the kernel density estimator with the optimal bandwidth is, approximately, a martingale  $\mathbb{E}_t[\hat{g}_{t+j}(\phi)|\mathcal{I}_t] \approx \hat{g}_t(\phi)$ . As a result, any changes in beliefs induced by new information are, in expectation, permanent. This property plays a central role in generating long-lived effects from transitory shocks.

**Example: Capital returns** We now illustrate how this belief formation mechanism works by applying the estimation procedure described above to a time series of returns to non-residential capital in the US. Since our goal here is purely to illustrate the effects of outlier realizations on beliefs, we could have used any time series with an outlier. We use capital returns for 2 reasons: (i) it shows very clearly the unusual aspects of the Great Recession, especially its effects on asset prices and (ii) it anticipates the driving force in our economic model in the following section. In that microfounded setting, returns will be endogenous but, as we will see, the dynamics of beliefs will turn out to be quite similar to what we preview here.

We measure the return on non-financial assets for US corporate business from Flow of Funds reports published by the Federal Reserve for 1947-2009. The return is defined as operating surplus (expressed as a percentage) plus holding gains from non-financial assets (i.e. changes in the market value of capital).<sup>8</sup> The return series is plotted in the first panel of Figure 3. It shows that realized returns during the financial crisis were significantly lower than any that were observed throughout the entire sample. This is driven mostly by large negative realizations for the holding gain component.

**Estimated belief changes** The estimated distributions using this data for two dates - 2007 (pre-crisis) and 2009 (post-crisis) - are shown in the second panel of Figure 3. We note that these adverse realizations lead to an increase in tail risk. The 2009 distribution,  $\hat{g}_{2009}$  shows a pronounced hump in the density around the 2008 and 2009 realizations, relative to the pre-crisis one. Crucially, even though these negative realizations were short-lived, this increase in left tail risk persists. To see how persistent beliefs are, we ask the following question: What would be the estimated probability distribution in 2039? To answer this question, we need to simulate future data. Since our best estimate of the distribution of future data in 2009 is  $\hat{g}_{2009}$ , we draw many 30-year sequences of future data from this  $\hat{g}_{2009}$  distribution. After each 30-year sequence,

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<sup>7</sup>See Hansen (2015).

<sup>8</sup>Operating surplus is obtained from table S.5.a, line FA106402101. Holding gains are from table R.103, lines FR105035005, FR10501520,5 FR105013765 and FR105020015. Non-financial assets are from table B.103, line FL102010005.

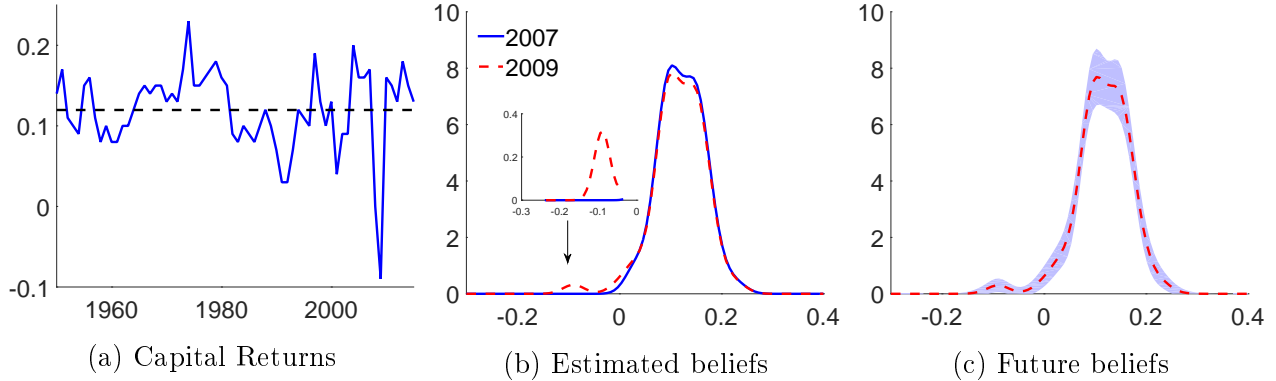


Figure 3: **Estimated Beliefs about Capital Returns.**

The first panel shows the realized capital returns. The second panel shows the estimated kernel density for 2007 and 2009. The third panel shows the mean belief (along with a 2 standard deviation band) in 2039 (computed by simulating data for the period 2010-2039 using the estimated distribution in 2009).

we re-estimate the distribution  $g$ , using all available data. The shaded area in the third panel of Figure 3 shows the results from this Monte Carlo exercise. Obviously, each simulated path gives rise to a different estimated distribution, but averaging across all those paths yields the 2009 distribution (dashed line). This simulation illustrates how tail risk induced by financial crisis may never go away. The left tail “hump” persists. Because we are drawing from the  $\hat{g}_{2009}$  distribution, every once in a long while, another crisis is drawn, which keeps the left tail from disappearing. If we instead drew future data from a distribution without tail risk (e.g.  $\hat{g}_{2007}$ ), the hump would still be very persistent, but not permanent (see Section 4).

Thus, every new shock to capital returns ( $\phi_t$ ), even a transitory one, has a persistent effect on beliefs. This pattern is reminiscent of Figure 2, which showed that price of tail risk in equity options markets continues to remain high. It is also consistent with rough proxies for beliefs in the wake of the financial crisis. Google searches for the terms “economic crisis,” “financial crisis,” or “systematic risk” all rose during the crisis and never returned to their pre-crisis levels (see Appendix C.1). If searches are any indication of concern about an event, then this evidence suggests the perceived risk of another crisis is elevated in a persistent way. To assess the implications of these belief changes for macroeconomic outcomes, we need a model that maps shocks and beliefs into investment, hiring and production decisions. However, we wish to re-iterate that this flexible, non-parametric approach to belief formation is a simple tool that can create persistent responses to transitory shocks in many economic environments.

## 2 Economic Model

To explore whether our belief formation mechanism can help explain the persistence of the recent stagnation, we need to embed it in an economic environment. To have a shot at quantitatively explaining the recent episode, our model needs two key features. First, since extreme shocks create the most persistence, we need a model whose shocks embody the extreme and unusual aspects of the 2008-'09 recession, such as the unusually low returns to non-residential capital. To generate these large fluctuations in capital returns, we use a shock to capital quality. These shocks, which scale up or down the effective capital stock, are not to be interpreted literally. A decline in capital quality captures the idea that a Las Vegas hotel built in 2007 may deliver less economic value after the financial crisis, because lower demand leaves it half-empty. This lower value would be reflected in a lower market value, a feature we will exploit later in our measurement strategy.<sup>9</sup> This specification is not intended as a deep explanation of what triggered the financial crisis. Instead, it is a summary statistic that stands in for many possible explanations and allows the model to speak to both financial and macro data. This agnostic approach to the cause of the crisis also puts the spotlight on our contribution, which is the ability of learning to generate persistent responses to extreme events.

Second, we need a setting where economic activity is sensitive to the probability of extreme capital shocks. [Gourio \(2012, 2013\)](#) presents a model optimized for this purpose. Two key ingredients – namely, Epstein-Zin preferences and costly bankruptcy – combine to generate significant non-linearity in policy functions. Adding the assumption that labor is hired in advance with an uncontingent wage increases the effective leverage of firms and therefore, accentuates the sensitivity of investment and hiring decisions to tail risk. Similarly, preferences that shut down wealth effects on labor avoid a surge in hours in response to crises.

Thus, this combination of assumptions offers a laboratory to assess the quantitative potential of our belief revision mechanism. It is worth emphasizing that none of these ingredients guarantees persistence, the main focus of this paper. The capital quality shock specification has a direct effect on output upon impact but, absent belief revisions, does not change the long-run trajectory of the economy. Similarly, the non-linear responses induced by preferences and debt influence the size of the economic response, but by themselves do not generate any internal propagation. Without these ingredients, our mechanism will still generate persistent responses. However, the magnitude of the impact, both in the short and long run, would be different.

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<sup>9</sup>Capital quality shocks have been employed for a similar purpose in [Gourio \(2012\)](#), as well as in a number of recent papers on financial frictions, crises and the Great Recession (e.g., [Gertler et al. \(2010\)](#), [Gertler and Karadi \(2011\)](#), [Brunnermeier and Sannikov \(2014\)](#)). Their use in macroeconomics and finance, however, goes back at least to [Merton \(1973\)](#), who uses them to generate highly volatile asset returns.

To this setting, we add a novel ingredient, namely our belief-formation mechanism. We model beliefs using the non-parametric estimation described in the previous section and show how to discipline this procedure with observable macro data, avoiding free parameters.

## 2.1 Setup

**Preferences and technology:** An infinite horizon, discrete time economy has a representative household, with preferences over consumption ( $C_t$ ) and labor supply ( $L_t$ ):

$$U_t = \left[ (1 - \beta) \left( C_t - \frac{L_t^{1+\gamma}}{1 + \gamma} \right)^{1-\psi} + \beta E_t (U_{t+1}^{1-\eta})^{\frac{1-\psi}{1-\eta}} \right]^{\frac{1}{1-\psi}} \quad (1)$$

where  $\psi$  is the inverse of the intertemporal elasticity of substitution,  $\eta$  indexes risk-aversion,  $\gamma$  is inversely related to the elasticity of labor supply, and  $\beta$  represents time preference.<sup>10</sup>

The economy is also populated by a unit measure of firms, indexed by  $i$  and owned by the representative household. Firms produce output with capital and labor, according to a standard Cobb-Douglas production function  $k_{it}^\alpha l_{it}^{1-\alpha}$ . Firms are subject to an aggregate shock to capital quality  $\phi_t$ . A firm that enters the period  $t$  with capital  $\hat{k}_{it}$  has effective capital  $k_{it} = \phi_t \hat{k}_{it}$ . These capital quality shocks, i.i.d. over time and drawn from a distribution  $g(\cdot)$ , are the only aggregate disturbances in our economy. The i.i.d. assumption is made in order to avoid an additional, exogenous, source of persistence.<sup>11</sup>

Firms are also subject to an idiosyncratic shock  $v_{it}$ . These shocks scale up and down the total resources available to each firm (before paying debt, equity or labor)

$$\Pi_{it} = v_{it} [k_{it}^\alpha l_{it}^{1-\alpha} + (1 - \delta)k_{it}] \quad (2)$$

where  $\delta$  is the rate of capital depreciation. The shocks  $v_{it}$  are i.i.d. across time and firms and are drawn from a known distribution,  $F$ .<sup>12</sup> The mean of the idiosyncratic shock is normalized to be one:  $\int v_{it} di = 1$ . The primary role of these shocks is to induce an interior default rate in equilibrium, allowing a more realistic calibration, particularly of credit spreads.

<sup>10</sup>This utility function rules out wealth effects on labor, as in Greenwood et al. (1988). Appendix B.7 relaxes this assumption.

<sup>11</sup>The i.i.d. assumption also has empirical support. In the next section we use macro data to construct a time series for  $\phi_t$ . We estimate an autocorrelation of 0.15, statistically insignificant. In Appendix B.8, we show that this generates almost no persistence in the economic response.

<sup>12</sup>This is a natural assumption - with a continuum of firms and a stationary shock process, firms can learn the complete distribution of any idiosyncratic shocks after one period.

**Labor, credit markets and default:** We make two additional assumptions about labor markets. First, firms hire labor in advance, i.e. before observing the realizations of aggregate and idiosyncratic shocks. Second, wages are non-contingent - in other words, workers are promised a non-contingent payment and face default risk. These assumptions create an additional source of leverage.

Firms have access to a competitive non-contingent debt market, where lenders offer bond price (or equivalently, interest rate) schedules as a function of aggregate and idiosyncratic states, in the spirit of [Eaton and Gersovitz \(1981\)](#). A firm enters period  $t + 1$  with an obligation,  $b_{it+1}$  to bondholders and a promise of  $w_{it+1}l_{it+1}$  to its workers. The shocks are then realized and the firm's shareholders decide whether to repay their obligations or default. Default is optimal for shareholders if, and only if,

$$\Pi_{it+1} - b_{it+1} - w_{it+1}l_{it+1} + \Gamma_{t+1} < 0$$

where  $\Gamma_{t+1}$  is the present value of continued operations. Thus, the default decision is a function of the resources available to the firm ( $\Pi_{it+1}$ ) and the *total* obligations of the firm to both bondholders and workers ( $b_{it+1} + w_{it+1}l_{it+1} \equiv B_{it+1}$ ). Let  $r_{it+1} \in \{0, 1\}$  denote the default policy of the firm.

In the event of default, equity holders get nothing. The productive resources of a defaulting firm are sold to an identical new firm at a discounted price, equal to a fraction  $\theta < 1$  of the value of the defaulting firm. The proceeds are distributed *pro-rata* among the bondholders and unpaid workers.<sup>13</sup>

Let  $q_{it}$  denote the bond price schedule faced by firm  $i$  in period  $t$ . The firm receives  $q_{it}$  in exchange for a promise to pay one unit of output at date  $t + 1$ .

Debt is assumed to carry a tax advantage, which creates incentives for firms to borrow. A firm which issues debt at price  $q_{it}$  and promises to repay  $b_{it+1}$  in the following period, receives a date- $t$  payment of  $\chi q_{it} b_{it+1}$ , where  $\chi > 1$ . This subsidy to debt issuance, along with the cost of default, introduces a trade-off in the firm's capital structure decision, breaking the Modigliani-Miller theorem.<sup>14</sup>

For a firm that does not default, the dividend payout is its total available resources times output shock, minus its payments to debt and labor, minus the cost of building next period's capital stock (the undepreciated current capital stock is included in  $\Pi_{it}$ ), plus the proceeds from

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<sup>13</sup>Default does not destroy resources - the penalty is purely private. This is not crucial - it is straightforward to relax this assumption by assuming that all or part of the cost of the default represents physical destruction of resources.

<sup>14</sup>The subsidy is assumed to be paid by a government that finances it through a lump-sum tax on the representative household.

issuing new debt, including its tax subsidy

$$d_{it} = \Pi_{it} - B_{it} - \hat{k}_{it+1} + \chi q_{it} b_{it+1}. \quad (3)$$

Importantly, we do not restrict dividends to be positive, with negative dividends interpreted as (costless) equity issuance. Thus, firms are not financially constrained, ruling out another potential source of persistence.

### Timing and value functions:

1. Firms enter the period with a capital stock  $\hat{k}_{it}$ , labor  $l_{it}$ , outstanding debt  $b_{it}$ , and a wage obligation  $w_{it}l_{it}$ .
2. The aggregate capital quality shock  $\phi_t$  and the firm-specific profit shock  $v_{it}$  are realized. Production takes place.
3. The firm decides whether to default or repay ( $r_{it} \in \{0, 1\}$ ) its bond and labor claims.
4. The firm makes capital  $\hat{k}_{it+1}$  and debt  $b_{it+1}$  choices for the following period, along with wage/employment contracts  $w_{it+1}$  and  $l_{it+1}$ . Workers commit to next-period labor supply  $l_{it+1}$ . Note that all these choices are made concurrently.

In recursive form, the problem of the firm is

$$V(\Pi_{it}, B_{it}, S_t) = \max \left[ 0, \max_{d_{it}, \hat{k}_{it+1}, b_{it+1}, w_{it+1}, l_{it+1}} d_{it} + \mathbb{E}_t M_{t+1} V(\Pi_{it+1}, B_{it+1}, S_{t+1}) \right] \quad (4)$$

subject to

$$\text{Dividends:} \quad d_{it} \leq \Pi_{it} - B_{it} - \hat{k}_{it+1} + \chi q_{it} b_{it+1} \quad (5)$$

$$\text{Discounted wages:} \quad \mathcal{W}_t \leq w_{it+1} q_{it} \quad (6)$$

$$\text{Future obligations:} \quad B_{it+1} = b_{it+1} + w_{it+1} l_{it+1} \quad (7)$$

$$\text{Resources:} \quad \Pi_{it+1} = v_{it+1} \left[ (\phi_{t+1} \hat{k}_{it+1})^\alpha l_{it+1}^{1-\alpha} + (1 - \delta) \phi_{t+1} \hat{k}_{it+1} \right] \quad (8)$$

$$\text{Bond price:} \quad q_{it} = \mathbb{E}_t M_{t+1} \left[ r_{it+1} + (1 - r_{it+1}) \frac{\theta \tilde{V}_{it+1}}{B_{it+1}} \right] \quad (9)$$

The first max operator in (4) captures the firm's option to default. The expectation  $\mathbb{E}_t$  is taken over the idiosyncratic and aggregate shocks, given beliefs about the aggregate shock distribution. The value of a defaulting firm is simply the value of a firm with no external obligations, i.e.  $\tilde{V}(\Pi_{it}, S_t) = V(\Pi_{it}, 0, S_t)$ .

Equation (6) requires that the firm's wage promise  $w_{it+1}$ , multiplied by bond price (recall that workers are essentially paid in bonds) is at least as large as  $\mathcal{W}_t$ , which is the representative household's marginal rate of substitution. This object, along with the stochastic discount factor  $M_{t+1}$  are defined using the representative household's utility function:

$$\mathcal{W}_t = \left( \frac{dU_t}{dC_t} \right)^{-1} \frac{dU_t}{dL_{t+1}} \quad M_{t+1} = \left( \frac{dU_t}{dC_t} \right)^{-1} \frac{dU_t}{dC_{t+1}} \quad (10)$$

The aggregate state  $S_t$  consists of  $(\Pi_t, L_t, \mathcal{I}_t)$  where  $\Pi_t \equiv AK_t^\alpha L_t^{1-\alpha} + (1-\delta)K_t$  is the aggregate resources available,  $L_t$  is aggregate labor input (chosen in  $t-1$ ) and  $\mathcal{I}_t$  is the economy-wide information set. Equation (9) reveals that bond prices are a function of the firm's capital  $\hat{k}_{it+1}$ , labor  $l_{it+1}$  and debt  $B_{it+1}$ , as well as the aggregate state  $S_t$ . The firm takes the aggregate state and the function  $q_{it} = q(\hat{k}_{it+1}, l_{it+1}, B_{it+1}, S_t)$  as given, while recognizing that its firm-specific choices affect its bond price.

**Information, beliefs and equilibrium** The set  $\mathcal{I}_t$  includes the history of all shocks  $\phi_t$  observed up to and including time- $t$ . For now, we specify a general function, denoted  $\Psi$ , which maps  $\mathcal{I}_t$  into an appropriate probability space. The expectation operator  $\mathbb{E}_t$  is defined with respect to this space. In the following section, we make this more concrete using the kernel density estimation procedure outlined in section 1 to map the information set into beliefs.

For a given belief function  $\Psi$ , a recursive equilibrium is a set of functions for (i) aggregate consumption and labor that maximize (1) subject to a budget constraint, (ii) firm value and policies that solve (4), taking as given the bond price function (9) and the stochastic discount factor and aggregate MRS functions in (10) and are such that (iii) aggregate consumption and labor are consistent with individual choices.

## 2.2 Characterization

The equilibrium of the economic model is a solution to the following set of non-linear equations. First, in the firm's problem (4), the constraints on dividends (5) and wages (6) will bind at the optimum. Using them to substitute out for  $d_{it}$  and  $w_{it}$  leaves us with 3 choice variables  $(\hat{k}_{it}, l_{it}, b_{it})$  and a default decision. Optimal default is characterized by a threshold rule in the idiosyncratic output shock  $v_{it}$ :

$$r_{it} = \begin{cases} 0 & \text{if } v_{it} < \underline{v}(S_t) \\ 1 & \text{if } v_{it} \geq \underline{v}(S_t) \end{cases}$$

It turns out to be more convenient to redefine variables and cast the problem as a choice of

$\hat{k}_{it+1}$ , leverage,  $lev_{it+1} \equiv \frac{B_{it+1}}{\hat{k}_{it+1}}$ , and the labor-capital ratio,  $\frac{l_{it+1}}{\hat{k}_{it+1}}$ . We relegate detailed derivations and the full characterization to Appendix A.1. Since all firms make symmetric choices for these 3 objects, we can suppress the  $i$  subscript and express the optimality condition for  $\hat{k}_{t+1}$  as:

$$1 + \chi \mathcal{W}_t \frac{l_{t+1}}{\hat{k}_{t+1}} = \mathbb{E}[M_{t+1} R_{t+1}^k] + (\chi - 1) \frac{B_{it+1}}{\hat{k}_{t+1}} q_t - (1 - \theta) \mathbb{E}[M_{t+1} R_{t+1}^k h(\underline{v})] \quad (11)$$

$$\text{where} \quad R_{t+1}^k = v_{t+1} \frac{\phi_{t+1}^\alpha \hat{k}_{t+1}^\alpha l_{t+1}^{1-\alpha} + (1 - \delta) \phi_{t+1} \hat{k}_{t+1}}{\hat{k}_{t+1}} \quad (12)$$

The term  $R_{t+1}^k$  is the *ex-post* per-unit, pre-wage return on capital, while  $h(\underline{v}) \equiv \int_{-\infty}^{\underline{v}} v f(v) dv$  is the default-weighted expected value of the idiosyncratic shock.

The first term on the right hand side of (11) is the usual expected direct return from investing, weighted by the stochastic discount factor. The other two terms are related to debt. The second term reflects the indirect benefit to investing arising from the tax advantage of debt - for each unit of capital, the firm raises  $\frac{B_{it+1}}{\hat{k}_{it+1}} q_t$  from the bond market and earns a subsidy of  $\chi - 1$  on the proceeds. The last term is the cost of this strategy - default-related losses, equal to a fraction  $1 - \theta$  of available resources.

The optimal labor choice equates the expected marginal cost of labor,  $\mathcal{W}_t$ , with its expected marginal product, adjusted for the effect of additional wage promises on the cost of default:

$$\chi \mathcal{W}_t = \mathbb{E}_t \left[ M_{t+1} (1 - \alpha) \phi_{t+1}^\alpha \left( \frac{\hat{k}_{t+1}}{l_{t+1}} \right)^\alpha J^l(\underline{v}) \right] \quad (13)$$

where  $J^l(\underline{v}) = 1 + h(\underline{v}) (\theta \chi - 1) - \underline{v}^2 f(\underline{v}) \chi (\theta - 1)$  represents the effect of the assumption that labor is chosen in advance in exchange for a debt-like wage promise. Finally, the firm's optimal choice of leverage,  $lev_{it+1}$  is

$$(1 - \theta) \mathbb{E}_t \left[ M_{t+1} \frac{lev_{it+1}}{R_{t+1}^k} f \left( \frac{lev_{it+1}}{R_{t+1}^k} \right) \right] = \left( \frac{\chi - 1}{\chi} \right) \mathbb{E}_t \left[ M_{t+1} \left( 1 - F \left( \frac{lev_{it+1}}{R_{t+1}^k} \right) \right) \right]. \quad (14)$$

The left hand side is the marginal cost of increasing leverage - it raises the expected losses from the default penalty (a fraction  $1 - \theta$  of the firm's value). The right hand side is the marginal benefit - the tax advantage times the value of debt issued.

The three firm optimality conditions, (11), (13), and (14), along with those from the household side (10), form the system of equations we solve numerically.



### 3 Measurement, Calibration and Solution Method

This section describes how we use macro data to estimate beliefs and parameterize the model, as well as our computational approach. One of the key strengths of our theory is that we can use observable data to estimate beliefs at each date.

**Measuring capital quality shocks** Recall from Section 1 that the Great Recession saw unusually low returns to non-residential capital, stemming from unusually large declines in the market value of capital. To capture this, we need to map the model’s aggregate shock, namely the capital quality shock, into market value changes. A helpful feature of capital quality shocks is that their mapping to available data is straightforward. A unit of capital installed in period  $t - 1$  (i.e. as part of  $\hat{K}_t$ ) is, in effective terms, worth  $\phi_t$  units of consumption goods in period  $t$ . Thus, the change in its market value from  $t - 1$  to  $t$  is simply  $\phi_t$ .

We apply this measurement strategy to annual data on non-residential capital held by US corporates. Specifically, we use two time series Non-residential assets from the Flow of Funds, one evaluated at market value and the second, at historical cost.<sup>15</sup> We denote the two series by  $NFA_t^{MV}$  and  $NFA_t^{HC}$  respectively. To see how these two series yield a time series for  $\phi_t$ , note that, in line with the reasoning above,  $NFA_t^{MV}$  maps directly to effective capital in the model. Formally, letting  $P_t^k$  the nominal price of capital goods in  $t$ , we have  $P_t^k K_t = NFA_t^{MV}$ . Investment  $X_t$  can be recovered from the historical series,  $P_{t-1}^k X_t = NFA_t^{HC} - (1 - \delta) NFA_{t-1}^{HC}$ . Combining, we can construct a series for  $P_{t-1}^k \hat{K}_t$ :

$$\begin{aligned} P_{t-1}^k \hat{K}_t &= (1 - \delta) P_{t-1}^k K_{t-1} + P_{t-1}^k X_t \\ &= (1 - \delta) NFA_{t-1}^{MV} + NFA_t^{HC} - (1 - \delta) NFA_{t-1}^{HC} \end{aligned}$$

Finally, in order to obtain  $\phi_t = \frac{K_t}{\hat{K}_t}$ , we need to control for nominal price changes. To do this, we proxy changes in  $P_t^k$  using the price index for non-residential investment from the National Income and Product Accounts (denoted  $PINDX_t$ ).<sup>16</sup> This yields:

$$\begin{aligned} \phi_t &= \frac{K_t}{\hat{K}_t} = \left( \frac{P_t^k K_t}{P_{t-1}^k \hat{K}_t} \right) \left( \frac{PINDX_{t-1}^k}{PINDX_t^k} \right) \\ &= \left[ \frac{NFA_t^{MV}}{(1 - \delta) NFA_{t-1}^{MV} + NFA_t^{HC} - (1 - \delta) NFA_{t-1}^{HC}} \right] \left( \frac{PINDX_{t-1}^k}{PINDX_t^k} \right) \end{aligned} \quad (15)$$

Using the measurement equation (15), we construct an annual time series for capital quality

<sup>15</sup>These are series FL102010005 and FL102010115 from Flow of Funds. See Appendix C.3.

<sup>16</sup>Our results are robust to alternative measures of nominal price changes, e.g. computed from the price index for GDP or Personal Consumption Expenditure, see Appendix B.1.

shocks for the US economy since 1950. The left panel of Figure 4 plots the resulting series. The mean and standard deviation of the series over the entire sample are 1 and 0.03 respectively. The autocorrelation is statistically insignificant at 0.15.

As the graph shows, for most of the sample period, the shock realizations are in a relatively tight range around 1, but we saw two large adverse realizations during the Great Recession: 0.93 in 2008 and 0.84 in 2009. These reflect the large drops in the market value of non-residential capital stock – in 2009, for example, the aggregate value of that stock fell by about 16%. What underlies these large fluctuations? The main contributor was a fall in the value of commercial real estate (which is the largest component of non-residential assets).<sup>17</sup> Through the lens of the model, these movements are mapped to a change in the economic value of capital – in the spirit of the hypothetical example of the Las Vegas hotel at the beginning of Section 2 whose market value falls due to a fall in demand.

**Belief Estimation** We then apply our kernel density estimation procedure to this time series to construct a sequence of beliefs. In other words, for each  $t$ , we construct  $\{\hat{g}_t\}$  using the available time series until that point. The resulting estimates for two dates - 2007 and 2009 - are shown in the right panel of Figure 4. They show that the Great Recession induced a significant increase in the perceived likelihood of extreme negative shocks. The estimated density for 2007 implies almost zero mass below 0.90, while the one for 2009 attach a non-trivial (approximately 2.5%) probability to this region of the state space.

**Calibration** A period is interpreted as a year. We choose the discount factor  $\beta$  and depreciation  $\delta$  to target a steady state capital-output ratio of 3.5 (this is taken from Cooley and Prescott (1995)) and an investment-output ratio of 0.12 (this is the average ratio of non-residential investment to output during 1950-2007 from NIPA accounts).<sup>18</sup> The share of capital in the production,  $\alpha$ , is 0.40, which is also taken from Cooley and Prescott (1995). The recovery rate upon default,  $\theta$ , is set to 0.70, following Gourio (2013). The distribution for the idiosyncratic shocks,  $v_{it}$  is assumed to be lognormal, i.e.  $\ln v_{it} \sim N\left(-\frac{\hat{\sigma}^2}{2}, \hat{\sigma}^2\right)$  with  $\hat{\sigma}^2$  chosen

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<sup>17</sup>One potential concern is that the fluctuations in the value of real estate stem mostly from land price movements. While the data in the Flow of Funds do not allow us to directly control for changes in the market value of land, they do suggest a limited role for land. Measured at historical cost, land accounts for less than 5% of total non-residential capital. The observed fluctuations in the value of these assets during 2008-09 are simply too large to be accounted for by land price movements, even if they are sizable.

<sup>18</sup>This leads to values for  $\beta$  and  $\delta$  of 0.91 and 0.03 respectively. These are lower than other estimates in the literature. However, when we used an alternative calibration strategy with  $\delta = 0.06$  (which is consistent with reported depreciation rates in the Flow of Funds data) and  $\beta = 0.95$  (which leads to the same capital-output ratio), the resulting impulse responses were almost identical.

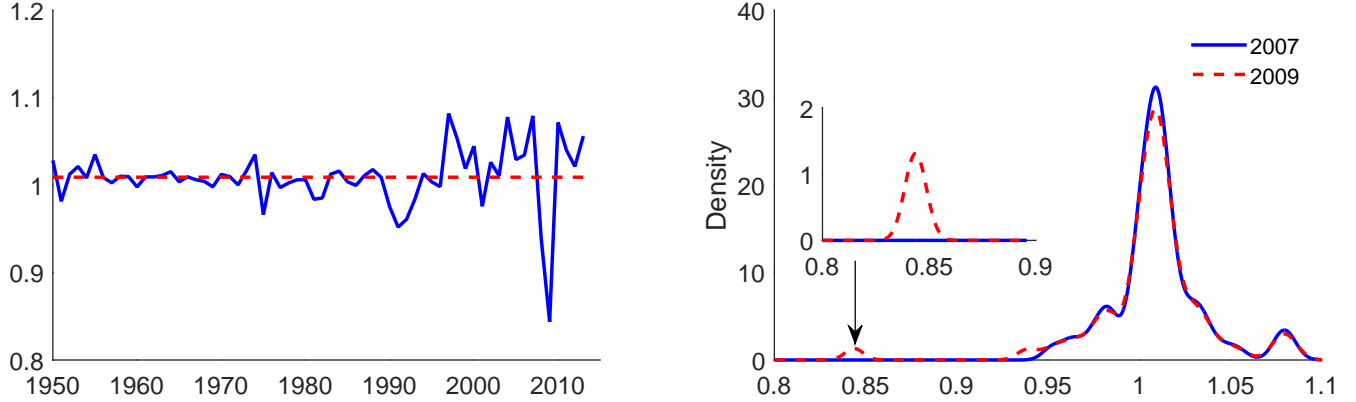


Figure 4: **Capital quality shocks.**

The left panel shows the time series of  $\phi_t$  measured from the US data using (15). The right panel shows the estimated kernel densities in 2007 (solid) and 2009 (dashed) respectively. The change in left tail shows the effect of the Great Recession.

to target a default rate of 0.02.<sup>19</sup> The labor supply parameter,  $\gamma$ , is set to 0.5, in line with [Midrigan and Philippon \(2011\)](#), corresponding to a Frisch elasticity of 2.

For the parameters governing risk aversion and intertemporal elasticity of substitution, we use standard values from the asset pricing literature and set  $\psi = 0.5$  (or equivalently, an IES of 2) and  $\eta = 10$ .<sup>20</sup> The tax advantage parameter  $\chi$  is chosen to match a leverage target of 0.70, which is obtained by adding the wage bill (approximately 0.2 of the steady state capital stock) to financial leverage (the ratio of external debt to capital, about 0.5 in US data - from [Gourio \(2013\)](#)). Table 1 summarizes the resulting parameter choices.

**Numerical solution method** Because curvature in policy functions is an important feature of the economic environment, our algorithm solves equations (11) – (14) with a non-linear collocation method. Appendix A.3 describes the iterative procedure. In order to keep the computation tractable, we need one more approximation. The reason is that date- $t$  decisions (policy functions) depend on the current estimated distribution ( $\hat{g}_t(\phi)$ ) and the probability distribution  $h$  over next-period estimates,  $\hat{g}_{t+1}(\phi)$ . Keeping track of  $h(\hat{g}_{t+1}(\phi))$ , (a compound lottery) makes a function a state variable, which renders the analysis intractable. However, the approximate martingale property of  $\hat{g}_t$  discussed in Section 1 offers an accurate and computationally efficient approximation to this problem. The martingale property implies that the average of the compound lottery is  $E_t[\hat{g}_{t+1}(\phi)] \approx \hat{g}_t(\phi)$ ,  $\forall \phi$ . Therefore, when computing policy functions, we approximate the compound distribution  $h(\hat{g}_{t+1}(\phi))$  with the simple lottery  $\hat{g}_t(\phi)$ , which is

<sup>19</sup>This is in line with the target in [Khan et al. \(2014\)](#), though a bit higher than the one in [Gourio \(2013\)](#). We verified that our quantitative results are not sensitive to this target.

<sup>20</sup>In Appendix B.6, we examine the robustness of our main results to these parameter choices. See also the discussion in [Gourio \(2013\)](#).

Parameter	Value	Description
Preferences:		
$\beta$	0.91	Discount factor
$\eta$	10	Risk aversion
$\psi$	0.50	1/Intertemporal elasticity of substitution
$\gamma$	0.50	1/Frisch elasticity
Technology:		
$\alpha$	0.40	Capital share
$\delta$	0.03	Depreciation rate
$\hat{\sigma}$	0.25	Idiosyncratic volatility
Debt:		
$\chi$	1.06	Tax advantage of debt
$\theta$	0.70	Recovery rate

Table 1: **Parameters**

today’s estimate of the probability distribution. Appendix B.2 uses numerical experiments to show that this approximation is quite accurate. The reason for the small approximation error is that  $h(\hat{g}_{t+1})$  results in distributions centered around  $\hat{g}_t(\phi)$ , with a small standard deviation. The shaded area in the third panel of Figure 3 reveals that even 30 periods out,  $\hat{g}_{t+30}(\phi)$  is still quite close to its mean  $\hat{g}_t(\phi)$ . For 1-10 quarters ahead, where most of the utility weight is, this standard error is tiny.

To compute our benchmark results, we begin by estimating  $\hat{g}_{2007}$  using the data on  $\phi_t$  described above. Given this  $\hat{g}_{2007}$ , we compute the stochastic steady by simulating the model for 1000 periods, discarding the first 500 observations and time-averaging across the remaining periods. This steady state forms the starting point for our results. Subsequent results are in log deviations from this steady state level. Then, we subject the model economy to two adverse realizations - 0.93 and 0.84, which correspond to the shocks that we observed in 2008 and 2009. Using these two additional data points, we re-estimate the distribution, to get  $\hat{g}_{2009}$ . To see how persistent economic responses are, we need a long future time series. We don’t know what distribution future shocks will be drawn from. Given all the data available to us, our best estimate is also  $\hat{g}_{2009}$ . Therefore, we simulate future paths by drawing many sequences of future  $\phi$  shocks from the  $\hat{g}_{2009}$  distribution and we plot the mean future path of various aggregate variables.

## 4 Main Results

Our contribution, and the model feature that we evaluate quantitatively in this section, is the assumption that people do not know the true distribution of aggregate economic shocks and

that they estimate it from available data. This is the source of the persistence at the heart of the secular stagnation puzzle. Of course, we don't need data to tell us that no person could possibly know, with certainty, the exact distribution of economic shocks. But, comparing a model with real-time estimation (learning) to the same model with full knowledge of the distribution (no learning) can reveal when incorporating this feature matters and the extent to which it can help explain features of the data. Our results reveal that when shocks are not unusual, beliefs change little, and the predictions of models with and without learning are nearly indistinguishable. This is reassuring for most existing theories, which focus on 'normal' times. It also teaches us that, to understand how learning might matter, we should examine episodes with unexpected shocks, or tail events. Finally, it explains why the Great Recession was so much more persistent than other recessions.

Observing a tail event like the financial crisis changes beliefs in a persistent way. This in turn shows up as persistent economic responses. Our first set of results compare the predictions of our model for macro aggregates (GDP, investment and labor) since 2008-'09 to an identical model without learning. They show that the model with learning does significantly better in terms of matching the observed behavior of macro variables. Then, to rule out the possibility that persistence comes primarily from the occurrence of future crises, we show that the economic responses are extremely persistent, even if no future crises occur. Next, we demonstrate how learning makes large, unusual recessions different from smaller, more normal ones by comparing the model's predictions for the response to the Great Recession to a counterfactual smaller shock. Then, we explore an economy where agents have learned from earlier episodes such as the Great Depression. We learn that beliefs about tail risk are particularly persistent, not because tail events were never seen before, but because relevant data on tail events is observed infrequently. Finally, we show that incorporating learning delivers more realistic equity, bond and option price predictions.

As described in Section 3, we start the economy at the 2007 steady state, subject it to the 2008 and 2009 shocks, and then draw many future sequences of shocks from  $\hat{g}_{2009}$ . The top left panel of Figure 5 shows the the average of all simulated time paths for  $\phi_t$ . Then we solve the model for each sequence of shocks, and average the results. In the remaining panels, output, investment and employment show a pattern of prolonged stagnation, where the economy (on average) never recovers from the negative shocks in 2008-'09. Instead, all aggregate variables move towards the new, lower (stochastic) steady state. These results do not imply that stagnation will continue forever. The flat response tells us that, from the perspective of an agent with the 2009 information set, recovery is not expected.

The solid line with circles in Figure 5 plots the actual data (in deviations from their re-

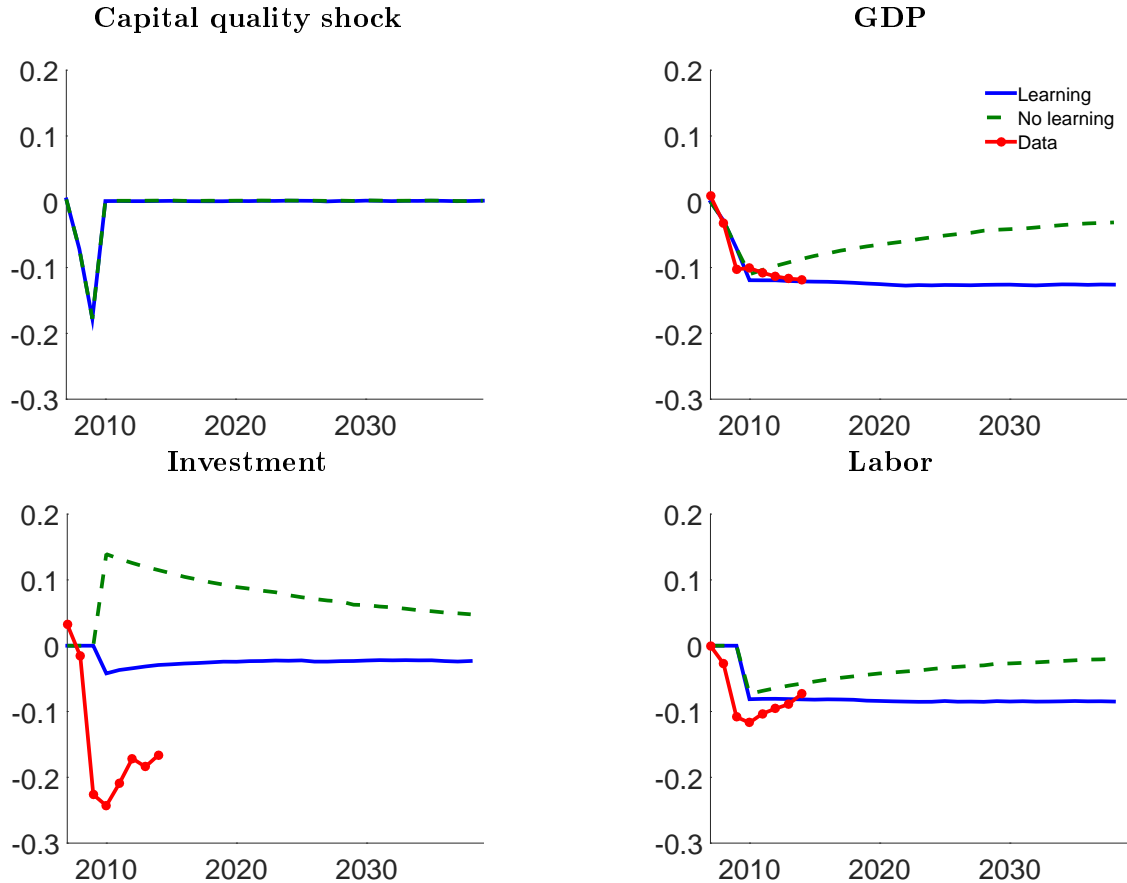


Figure 5: **Persistent responses in output, investment and labor.**

*Solid line shows the change in aggregates (relative to the stochastic steady state associated with  $\hat{g}_{2007}$ ). The circles show de-trended US data for the period 2008-2014. For the dashed line (no learning), agents believe that shocks are drawn from  $\hat{g}_{2009}$  and never revise those beliefs.*

spective 1950-2007 trends) for the US economy.<sup>21</sup> As the graph shows, the model’s predictions for GDP and labor line up well with the recent data, though none of these series were used in the calibration or measurement of the aggregate shock  $\phi_t$ . The predicted path for employment lags and slightly underpredicts the actual changes, largely due to the assumption that labor is chosen in advance. Including shock realizations post-2009 does not materially change these findings (see Appendix B.3).<sup>22</sup>

For investment, the model performs poorly. It predicts less than half of the observed drop. However, without learning, the results are much worse. When agents do not learn, investment surges, instead of plummets. The reason is that the effective size of the capital stock was

<sup>21</sup>Data on output and labor input are obtained from Fernald (2014). Data on investment comes from the series for non-residential investment from the NIPA published by the Bureau of Economic Analysis, adjusted for population and price changes. Each series is detrended using a log-linear trend estimated using data from 1950-2007, see Appendix C.4.

<sup>22</sup>Additional outcomes are reported in Appendix B.11.

already diminished by the capital quality shock. The shock itself is like an enormous, exogenous disinvestment. We could solve this problem by adding more features and frictions.<sup>23</sup> But our main point is about learning and persistence. Despite only partially fixing the investment problem of the capital quality model, Figure 5 clearly demonstrates the quantitative potential of learning as a source of persistence.

Table 2 summarizes the long-run effects of the belief changes, by comparing the stochastic steady states associated with  $\hat{g}_{2007}$  and  $\hat{g}_{2009}$ . It shows that capital and labor are 17% and 8% lower under the latter, which translates into a drop in output and consumption levels of about 12%. Investment is also lower by about 7%. Thus, even though the  $\phi_t$  shocks experienced during the Great Recession were transitory, the resulting changes in beliefs persistently reduce economic activity.

	Stochastic steady state levels		Change
	$\hat{g}_{2007}$	$\hat{g}_{2009}$	
Output	6.37	5.67	-12 %
Capital	27.52	22.80	-17%
Investment	0.71	0.66	- 7%
Labor	2.40	2.20	-8%
Consumption	5.66	5.01	-12%

Table 2: **Belief changes from 2008-'09 shocks lead to significant reductions in economic activity.**

*Columns marked  $\hat{g}_{2007}$  and  $\hat{g}_{2009}$  represent average levels in the stochastic steady state of a model where shocks are drawn from  $\hat{g}_{2007}$  or  $\hat{g}_{2009}$  distributions respectively.*

**Turning off belief updating** To demonstrate the role of learning, we plot average simulated outcomes from an otherwise identical economy where agents know the final distribution  $\hat{g}_{2009}$  with certainty, from the very beginning (dashed line in Figure 5). Now, by assumption, agents do not revise their beliefs after the Great Recession. This corresponds to a standard rational expectations econometrics approach, where agents are assumed to know the true distribution of shocks hitting the economy and the econometrician estimates this distribution using all the available data. The post-2009 paths are simulated as follows: each economy is assumed to be at its stochastic steady state in 2007 and is subjected to the same sequence of shocks – two large negative ones in 2008 and 2009 and subsequently, sequences of shocks drawn from the estimated 2009 distribution.

<sup>23</sup>Financial frictions which impeded investment include those in [Gertler and Karadi \(2011\)](#) and [Brunnermeier and Sannikov \(2014\)](#). Alternative amplification mechanisms are studied in [Adrian and Boyarchenko \(2012\)](#); [Jermann and Quadrini \(2012\)](#); [Khan et al. \(2014\)](#); [Zetlin-Jones and Shourideh \(2014\)](#); [Bigio \(2015\)](#); [Moriera and Savov \(2015\)](#), among others.

In the absence of belief revisions, the negative shocks lead to an investment boom, as the economy replenishes the lost effective capital. While the curvature in utility moderates the speed of this transition to an extent, the overall pattern of a steady recovery back to the original steady state is clear.<sup>24</sup> This shows that learning is what generates long-lived reductions in economic activity.

**What if shocks are persistent?** An alternative explanation for persistence is that there was no learning. Instead, the shocks simply had persistently bad realizations. In Appendix B.8, we show that allowing for a realistic amount of persistence in the  $\phi_t$  shocks does not materially change the dynamics of aggregate variables. This is because the the observed autocorrelation of the  $\phi_t$  process is too low to generate any meaningful persistence.

**What if there are no more crises?** In the results presented above, we put ourselves on the same footing as the agents in our model and draw future time paths of shocks using the updated beliefs  $\hat{g}_{2009}$ . One potential concern is that persistent stagnation comes not from belief changes *per se* but from the fact that future paths are drawn from a distribution where crises occur with non-trivial probability. This concern is not without merit. If we draw future shocks from the distribution,  $\hat{g}_{2007}$ , where the probability of a crisis is near zero, beliefs are not Martingales. In that world, beliefs change by the same amount on impact, but then converge back to their pre-crisis levels. Without the permanent effect on beliefs, persistence should fall.

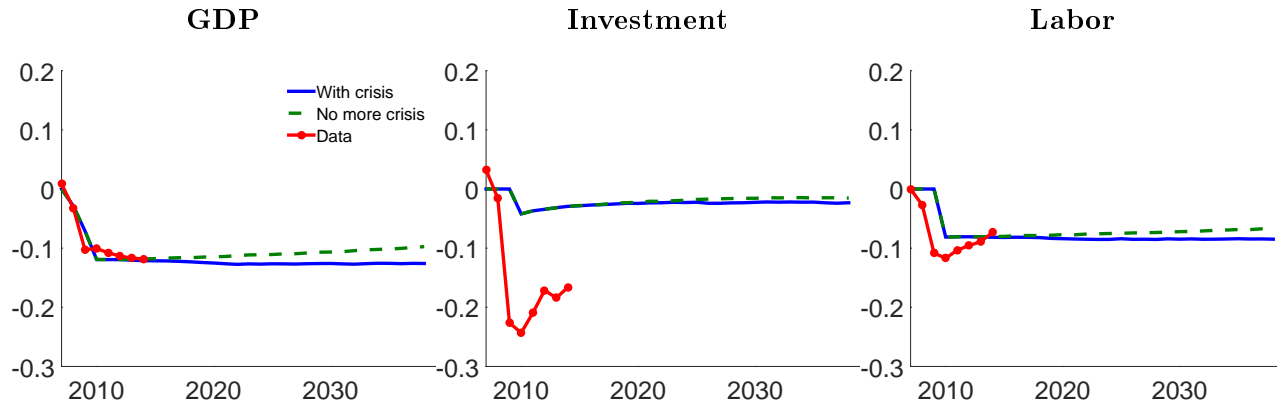


Figure 6: **What if there are no more crises?**

*Solid (With crisis) line shows the change in aggregates when the data generating process is  $\hat{g}_{2009}$  and agent updates beliefs. Dashed line (No more crisis) is an identical model in which future shocks are drawn from  $\hat{g}_{2007}$ . The circles show de-trended US data for the period 2008-2014.*

<sup>24</sup> Since the no-learning economy is endowed with the same end-of-sample beliefs as the learning model, they both ultimately converge to the same *levels*. But, they start at different steady states (normalized to 0 for each series).



However, Figure 6 shows that the persistence over a 30 year horizon is almost the same with and without future crises (solid and dashed lines). The reason belief effects are still so long-lived is that it takes many, many no-crisis draws to convince someone that the true probability of a crisis is less than an already-small probability. For example, if one observed 100 periods without a crisis, this would still not be compelling evidence that the odds are less than 1%. This highlights that beliefs about tail probabilities are persistent because tail-relevant data arrives infrequently.

The fact that most data is not relevant for inferring tail probabilities is a consequence of our non-parametric approach. If instead, we imposed a parametric form like a normal distribution, then tail probabilities would depend only on the mean and variance of the distribution. Since mean and variance are informed by all data, tail probability revisions are frequent and small. As a result, the effects of the ‘08 and ‘09 shocks are more transitory. See Appendix B.9 for quantitative results.

## 4.1 Shock Size and Persistence

The secular stagnation puzzle is not about why all economic shocks are so persistent. The question is why this recession had more persistent effects than others. Assuming that shocks are persistent does not answer this question. Our model explains why persistent responses arise mainly after a tail event. Every decline in capital quality has a transitory direct effect (it lowers effective capital) and a persistent belief effect. Thus, the extent to which a shock generates persistent outcomes depends on the relative size of these two effects. Observing a tail event, one we did not expect, change beliefs a lot and generates a large persistent effect. A small shock has a negligible effect on beliefs and therefore, generates little persistence. This finding – that learning does not matter when ‘normal’ shocks hit – is also the reason why we focus on the Great Recession. We could use the model to explore regular business cycles, but the versions with and without learning would be almost observationally equivalent, yielding little insight into the role of learning.

Figure 7 shows the effects on output of a small adverse shock (1 standard deviation below the mean<sup>25</sup>), again starting from the stochastic steady state associated with  $\hat{g}_{2007}$ . Obviously, the effects are smaller than the baseline model (note the scale on the y-axis). The smaller initial impact reflects the non-linearity of the model’s policy functions.

More importantly for our mechanism, the effect of small shocks is transitory and nearly the same with or without learning. Learning is still a source of persistence, but quantitatively, it amounts to very little. The bulk of the persistence from the small shock just comes from agents

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<sup>25</sup>This is roughly the magnitude of the shock observed during the 2001-’02 recession.

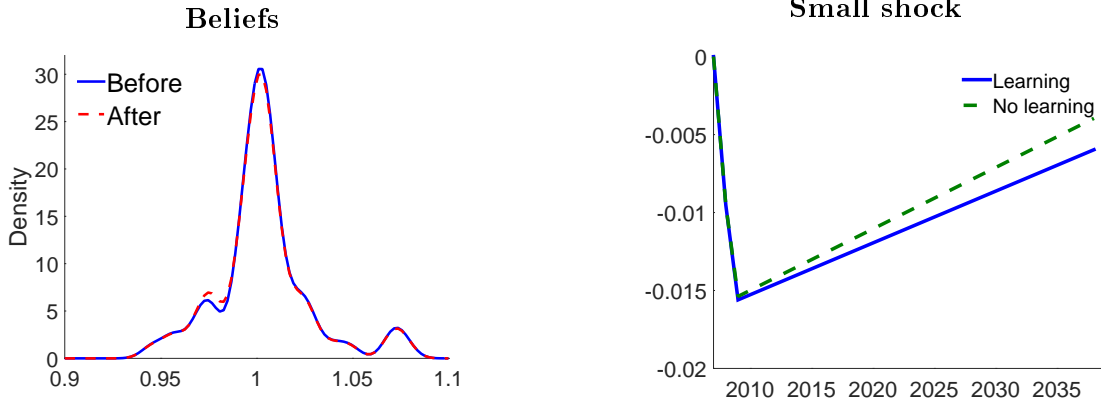


Figure 7: **Small shocks create negligible persistence.**

*The first panel shows the estimated density before the shock (solid blue) and after a one standard deviation shock (dashed red). The second panel shows the response of output to the small shock under learning and no learning.*

gradually building the capital stock back up, an effect that is there in the no-learning model as well.

This effect is really more about the likelihood than about the size of a shock. The reason that persistence is so low for small shocks is that beliefs do not change much. The left panel of Figure 7 shows that the only difference in beliefs is a small deviation of the red line from the blue around 0.97. But if large shocks were observed frequently and small ones infrequently, then small shocks would be surprising, would change beliefs by more and would have more persistent effects. Thus, our learning mechanism offers a novel explanation for why fluctuations triggered by rare events (like financial crises) are particularly persistent.

## 4.2 Longer data sample and the Great Depression

Since our simulations start in 1950, the Great Depression is not in our agents' information set. This raises the question: How would access to more data, with large adverse shocks in it, affect the response of beliefs to the recent financial crisis? In the limit, as data accumulates, agents know the true distribution; new data ceases to affect beliefs. However, beliefs about tail events converge more slowly than those elsewhere in the distribution, because of infrequent observations. In this section, we approximate data extending back to the 19th century and show that the belief changes induced by the 2008-09 experience continue to have a large, persistent effect on economic activity.

The difficulty with extending the data is that the non-financial asset data used in  $\phi_t$  is available only for the post-WW II period. Other macro and financial series turn out to be unreliable proxies.<sup>26</sup> But our goal here is not to explain the Great Depression. It is to understand how

<sup>26</sup>We projected the measured  $\phi_t$  series post-1950 on a number of variables and used the estimated coefficients

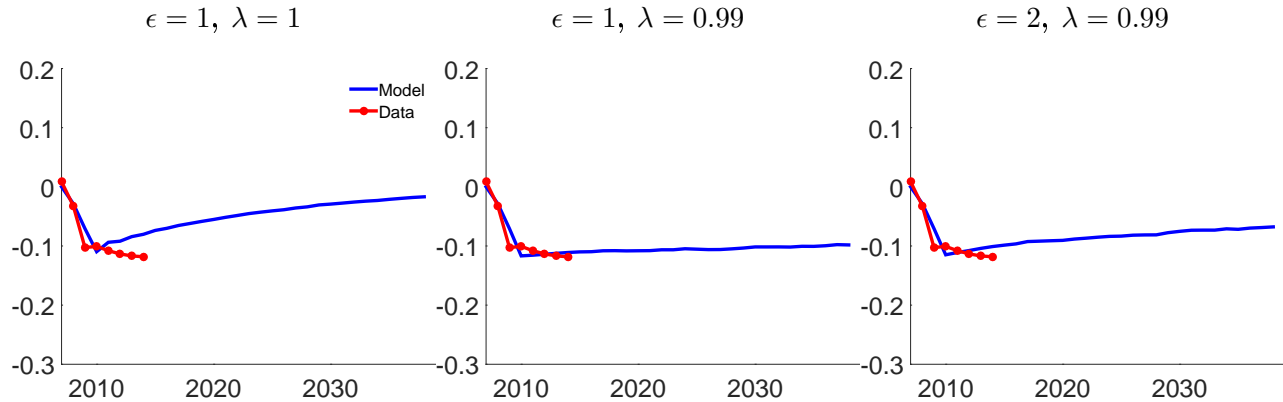


Figure 8: **Extending the data sample tempers persistence slightly.**

Each panel plots the response of GDP to the 2008-09 shocks under a hypothetical information set, starting from 1890. To fill in the data for the period 1890-1949, we use the observed time series from 1950-2009, with  $\{\phi_{1929}, \phi_{1930}\} = \{\phi_{2008}^\varepsilon, \phi_{2009}^\varepsilon\}$ . The parameter  $\lambda$  indexes the extent to which older observations are discounted where  $\lambda = 1$  represents no discounting.

having more data, especially previous crises, affects learning today. So we use the post-WW II sample to construct pre-WW II scenarios. Specifically, we assume that  $\phi_t$  realizations for the period from 1890-1949 were identical to those in 1950-2009, with one adjustment: The Great Depression shocks were as bad or worse those in the Great Recession. To make this adjustment, we set  $\{\phi_{1929}, \phi_{1930}\} = \{\phi_{2008}^\varepsilon, \phi_{2009}^\varepsilon\}$ , with  $\varepsilon \geq 1$ . Recall that  $\phi$  in 2008 and 2009 are less than one. So, raising them to a power greater than one makes them smaller.

We then repeat our analysis under the assumption that agents are endowed with this expanded 1890-2007 data series. Now, when the financial crisis hits, the effect on beliefs is moderated by the larger data sample, which contains a similar or worse previous crisis.

Once we include data from a different eras, the assumption that old and new data are treated as equally relevant becomes less realistic. We consider the possibility that agents discount older observations. This could reflect the possibility of unobserved regime shifts or experiential learning with overlapping generations (Malmendier and Nagel, 2011).<sup>27</sup> To capture such discounting, we modify our kernel estimation procedure. Observation from  $s$  periods earlier are assigned a weight  $\lambda^s$ , where  $\lambda \leq 1$  is a parameter. When  $\lambda = 1$ , there is no discounting.

The first panel of Figure 8 reveals that, even without discounting ( $\lambda = 1$ ), the difference between the model with and without Great Depression data is modest, as of 2016: There is a

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to impute values for  $\phi_t$  pre-1950. However, this did not produce accurate estimates in-sample. Specifically, it missed crises. We explored a wide range of macro and asset pricing variables - including GDP, unemployment, S&P returns and the Case-Shiller index of home prices. We also experimented with lead-lag structures. Across specifications, the resulting projections for 1929-1930 showed only modestly adverse realizations.

<sup>27</sup>This discounting procedure is similar to Sargent (2001), Cho et al. (2002) and Evans and Honkapohja (2001).

similar output drop on impact, with attenuated persistence from the additional data. When older data is discounted by 1% ( $\lambda = 0.99$ , the center panel), this attenuation almost completely disappears and the impulse responses replicate our baseline estimates.<sup>28</sup>

Perhaps the true magnitude of the Great Depression shocks is far larger than those seen in 2008-09. Suppose  $\varepsilon = 2$ , so that  $(\phi_{1929}, \phi_{1930}) = (0.86, 0.70)$ . These are very large shocks - 5 and 10 standard deviations below the mean. Taken together, they imply an erosion of almost 50% in the stock of effective capital. The third panel of Figure 8 shows that, with 1% annual discounting ( $\lambda = 0.99$ ), persistence is attenuated, but only modestly.

In sum, expanding the information set by adding more data does not drastically alter our main conclusions, especially once we allow agents to discount older data.

### 4.3 Evidence from Asset Markets

Our goal in this section is not to address standard shortcomings of macroeconomic models, but rather to compare the asset pricing predictions of the models with and without learning to asset price data. Since the effect of learning is detectable only after tail events, we consider the difference in asset prices before and after the Great Recession. We find that while the model's predictions for credit spreads and equity prices are broadly consistent with the data, these variables are not very sensitive to, and therefore, not very informative about tail risk. On the other hand, option-implied tail risk – the probabilities of extreme events priced into options – are a much better indicator. On that metric, the model's predictions line up quite well with the observed changes in those probabilities.

Credit spreads – the difference between the interest on a risky and a riskless loan – are commonly interpreted as a measure of risk. This spread surged at the height of the crisis but is now back to just slightly above its pre-crisis levels. Hall (2015a) argues that the low spreads imply low tail risk and therefore, persistent tail risk is not a likely explanation for stagnation.

The results in Table 3 argue against this conclusion. The connection between spreads and tail risk is weak – our calibrated model predicts a negligible, 2 basis point, rise in spreads. Since the model without learning predicts no long-run changes in asset prices, the small change in spread means that credit spreads are not a useful device for divining beliefs about tail risk. This is due, in part, to equilibrium effects: An increase in bankruptcy risk induces firms to issue less debt. Debt in the new steady state is about 17% lower.<sup>29</sup> In the data, total liabilities

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<sup>28</sup>If we keep increasing the discount, the decline in long-run GDP becomes *bigger*. Intuitively, with high enough discounting, the weight of recent observations increases beyond the level in the undiscounted, reduced sample used for our baseline analysis. For example, with  $\lambda = 0.98$ , GDP drops by about 16% in the new steady state.

<sup>29</sup>The leverage ratio (debt and wage obligation divided by total assets) is also slightly lower, by about 0.5%.

Changes in	Model	Data
<b>Asset prices and debt</b>		
Credit Spreads	0.02%	0.14%
Equity Premium	1.41%	3.27%
Equity (Market value)/Assets	1%	21%
Risk free rate	-0.54%	-1.42%
Debt	-17%	-19%
<b>Tail risk for equity</b>		
Third moment	-0.27%	-0.28%
Tail risk	1.48%	2.23%

Table 3: **Changes in financial market variables, Model vs data.**

*Model results are log differences between the model's 2007 level and the long-run average with future shocks drawn from  $\hat{g}^{2009}$ . Data reports the 2013-2015 average minus 2005-2007 average. Third moment is  $E[(R^e - \bar{R}^e)^3]$ , where  $R^e$  is the return on equity. Tail risk is  $\text{Prob}(R^e - \bar{R}^e \leq -0.3)$ . Both the expectation and the probability are taken under the risk-neutral measure. For the no-learning model, all changes are zero.*

of nonfinancial corporations (relative to trend)<sup>30</sup> show a similar change – about 19%. This de-leveraging lowers default risk and therefore, credit spreads. In the model, the net effect of higher tail risk and lower firm debt on credit spreads is nearly zero. Thus, the fact that spreads are back to their pre-crisis levels does not rule out tail risk – one of the surprising predictions of the model.

Similarly, one might think that equity should be worth less when risk is high. The fact that equity prices have surged recently and are higher than their pre-crisis levels thus appears inconsistent with a rise in tail risk. But again, the model teaches us why this logic is incomplete. When firms face higher tail risk and reduce debt, equity becomes less risky and thus more valuable (Modigliani and Miller, 1958). In our model, the market value of a dividend claim associated with a unit of capital is slightly higher under the post-crisis beliefs than under the pre-crisis ones. In other words, the combined effect of the changes in tail risk and debt is mildly positive.<sup>31</sup> While the magnitudes differ – we don't claim to solve the equity premium puzzle here – our point is simply that rising equity valuations are not evidence against tail risk.

Furthermore, the changes in equity premia are in the right ballpark. The model predicts an

<sup>30</sup>Total liabilities of nonfinancial corporate business is taken from series FL104190005 from Table B.103 in the Flow of Funds. As with the other macro series, we adjust for inflation and population growth and then detrend using a simple log-linear trendline. The number reported in the table is the difference between the 2013-15 and 2005-07 averages.

<sup>31</sup>The aggregate market capitalization in our model can be obtained by simply multiplying the value of the dividend claim by the aggregate capital stock. In the data, the ratio of the market capitalization of the non-financial corporate sector to their (non-financial) asset positions shows a much more dramatic increase. We interpret this discrepancy as reflecting, at least partly, the limitations of our model as an asset pricing framework.

equity premium (the difference between expected return on equity and the riskless rate) that is about 1.5% higher under the 2009 beliefs than under the 2007 beliefs. To compute the analogous object in the data, we follow the methodology in [Cochrane \(2011\)](#) and [Hall \(2015b\)](#).<sup>32</sup> This approach estimates that equity premia in 2013-15 were about 3.27% higher than in 2005-07. In other words, tail risk can account for about half of the recent rise in equity premia.

The behavior of riskless rates since 2008-09 is also consistent with the model. Heightened tail risk increases the premium for safe assets, which depresses riskless rates. Under our calibration, the change in beliefs induced by the 2008-09 realizations leads to a 54 bp drop in the riskless rate. In the data, the riskfree real interest rate (computed as the difference between nominal yield of 1-year US treasuries and inflation) averaged -0.81 % between 2013-15, as against 0.61% during 2005-07, a drop of about 1.4%. Obviously, we do not want to claim that increased tail risk is the only force behind the current low level of interest rates.

In sum, none of these trends in asset markets is at odds with the tail risk story we are advancing. If credit spreads and equity premia are not clear indicators of tail risk, what is? For that, we need to turn option prices, in particular out-of-the-money put options on the S&P 500, which can be used to isolate changes in perceived tail risk. A natural metric is the third moment of the distribution of equity returns. It is straightforward to compute this from the SKEW and VIX indices reported by the CBOE.<sup>33</sup> As [Table 3](#) shows, the market-implied distribution has become more negatively skewed after the Great Recession. We compute the same risk-neutral third moment in the model (using the distribution for stock returns under the 2009 and 2007 beliefs) and the predicted change lines up almost exactly with the data. To show how this change maps into probabilities of tail events, we also report the change in the implied risk-neutral odds of a return realization 30% less than the mean.<sup>34</sup> The likelihood of that event increased by about 2.2% in the data and 1.5% in the model.

## 4.4 Understanding the Economic Response to Belief Changes

What model ingredients are needed for belief to have substantial aggregate effects and why? To answer this, we perform a series of experiments, varying and turning off specific features of

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<sup>32</sup>We estimate one-year ahead forecast from a regression where the left-hand variable is the one-year real return on the S&P and the right hand variables are a constant, the log of the ratio of the S&P at the beginning of the period to its dividends averaged over the prior year, and the log of the ratio of real consumption to disposable income in the month prior to the beginning of the period.

<sup>33</sup>Formally, the 3rd central moment under the risk-neutral measure is given by

$$E(R^e - \bar{R}^e)^3 = \frac{100 - SKEW_t}{10} \cdot VIX_t^3$$

For more information, see <http://www.cboe.com/micro/skew/introduction.aspx>.

<sup>34</sup>For details of the computation, see [Appendix B.10](#).

the model – learning about the mean vs higher order moments, curvature in utility and debt – one-by-one in order to isolate how much each one contributes. The bottom panel of Table 4 shows that removing any of these elements would eliminate between one-fourth and one-half of our long-run effects.<sup>35</sup>

	2014	Long run
Data	-0.12	
Benchmark model	-0.12	-0.12
<i>Counterfactuals:</i>		
Constant mean	-0.09	-0.06
No curvature in utility	-0.07	-0.07
No debt	-0.12	-0.09

Table 4: **Change in GDP relative to 2007 steady state.**

**Learning about the mean capital quality shock.** We decompose the total effect of belief revisions into a component attributable to changes in the mean (average  $\phi$ ) and the remaining attributable to changes in higher moments. To do this, we adjust the estimated distribution in 2009 so that  $\mathbb{E}_{2009}(\phi_t) = \mathbb{E}_{2007}(\phi_t)$ . The change in the mean  $\mathbb{E}_t[\phi_t]$  between 2007 and 2009 is relatively modest, only about 0.4%. Even with the mean change taken out, the long-run fall in GDP is about 6%, about half of the total effect in our baseline case (Figure 9, left panel). In Appendix B.4, we explore this high sensitivity using a deterministic version of the model without debt. This simplified model reveals, in closed form, the elasticity of long-run, steady-state capital to the mean capital quality:

$$\frac{d \ln k_{ss}}{d \ln \phi_{ss}} = \left( \frac{1 + \gamma}{\gamma} \frac{\alpha}{1 - \alpha} \right) + \left( \frac{1}{1 - \alpha} \frac{\alpha + \gamma}{\gamma} \right) \frac{(1 - \delta)}{1/\beta - (1 - \delta)\phi_{ss}} = 2 + 3(7.5) = 24.5.$$

Capital, and thus output, is highly sensitive to capital quality because it affects current returns (first term) and holdings gains (second term), which come from the undepreciated capital stock. This sensitivity, which is far greater than to total factor productivity, lies at the heart of the significant economic effects.

**Role of curvature in utility** Next, we explore the role of curvature in utility, by exploring an otherwise identical economy with quasilinear preferences. If  $\psi = \eta = 0$ , the utility function reduces to  $C_t - \frac{L_t^{1+\gamma}}{1+\gamma}$ . Because this eliminates risk aversion and the desire for consumption smoothing, the economy transitions immediately to any new steady state (second panel of

<sup>35</sup>These patterns are robust to drawing future time paths under the assumption that no future crises occur. For details, see Table 6 in Appendix B.5.

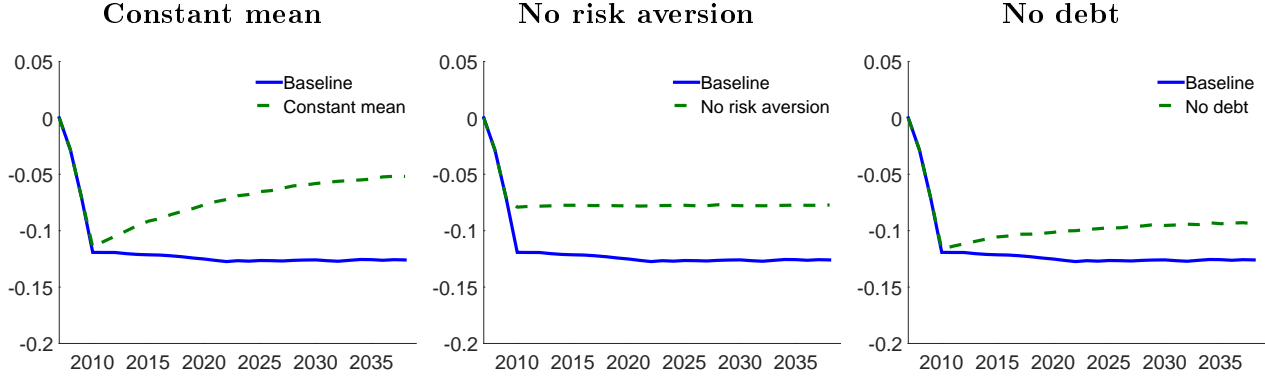


Figure 9: **Understanding the role of expected return, risk aversion and debt.**

*Change in  $\ln$  GDP under 3 different scenarios: (1) the mean capital quality shock  $E[\phi_t]$  is held fixed; (2) no risk aversion, and (3) no debt.*

Figure 9). However, belief revisions still have long-lived effects – long-run output is about 7% lower (compared to 12% in the baseline model). In other words, curvature in utility accounts for roughly 40% of long-run stagnation.

Risk aversion matters because it introduces a risk premium for capital and labor. Tail risk raises this premium, further dampening incentives to invest and hire. Appendix B.6 shows that the effect of tail risk on macro aggregates is increasing, albeit modestly, in both risk aversion and the intertemporal elasticity of substitution. These results highlight the role of Epstein-Zin preferences. With CRRA preferences, high risk aversion implies low intertemporal elasticity, dampening the drop in long-run economic activity.

**Role of debt** When we set the tax advantage parameter  $\chi$  to 1, all investment is financed through equity. Debt and leverage are 0. The third panel of Figure 9 shows that belief revisions trigger a 9% long-run reduction in output without debt, compared to 12% with debt. Thus, defaultable debt contributes about a fourth of the long run stagnation.

Debt also plays an important role in one of the main questions of the paper, namely why some shocks generate more persistent responses than others. The attractiveness of debt (and therefore, the incentives to borrow) is affected disproportionately by perceived tail risk - and since larger shocks changes belief further out in the tail, they are amplified by debt. Since tail risk is the source of persistence, by amplifying its effects increases persistence as well.

In Figure 10, we subjected our model economy to shocks ranging in size from 1 to 5 standard deviations and plotted the corresponding long-run GDP effect. The responsiveness to small shocks is almost the same with and without debt. Because debt adds aggregate non-linearity, larger shocks see significant amplification. Since the risk of a larger shock is what persists, debt makes the severity and persistence of unusual events differ from common downturns.



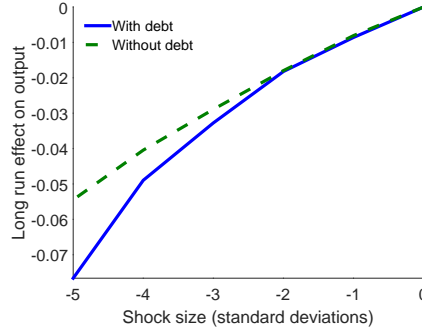


Figure 10: **Debt amplifies belief revisions from large shocks.**

*Change in long-run GDP both with (solid line) and without debt (dashed line) in response to negative shocks of various sizes. The initial condition is the  $\hat{g}_{2007}$  steady state.*

## 5 Conclusion

No one knows the true distribution of shocks to the economy. Economists typically assume that agents in their models know this distribution, as a way to discipline beliefs. But assuming that agents do the same kind of real-time estimation that an econometrician would do is equally disciplined and more plausible. For many applications, assuming full knowledge has little effect on outcomes and offers tractability. But for outcomes that are sensitive to tail probabilities, the difference between knowing these probabilities and estimating them with real-time data can be large. The estimation error can introduce new, persistent dynamics into a model with otherwise transitory shocks. The essence of the persistence mechanism is this: Once observed, a shock (a piece of data) stays in one's data set forever and therefore persistently affects belief formation. The less frequently similar data is observed, the larger and more persistent the belief revision.

When firms finance investments with debt, they make investment and output sensitive to tail risk. Debt is an asset whose payoffs are flat throughout most of the state space, but very sensitive to the state for left-tail, default events. Therefore, the cost of debt depends precisely on the probabilities of a tail event, which are hardest to estimate and whose estimates fluctuate greatly. When debt (leverage) is low, the economy is not very sensitive to tail risk, and economic shocks will be more transitory. The combination of high debt levels and a shock that is a negative outlier makes tail risk surge, investment fall and depresses output in a persistent way.

When we quantify this mechanism and use capital price and quantity data to directly estimate beliefs, our model's predictions resemble observed macro outcomes in the wake of the great recession. These results suggests that perhaps persistent stagnation arose because, after seeing how fragile our financial sector is, market participants will never think about tail risk in the same way again.

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All of this material is for a separate, on-line appendix. It is not intended to be printed with the paper.

# A Model's solution

## A.1 Optimality conditions from firm's problem

Let

$$R^k \left( \frac{l_{it+1}}{\hat{k}_{it+1}}, \phi_{t+1} \right) \equiv \frac{\Pi_{it+1}}{\hat{k}_{it+1}} = v_{it} \left( \phi_{t+1}^\alpha \left( \frac{l_{it+1}}{\hat{k}_{it+1}} \right)^{1-\alpha} + (1-\delta)\phi_{t+1} \right).$$

Substituting in dividends and wages from (5) and (6), we can restate the firm's maximization problem as:

$$\Gamma_{it} = \max_{\hat{k}_{it+1}, lev_{it+1}, \frac{l_{it+1}}{\hat{k}_{it+1}}} \hat{k}_{it+1} \left( -1 - \chi \mathcal{W}_t \frac{l_{it+1}}{\hat{k}_{it+1}} + \chi q lev_{it+1} + \mathbb{E} M_{t+1} r_{t+1} \left( v_{it} R_{t+1}^k - lev_{it+1} + \frac{\Gamma_{it+1}}{\hat{k}_{it+1}} \right) \right)$$

and

$$q \left( \frac{l_{it+1}}{\hat{k}_{it+1}}, lev_{it+1}, S_t \right) = \mathbb{E} M_{t+1} \left[ r_{t+1} + (1-r_{t+1}) \theta \frac{v_{it} R_{t+1}^k + \frac{\Gamma_{it+1}}{\hat{k}_{it+1}}}{lev_{it+1}} \right].$$

We guess (and later verify) that  $\Gamma_{it} = 0$ .<sup>36</sup> Substituting for the bond price function and rearranging terms yields

$$\Gamma_{it} = \max_{\hat{k}_{it+1}, lev_{it+1}, \frac{l_{it+1}}{\hat{k}_{it+1}}} \hat{k}_{it+1} \left( -1 - \chi \mathcal{W}_t \frac{l_{it+1}}{\hat{k}_{it+1}} + \mathbb{E} M_{t+1} \tilde{J}_{t+1}^k \right)$$

$$\text{where } \tilde{J}_{t+1}^k = R_{t+1}^k + lev_{it+1} (\chi - 1) r_{t+1} + (\chi\theta - 1) (1 - r_{t+1}) v_{it} R_{t+1}^k.$$

From the definition of the default threshold, we have  $\mathbb{E} r_{t+1} = 1 - F(\underline{v})$ . Also, note that the threshold is  $\underline{v} = \frac{lev_{it+1}}{R_{t+1}^k}$ . Hence

$$\tilde{J}_{t+1}^k = R_{t+1}^k (1 + \underline{v} (\chi - 1) (1 - F(\underline{v})) + (\chi\theta - 1) h(\underline{v}))$$

where  $h(v) = \int_{-\infty}^v v dF(v)$ . Finally, the problem is

$$\begin{aligned} \Gamma_{it} &= \max_{\hat{k}_{it+1}, lev_{it+1}, \frac{l_{it+1}}{\hat{k}_{it+1}}} \hat{k}_{it+1} \left( -1 - \chi \mathcal{W}_t \frac{l_{it+1}}{\hat{k}_{it+1}} + \mathbb{E} M_{t+1} R_{t+1}^k J^k(\underline{v}) \right) \\ J^k(\underline{v}) &= 1 + (\chi - 1) \underline{v} (1 - F(\underline{v})) + (\chi\theta - 1) h(\underline{v}) \\ \underline{v} &= \frac{lev_{it+1}}{R_{t+1}^k} \end{aligned}$$

$J^k(\underline{v})$  reflects the net effect of distortions induced by debt and can be interpreted as a wedge. It distorts equilibrium capital choice away from the choices of a planner. In the absence of debt (e.g. if  $\chi = 1$ ),  $J^k(\underline{v}) = 1$ , reducing (11) to a standard Euler equation.

**Capital choice:** The problem is linear in  $\hat{k}_{it+1}$  therefore in equilibrium we must have that

$$1 + \chi \mathcal{W}_t \frac{l_{it+1}}{\hat{k}_{it+1}} = \mathbb{E} M_{t+1} R_{t+1}^k J^k(\underline{v}),$$

which implies equation (11) in the main text and in turn it verifies the guess,  $\Gamma_{it} = 0$ .

<sup>36</sup>Intuitively, given constant returns to scale, the firm's problem turns out to be linear in capital. In equilibrium, therefore, in order for the firm's value to be bounded, we must have  $\Gamma_{it} = 0$ . See Navarro (2014).

**Labor choice:** Next, the first order condition with respect to  $\frac{l_{t+1}}{\hat{k}_{it+1}}$  is

$$\chi \mathcal{W}_t = \mathbb{E}M_{t+1} R^k \frac{\partial J^k(\underline{v})}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} + \mathbb{E}M_{t+1} \frac{\partial R^k}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} J^k(\underline{v}),$$

Now,

$$\begin{aligned} R_{t+1}^k \frac{\partial J^k(\underline{v})}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} &= R_{t+1}^k \frac{\partial \underline{v}}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} \left( (\chi - 1)(1 - F(\underline{v})) - \underline{v}(\chi - 1)f(\underline{v}) + (\chi\theta - 1) \frac{\partial h(\underline{v})}{\partial \underline{v}} \right) \\ \frac{\partial \underline{v}}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} &= -\frac{lev_{it+1}}{(R^k)^2} \frac{\partial R^k}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} = -\frac{\underline{v}^2}{lev_{it+1}} \frac{\partial R^k}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} \\ \frac{dh(\underline{v})}{d\underline{v}} &= \underline{v}f(\underline{v}) \\ \frac{\partial R_{t+1}^k}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} &= v_{it}(1 - \alpha) \phi_{t+1}^\alpha \left( \frac{l_{it+1}}{\hat{k}_{it+1}} \right)^{-\alpha}. \end{aligned}$$

Rearranging terms yields (13) in the main text:

$$\begin{aligned} \chi \mathcal{W}_t &= \mathbb{E}M_{t+1} \frac{\partial R^k}{\partial \frac{l_{t+1}}{\hat{k}_{it+1}}} J^l(\underline{v}) \\ J^l(\underline{v}) &= 1 + \underline{v}^2 f(\underline{v}) \chi(1 - \theta) - (1 - \chi\theta) h(\underline{v}), \end{aligned}$$

**Leverage choice:** The first order condition with respect to leverage is

$$\mathbb{E}M_{t+1} R_{t+1}^k \frac{\partial J_{t+1}^k}{\partial lev_{it+1}} = 0,$$

where

$$\begin{aligned} \frac{\partial J_{t+1}^k}{\partial lev_{it+1}} &= \frac{\partial \underline{v}}{\partial lev_{it+1}} \left( (\chi - 1)(1 - F(\underline{v})) - (\chi - 1)\underline{v}f(\underline{v}) + (\chi\theta - 1)\underline{v}f(\underline{v}) \right) \\ &= \frac{1}{R_{t+1}^k} \left( (\chi - 1)(1 - F(\underline{v})) - \chi(1 - \theta)\underline{v}f(\underline{v}) \right). \end{aligned}$$

Substituting and re-arranging, we obtain (14) in the main text:

$$(1 - \theta) \mathbb{E}_t [M_{t+1} \underline{v}f(\underline{v})] = \left( \frac{\chi - 1}{\chi} \right) \mathbb{E}_t [M_{t+1} (1 - F(\underline{v}))],$$



## A.2 Equilibrium Characterization

Thus, an equilibrium is the solution to the following system of equations:

$$1 + \chi \mathcal{W}_t \frac{L_{t+1}}{\hat{K}_{t+1}} = \mathbb{E} M_{t+1} \left[ \phi_{t+1}^\alpha \left( \frac{\hat{K}_{t+1}}{L_{t+1}} \right)^{\alpha-1} + (1 - \delta) \phi_{t+1} \right] J^k(\underline{v}) \quad (16)$$

$$\chi \mathcal{W}_t = \mathbb{E} M_{t+1} \left[ (1 - \alpha) \phi^\alpha \left( \frac{\hat{K}_{t+1}}{L_{t+1}} \right)^\alpha \right] J^l(\underline{v}) \quad (17)$$

$$(1 - \theta) \mathbb{E}_t [M_{t+1} \underline{v} f(\underline{v})] = \left( \frac{\chi - 1}{\chi} \right) \mathbb{E}_t [M_{t+1} (1 - F(\underline{v}))] \quad (18)$$

$$C_t = \phi_t^\alpha \hat{K}_t^\alpha L_t^{1-\alpha} + (1 - \delta) \phi_t \hat{K}_t - \hat{K}_{t+1} \quad (19)$$

$$U_t = \left[ (1 - \beta) (u(C_t, L_t))^{1-\psi} + \beta \mathbb{E} \left( U_{t+1}^{1-\eta} \right)^{\frac{1-\psi}{1-\eta}} \right]^{\frac{1}{1-\psi}} \quad (20)$$

where

$$\begin{aligned} \underline{v} &= \frac{lev_{t+1}}{\phi_{t+1}^\alpha \left( \frac{\hat{K}_{t+1}}{L_{t+1}} \right)^{\alpha-1} + (1 - \delta) \phi_{t+1}} \\ J^k(\underline{v}) &= 1 + (\chi - 1) \underline{v} (1 - F(\underline{v})) + (\chi\theta - 1) h(\underline{v}) \\ J^l(\underline{v}) &= 1 + \underline{v}^2 f(\underline{v}) \chi (1 - \theta) - (1 - \chi\theta) h(\underline{v}) \\ M_{t+1} &= \left( \frac{dU_t}{dC_t} \right)^{-1} \frac{dU_t}{dC_{t+1}} = \beta \left[ \mathbb{E} \left( U_{t+1}^{1-\eta} \right) \right]^{\frac{\eta-\psi}{1-\eta}} U_{t+1}^{\psi-\eta} \left( \frac{u(C_{t+1}, L_{t+1})}{u(C_t, L_t)} \right)^{-\psi} \\ \mathcal{W}_t &= \left( \frac{dU_t}{dC_t} \right)^{-1} \frac{dU_t}{dL_{t+1}} = \left( \frac{dU_t}{dC_t} \right)^{-1} \mathbb{E} \frac{dU_t}{dC_{t+1}} \left( \mathbb{E} \frac{dU_t}{dC_{t+1}} \right)^{-1} \frac{dU_t}{dL_{t+1}} = L_{t+1}^\gamma \mathbb{E} M_{t+1} \end{aligned}$$

## A.3 Solution Algorithm

To solve the system described above at any given date  $t$  (i.e. after any observed history of  $\phi_t$ ), we recast it in recursive form with grids for the aggregate state  $(\Pi, L)$  and the shocks  $\phi$ . We then use an iterative procedure:

- Estimate  $\hat{g}$  on the available history using the kernel estimator.
- Start with a guess (in polynomial form) for  $U(\Pi, L), C(\Pi, L)$ .
- Solve (16)-(18) for  $\hat{K}'(\Pi, L), L'(\Pi, L), lev'(\Pi, L)$  using a non-linear solution procedure.
- Verify/update the guess for  $U, C$  using (19)-(20) and iterate until convergence.

## B Additional Results

### B.1 Measurement of $\phi_t$ : Alternative price indices

Figure 11 shows that the measurement of capital quality shocks is unaffected when we use the price index for GDP or Personal Consumption Expenditure to control for nominal price changes.

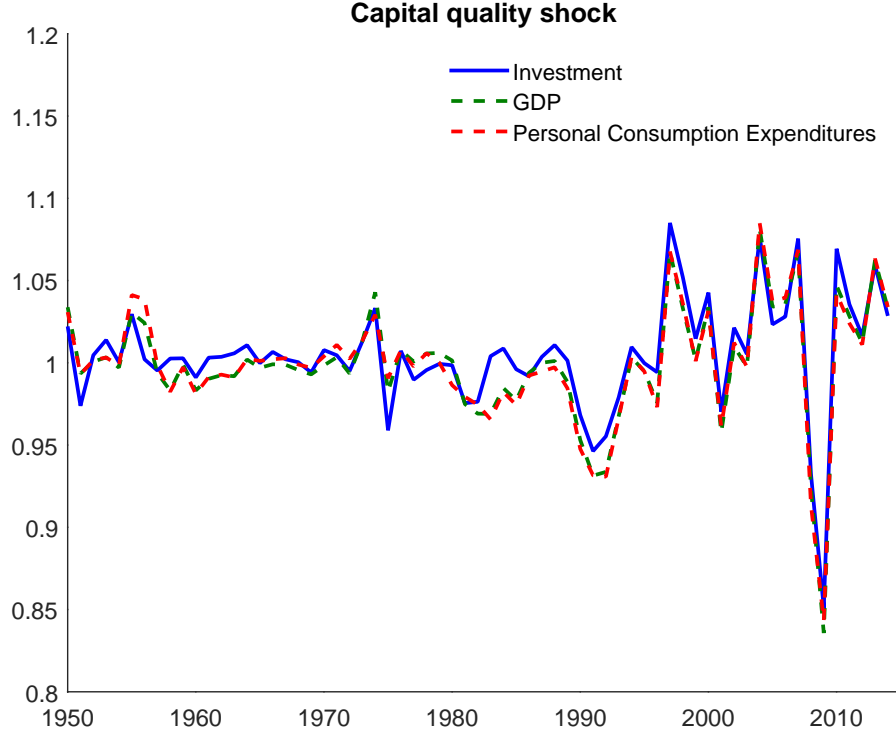


Figure 11: **Time series of measured capital quality shocks using different indices to control for nominal price changes.**

## B.2 Numerical accuracy of solution method

To test the numerical accuracy of our solution method, we perform the following exercise. Starting from the steady state of  $\hat{g}_{2007}$ , we simulate time paths for two different economies. In Model I, as new data arrives, we update beliefs and policy functions at each date and history. In Model II, beliefs and policy functions are fixed at  $\hat{g}_{2007}$ . In our solution, we essentially assume that agents use Model II as an approximation for Model I, while evaluating continuation values. Table 5 shows the sample mean and coefficient of variation for output at different horizons for these two versions.<sup>37</sup> It is easy to see that aggregates (or at least, the first two moments thereof) are very well-approximated by replacing the sequence of future distributions with their conditional mean. Recall that this numerical procedure works reasonable well thanks to the martingale property of beliefs.

## B.3 Effect of 2010-2014 shocks

Here, we subject our baseline calibrated model to the full sequence of shocks, from 2008 through 2014. Agents' decisions in each year are a function of the estimated distribution at that date. The resulting time paths are plotted in Figure 12, along with the de-trended data. We note that the patterns implied by the model are quite close to the observed ones.

<sup>37</sup>These are averages over 4000 paths. Other aggregate variables, e.g. capital and labor, show similar patterns.

	Horizon			
	$s = 1$	$s = 5$	$s = 10$	$s = 15$
$\mathbb{E}_t [y_{t+s}]$				
Model I:	6.378	6.385	6.393	6.397
Model II:	6.378	6.385	6.394	6.398
$\text{CV}_t [y_{t+s}]$				
Model I:	0.010	0.032	0.042	0.046
Model II:	0.010	0.031	0.040	0.044

Table 5: **Numerical accuracy.**

The rows labeled *Model I* show the actual moments under the assumption that beliefs  $\hat{g}_{2007+s}$  are re-estimated at each date. *Model II* corresponds to the assumption underlying our solution method, where future beliefs are replaced by  $\hat{g}_{2007}$ .

## B.4 Steady State Analysis

To dig a little deeper into why long-run outcomes are so sensitive to  $\phi$ , we turn to a special case - a deterministic version of our economy without debt. The level of steady state capital is given by the following equation<sup>38</sup>

$$\ln k_{ss} = \text{Const.} + \left( \frac{1+\gamma}{\gamma} \frac{\alpha}{1-\alpha} \right) \ln \phi_{ss} - \left( \frac{1}{1-\alpha} \frac{\alpha+\gamma}{\gamma} \right) \ln \left( \frac{1}{\beta} - (1-\delta) \phi_{ss} \right). \quad (21)$$

Hence, the effect of the mean shock on steady state capital is given by

$$\frac{d \ln k_{ss}}{d \ln \phi_{ss}} = \left( \frac{1+\gamma}{\gamma} \frac{\alpha}{1-\alpha} \right) + \left( \frac{1}{1-\alpha} \frac{\alpha+\gamma}{\gamma} \right) \frac{(1-\delta)}{1/\beta - (1-\delta)\phi_{ss}}.$$

Under our parameterization,

$$\frac{1+\gamma}{\gamma} \frac{\alpha}{1-\alpha} = 2, \quad \frac{1}{1-\alpha} \frac{\alpha+\gamma}{\gamma} = 3, \quad \left( \frac{(1-\delta)}{1/\beta - (1-\delta)\phi_{ss}} \right)_{\phi_{ss}=1} = 7.5$$

which implies  $\frac{d \ln k_{ss}}{d \ln \phi_{ss}} = 2 + 3(7.5) = 24.5$ . This simple calculation shows the source of the high sensitivity - the fact that capital quality shock affects not just the current return component but also the portion that comes from the undepreciated stock.

## B.5 What if there are no more crises?

The bottom panel of Table 6 reports the change in GDP under the assumption that a crisis never occurs again, i.e. future time paths are drawn from  $\hat{g}_{2007}$ , under various assumptions about learning and the presence of debt. For comparison, the middle panel reproduces the corresponding numbers for the baseline version (where time paths are drawn  $\hat{g}_{2009}$ ). Both cases are remarkably similar over a 30 year horizon, underscoring the persistent

<sup>38</sup>In steady state,  $M_t = 1$  and the intertemporal Euler equation and labor optimality conditions reduce to

$$\begin{aligned} 1 &= \beta (\alpha \phi_{ss}^\alpha k_{ss}^{\alpha-1} l_{ss}^{1-\alpha} + \phi_{ss} (1-\delta)) \\ l_{ss}^\gamma &= W_{ss} = (1-\alpha) \phi_{ss}^\alpha k_{ss}^\alpha l_{ss}^{-\alpha}. \end{aligned}$$

Substituting for  $l_{ss}$  from the second into the first and re-arranging yields the expression (21).

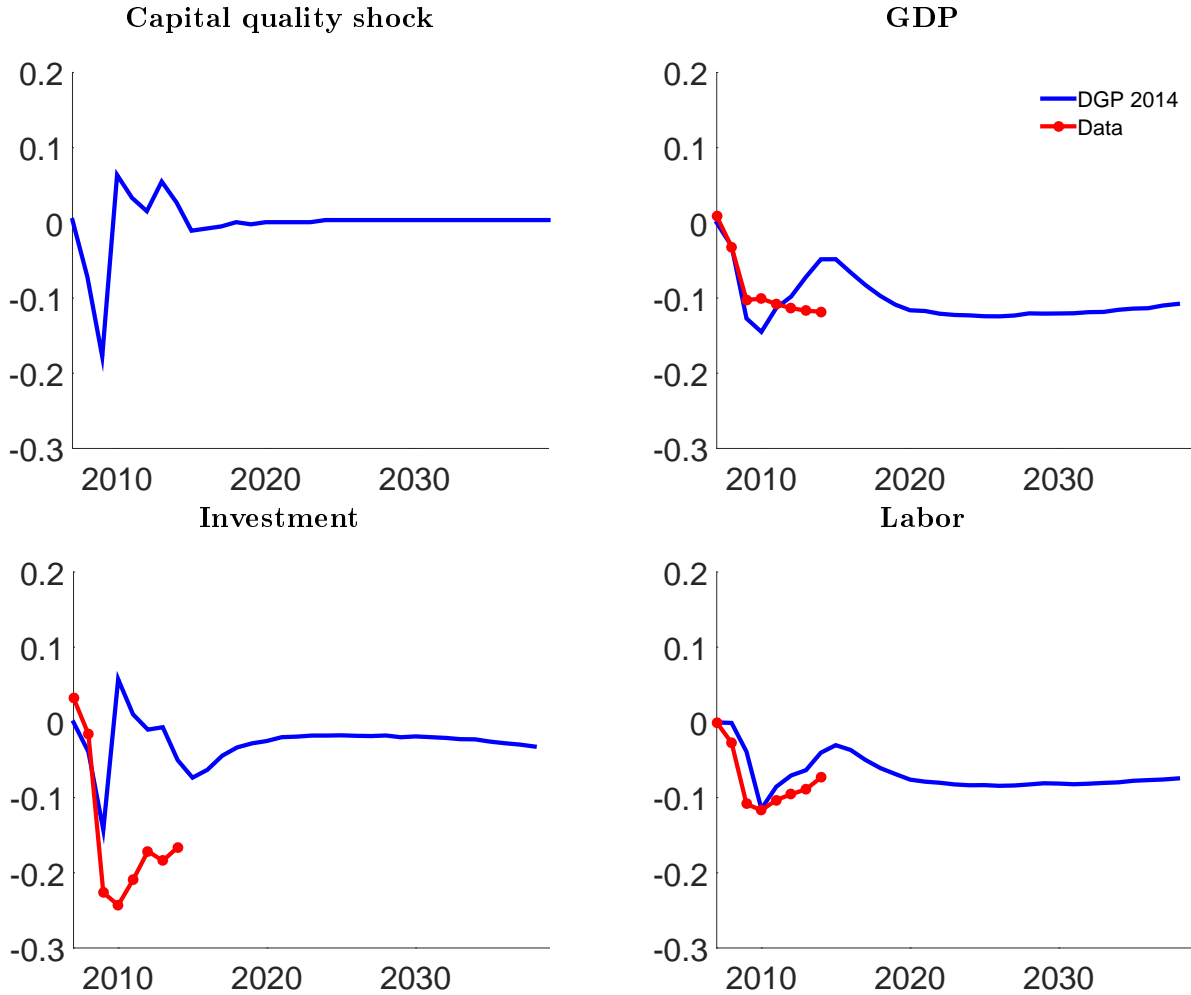


Figure 12: **Model vs data from 2008-2014.**

*Solid line is the baseline model subjected to the observed sequence of shocks from 2008-2014. The red circles are US data, in deviations from their pre-crisis trends.*

nature of belief revisions, even in the absence of crises.

## B.6 Role of Risk Aversion, Intertemporal Elasticity of Substitution

Risk aversion, IES and debt all play a role in determining the magnitude of the effects of increased tail risk. In order to show how much, here we compare our baseline results to a number of alternative parameterizations/assumptions. The results for the role of recursive preferences and assumptions are collected here in Table 7. The first column reproduces our benchmark results, which sets risk aversion = 10 and  $IES = 2$ . The next two columns vary, respectively, risk aversion holding IES constant and IES holding risk aversion constant. The last 2 columns show results under CRRA utility, with a risk aversion coefficient of 2 and 0.5 respectively.

Our estimate for the IES was drawn from the macro and asset-pricing literature – see, e.g., Bansal and Yaron (2004), Barro (2009), Baron et. al. (2014). In order to assess the robustness of our results to this parameter, we ran the model with an IES of 1 – the results are presented in Column 2. Under this parameterization, the

	2014	2039
Data	-0.12	
Benchmark: Draws from $\hat{g}_{2009}$		
Learning, debt	-0.12	-0.12
Learning, no debt	-0.11	-0.09
No learning, debt	-0.9	0.00
No learning, no debt	-0.08	0.00
No more crises: Draws from $\hat{g}_{2007}$		
Learning, debt	-0.12	-0.10
Learning, no debt	-0.10	-0.06
No learning, debt	-0.08	0.00
No learning, no debt	-0.07	0.00

Table 6: Changes in GDP (relative to 2007 steady state)

Parameters	EZ			CRRA	
	10	10	5	0.5	2
Risk Aversion ( $\eta$ )	10	10	5	0.5	2
IES ( $1/\psi$ )	2	1	2	2	0.5
<b>Change in</b>					
GDP	-0.12	-0.09	-0.09	-0.08	-0.07
Labor	-0.18	-0.15	-0.15	-0.12	-0.11
Investment	-0.06	-0.03	-0.03	-0.01	0.01

Table 7: Role of risk aversion and intertemporal elasticity of substitution. The second panel reports the difference in the value of the variable in the new (post-crisis) and old (pre-crisis) stochastic steady states.

model predicts a slightly lower, but importantly just as persistent, drop in GDP (9% vs 12% in the benchmark). This is due to a precautionary channel – agents dislike intertemporal fluctuations in consumption, so faced with the increased likelihood of a tail event, they have an incentive to hold *more* capital to mitigate the potential consumption drop. This channel is stronger, the lower is IES. In fact, as the IES approaches 0, this channel becomes so powerful that it can overwhelm the disincentives to invest and can lead agents to *increase* investment in response to higher tail risk. However, in the region that the macro and asset-pricing literature typically focuses on, the effects of varying IES are relatively modest.

Analogously, column 3 reveals that the size of the drop in economic activity from increased tail risk is lower when agents are less risk averse. This is intuitive – the extent to which agents dislike the increased riskiness of investment depends on their aversion to risk. However, as with IES, the magnitude of our effects is not particularly sensitive to this parameter.

The previous two exercises show that the magnitude of effects of increased tail risk on the macro economy are increasing, albeit modestly, in both risk aversion and IES. Under CRRA utility, of course, the two are tightly (and negatively) linked – a high risk aversion necessarily implies a low IES and vice-versa. For example, in Column 4 of Table 7, we show results for a CRRA specification with the same IES as the benchmark parameterization. However, this now comes with a much lower risk aversion (0.5 vs 10), which attenuates the long-run drop in GDP (from 11% to 8%). Finally, Column 5 shows results for a CRRA specification with an IES of 0.5 (or equivalently, risk aversion of 2). Now, GDP in the new steady state is lower by about 7%.

## B.7 Role of GHH preferences

The GHH specification of utility has criticized as being inconsistent with the facts on long run growth, specifically the observation that labor input is more or less constant (or maybe, slightly declining) in most advanced economies. One resolution is the following specification proposed by [Jaimovich and Rebelo \(2006\)](#):

$$u(C_t, L_t) = C_t - X_t \frac{L_t^{1+\gamma}}{1+\gamma} \quad X_t = X_{t-1}^{1-\varrho} C_t^\varrho$$

Now, on the balanced growth path, the state variable  $X_t$  grows at the same rate as wages, ensuring labor stays constant. The parameter  $\varrho$  governs the strength of wealth effects on labor supply away from the long run. The lower value of  $\varrho$ , the closer the behavior of the economy is to the GHH specification in the short-to-medium run. In their baseline calibration, Jaimovich and Rebelo use  $\varrho = 0.001$  at a quarterly frequency.

Solving this version of our model with learning involves an additional state variable and considerable computational complexity. However, a simple back-of-the-envelope calculation suggests that the drop in GDP and consumption over a 30 year horizon would only be slightly lower than our baseline (GHH) specification (about 10% instead of 12%). To see why, a 10% drop in consumption, along with  $\varrho = 0.001$ , implies a change in  $X_t$  over 30 years of approximately  $0.1(1 - 0.999^{120}) = 0.011$ . Assuming that wages change by about the same as in the baseline, the optimality conditions for labor and capital imply that the drops in  $L_t$  and  $K_t$  are about 2% lower than under GHH (6% instead of 8% and 15% instead of 17%, respectively), which are consistent with the conjectured 10% drop in GDP and consumption. Over shorter horizons, e.g. the 7 years or so for which we actually have data, the two specifications would be virtually indistinguishable. <sup>39</sup>

## B.8 Exogenous persistence in $\phi_t$

In this section, we show that the observed degree of persistence in the data is just not enough to explain the prolonged stagnation since 2008-'09 in the absence of learning. To do this, we solved a rational expectations (i.e. no learning) version of our model where the  $\phi_t$  shocks are no longer iid, but follow an AR(1) process (computationally, this requires an additional state variable). Recall from Section 3 that the autocorrelation of the observed  $\phi_t$  series was 0.15. In Figure 13, we plot the impulse responses from the large negative realizations observed during 2008-09 in this version of the model, with persistence set to 0.15. As the graph shows, the implications are quite similar to the iid, no-learning case – investment surges and the economy slowly but steadily recovers back to the pre-crisis level. Even if we used a shock process that was twice as persistent ( $\rho = 0.30$ ) as the data, the results do not change significantly, as we see in Figure 14. From these results, it seems reasonable to conclude that persistence of the shock itself is an unlikely explanation for the last 8 years.

## B.9 Learning with a Normal distribution

Here, we repeat our analysis under the assumption that agents fit a normal distribution to the available data. The resulting beliefs revisions are shown in the second panel of figure 15 (the first panel reproduces the baseline kernel density estimates). The large, negative tail realizations in 2008-09 lowers the mean and increases the

<sup>39</sup>As an additional robustness exercise, we repeated the steady-state exercise in Appendix B.4 with Cobb-Douglas preferences:  $u(C_t, L_t) = C_t^\alpha (1 - L_t)^{1-\alpha}$ . The responsiveness of capital and output to a change in the steady-state level of  $\phi$  is about 70% of the elasticity in the baseline case. In other words, even with wealth effects on labor supply, the effects of increased tail risk in the long run are quite significant.

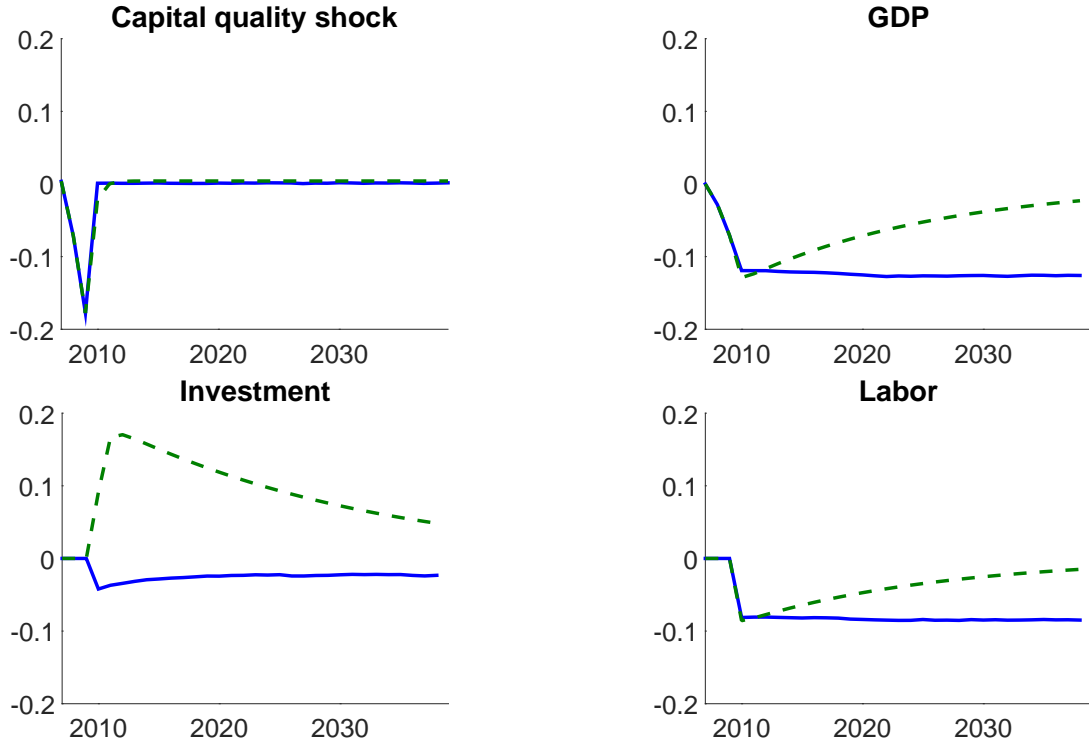


Figure 13: No learning model, with persistent shocks (dashed line,  $\rho = 0.15$ ) vs. learning model with iid shocks.

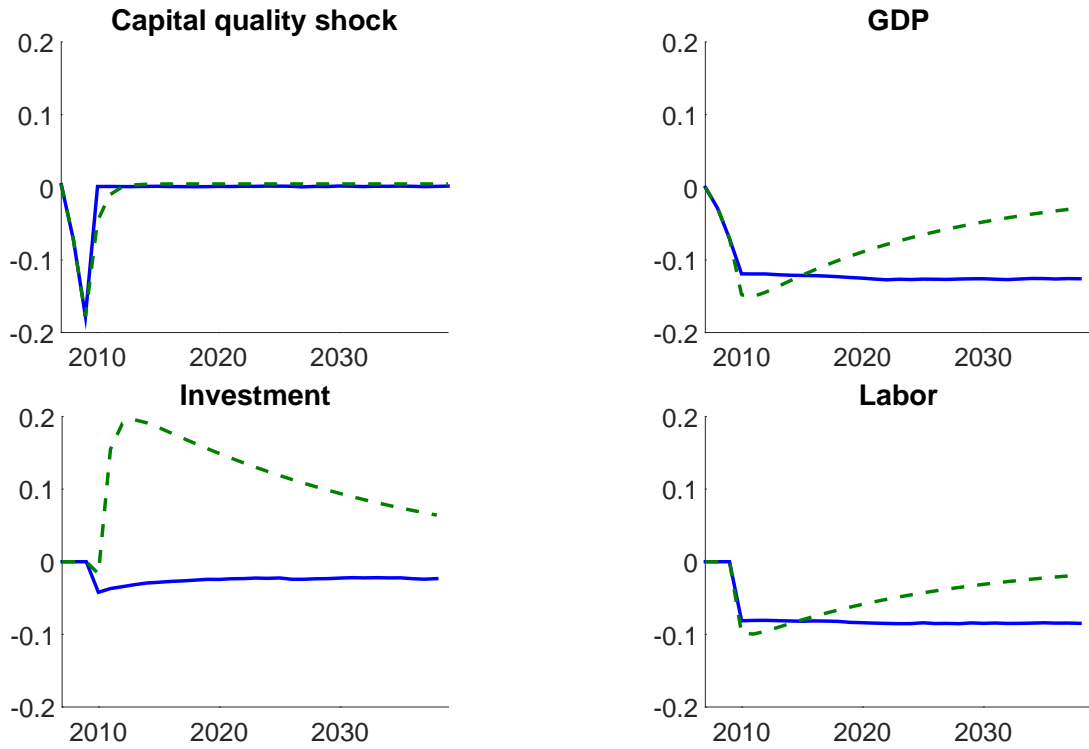


Figure 14: No learning model, with  $2\times$  estimated persistence (dashed line,  $\rho = 0.30$ ) vs. learning model with iid shocks (solid line).

variance of the estimated normal distribution. Qualitatively, these belief revisions are also long-lived, for the same reason as those under the kernel density estimation. The economic implications are also sizable and similar to our baseline, especially in the short run. This is partly the result of the direct impact of the shock itself and partly from the fact that changes in the first two moments have an substantial effect in this highly non-linear setting.

However, the two procedures imply different time paths for beliefs and economic activity. This is seen most clearly in the exercise where we simulate the economy by drawing time paths from the pre-crisis distribution. The third panel compares the average path for GDP when agents estimate a lognormal distribution to the baseline (kernel density) case. The graph shows faster recovery for macro variables under the former. This is because realizations anywhere in the support contain information about the mean and variance of the normal distribution. The kernel estimate of the distribution at a particular point in the support, on the other hand, places relatively more weight on the observed history close to it, making learning more ‘local’. The non-parametric procedure captures the idea that tail events are harder to learn about, because they are, by definition, rare. Imposing a parametric form on the distribution essentially allows the agent to learn about the probability of disasters from more normal times, and therefore, ties learning about tail risk much more closely to learning about the rest of the distribution. Obviously, if the parametric form of the distribution was known, this is the efficient thing to do, but this exercise illustrates how the assumption can have a significant effect.

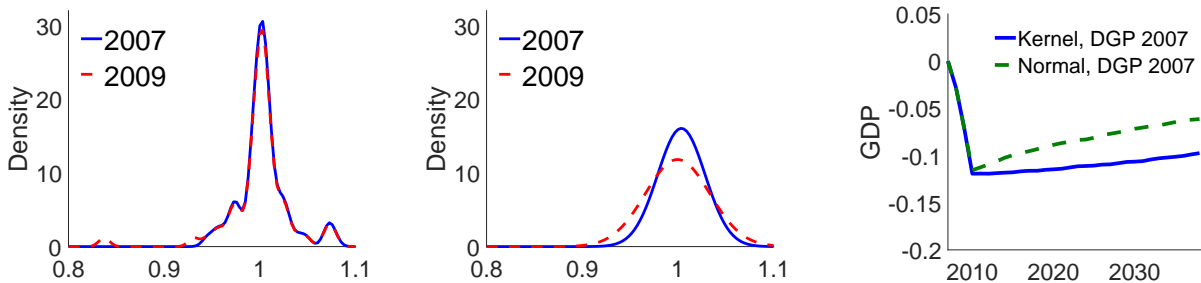


Figure 15: **Learning with a Normal distribution.**

*Beliefs under our baseline non-parametric procedure (first panel) and assuming a normal distribution (second panel). The third panel shows the exercise where we simulate the economy by drawing time paths from the pre-crisis distribution.*

## B.10 Computing option-implied tail probabilities

To compute tail probabilities, we follow Backus et al. (2008) and use a Gram-Charlier expansion of the distribution function.<sup>40</sup> This yields an approximate density function for the standardized random variable,  $\omega = \frac{x-\mu}{\sigma}$ :

$$f(\omega) = \varphi(\omega) \left[ 1 - \gamma \frac{(3\omega - \omega^3)}{6} \right] \quad \text{where} \quad \gamma = E \left[ \frac{x - \mu}{\sigma} \right]^3$$

where  $\varphi(\omega)$  is the density function of a standard normal random variable and  $\gamma$  is the skewness.<sup>41</sup>

<sup>40</sup>The CBOE also follows this method in their white paper on the SKEW Index to compute implied probabilities.

<sup>41</sup>The Gram-Charlier expansion also includes a term for the excess kurtosis, but is omitted from the expansion because, as shown by Bakshi et al. (2003), it is empirically not significant.



The VIX and the SKEW indices provide the standard deviation and the skewness of the implied risk-neutral distribution of the returns on the S&P 500. The numbers reported for tail probabilities in Table 3 are computed using this distribution.

## B.11 Consumption

Figure 16 shows that the behavior of consumption, as predicted by the model and the corresponding pattern in the data. The model overpredicts the drop in consumption in the years immediately following impact – the flip side of its inability to match the full extent of the drop in investment during that time – but over a longer horizon, the predicted drop lines up quite well with the data.

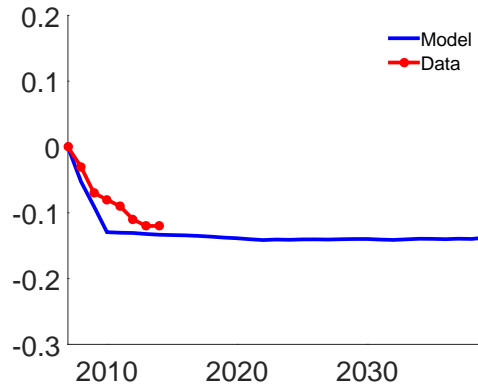


Figure 16: **Consumption.**

## C Other evidence

### C.1 Internet search

Data on internet search behavior lends support to the idea that assessments of tail risk are persistently higher after the financial crisis. Figure 17 shows that the frequency of searches for the terms “financial crisis,” “economic crisis,” and “systemic risk” spiked during the crisis and then came back down. But this search frequency did not return to its pre-crisis level. In each case, there was some sustained interest in crises at a higher level than pre-2007. We find similar results for searches on the terms “economic collapse,” “financial collapse,” and “tail risk” yielded similar results.

### C.2 Stock market

One question that often arises is whether other unusual events, such as the large stock market drop in 2008, might trigger a persistent economic response. Here, we illustrate what belief revisions would look like for agents learning about the distribution of stock returns. Of course, we acknowledge that this is not the driving force in our model. It is only intended to further illustrate possible future applications of our persistence mechanism.

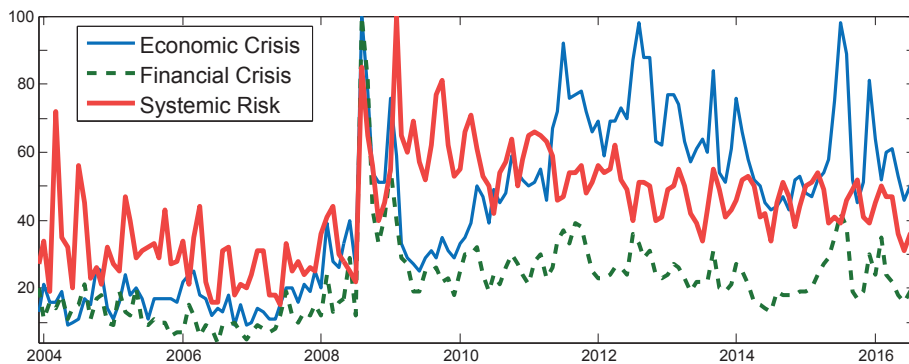


Figure 17: **Tail risk-related Google searches rose permanently after 2008.**

*Search frequency for the terms 'financial crisis,' 'economic crisis,' and 'systemic risk' world-wide, from December 2003 - September 2016. Each series is normalized so that the highest intensity month is set to 100. Source: Google trends.*

Figure 18 shows the belief revision after observing 2008-09 equity returns, and the distribution of future beliefs under two different assumptions about the true distribution of shocks. Annual returns 1950-2009 come from Robert Shiller's website.

What we see is that large negative equity returns during 2008-09 are not all that unusual. The stock market has plunged many times. Seeing one more drop, while not very common, was not so unusual as to change beliefs by much. We conclude that while stock returns can also generate some persistence through belief updating, this force is not a likely candidate for the recent stagnation, relative to the capital quality shock, because the downturn in stock prices was less unusual.

### C.3 Returns during the Great Recession

Not all authors agree that the Great Recession was an unusual event. For example, Gomme et al. (2011) present a series for returns on capital that show adverse realizations for 2008-09 that are not as extreme as our measures. The difference stems from their measurement strategy. To compute capital gains, they use data from the NIPA, which values non-residential capital (structures, equipment and software) at *replacement* cost. During 2008-09, we saw massive declines in the *market value* (particularly, for commercial real estate), even though the replacement cost of structures fell only modestly. While appropriate for their purposes, these NIPA measures miss one of the unusual aspects of the Great Recession – large declines in the market value of business capital, notably commercial real estate.

### C.4 De-trending

Our learning mechanism generates persistent movements in aggregate variables after extreme events. Therefore, in order to make a meaningful comparison with the data, the choice of the right de-trending procedure for the data is very important. We use a log-linear trend, which removes only the lowest-frequency (permanent) part of the series. A common approach in business cycle analysis is to non-linear filters (like the Hodrick-Prescott filter), which take out more of the persistent movements in the series. By design, what is left will not have much persistence left. In figure 19, we illustrate this using aggregate non-residential investment (other aggregate series

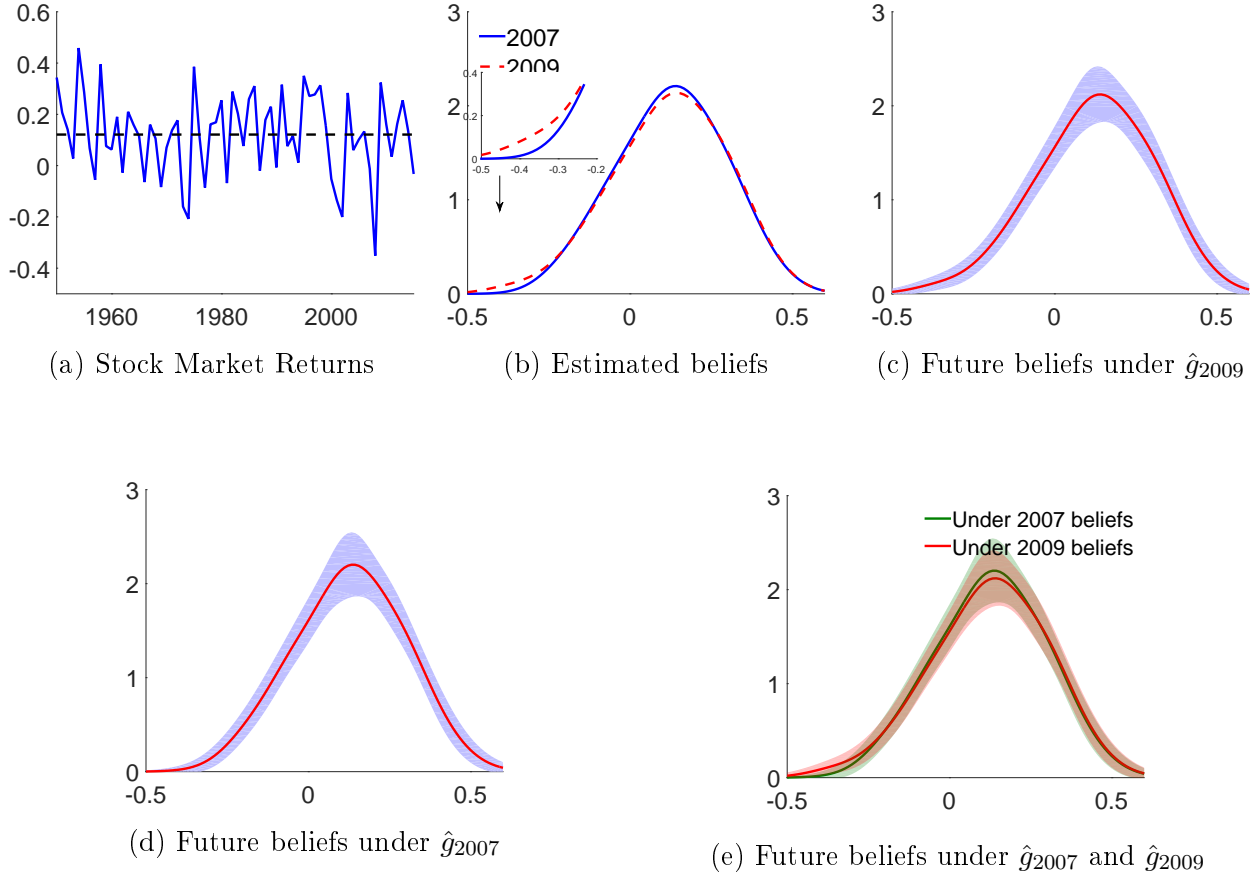


Figure 18: **Estimated beliefs about stock market returns.**

The first panel shows the realized returns on the stock market. The second panel shows the estimated kernel density for 2007 and 2009. The third panel shows the mean belief (along with a 2 standard deviation band) in 2039 (computed by simulating data for the period 2010-2039 using the estimated distribution in 2009).

show very similar patterns). As the graph reveals, the trend component of the HP filter (smoothing parameter 100) picks up some of the deviation from the linear trend. Given that our focus is on low-frequency or persistent components, a linear detrending procedure seems most appropriate.

## C.5 Productivity

While a productivity slowdown may have contributed to low output, it does not explain the timing or the rise in tail risk indicators. Figure 20 shows the time series of raw total factor productivity, constructed as  $dfpt = dY_t - \alpha_t dk_t - (1 - \alpha_t)(dhours_t + dLQ_t)$  from Fernald (2014). When we examine instead utilization-adjusted TFP, we find a slight decline during the recession, but a decline that is well within two-standard deviation bands of the distribution of TFP changes. Productivity did not have a precipitous decline that could be considered a tail event.

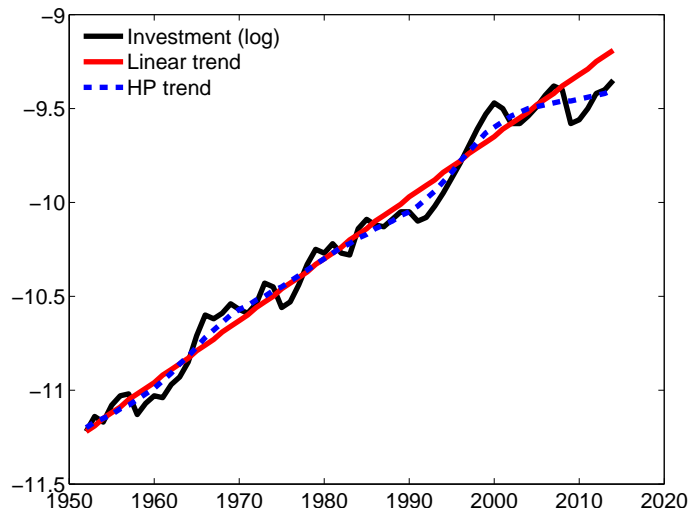


Figure 19: Non-residential Investment, with log-linear and HP trends.

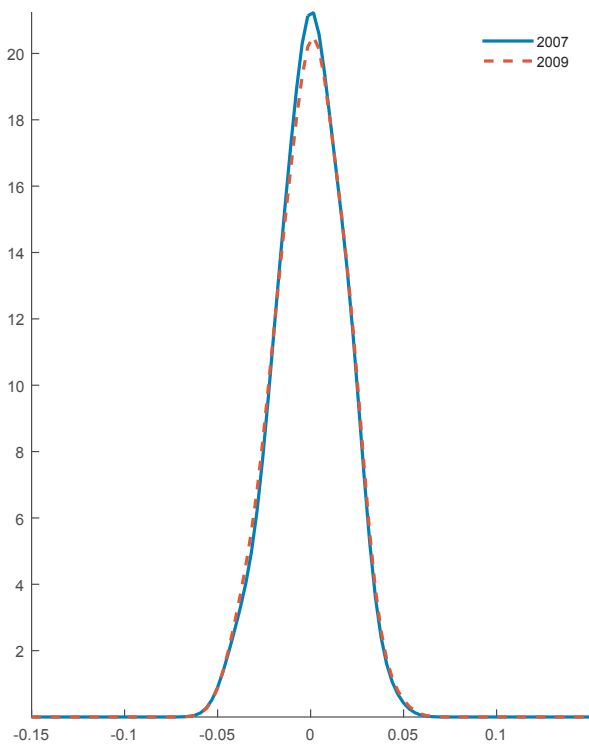
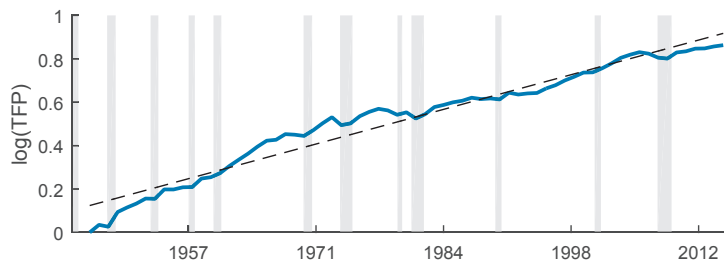


Figure 20: **Productivity.**