

The Decline in Corporate Investment

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Preliminary

February 12, 2018

We use a dynamic stochastic model of firm investment to investigate quantitatively the causes behind the ongoing decline in corporate investment. Our analysis focuses on three of the most commonly proposed explanations: (i) a secular decline in productivity growth; (ii) a tightening of financial constraints in the period surrounding the Great Depression; and (iii) the recent increase in policy uncertainty. We find that all three factors are important to account for the sharp decline in investment during the Great Recession. However only slow productivity growth can best account for the long term decline in investment.

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1 Introduction

From the depths of the Great Recession, economic growth in the US and most advanced economies has been persistent but slow. Several explanations affecting the behaviors of consumers, producers and governments have been put forward to account for slow growth. Our focus is on the dynamics of corporate investment. Although overshadowed by the collapse of housing markets, private non-residential investment contracted sharply during the Great Recession in most advanced economies, and remains well below its pre-2008 trend. While some economists worry this weakness in business investment accounts for a short term drop in aggregate demand for goods and services, a persistent decline in new capital formation will also have long lasting effects on aggregate supply. As a result a number of policies have been proposed in recent years to encourage firms to increase capital spending. In spite of this, there is little consensus as to what lies behind this on-going weakness.

This paper offers a detailed quantitative investigation of the possible factors behind the overall slump in corporate investment. Specifically, we construct and calibrate a dynamic stochastic model with heterogeneous firms and financial market imperfections to examine three commonly proposed arguments: (i) a secular decline in productivity growth; (ii) a tightening of financial constraints; and (iii) an increase in policy uncertainty.

We show that each of these arguments has a differential impact on the optimal behavior of firms and their implied investment policies. Moreover, we can either observe or construct measures for all three of these factors to quantify the extent to which they affected corporate investment since 2008. Our findings suggest that all three factors are important to explain the sharp decline in investment during the Great Recession. However, below trend productivity alone offers the best explanation for the anemic recovery since 2010-11.

Although not an exclusive account of all possible causes of the recent behavior for corporate investment, we believe our setting captures the most commonly proposed one, at least in economic policy circles. As such we believe our setting offers many useful insights into the types of policies that can both aid a recovery in investment and in preventing future collapses of the magnitude seen during the Great Recession.

Our dynamic stochastic model focuses on heterogeneous firms facing productivity shocks, uncertainty shocks, and financing shocks. Specifically, firms choose their optimal level of capital investment in each period to maximize their value, subject to capital adjustment costs and external financing constraints. The model is calibrated to match the pre-crisis experience of the US economy. We use data on total factor productivity (Basu, Fernald, and Kimball, 2006), economic policy uncertainty (Baker, Bloom, and Davis, 2016) and credit spreads (Gilchrist and Zakrajšek, 2012) to construct measures of productivity, uncertainty and financing shocks, respectively. We then feed our empirical measures of shocks to the calibrated model to quantify their relative importance in explaining the dynamics of non-residential investment since 2008.

Using only total factor productivity shocks produces a sharp drop in investment in 2008 followed by a quick recovery in 2010. While failing to fully matching the unprecedented collapse of investment during the Great Recession, the model with only productivity shocks does a fairly good job in explaining the continued slump of investment after 2010. Adding uncertainty shocks along with external financing shocks helps matching the collapse of investment during the Great Recession since both increasing economic uncertainty and tightening of financial constraints, which were both at their peak values during the Great Recession, substantially depress capital investment. In fact, the model with all three shocks results in a root mean squared error (RMSE) of only 0.07 during the period 2007-2010 versus 0.12 for the model with productivity shocks only. However, given the relatively lower economic uncertainty and relaxed financial constraints after 2010, the model with all three shocks overestimates substantially the investment recovery. In fact, the model with all three shocks yields a RMSE of 0.17 after 2010, while the model with only productivity shocks performs substantially better with a RMSE of only 0.09.

In his 2011 AEA Presidential Address, Robert E. Hall defines the post financial crisis US economy as in a long slump. Hall (2011) focuses on the causes behind the low resources utilization after the financial crisis, attributing mainly to financial frictions faced by households and intermediaries, the reasons for the overhang of housing and consumer durables. We contribute to this important debate by focusing instead on the decline in corporate investment which causes a significant slow down of the economic recovery. Besides studying the effects of financial frictions

and the important decline in productivity growth, we also explore the role of economic policy uncertainty in shaping corporate investment.

Our work is also closely related to the growing literature on the impact of economic uncertainty on the economy. In terms of modeling economic uncertainty, our paper is close to Bloom (2009), and Alfaro, Bloom, and Lin (2016). Our contribution to this literature is to quantitatively investigate the importance of economic uncertainty in explaining the collapse of corporate investment post financial crisis and the slow recovery afterwards.

Finally, our paper is also related to a large literature on investment in presence of financial frictions. As in Gilchrist and Himmelberg (1995), Gomes, Yaron and Zhang (2006) and Whited and Wu (2006), we model the shadow cost of external financing as functions of observables. This method enables us to link the model frictions directly to their data counterparts like credit spreads.

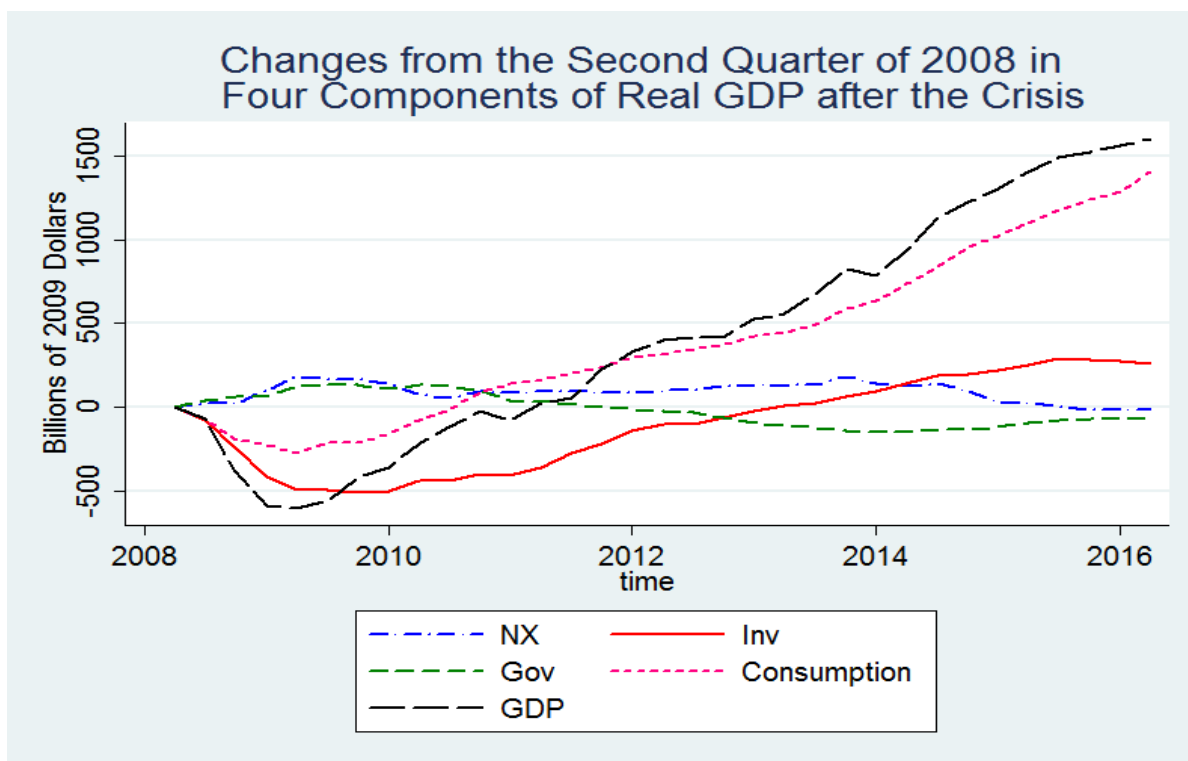
The outline is as follows. The next section reviews the main facts that motivate this paper, namely the sharp decline in corporate investment in 2008-09 and its weak recovery post 2010. Section 3 describes the dynamic stochastic model of firm investment used throughout our analysis. Section 4 details the steps involved in taking the model to the data and using it to evaluate the three proposed explanations of the investment decline and slow recovery. Section 5 discusses our main findings. Section 6 summarizes and concludes.

2 The Decline in Corporate Investment

In this section we provide some stylized facts about the behavior of both aggregate and business investment in the US during and after the Great Recession. Our data is aggregate and comes directly from the Bureau of Economic Analysis' National Income and Product Accounts (NIPA), Table 1.1.6. All data is in billions of chained 2009 dollars.

Figure 1 decomposes the changes in real GDP after the second quarter of 2008 into four core components of national spending: consumption, investment, net exports and government expenditures. It shows both the massive decline in aggregate investment that took place until late 2009 and the very slow recovery afterwards. Expressing the data in dollar terms shows how, during

Figure 1: GDP Decomposition



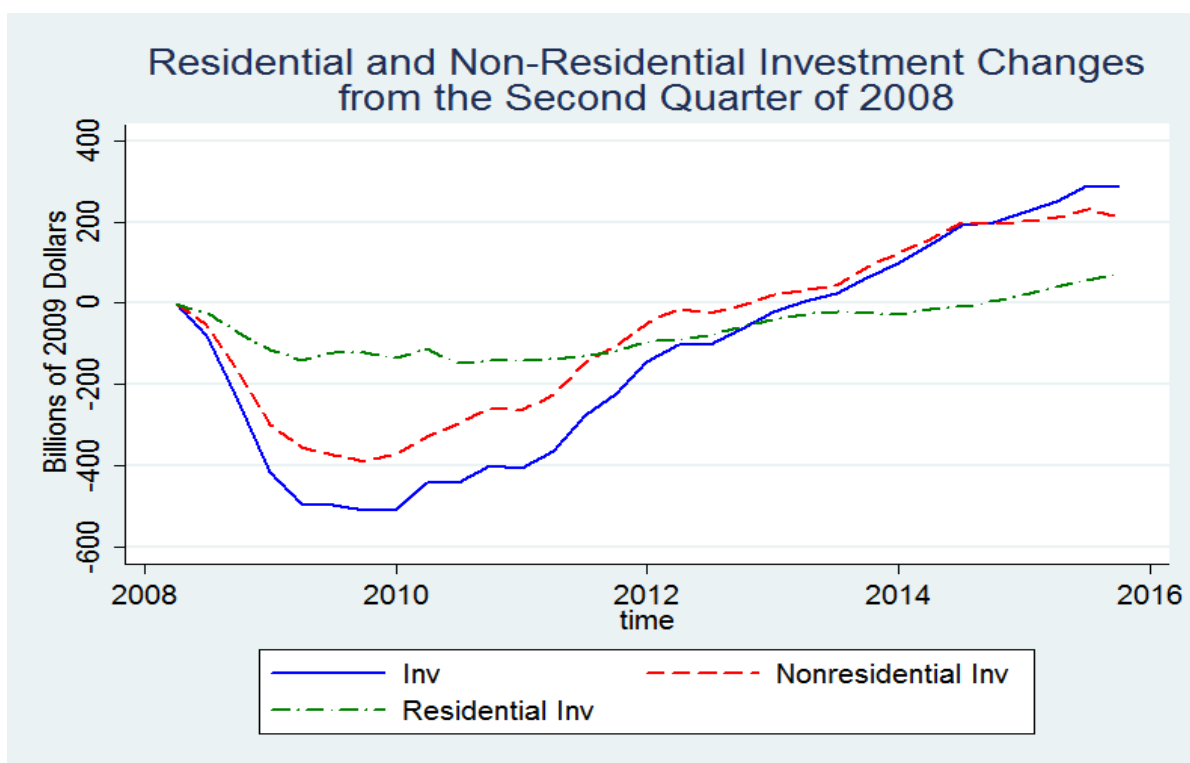
All the data series are from the Bureau of Economic Analysis' NIPA table 1.1.6. Consumption is defined as the sum of non-durable goods, durable goods and services. Investment is defined as the sum of non-residential investment and residential investment. Net exports and government expenditures are the same as defined in NIPA table 1.1.6.

the crisis, the investment and output fell by essentially the same amounts. Figure 1 also shows that, while consumption recovers relatively quickly, it took more than four years for investment to return to the peak reached in the second quarter of 2008 quarter.

Figure 2 further decomposes the observed movements in investment into their non-residential and residential investment components. While much of the focus has been on the decline in residential investment, the figure shows clearly that non-residential investments actually contributes to about 2/3 of the drop in total investment between 2008 and 2010. Between 2010 and 2016, the growth rate of non-residential investment is generally higher than that of residential investment. As a result the former remains above its peak value in 2008.

It is possible that using the second quarter of 2008 as the benchmark for these comparisons is

Figure 2: Investment Composition



Here residential investment is fixed investment from the residential sector. Non-residential investment is the business fixed investment. The graph covers the period from 2008 quarter 2 to 2016 quarter 2.

Table 1: Log Business Investment and Trend

Starting Year	Trend Growth	R squared
1955	4.73	98.68
1960	4.70	98.35
1965	4.51	98.17
1970	4.60	97.61
1975	4.68	96.71
1980	4.70	95.43
1985	5.00	94.02

This table reports the results of fitting a linear trend to fixed non-residential investment for various sub-periods in post war US ending in 2007. The first column shows the starting year for each regression. The second column indicates the slope coefficient and the last one reports the R-squared on these regressions.

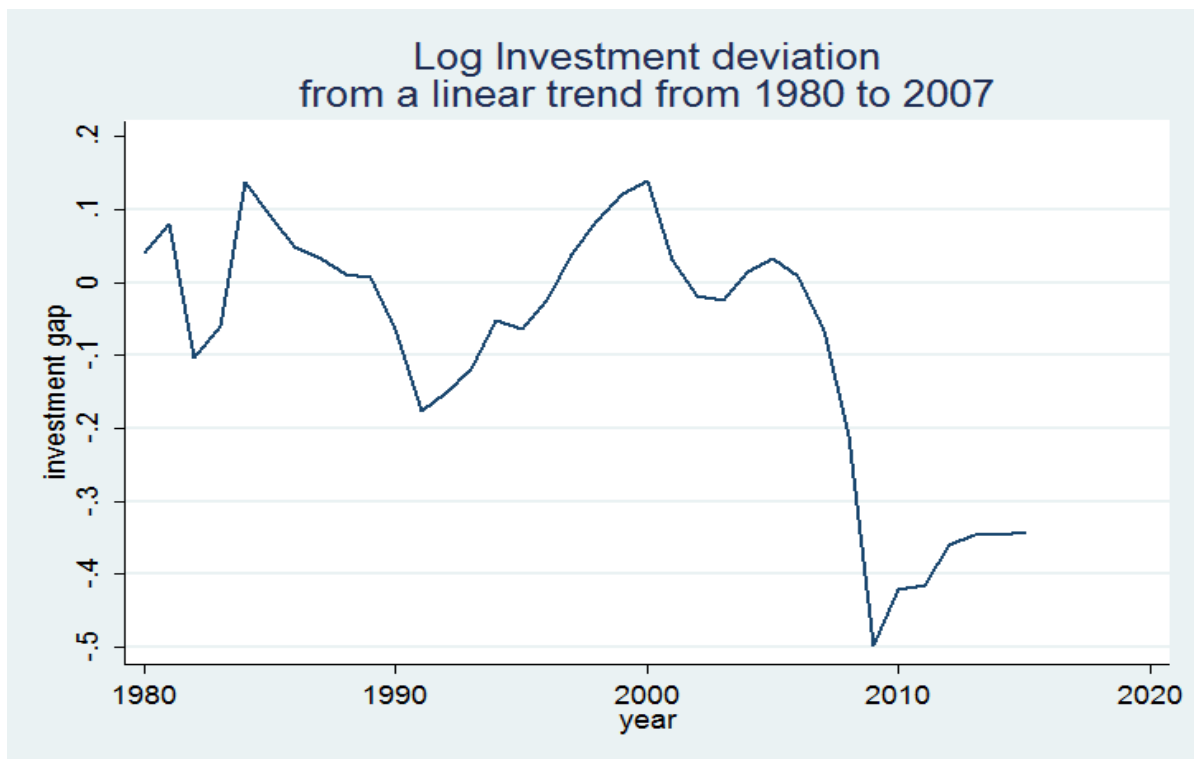
inappropriate. After all, the various investment measures might have been substantially higher at this point in time than their historical averages, making their post 2008 drops seem more severe. This is not the case. Table 1, reports the average growth rate of non-residential investment over alternative post-war periods up to 2007, by fitting a simple linear trend model to log investment. Regardless of the starting period, the linear trend model fits the data quite well and produces very similar estimates of around 4.5%-5% for the average annual growth in this series.

Figure 3 then plots the deviation of business investment from this linear trend.¹ Two startling facts emerge. First, the magnitude of drop in non-residential investment post 2008 is unprecedented. While corporate investment was -16.7% below trend in 1992, its value in 2010 was -28.5% below its trend, almost twice as large.² Second, the recovery is extremely slow. While in all the previous episodes investment quickly bounced back to its long run trend, there is virtually no recovery since 2010.

¹We use the linear trend coefficient from 1960 to 2007 to detrend the time series of non-residential investment.

²Prior to the crisis the largest one year drop in corporate investment occurred in 1974 and was also about half the size of the drop observed in 2009.

Figure 3: The Collapse of Corporate Investment



This figure reports the the difference between log non-residential investment and its predicted value from a linear trend using data between 1960 to 2007. The vertical line shows the year 2008.

3 Model

In this section we describe a dynamic stochastic model with heterogeneous firms facing productivity shocks, uncertainty shocks and financing shocks. Firms choose their optimal level of physical capital investment in each period to maximize their value.

3.1 Technology

We consider an environment with a continuum of firms, index by $j \in [0, 1]$. Each firm j produces a differentiated good, y_j , using the following production function:

$$y_{jt} = \exp(x_t + z_{jt})k_{jt}^\gamma, \quad \gamma \leq 1 \quad (1)$$

where x_t denotes aggregate productivity shock, z_{jt} denotes firm j 's idiosyncratic shock and k_{jt} denotes the firm's productive capital. For simplicity we assume that in this representation all fully flexible inputs, such as labor and materials, have already been optimized out.

Each firm operates in a monopolistically competitive setting and faces an isoelastic demand curve with elasticity, ϵ :

$$Q_t = BP_t^{-\epsilon}, \quad B > 0 \quad (2)$$

where B is a demand shifter. Production and demand can be combined into a single per period revenue function:

$$s_{jt} = s(x_t, z_{jt}, k_{jt}) = \exp(x_t + z_{jt})^\eta k_{jt}^\alpha \quad (3)$$

where we define $\eta = 1 - \frac{1}{\epsilon}$ and $\alpha = \gamma(1 - \frac{1}{\epsilon})$. Since B only matters for the scale of the economy, we normalize it to be 1.

Aggregate and firm level productivity follow the independent stochastic processes:

$$x_t = (1 - \rho_x)\bar{x} + \log(1 + g)t + \rho_x x_{t-1} + \sigma_t \epsilon_{xt} \quad (4)$$

$$z_{jt} = \rho_z z_{jt-1} + \nu \sigma_t \epsilon_{zjt} \quad (5)$$

in which ϵ_{xt} and ϵ_{zjt} are independently and identically distributed shocks drawn from standard normal distributions. We further assume ϵ_{zjt} and ϵ_{zit} are uncorrelated if $i \neq j$. In line with our analysis of the data, we allow for the presence of a linear trend in the process for aggregate productivity, with g denoting the average annual growth rate in aggregate productivity.

3.2 The Role of Uncertainty

Both the volatilities of aggregate and firm-level productivity vary stochastically over time. Each is assumed to obey a first order Markov process. Following Bloom (2009), Bloom (2014) and Alfaro et al (2016), this is assumed to take the form of a two-state Markov chain:

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{ where } \Pr(\sigma_{t+1} = \sigma_i | \sigma_t = \sigma_k) = \pi_{ki}. \quad (6)$$

As in Bloom (2009), we assume that the volatility processes for firm and aggregate shocks are perfectly correlated.

As emphasized in Caballero (1991), theoretically the relationship between investment and uncertainty hinges on the concavity of the revenue function $s(\cdot)$ in productivity. If the revenue function is concave in productivity, then a risk neutral firm will always invest **less** in high uncertainty states, i.e. when σ is high. On the other hand, if the revenue function is convex in productivity, a risk neutral firm invests **more** in high uncertainty states, a result already documented by Abel (1983).

Because several recent empirical studies emphasize the negative impact of uncertainty on investment we restrict our revenue function to have a concave relation with firm and aggregate

productivity levels.^{3,4}

3.3 Investment and Financing

Physical capital accumulation is given by:

$$k_{jt+1} = i_{jt} + (1 - \delta)k_{jt} \quad (7)$$

where i_j represents capital expenditures in period t and δ denotes the capital depreciation rate.

In addition, we assume that investment incurs capital adjustment costs which are captured by the convex function:

$$\Phi(i, k) = \frac{\theta}{2} \left(\frac{i_{jt}}{k_{jt}} \right)^2 k_{jt}, \quad \theta > 0. \quad (8)$$

The value of θ fully governs the marginal cost of investment. Later we will extend the model to allow for both non-convexities and asymmetries in capital adjustment costs.

In our model, financing frictions also play a role in determining aggregate investment. To examine their importance we split the universe of firms in our model into two groups. A fraction $p \leq 1$ is assumed to have full access to external capital markets, while the remaining fraction $1 - p$ is assumed to have only a limited access to outside funds.

The dynamic problem for a typical firm j with full access to external funds is then described by the following Bellman equation:

$$v^u(x, z, k) = \max_{k', i} \{d(x, z, k, i) + E(\beta v^u(x', z', k'))\} \quad (9)$$

$$\text{s.t.} \quad d(x, z, k, i) = s(x, z, k) - i - \Phi(i, k) \quad (10)$$

$$k' = i + (1 - \delta)k$$

³This is consistent with the evidence in Bloom (2009), Gulen and Ion (2015), Kim and Kung (2015).

⁴In addition, non-convex adjustment costs create a real option effect of uncertainty on investment and could potential amplify the uncertainty impact on investment. We will examine the impact of this effect at a later stage.

where $d(\cdot)$ denotes the net distributions to investors and β is the discount factor of the firm's investors. The net distributions can be negative in the event the firm chooses to access capital markets to fund its current period capital expenditures.

The problem for firms with limited access to external funds must be augmented with the additional constraint that net distributions to investors must be non-negative, so that $d(x, z, k, i) \geq \bar{d}$. We denote the value function for these firms as $v^c(x, z, k) \leq v^u(x, z, k)$ for any feasible triplet (x, z, k) . Similarly, we use the superscripts u and c to denote the optimal policies of firms with and without access to capital markets, respectively.

3.3.1 Discussion: The Role of Financing Frictions

As show in Gomes et al (2006) and Chari et al (2007), imperfect access to capital markets creates a wedge between the optimal investment policy of constrained firms and those that are unconstrained. Specifically, letting μ denote the (possibly 0) Lagrangian multiplier associated with the payout constraint, we have the following first order condition for each firm j :

$$1 = \beta E \left\{ \frac{1 + \mu' s_k(x', z', k') - \Phi_k(i', k') + (1 - \delta)}{1 + \mu \Phi_i(i, k)} \right\} \quad (11)$$

where s_k is the partial derivative of $s(\cdot)$ with respect to k and $\Phi_i(\cdot)$ and $\Phi_k(\cdot)$ are the derivatives of $\Phi(\cdot)$ with respect to i and k , respectively.

We can see that the overall impact of access to capital markets on investment is completely determined by the *shadow cost* of external funds $\omega = (1 + \mu')/(1 + \mu)$. Time variation in either expected marginal productivity of capital or the cap on external funds, $\bar{d}$, will lead to variations in the shadow cost of external funds.

Our basic empirical strategy then consists in using credit market data to construct plausible empirical measures of the marginal cost of external funds and use this information to estimate the likely impact on corporate investment.

3.4 Aggregation

Our model is a partial equilibrium one. In particular, we do not endogeneize the discount factor of the firms, which would require aggregate output and investment of the productive sector to equalize aggregate household consumption. In models with heterogeneous firms this would require us to keep track of the movements in the cross sectional distribution of firms over time. Instead in our partial equilibrium setting, aggregate output, Y , and investment, I , are constructed as:

$$Y = p \int y^u(x, z, k) dF(x, z, k) + (1 - p) \int y^c(x, z, k) dF(x, z, k) \quad (12)$$

and

$$I = p \int i^u(x, z, k) dF(x, z, k) + (1 - p) \int i^c(x, z, k) dF(x, z, k) \quad (13)$$

where $F(\cdot)$ denotes the cross-sectional distribution of firms, and the superscripts u and c indicate whether the production and investment choices are being made by unconstrained firms or those with limited access to capital markets.

4 Calibration and Measurement

The model discussed above is suitable to investigate the contribution of three major explanations of the collapse and weak recovery in corporate investment since 2008. To do so we need to (i) specify key parameter values; and (ii) construct quantitative measures of the movements in total factor productivity (TFP), uncertainty and financial market conditions. This section discusses our approach in some detail.

4.1 Calibration

Although our model applies equally well at annual or quarterly frequency, the picture is somewhat clearer when using annual data. All of our parameters are either calibrated from the data or are

Table 2: Technology Parameters

Parameter	Value	Description
g	0.045	Average investment growth
α	0.8756	Returns to scale
δ	0.08	Annual rate of capital depreciation
ϵ	4	From Bloom (2009), implies a markup of 33%
θ	0.1	Volatility of investment
β	1/1.063	Expected real post return on capital

from previous studies.

The growth rate of investment is directly taken from data and set equal to 4.5%. The elasticity of demand, ϵ , is set to 4, which implies a markup of 33%, broadly in line with much of the empirical evidence (e.g. Bloom 2009). This implies our $\eta = 0.75$. The annual capital depreciation rate is 8%. The value of α is set so that in the steady state, the growth rate of TFP and growth rate of investment are consistent.⁵ The capital adjustment cost parameter θ are chosen to match the investment volatility in the data. Table 2 summarizes our baseline choices for the key structural parameters.

4.2 Measuring Aggregate TFP

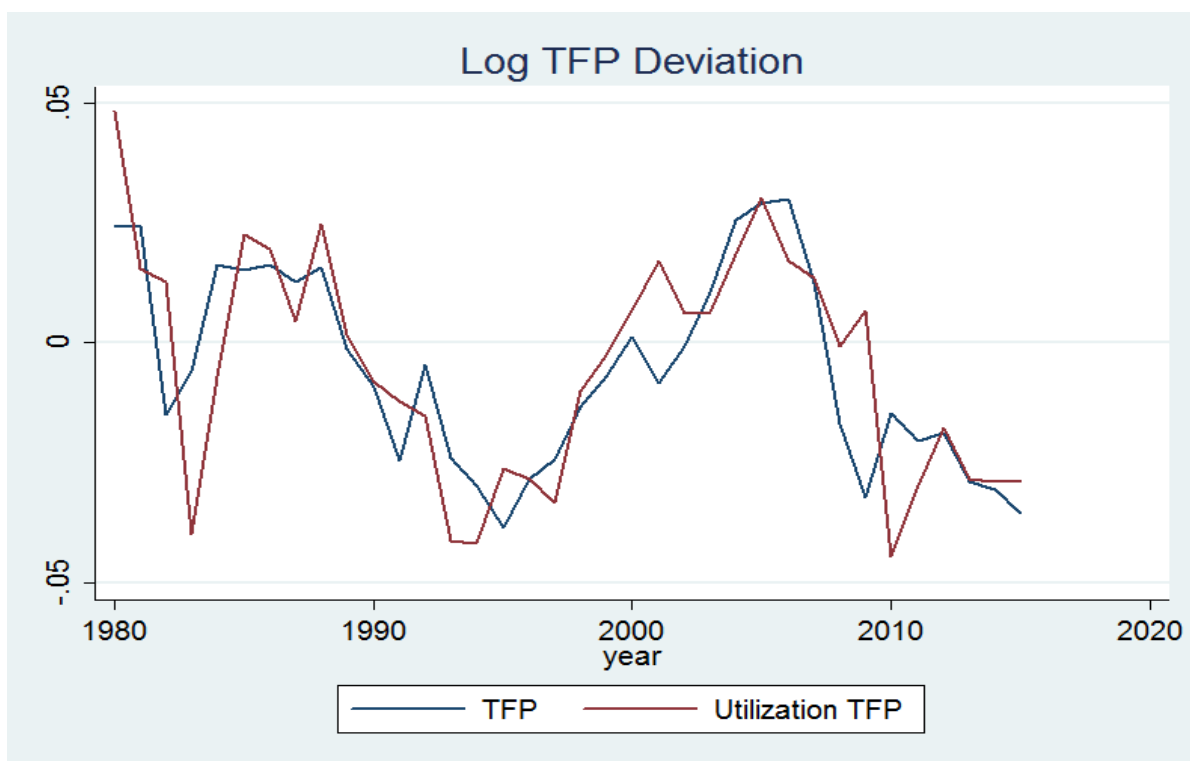
The series for aggregate TFP comes from the Federal Reserve Bank of San Francisco.⁶ Figure 4 illustrates the cyclical components of both standard TFP and utilization-adjusted TFP, by plotting their deviations from a simple linear trend.⁷ Although there are some differences in the timing of the productivity decline during the Great Recession the broad pattern of a steep decline followed by no real recovery is common across both productivity series. Because our model makes no allowance for variable utilization, the most appropriate measure for our model is the standard TFP measure.

⁵Formally, $\alpha = 1 - \eta \frac{g_i}{g_{TFP}}$.

⁶Details provided in <http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/>.

⁷The annual growth rate of TFP since 1960 is about 1% per year.

Figure 4: TFP Measures: Standard and utilization-adjusted TFP



This figure plots the cyclical component of standard TFP and Utilization-adjusted TFP. The figure starts from 1980 and ends in 2015. We detrend the log TFP index by a linear trend from 1980 to 2007.

Using this data we estimate a stochastic process for aggregate TFP shocks, x_t . The annual autocorrelation coefficient equals 0.83 and its standard deviation equals 0.021. These estimates are very similar to those reported in the literature.

4.3 Measuring Uncertainty

Uncertainty as a potential driving force for the business cycles has received substantial attention, especially after the financial crisis. Among various kind of uncertainty, economic policy uncertainty (EPU) might be the most important one. Politicians and regulatory institutions frequently make changes that would affect firm's profitability, investments' plan and other aspects of the business environment. We use the economic policy uncertainty (EPU) index of Baker, Bloom, and Davis (2016). This index contains three main components: News Coverage about Policy Related Economic Uncertainty, Tax Code Expiration and Economic Forecaster Disagreement.⁸

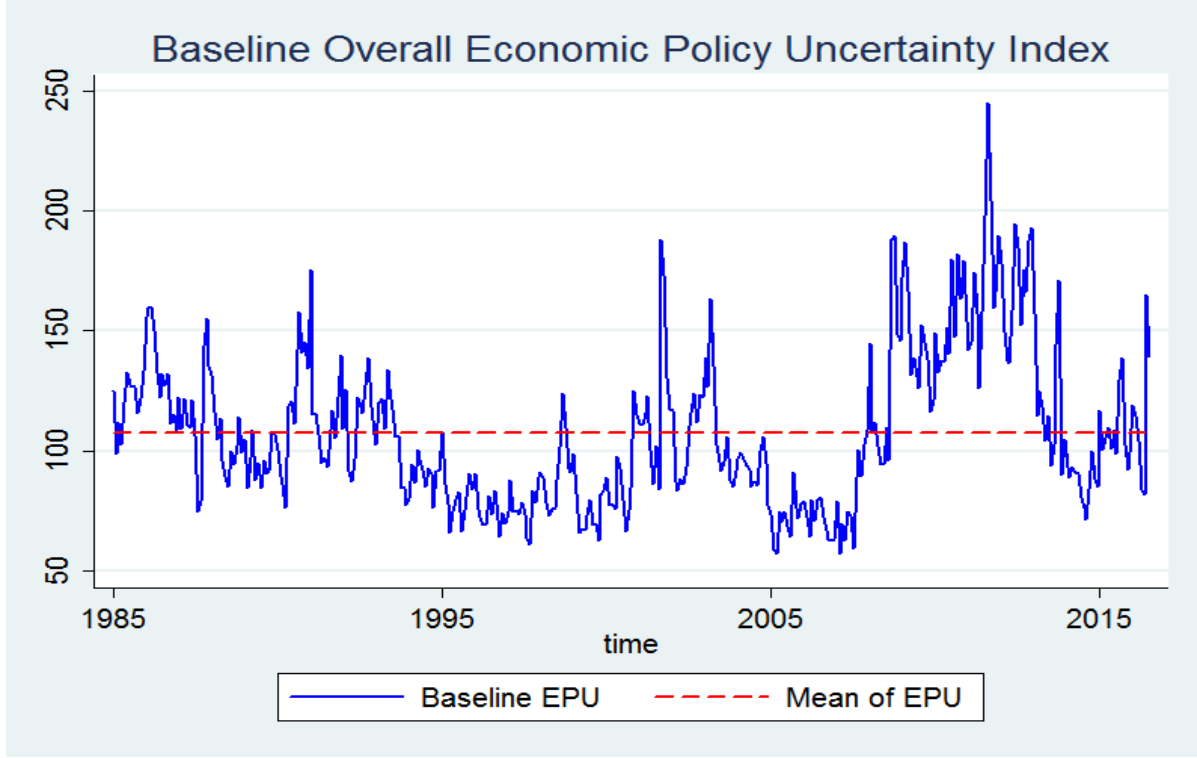
Figure 5 plots the baseline overall EPU index and figure 6 plots an alternative news only measure of EPU. Although we use the baseline index to construct our measure of uncertainty, the similarity between these measures implies that our results are not sensitive to this choice.

To determine whether a given year is a high uncertainty or low uncertainty year we count the number of months in a given year in which the EPU index exceeds its historical mean. If the number of months is larger than six, we label this year as a high uncertainty year. Because there are four years with high uncertainty out of thirty-one years of data, we set the transition probabilities of $\pi_{L,H}^\sigma = 4/31$ and $\pi_{L,L}^\sigma = 1 - 4/31$. Following Bloom (2009), we choose the ratio between high uncertainty and low uncertainty to equal 2. The uncertainty levels are chosen such that the stationary mean of uncertainty equals the unconditional mean of uncertainty in the data.⁹ Table 3 summarizes our choices regarding the calibration of the volatility parameters.

⁸For the detail of the construction of the index refer to Baker, Bloom, and Davis (2016).

⁹Note that, by construction, $\phi_L \sigma_L + \phi_H \sigma_H = \sigma$

Figure 5: Policy Uncertainty Indexes: Baseline Overall Index

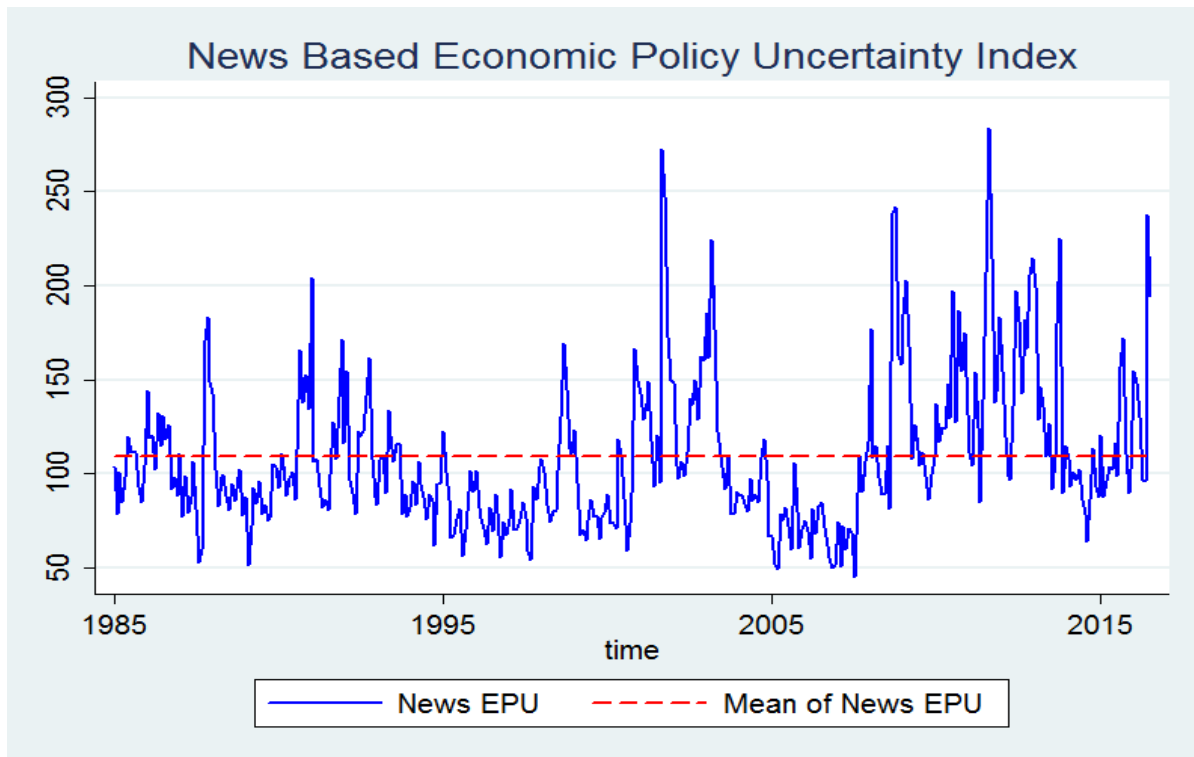


This figure reports the baseline overall economic policy uncertainty indexes from Baker et al (2016). The horizontal line is the time series mean of EPU.

Table 3: Volatility Parameters

Parameter	Value	Description
σ_L	0.0135	From Bloom (2009)
σ_H	$2 \times \sigma_L$	From Bloom (2009)
$\pi_{L,H}^\sigma$	4/31	From Baker et al (2016)
$\pi_{L,L}^\sigma$	1-4/31	From Baker et al (2016)

Figure 6: Policy Uncertainty Indexes: News Based Index



This figure reports the news based economic policy uncertainty indexes from Baker et al (2016). The horizontal line is the time series mean of EPU.

4.4 Measuring Financial Frictions

Equation (11) shows how limited access to capital markets introduces a wedge into the optimal investment decision of some firms. Formally, this wedge represents the shadow cost of financing to this firm. Alternatively, we can think of ω as the wedge between the opportunity cost of internal and external funds.

Both interpretations suggest that we should quantify these investment distortions by looking at capital market data, and in particular, measures of credit spreads. In our implementation, we consider two types of measures of credit spreads: (i) the popular yield spread between seasoned corporate bonds with a (Moody's) Baa rating and those rated Aaa. This spread is available from the Federal Reserve for the entire sample period in our analysis; and (ii) the more recent Gilchrist and Zakrajšek (2012) spread (GZ). The latter is a credit-spread index that is based on secondary market prices of outstanding bond securities in all publicly traded firms. Relative to the more standard Baa-Aaa spread, the GZ index has the advantage of capturing the entire maturity spectrum and the range of credit quality in the corporate bond market.¹⁰

Figure 7 depicts these two series over the period 1985-2015. As we can see they behave in strikingly similar ways. The main difference is that the GZ spread (right scale) is much higher on average. Again this is unsurprising since this index includes the many ratings below Baa.

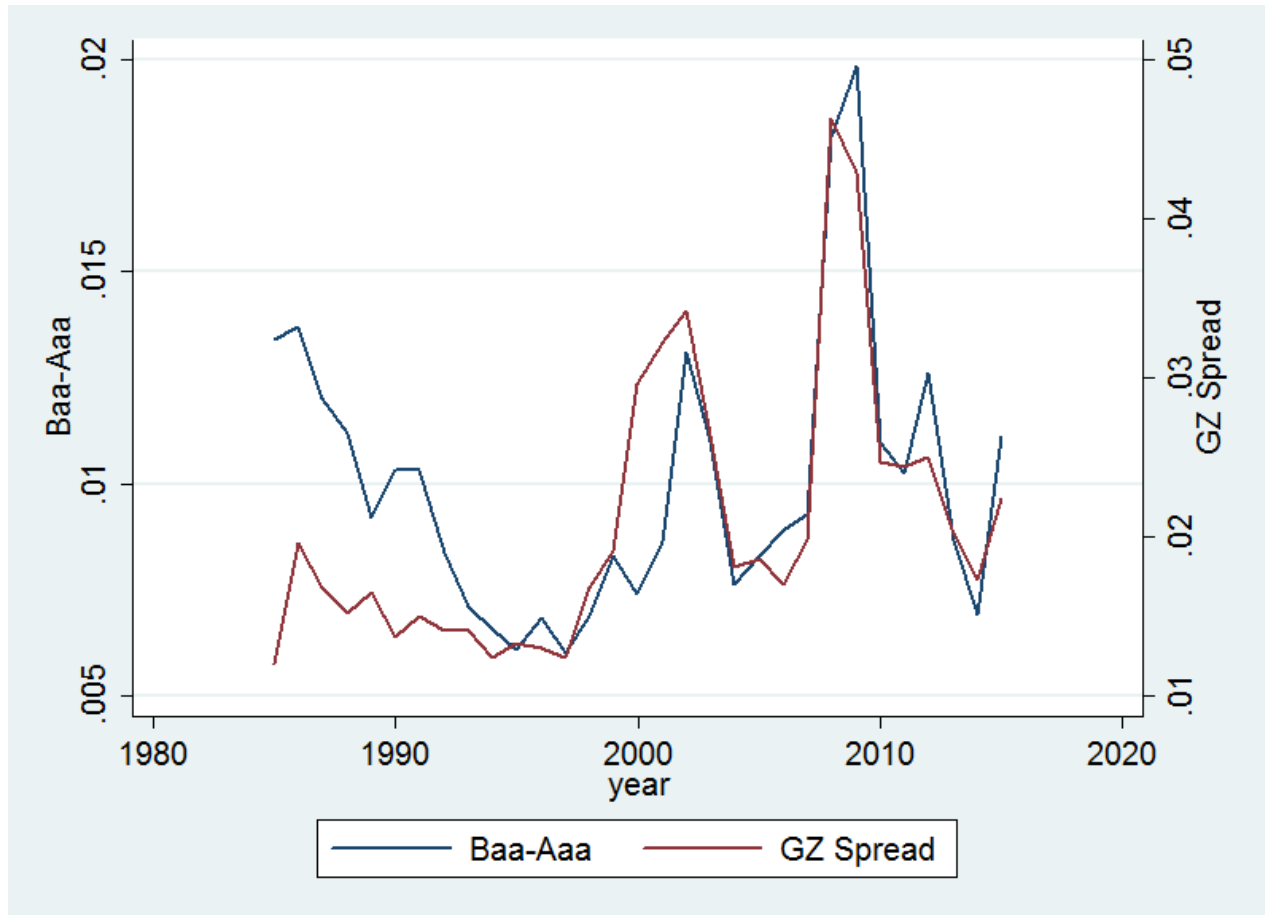
To calibrate the model we assume firms take credit market conditions as exogenous and estimate an AR(1) process to the credit wedge, ω :

$$\log \omega_{t+1} = (1 - \rho_\omega) \log \bar{\omega} + \rho_\omega \log \omega_t + \sigma_\omega \epsilon_{\omega t+1}. \quad (14)$$

The estimated parameters for both credit spread series are reported in Table 4. We can see again that these estimates are quite similar.

¹⁰Data on the GZ index can be downloaded from <http://people.bu.edu/sgilchri/Data/data.htm>

Figure 7: Credit Spreads Measures



This figure shows the values of the Moody's Seasoned Baa-Aaa Yield Spread (left axis) and the Gilchrist and Zakrajšek (2012) spread (right axis).

Table 4: Parameter Values for Credit Spreads

Moody's Data		
Parameter	Value	Description
ρ_ω	0.76	Autocorrelation in credit spreads
σ_ω	0.37	Conditional volatility in credit spreads

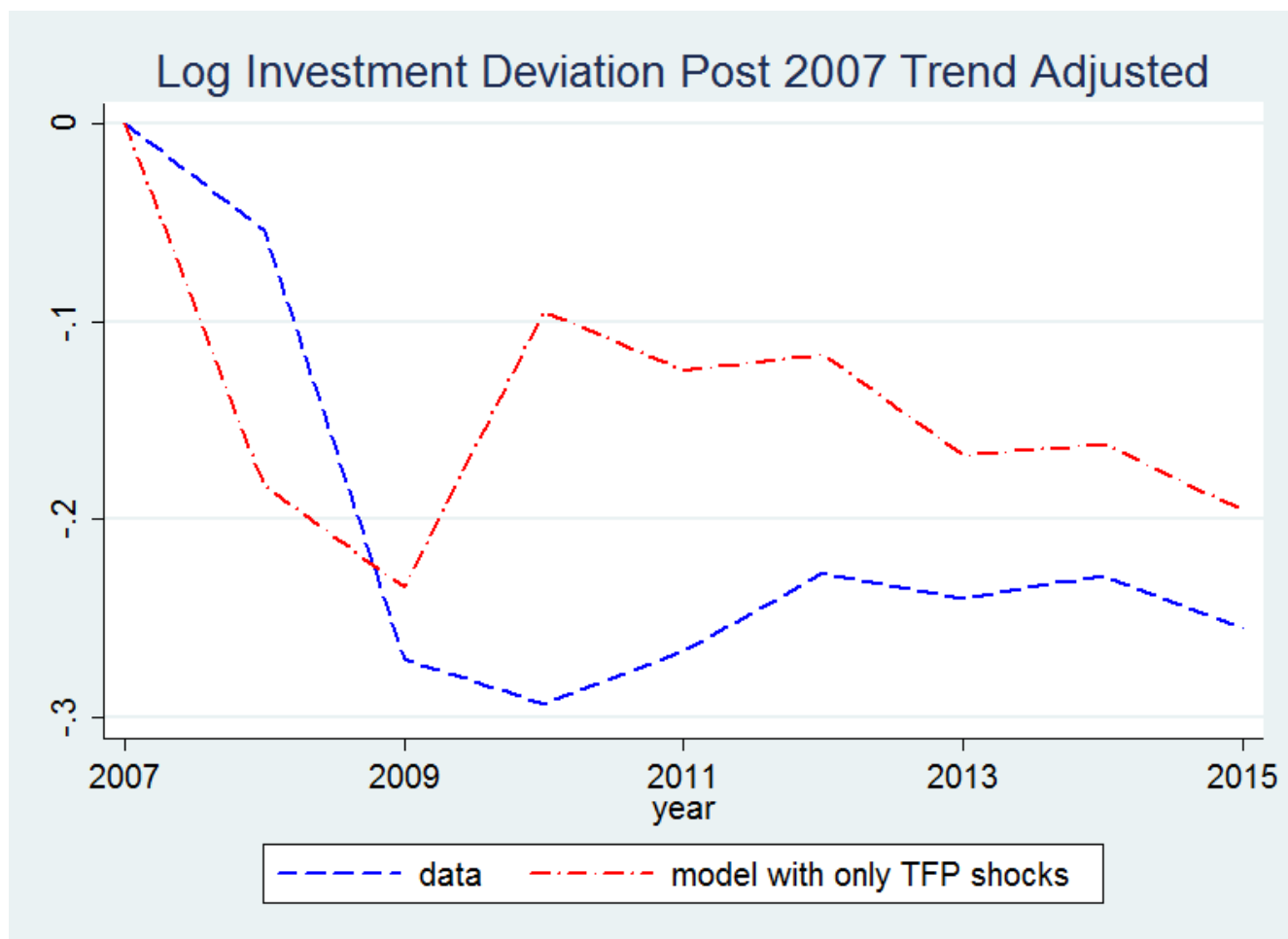
GZ Data		
Parameter	Value	Description
ρ_ω	0.73	Autocorrelation in GZ spreads
σ_ω	0.39	Conditional volatility in GZ spreads

5 Model Solution and Findings

5.1 Methodology

Appendix describes our numerical approach to solve the model. With a solution at hand, we can study the dynamics induced by the real time series of TFP shocks, uncertainty shocks and credit spread shocks. To do so we conduct the following simulation. Starting with initial values of x , σ and ω for 1985, we feed the innovations into the model and compute the responses for key variables of interest up to 2015. The macroeconomic effects are then captured by the aggregation of the individual firm level responses of these shocks. It is important to note that although we use the actual sequence of shocks, these are innovations that are not perfectly anticipated by firms. Each firm continues to forecast future values of the shocks using the laws of motion (4),(6) and (14).

Figure 8: A Model with TFP Shocks Only



This figure compares the behavior of fixed non-residential investment in the data with the response of aggregate investment to the observed path of total factor productivity in the model.

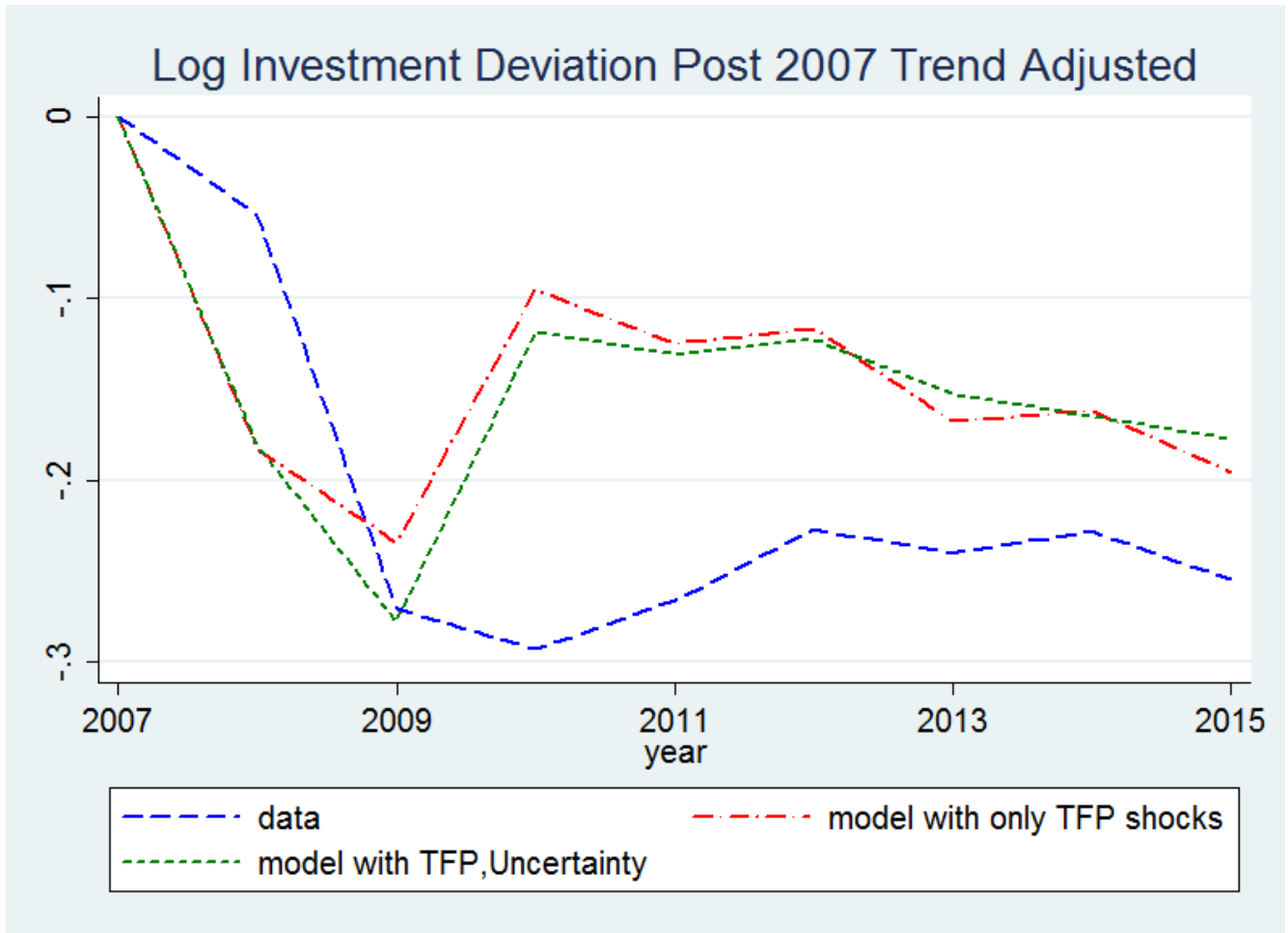
5.2 Findings

5.2.1 Productivity and Uncertainty

Figure 8 plots the post 2007 trend adjusted investment dynamics for the model driven by productivity shocks alone. The blue line captures the log investment deviation from its linear trend in the data, while the red line represents the behavior of aggregate investment in the model with only TFP shocks.

As we can see the model produces a sharp drop in investment in 2008 followed by a quick recovery in 2010. Although the collapse of investment during the Great Recession are exaggerated,

Figure 9: TFP vs TFP plus Uncertainty shocks



the model with only productivity shocks does a very good job of explaining the continued slump of investment after 2010. In fact, we predict that aggregate investment should be nearly 20% below trend in 2015, a value that is not too far from the observed 25% decline in the data.

Figure 9 adds a third line depicting the model response when we feed both the observed path for TFP and uncertainty shocks (in green). The main effect of adding uncertainty is that it produces a more realistic decline in corporate investment for 2009. Higher uncertainty also slightly slows down the implied recovery in 2010/11 but it has no measurable impact on investment afterwards. The similarity in investment behavior after 2010 with and without uncertainty shocks suggests they are not behind the failure of corporate investment to recover from the depths of the Recession. Note that this is true even though the high uncertainty years ended only after 2012.

The main problem is that both versions of the model predict a relatively sharp recovery in 2010,

whereas in the data investments falls further below trend. This is because our productivity jumps up by almost a full standard deviation in 2010, while uncertainty remains unchanged between 2009 and 2010. This discrepancy between model and data requires a different explanation. We next investigate the role of financial market frictions in generating the observed movements in investment.

5.2.2 Productivity and Financial Frictions

Figure 10 considers a model with both productivity and financial market shocks (in black). The financial market shocks are quantified by looking at the observed time path for the Baa-Aaa credit spread. Credit market shocks help substantially, particularly in the early stages of the recession and again early in the recovery. By introducing credit spread into the model, we improved on two dimensions. First, we can see that in year 2008, the model with financial constraint predicts an investment which is closer to the data. This is because even though TFP fell in 2008 the credit spread only begins to rise in the second half of 2008.

By contrast credit shocks exacerbate the investment drop in 2009 as credit spreads spike. As we discussed above, TFP recovers significantly in year 2010, however credit spreads remain elevated and slow down the recovery in corporate investment in 2010 and 2011. In this version of the model investment now recovers only 6%, relative to its trend level, instead of nearly 14% when we considered the version with only productivity shocks. Taken together these findings indicate, that movements in financial markets played a very important role in the first half of this sample.

After 2012 however, credit spreads have begun to return to more historically normal levels and their deleterious impact on investment has dissipated completely. The impact of credit market movements is so benign that the model predicts a stronger recovery in investment than what we get when accounting for movements in TFP alone.

Figure 11 shows that the picture is very similar when we use instead the (broader) GZ index of credit market spreads. Both the initial decline and the recovery exhibit a near identical pattern regardless of how we measure credit market conditions.

Figure 10: TFP and Financial Shocks

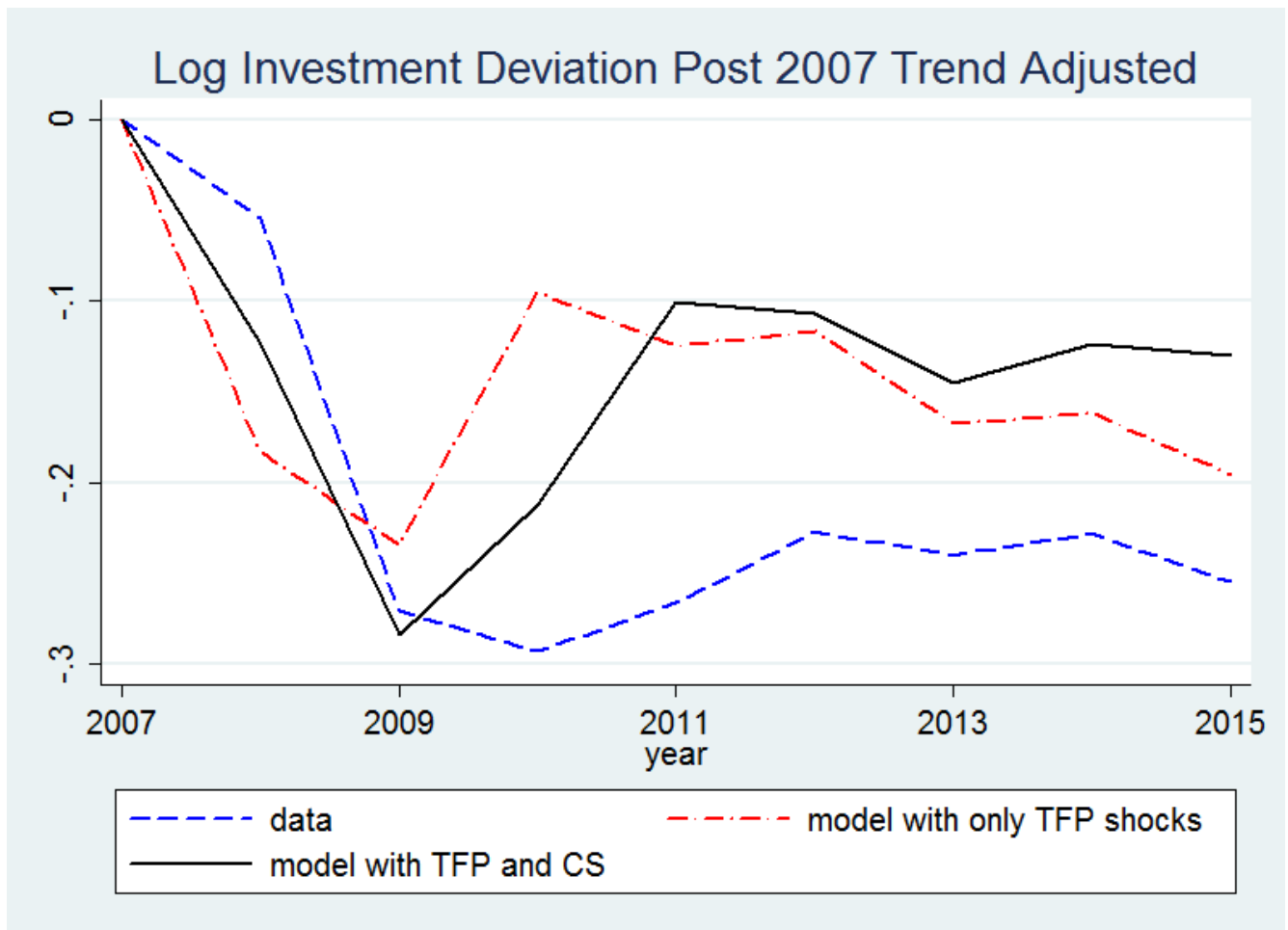


Figure 11: TFP and Financial Shocks (CS vs GZ Spread)

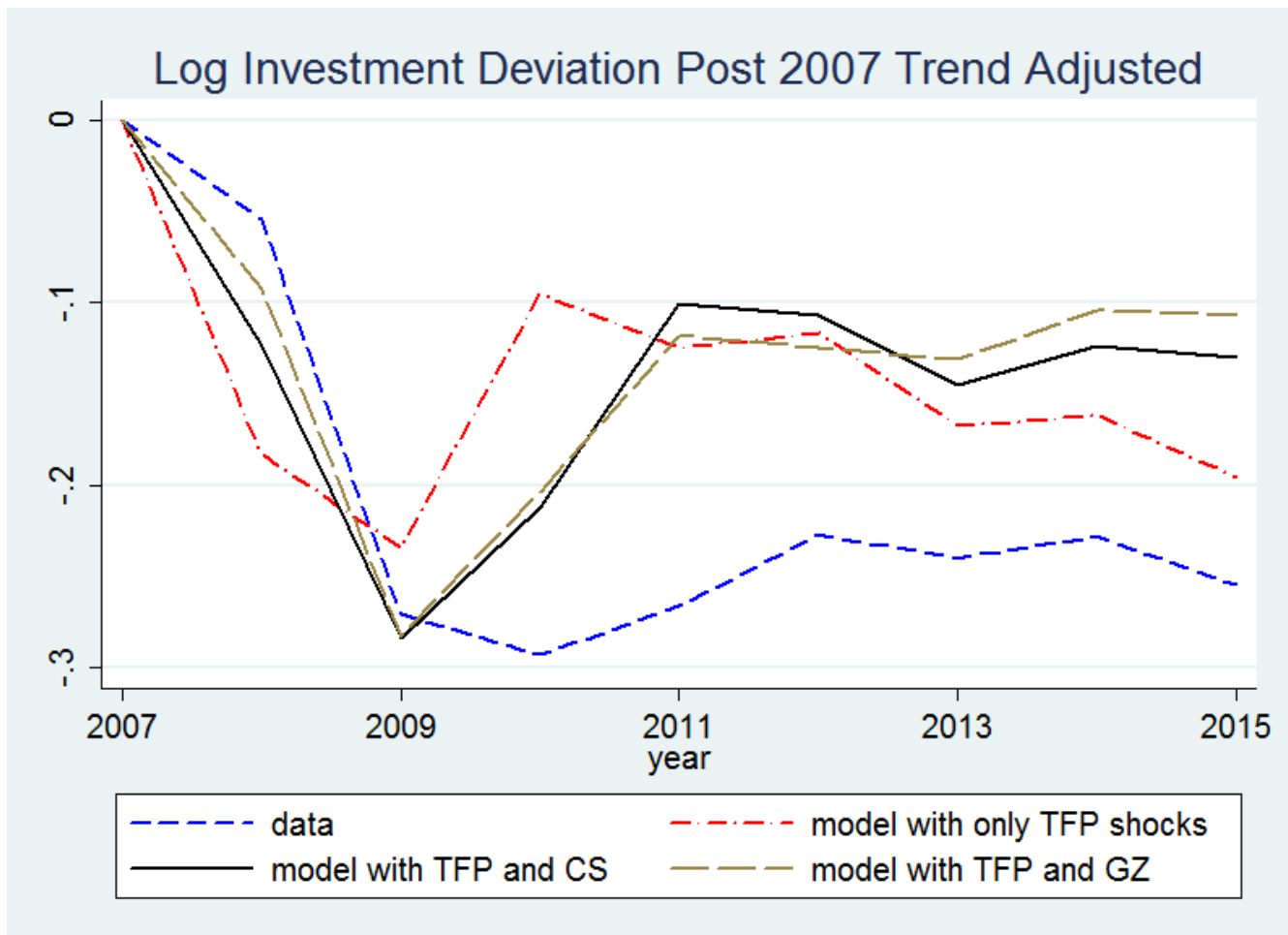
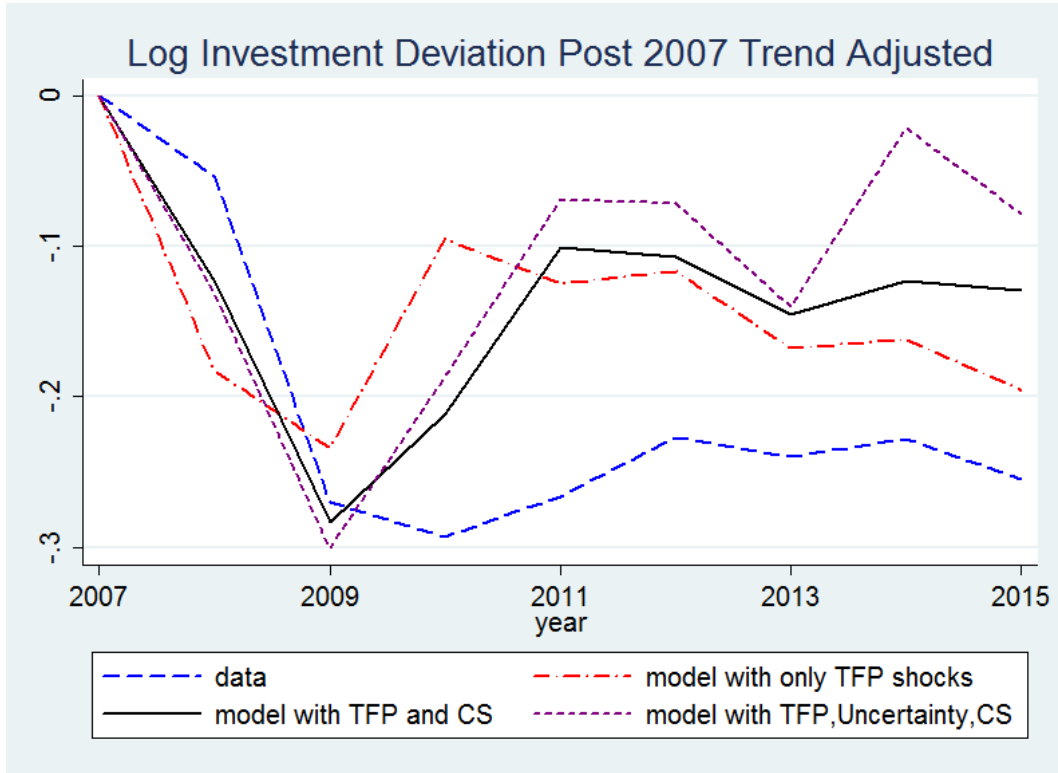


Figure 12: Combining All Shocks



5.2.3 Combining all Three Factors

Figure 12 reports the results of introducing all three shocks at the same time. Combined them together creates a larger drop in 2009. The root mean squared error (RMSE) of the model with all three shocks is 0.07 during the period 2007-2010 versus 0.12 for the model with TFP shocks only. However, the performance in later years, especially on the persistence of investment, is far off the slow recovery in the data. During the post-2010 period the model with TFP shocks only actually performs substantially better with a RMSE of only 0.09 versus 0.17 for the model with all three shocks.

The reason why the model with all three shocks overestimates the investment recovery during the later part of the sample is due to the joint effect of low uncertainty and low credit spreads that induce firms to invest substantially more.

6 Conclusion

This paper offers a detailed quantitative investigation of the possible factors behind the overall slump in corporate investment. Specifically, we construct and calibrate a dynamic stochastic model with heterogeneous firms and financial market imperfections to examine three commonly proposed arguments: (i) a secular decline in productivity growth; (ii) a tightening of financial constraints; and (iii) an increase in policy uncertainty.

We show that each of these arguments has a differential impact on the optimal behavior of firms and their corresponding optimal investment policies. After constructing appropriate empirical measures to capture all three of these factors, we quantify within a calibrated model the relative importance in explaining the dynamics of corporate investment since 2008. Our findings suggest that all three factors are important to explain the sharp decline in investment during the Great Recession, but below trend productivity alone offers the best explanation for the slow recovery post 2010.

Clearly, this is not an exhaustive investigation of all possible causes of the recent behavior of fixed non-residential investment. Nevertheless we believe our analysis captures the most popular explanations with policy makers and thus offers many relevant insights for economists and policy makers alike

References

- [1] ABEL, ANDREW B., 1983, Optimal Investment Under Uncertainty, *American Economic Review*, Vol. 73, 228-233.
- [2] ABEL, ANDREW B., JANICE EBERLY, 1996, Optimal Investment With Costly Reversibility, *Review of Economic Studies*, Vol. 63, 581-593.
- [3] ALFARO, IVAN, NICHOLAS BLOOM, XIAOJI LIN, 2016, The Finance-Uncertainty Multiplier, *Working Paper*.
- [4] BAKER, SCOTT R., NICHOLAS BLOOM, STEVEN J. DAVIS, 2016, Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics*, forthcoming.
- [5] BASU, SUSANTO, JOHN G. FERNALD, MILES S. KIMBALL, 2006, Are Technology Improvements Contractionary?, *American Economic Review*, Vol. 96, No. 5 (Dec., 2006), pp. 1418-1448.
- [6] BELO, FEDERICO, VITO D. GALA, JUN LI, 2013, Government Spending, Political Cycles, and the Cross Section of Stock Returns, *Journal of Financial Economics*, Vol. 107, No.2, 305-324.
- [7] BERNANKE, BEN S., MARK GERTLER, AND SIMON GILCHRIST, 1999, The Financial Accelerator in a Quantitative Business Cycle Framework, *Handbook of Macroeconomics*, Vol. 1B, 1341-1393.
- [8] BLOOM, NICOLAS, 2009, The Impact of Uncertainty Shocks, *Econometrica*, Vol 77, No. 3, 623-685.
- [9] BLOOM, NICOLAS, 2014, Fluctuation in Uncertainty, *Journal of Economic Perspectives*, 28, 153-176.
- [10] BLOOM, NICK, STEPHEN BOND, JOHN VAN REENEN, 2007, Uncertainty and Investment Dynamics, *The Review of Economic Studies*, 74.2 (2007): 391-415.

- [11] BUERA, FRANCISCO, JUAN PABLO NICOLINI, 2016, Liquidity Traps and Monetary Policy: Managing a Credit Crunch, *Working Paper*.
- [12] BLOOM, NICHOLAS, MAX FLOETOTTO , NIR JAINOVICH ,ITAY SAPORTA-EKSTEN, STEPHEN J. TERRY, 2016, Really Uncertain Business Cycles, *Working Paper*.
- [13] CABALLERO, RICARDO J.,1991, On the Sign of the Investment-Uncertainty Relationship, *American Economic Review*, Vol. 81, 279-288.
- [14] CABALLERO, RICARDO J., E. ENGEL, 1999, Explaining Investment Dynacmis in US Manufacturing: A generalized (S,s) approach, *Econometrica*, Vol. 67, 741-782.
- [15] CHARI, V.V., PATRICK J. KEHOE, ELLEN R. MCGRATTAN, 2007, Business Cycle Accounting, *Econometrica*, Vol 75, No. 3, 781-836.
- [16] COOPER, R. W., J.C. HALTIWAGER, 2006, On the nature of capital adjustment costs, *Review of Economic Studies*, Vol 73, 611-633.
- [17] DOMS, M., T. DUNNE, 1998, Capital adjustment patterns in manufacturing plants, *Review of Economic Dynamics*, Vol 1, 409-429.
- [18] GILCHRIST, SIMON, JAE SIM, EGON ZAKRAJŠEK, 2014, Uncertainty, Financial Frictions and Investment Dynamics, *Boston University Mimeo*.
- [19] GALA, VITO, JOAO GOMES, 2016, Investment without Q, *Working Paper*, The Wharton School, University of Pennsylvania.
- [20] GILCHRIST, SIMON, CHARLES HIMMELBERG, 1995, Evidence on the Role of Cash Flow in Investment, *Journal of Monetary Economics*, 36, 541-572.
- [21] GILCHRIST, SIMON, EGON ZAKRAJŠEK, 2012, Credit Spreads and Business Cycle Fluctuations, *American Economic Review*, 102(4), 1692-1720.
- [22] GOMES, JOAO F., 2001, Financing Investment, *American Economic Review* Vol. 91 (2001): 1263-1285.

- [23] GOMES, JOAO F., AMIR YARON, LU ZHANG, 2006, Asset Pricing Implications of Firms' Financing Constraints, *Review of Financial Studies* 19.4 (2006): 1321-1356.
- [24] GOMES, JOAO F., LUKAS SCHMID, 2016, Equilibrium Asset Pricing with Leverage and Default, *Working Paper*.
- [25] GULEN, HUSEYIN, MIHAI ION., 2016, Policy Uncertainty and Corporate Investment, *Review of Financial Studies*, 29.3 (2016): 523-564.
- [26] HALL, ROBERT E., 1988, The Relation between Price and Marginal Cost in U.S. Industry, *Journal of Political Economy*, vol 96, 921-947.
- [27] HALL, ROBERT E., 2010, Why Does the Economy Fall to Pieces after a Financial Crisis?, *Journal of Economic Perspectives*, vol 24, 3-20.
- [28] HALL, ROBERT E., 2011, The Long Slump, *American Economic Review*, 101(2), 431-469.
- [29] JERMANN, URBAN, VINCENZO QUADRINI, 2012, Macroeconomic Effects of Financial Shocks, *American Economic Review*, 102.1 (2012): 238-271.
- [30] KAHN, AUBHIK, THOMAS JULIA, 2008, Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics, *Econometrica*, 76 , 395-436.
- [31] KIM, HYUNSEOB, HOWARD KUNG, 2016, How Uncertainty Affects Corporate Investment: The Asset Redeployability Channel, *Review of Financial Studies*, Forthcoming.
- [32] MYERS, STEWART C., NICHOLAS MAJLUF, 1984, Corporate Financing and Investment Decisions When Firms Have Information that Investors Do Not Have, *Journal of Financial Economics*, 13, 187-221.
- [33] SCHAAL, EDOUARD, MATHIEU TASCHEREAU-DUMOUCHEL, 2016, Coordinating Business Cycles, *Working Paper*, 81-135.
- [34] STOCK, JAMES, MARK WATSON, 2012, Disentangling the Channels of the 2007-2009 Recession, *Brookings Panel on Economic Activity*, 81-135.

- [35] TAUCHEN, GEORGE, 1986, Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions, *Economic Letters*, 20, 177-181.
- [36] WHITED, TONI M, GUOJUN WU, 2006, Financial Constraints Risk, *Review of Financial Studies*, Vol. 19, No. 2 (Summer, 2006), pp. 531-559.
- [37] INTERNATIONAL MONETARY FUND, 2016, World Economic Outlook, *IMF Press*, (2016).
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A Appendix

A.1 Computational Details

In this section we provide all the computational details related to the models in the paper. We first solve the problem of a single firm under a variety of settings, and construct the optimal investment policy function. With these policies at hand we construct the economy wide aggregate.

A.1.1 Solution Method

A.1.2 Solution of the Model with TFP Shocks Only

We use the standard value function iteration method to solve the maximization problem of the firm. The state variables are x_t the aggregate shocks, z_t the idiosyncratic shocks and current capital level k_t . We use Tauchen(1986) method to generate the discretized Markov process that approximate the AR(1) process. We normalize our $\bar{x}$, the long run mean of the productivity shocks such that the long run mean of capital is around 1. To improve accuracy we use an interpolation method to solve for the optimal investment policy function very accurately.

The algorithm can be described as follows:

1. Make a guess for v^{n-1}
2. For each combination of (x, z, k) , use linear interpolation method to interpolate $v(x, z, k)$ into $v(x, z, \hat{k})$, where $\hat{k}$ has the same boundary as k grid, but much finer points.
3. Take the numerical expectation of $v(x', z', k)$ and solve the firm's problem.
4. Check for the convergence using maximum error criterion.

A.1.3 Adding Uncertainty Shocks

Now besides (x, z, k) , we have an additional state variable σ that follows a two state Markov process. Our aggregate productivity process is adjusted to compensate for the variance shocks, as described in section A.2. When constructing our grids we generate the high volatility discretized

states first and then use the same states (after adjusting the transition probabilities) for the low volatility economy. This avoids the need to interpolate the value function on the volatility dimension.

A.1.4 Adding Financial Constraints

For firms with limited access to external capital markets we also need to discretize the ω process. Again we use Tauchen (1986) method to discretize the log process for ω .

To compute the optimal investment policy, we iterate repeatedly on 11 as follows:

1. Make a guess for k'^{n-1}
2. For each combination of (x, z, k, μ) , we can find the policy implied next period capital k' . Use k' and expected value of x, z, μ , we can get the next next period's capital k'' . Then we can plug, k, k', k'' into the following function:

$$f = 1 - \beta \mathbb{E} \left\{ \frac{1 + \mu' s_k(x', z', k') - \Phi_k(i', k') + (1 - \delta)}{1 + \mu \Phi_i(i, k)} \right\} \quad (15)$$

3. Find out the optimal policy function for (x, z, k, μ) that minimize the absolute value of the above function.

A.2 Compensating Variance Shocks

Since the production function is a convex exponential function of $(x_t + z_t)$ (we omit firm subscripts wherever possible) increases in the volatility of $x_t + z_t$ without any compensating adjustment, lead to increases in the mean of $\exp(x_t + z_t)$. To ensure the conditional expectation of $\exp(x_t + z_t)$ remains unchanged across volatility states we make the adjustments discussed below.

If currently the economy is in the high uncertainty state, conditional on x_{t-1}, z_{t-1} and taking

exceptions of $\exp(x_t + z_t)$, we can find:

$$\begin{aligned}
E^H(\exp(x_t + z_t)) &= E(\exp(\pi_{HH}((1 - \rho_x)\bar{x}^H + \log(1 + g)t + \rho_x x_{t-1} + \sigma^H \nu_{x,t} + \rho_z z_{t-1} + \sigma^H \nu_{z,t}) \\
&\quad + \pi_{HL}((1 - \rho_x)\bar{x}^L + \log(1 + g)t + \rho_x x_{t-1} + \sigma^L \nu_{x,t} + \rho_z z_{t-1} + \sigma^L \nu_{z,t}))) \\
&= \exp(\log(1 + g)t + \rho_x x_{t-1} + \rho_z z_{t-1} + \pi_{HH}(1 - \rho_x)\bar{x}^H + \pi_{HL}(1 - \rho_x)\bar{x}^L \\
&\quad + (\pi_{HH}\sigma^H + \pi_{HL}\sigma^L)^2)
\end{aligned} \tag{16}$$

If currently the economy is in the low uncertainty state, conditional on x_{t-1}, z_{t-1} and taking exceptions of $\exp(x_t + z_t)$, we can find a similar expression:

$$\begin{aligned}
E^L(\exp(x_t + z_t)) &= E(\exp(\pi_{LH}((1 - \rho_x)\bar{x}^H + \log(1 + g)t + \rho_x x_{t-1} + \sigma^H \nu_{x,t} + \rho_z z_{t-1} + \sigma^H \nu_{z,t}) \\
&\quad + \pi_{LL}((1 - \rho_x)\bar{x}^L + \log(1 + g)t + \rho_x x_{t-1} + \sigma^L \nu_{x,t} + \rho_z z_{t-1} + \sigma^L \nu_{z,t}))) \\
&= \exp(\log(1 + g)t + \rho_x x_{t-1} + \rho_z z_{t-1} + \pi_{LH}(1 - \rho_x)\bar{x}^H + \pi_{LL}(1 - \rho_x)\bar{x}^L \\
&\quad + (\pi_{LH}\sigma^H + \pi_{LL}\sigma^L)^2)
\end{aligned} \tag{17}$$

By solving the equation $E^L(\exp(x_t + z_t)) = E^H(\exp(x_t + z_t))$, we can have the difference between $\bar{x}^H$ and $\bar{x}^L$ as a function of all the other parameters. This ensures the long run mean of productivities remains the same across high and low uncertainty states.

A.3 Uncertainty and Investment with Concavity

Here we use a simple example to demonstrate that only $\eta < 1$ is enough to generate the negative relationship between uncertainty and investment. Assume in the model just described before, there is no financial friction ($\mu_t = 0$), no adjustment cost $\theta = 0$. Also assume the uncertainty level is fixed either at high level or low level. We can first do the adjustment of the mean which we have :

$$E^H(\exp(x_t + z_t)) = \exp((1 - \rho_x)\bar{x}^H + \log(1 + g)t + \rho_x x_{t-1} + \rho_z z_{t-1} + 0.5(\sigma^H)^2 + 0.5(\sigma^H)^2) \quad (18)$$

$$E^L(\exp(x_t + z_t)) = \exp((1 - \rho_x)\bar{x}^L + \log(1 + g)t + \rho_x x_{t-1} + \rho_z z_{t-1} + 0.5(\sigma^L)^2 + 0.5(\sigma^L)^2) \quad (19)$$

To equate the above two equations, we can find that

$$\bar{x}^L - \bar{x}^H = \frac{(\sigma^H)^2 - (\sigma^L)^2}{1 - \rho_x} \quad (20)$$

Then we can write the next period's capital level as a function of parameters and expected productivity shocks:

$$\tilde{k}_{t+1} = \left(\frac{\alpha E_t(\exp(x_{t+1} + z_{t+1})^\eta)}{r + \delta} \right)^{\frac{1}{1-\alpha}} \quad (21)$$

We can compute the value of $E_t(\exp(x_{t+1} + z_{t+1})^\eta)$ in the high and low uncertainty stages.

$$E^H(\exp(x_t + z_t)^\eta) = \exp(\eta((1 - \rho_x)\bar{x}^H + \log(1 + g)t + \rho_x x_{t-1}) + 0.5\eta^2(\sigma^H)^2 + 0.5\eta^2(\sigma^H)^2) \quad (22)$$

$$E^L(\exp(x_t + z_t)^\eta) = \exp(\eta((1 - \rho_x)\bar{x}^L + \log(1 + g)t + \rho_x x_{t-1}) + 0.5\eta^2(\sigma^L)^2 + 0.5\eta^2(\sigma^L)^2) \quad (23)$$

Take the ratio of the above two expressions, it is

$$\exp(\eta(1 - \rho_x)(\bar{x}^H - \bar{x}^L) + \eta^2(\sigma_{xt}^H - \sigma_{xt}^L))$$

We can substitute $\bar{x}^H - \bar{x}^L$ into the above expression which yields:

$$\exp(\eta(\eta - 1)(\sigma_{xt}^H - \sigma_{xt}^L)).$$

The above expression is smaller than 1 if $\eta < 1$. Thus, in a frictionless economy, $\eta < 1$ implies negative relationship between uncertainty and investment. Adding back the time varying volatility

process makes the difference smaller since both the persistence of the high and low uncertainty process will decrease.

Finally, with adjustment cost and financial frictions we no longer have an analytical solution. But the numerical results confirm the negative relationship between uncertainty and investment is preserved in those settings as well.