

Does the Real Interest Rate Drive Investment? A Structural-Estimation Approach

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August 30, 2013

Abstract

This paper revisits the question if the real interest rate plays an important role for investment decisions by estimating a structural model using likelihood-based Bayesian methods. This approach systematically exploits all short-term variation in the data, whereas other tests only rely on movements in investment or capital in the very low frequencies. I use interest-rate and aggregate investment data from six industrial sectors in the UK to estimate a parsimonious partial-equilibrium model. The main finding is that the real interest rate accounts for no more than 2 percent of the variance in investment in the six sectors.

Keywords: Investment, real interest rates, Bayesian estimation

JEL codes: E22, E27

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1 Introduction

Surprisingly, it is still an open question in macroeconomics if the real interest rate matters for investment. On a theoretical level, all standard models predict that the real interest rate should have a major impact on investment (see for example the neo-classical models by Abel & Eberly, 1994 and Hayashi, 1982). On an empirical level, however, this effect is hard to find. Caballero (2000) notes in his review of the investment literature: “Our understanding of [the] determinants [of investment], both at the microeconomic as well as the macroeconomic level, has remained limited. The empirical investment literature has been nearly merciless in evaluating investment theories.” He summarizes the empirical literature by saying that even studies that *do* find an impact of the user cost of capital on investment leave a large fraction of the variance in investment unexplained.

Caballero (2000) divides the empirical literature on the estimation of investment equations into two main strands: The first directly estimates the long-run relationship between investment and the user-cost of capital and neglects short-run variation (e.g. Bernanke, 1983). A second strand (e.g. Cummins, Hassett & Hubbard, 1996) considers episodes of tax reform that had a significant impact on the user cost of capital and focuses on firm-level rather than aggregate data in order to recover degrees of freedom in the estimation.¹ In this article, I attempt a third avenue that exploits both short- and long-run variation in the data by estimating a structural model of investment. The estimation is carried out on the sector level, which makes it reasonable to assume that the real interest rate is exogenous.

Likelihood-based Bayesian methods offer the following advantages over other methods in this context. First, as already mentioned, they systematically exploit all short- and long-run variation in the data. Second, they give the researcher the possibility to force certain model parameters into the economically sensible range by specifying a prior distribution for parame-

¹There are some more recent papers, such as Gilchrist & Zakrajsek (2007) and Gilchrist, Yankov & Zakrajsek (2009), who find that the firm-specific user cost of capital as measured by corporate-bond prices does have a quantitatively important effect on firms’ investment. However, corporate bond prices contain the information about the firm’s default probability that is available to markets. This probability is highly correlated with other relevant firm-specific data, such as its productivity, pending lawsuits, its patents, its customer base etc. This paper is concerned with the impact of macroeconomic conditions (specifically the real interest rate) on firms’ investment, as opposed to the effect of the narrower firm-specific user cost of capital that the above authors study.

ters. Finally, the Bayesian approach yields exact confidence intervals for the parameters as well as for functions of these, here the fraction of variance in investment explained by movements in the interest rate. If this fraction is close to zero, as it turns out in the estimation, the Bayesian approach yields confidence intervals that are much more credible than the ones obtained from first-order approximations in a classical framework. The latter are bound to be symmetric and will extend below zero in many cases although they refer to a fraction, which by definition has to be non-negative.

In this paper, I estimate a parsimonious partial-equilibrium model for aggregate investment in six industrial sectors in the UK employing Bayesian methods. Linearizing the model, I derive a closed-form variance decomposition for investment and the capital stock in terms of structural parameters which is easy to interpret. I use the Kalman Filter to evaluate the likelihood and draw from the posterior distribution of the parameters and the hidden state of the model using Markov-Chain Monte-Carlo (MCMC) methods. The real interest rate is estimated to account for less than 2 percent of the variance in investment in all sectors; it accounts for less than 11 percent of the variance under a 99-percent confidence level in all sectors.

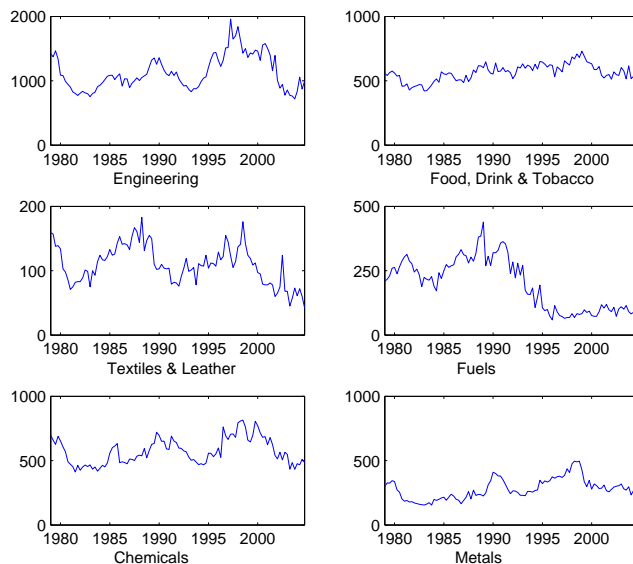
The paper is organized as follows: Section 2 describes the data, Section 3 introduces the theoretical model, Section 4 presents the estimation results and Section 5 concludes.

2 Data

The data set for investment is taken from the UK's *Office for National Statistics*'s web site. It consists of six quarterly time series for aggregate business investment by industry at 2001 prices in millions of British Pounds. The six industries are: Chemicals; Engineering; Food, Drink & Tobacco; Fuels; Metals; Textiles & Leather. The data set ranges from the first quarter of 1979 to the fourth quarter of 2004, yielding 104 observations. The time series are seasonally adjusted and measure investment by total capital expenditure in the sector. The time series are plotted in Figure 1.

As for the cost of capital, it would be desirable to use some direct measure of the real interest rate in the estimation. Inflation-indexed bonds traded on the British capital markets come very close to such a direct measurement. However, these instruments are only traded at very long maturities. Also, as Barr & Campbell (1996) note, these bonds are only imperfect measures

Figure 1: Investment Data



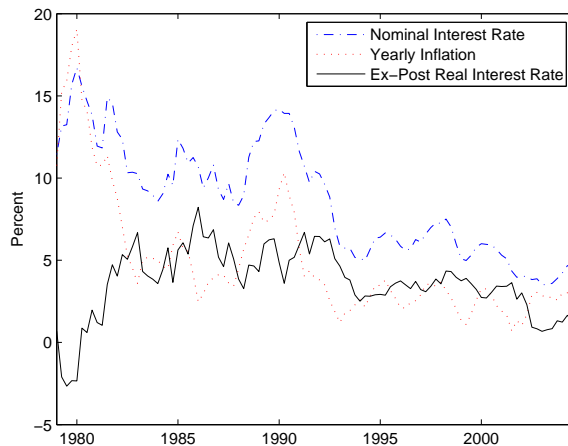
of real interest rates — even in the long term — since they leave the buyer unprotected against inflation occurring in the last months before maturity.

Instead of inflation-indexed bonds, I thus choose to use the ex-post real interest rate and regard it as a noisy signal of the expected real interest rate in the market. I calculate the expected real interest rate with a filtering procedure due to Fama & Gibbons (1982), which will be explained in detail in Sections 3 and 4. The ex-post real interest rate is defined as the difference between the nominal interest rate and inflation. Data for inflation and the nominal interest rate are taken from the *Bank of England's* web site. Figure 2 shows the respective time series over the sample period.

For inflation, I take the difference between the logarithm of the price level over one year.² Hamilton (1994b) suggests this as a simple procedure to remove seasonality. Technically, the resulting figure is a 4-quarter moving average over annualized quarterly inflation (seasonally adjusted) and *not* annualized quarterly inflation. Yet, this smoothing of the inflation time series essentially removes noise from the data and should not have a significant

²Technically: $\pi_t = \log CPI_{t+4} - \log CPI_t$, where π_t is annualized inflation in quarter t and CPI_t is the consumer price index in quarter t .

Figure 2: Interest-Rate Data



effect on the results — the relevant variable in the estimation procedure is the underlying *expected inflation* (in seasonally adjusted terms), which has certainly less variance in the high frequencies than realized inflation.

For the nominal interest rate, I take the average between bid and ask price in interbank-trade rate.

Visual inspection suggests that it reasonable to assume that all series can be assumed stationary over the sample period. Hence, no time trend is included in model and estimation.

3 The Model

The model describes a dynamic partial equilibrium in a competitive industrial sector, where the interest rate and demand are exogenous. The representative firm in the sector produces a single good with a constant-returns-to-scale technology. The only factor employed is capital:

$$y_t = Ak_t,$$

where y_t is the quantity of the good produced by the firm in period t , k_t is the capital stock in t , and $A > 0$ is a productivity coefficient. I use lower-case letters to denote quantities on the firm level and capitals to denote their

aggregate analogon. Capital accumulation is frictionless:

$$k_{t+1} = (1 - \delta)k_t + i_t, \quad (1)$$

where i_t is investment by the firm in period t and $0 \leq \delta \leq 1$ is the depreciation rate. The investment good i_t can be obtained at the constant price of one unit of the output good. Demand for the good produced in the sector is given by

$$P_t = C_d Y_t^{-\gamma} \nu_t = C_d A^{-\gamma} K_t^{-\gamma} \nu_t, \quad (2)$$

where P_t is the price of the good, $C_d > 0$ is a sector-specific constant, and Y_t is the aggregate quantity demanded in the sector. The elasticity of demand $\gamma \geq 0$ is constant and time-invariant. The demand shifter ν_t induces time-varying investment incentives in the sector; its logarithm $\tilde{\nu}_t \equiv \log \nu_t$ is assumed to follow an AR(1) process with a Gaussian innovation:

$$\tilde{\nu}_{t+1} = \rho_\nu \tilde{\nu}_t + \sigma_\nu \tilde{\varepsilon}_{t+1}^\nu, \quad (3)$$

where $\tilde{\varepsilon}_t^\nu$ is a serially uncorrelated normal shock with variance 1. To simplify notation, I introduce $C \equiv C_d A^{-\gamma} > 0$.

Notice that technology shocks can easily be accommodated in this framework. Suppose we introduce an adequately scaled process ξ_t for the productivity of capital: $y_t = A k_t \xi_t$. Then, Equation (2) becomes: $P_t = C K_t^{-\gamma} \nu_t \xi_t^{-\gamma}$. In this alternative framework, $\hat{\nu}_t \equiv \nu_t \xi_t^{-\gamma}$ would be the demand shifter.³

The representative firm is risk-neutral and has access to complete, actuarially fair capital markets. There is an exogenously given stochastic sequence for the real interest rate R_t . Specifically, I assume that its deviation from the logarithmic mean, $\tilde{r}_t \equiv \log R_t - E[\log R_t]$, follows an AR(1) process with a standard normal serially uncorrelated shock:

$$\tilde{r}_{t+1} = \rho_r \tilde{r}_t + \sigma_r \tilde{\varepsilon}_{r,t+1}. \quad (4)$$

The following notation is adopted to facilitate the ensuing discussion:

$$R_{0,t}^{-1} = \prod_{i=0}^{t-1} R_i^{-1}.$$

³Unfortunately, I did not find data series that allow me to disentangle the effects of demand and technology. This would be an interesting extension of this project, however it is not central to the issue at hand since we are mainly interested in the contribution of the user cost of capital to investment incentives.

The firm ranks stochastic sequences of profits by the criterion

$$Q(\{k_{t+1}\}_{t=0}^{\infty}, \cdot) = E_0 \sum_{t=0}^{\infty} R_{0,t}^{-1} \left[CK_t^{-\gamma} \nu_t k_t - k_{t+1} + (1 - \delta)k_t \right]$$

given $k_0, \{K_{t+1}\}_{t=0}^{\infty}, \{R_t\}_{t=0}^{\infty},$

where the sequences $\{K_{t+1}\}_{t=0}^{\infty}, \{R_t\}_{t=0}^{\infty}$ are exogenous to the firm and the sequence $\{k_{t+1}\}_{t=0}^{\infty}$ is under control of the firm. The term in brackets is the firm's profit in period t , which consists of the revenue from sales and the cost of investing in the capital stock.

Taking first-order conditions with respect to k_{t+1} and re-arranging yields the following familiar expression:

$$R_t = CK_{t+1}^{-\gamma} E_t[\nu_{t+1}] + (1 - \delta) \quad (5)$$

This equation says that the expected profits from investing a marginal unit in a company in the sector must be equal to the interest rate on the capital market. Notice that no variable under control of the firm enters in (5). The equation only gives a restriction on aggregate quantities which makes a risk-neutral investor indifferent between investing a marginal unit in the sector or holding a bond in the wider capital market. In order to obtain a tractable linear expression, I log-linearize (5) around the deterministic steady state and re-arrange to obtain⁴

$$\tilde{k}_{t+1} = \frac{\rho_\nu}{\gamma} \tilde{\nu}_t - \frac{\bar{R}}{\gamma[\bar{R} - (1 - \delta)]} \tilde{r}_t, \quad (6)$$

where $\tilde{k}_t \equiv \log K_t - E[\log K_t]$ and $\bar{R} \equiv E[\log K_t]$. Using equations (3), (4) and the expectation of (6), the impulse response for capital with respect to the driving processes is

$$\tilde{k}_{t+1} = \frac{\rho_\nu \sigma_\nu}{\gamma} \sum_{j=0}^{\infty} \rho_\nu^j \tilde{\varepsilon}_{\nu,t-j} - \frac{\bar{R} \sigma_r}{\gamma[\bar{R} - (1 - \delta)]} \sum_{j=0}^{\infty} \rho_r^j \tilde{\varepsilon}_{r,t-j}. \quad (7)$$

This shows us which part of variation in K is accounted for by the demand and interest-rate shocks.

⁴The so-called “deterministic steady state”, in which the logged shock $\tilde{\nu}$ is set to its mean, we have: $\bar{R} - (1 - \delta) = CK^{-\gamma}$.

To obtain an expression for investment, use the log-linearized law of motion of capital, $\tilde{k}_{t+1} = (1 - \delta)\tilde{k}_t + \delta\tilde{i}_t$:

$$\tilde{i}_t = \frac{\rho_\nu \sigma_\nu}{\gamma} \left(\frac{1}{\delta} \tilde{\varepsilon}_{\nu,t} + \sum_{j=1}^{\infty} \rho_\nu^j \tilde{\varepsilon}_{\nu,t-j} \right) - \frac{\bar{R} \sigma_r}{\gamma [\bar{R} - (1 - \delta)]} \left(\frac{1}{\delta} \tilde{\varepsilon}_{r,t} + \sum_{j=1}^{\infty} \rho_r^j \tilde{\varepsilon}_{r,t-j} \right) \quad (8)$$

The variance of investment can thus be decomposed as

$$Var(\tilde{i}_t) = \left(\frac{\rho_\nu \sigma_\nu}{\gamma} \right)^2 \left(\frac{1}{\delta} + \frac{\rho_\nu^2}{1 - \rho_\nu^2} \right) + \left(\frac{\bar{R} \sigma_r}{\gamma [\bar{R} - (1 - \delta)]} \right)^2 \left(\frac{1}{\delta} + \frac{\rho_r^2}{1 - \rho_r^2} \right), \quad (9)$$

where the first term captures the contribution from demand shocks and the second term the contribution from interest-rate shocks. This variance decomposition will be the primary object of interest in the estimation. Its interpretation is as follows. The higher the variance and persistence of a shock, the more it affects investment. The more elastic demand, the weaker the response to either shock: a high elasticity γ means that additional capacity in the sector drives down marginal revenue fast, so that the marginal benefit of investment drops to zero quickly. The depreciation rate δ has an effect that is opposite to the persistence of shocks ρ_ν when it comes to demand shocks: the lower the lifetime of installed capital (the higher δ), the less it is worth to invest in response to a demand shock. As for interest-rate shocks, the effect of δ – as well as that of \bar{R} – are ambiguous.

Investment, as given by Equation (8), is the first variable in the estimation. The second is the real interest rate. The ex-post real interest rate $r_{p,t}$ is defined as $r_{n,t} - \pi_t$, where $r_{n,t}$ is the nominal interest rate and π_t is inflation. The ex-ante real interest rate r_t is defined as $r_{n,t} - \pi_{e,t}$, where $\pi_{e,t}$ is the inflation rate expected for period t by the public when entering this period. I follow Fama & Gibbons (1982) and decompose realized inflation into $\pi_t = \pi_{e,t} + \eta_t$, where $\pi_{e,t}$ is expected inflation and η_t is a rational-expectations error. Regarding r_t as a hidden state and combining the expressions before, we have

$$r_{p,t} = r_{i,t} - \pi_t = r_t - \eta_t. \quad (10)$$

Since η_t is a rational-expectations error, it is uncorrelated over time and also uncorrelated to other variables known to the agents in the market at time t . I furthermore assume that η_t has constant variance σ_η .

Now, everything is in place to write down a state-space system combining

(3), (4), (8) and (10):

$$\begin{pmatrix} \tilde{\nu}_{t+1} \\ \tilde{r}_{t+1} \\ \tilde{k}_0 \end{pmatrix} = \begin{pmatrix} \rho_\nu & 0 & 0 \\ 0 & \rho_r & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \tilde{\nu}_t \\ \tilde{r}_t \\ \tilde{k}_0 \end{pmatrix} + \begin{pmatrix} \sigma_\nu & 0 \\ 0 & \sigma_r \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \tilde{\varepsilon}_{\nu,t} \\ \tilde{\varepsilon}_{r,t} \end{pmatrix}, \quad (11)$$

$$\begin{pmatrix} \tilde{i}_t \\ \tilde{r}_{p,t} \end{pmatrix} = \begin{pmatrix} -\sum_{j=1}^t (1-\delta)^j L^j \\ 0 \end{pmatrix} \tilde{i}_t + \begin{pmatrix} \frac{\rho_\nu}{\delta\gamma} & \frac{-\bar{R}}{\delta\gamma[R-(1-\delta)]} & -\frac{(1-\delta)^t}{\delta} \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \tilde{\nu}_t \\ \tilde{r}_t \\ \tilde{k}_0 \end{pmatrix} + \begin{pmatrix} 0 \\ \sigma_\eta \end{pmatrix} \eta_t, \quad (12)$$

where $(\tilde{\varepsilon}'_{\nu,t+1}, \tilde{\varepsilon}'_{r,t+1}, \eta'_t)'$ is Gaussian white noise with the identity covariance matrix \mathbf{I}_3 and L is the lag operator: $Lx_t = x_{t-1}$. In the language of state-space systems, (11) is the state equation (containing the *hidden state* $(\tilde{\nu}_t, \tilde{r}_t, \tilde{k}_0)'$) and (12) is the observation equation (containing the *observed state* $(\tilde{i}_t, \tilde{r}_{p,t})'$). The lagged values of \tilde{i}_t are pre-determined at t and can hence be treated as fixed. The timing convention is as follows: The first observation is made at $t = 1$, the last at $t = T$.

The distribution of the hidden state at $t = 0$, which is needed to start the recursions of the Kalman Filter, is taken to be the unconditional variance of the variables. From (8), the unconditional variance of \tilde{k}_0 can be seen to be

$$Var(\tilde{k}_{t+1}) = \left(\frac{\rho_\nu}{\gamma}\right)^2 Var(\tilde{\nu}_t) + \left(\frac{\bar{R}}{\gamma[\bar{R} - (1-\delta)]}\right)^2 Var(\tilde{r}_t),$$

where $Var(\tilde{\nu}_t) = \frac{\sigma_\nu^2}{1-\rho_\nu^2}$ and $Var(\tilde{r}_t) = \frac{\sigma_r^2}{1-\rho_r^2}$. The covariances of \tilde{k}_{t+1} with $\tilde{\nu}_t$ and \tilde{r}_t are

$$Cov(\tilde{k}_{t+1}, \tilde{\nu}_{t+1}) = Cov(\tilde{k}_{t+1}, \rho_\nu \tilde{\nu}_t) + Cov(\tilde{k}_{t+1}, \sigma_\nu \tilde{\varepsilon}_{\nu,t+1}) = \frac{\rho_\nu^2}{\gamma} Var(\tilde{\nu}_t),$$

$$Cov(\tilde{k}_{t+1}, \tilde{r}_{t+1}) = Cov(\tilde{k}_{t+1}, \rho_r \tilde{r}_t) + Cov(\tilde{k}_{t+1}, \sigma_r \tilde{\varepsilon}_{r,t+1}) = \frac{\rho_r \bar{R}}{\gamma[\bar{R} - (1-\delta)]} Var(\tilde{r}_t).$$

4 Estimation and results

I adopt a two-stage strategy to estimate the model described in (11). In the first stage, the parameters ρ_r , σ_r and σ_η are determined solely from the interest-rate data by maximum-likelihood estimation (MLE). In the second stage, these parameters are fixed at the estimated values and the remaining

Table 1: Prior Distribution

Parameter	Distribution Family	Shape	Scale	Support	
		Parameter	Parameter	from	to
ρ_ν	Beta	2	1.2	0	1
σ_ν	Inverse Gamma	2	4.5	0	∞
δ	Beta	1.2	3	0	1
γ	Inverse Gamma	2	3	0	∞

four parameters in (11) are estimated from the investment data in a particular sector and the interest-rate data employing Bayesian methods.

The first step evaluates the likelihood of observing the data for $\{\tilde{r}_{p,t}\}_{t=1}^{104}$ for a fixed triplet of parameters $(\rho_r, \sigma_r, \sigma_\eta)'$ by applying the Kalman Filter to the simplified system⁵

$$\begin{aligned}\tilde{r}_{t+1} &= \rho_r \tilde{r}_t + \sigma_r \varepsilon_{\nu,t} \\ \tilde{r}_{p,t} &= \tilde{r}_t + \sigma_\eta \eta_t.\end{aligned}$$

The series $\{\tilde{r}_{p,t}\}_{t=1}^{104}$ is obtained by de-meaning the logarithm of the ex-post real interest rate, as described in Section 2. Notice that this procedure yields a method-of-moments estimate for the parameter \bar{R} , which will be used in the second step as well.

In the second stage, the Metropolis-Hastings algorithm⁶ is used to draw from the posterior distribution of the remaining four parameters ρ_ν , σ_ν , δ and γ . The prior distribution of the parameters is given in Table 4. The four parameters are independently distributed under the prior. At this point, the Bayesian approach is very convenient since it allows to bound parameters in their economically sensible range.

The results of this first step are summarized in Table 2. Figure 3 shows the filtered series (i.e. $E[r_t | r_{p,t}, r_{p,t-1}, \dots]$) with confidence intervals, derived from the conditional variance of the true state r_t around its conditional mean $E[r_t | r_{p,t}, \dots]$.

As for the second step, the estimation yielded very similar results across the six sectors. Table 3 shows posterior mean and variance for the model

⁵See Hamilton (1994a), for example, for the exact procedure of obtaining the likelihood in a state-space system.

⁶See Johannes & Polson (2005), for example, for a description of how to MCMC techniques.

Table 2: Results of 1st-stage Estimation (MLE)

Parameter	ρ_r	σ_r	σ_η	R
Estimate	0.92	0.85	0.25	3.66

Figure 3: Filtered Series for r_t (first stage)

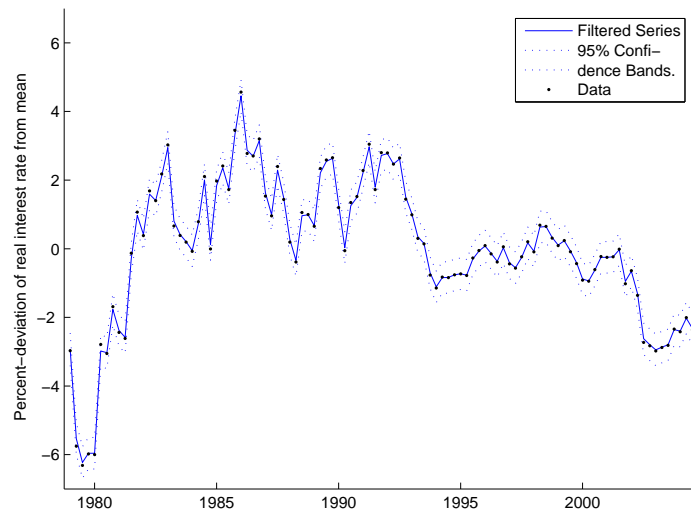


Table 3: Posterior Mean and Standard Deviation

Sector	ρ_ν	σ_ν	δ	γ	\tilde{k}_0
Engineering	0.926	31.845	0.876	3.619	0.253
	0.033	12.01	0.072	1.479	9.8
Food, Drink & Tobacco	0.916	46.891	0.667	10.245	0.047
	0.035	21.159	0.076	4.702	6.129
Textiles & Leather	0.927	13.91	0.766	1.1	0.247
	0.039	8.39	0.111	0.716	26.399
Fuels	0.974	24.275	0.608	2.28	-0.09
	0.014	7.456	0.086	0.805	18.095
Chemicals	0.903	32.671	0.841	4.128	0.249
	0.04	14.65	0.085	1.951	8.988
Metals	0.928	16.758	0.895	1.647	0.558
	0.03	13.047	0.067	1.309	24.983

(Means are given above in normal script size, standard deviations below in footnote size.)

parameters and \tilde{k}_0 . Figure 4 shows the marginal distribution of the parameters and the proportion of variance in capital and investment caused by interest-rate movements under the posterior for the sector *Engineering*. The black curves describe the distribution of the respective parameter under the prior⁷ — it is easy to see that the priors are not very restrictive and have little influence on the posterior.

The most striking result of the estimations is the very low fraction of variance accounted for by the interest rate — see Table 4 for some percentiles of this statistic across the different sectors. Its mean is below 2.5 percent in all sectors, and only in one sector does the 99th percentile exceed 10 percent. The estimation tells us that the interest rate has a negligible impact on investment when compared to demand and productivity shocks.

The impulse responses of investment to a one-standard-deviation shock to the demand shifter and the real interest rate are given in Figure 5. The solid line depicts the mean of the analytical impulse response as given in (7) and (8) under the posterior; the dotted lines are 95-percent confidence intervals (note

⁷For the two bottom panels, which describe functions of the deep model parameters, a 1,000,000 draws was taken from the independent distributions of the deep model parameters and the respective function values were calculated to obtain a histogram.

Figure 4: Posterior Distribution for the Sector *Engineering*

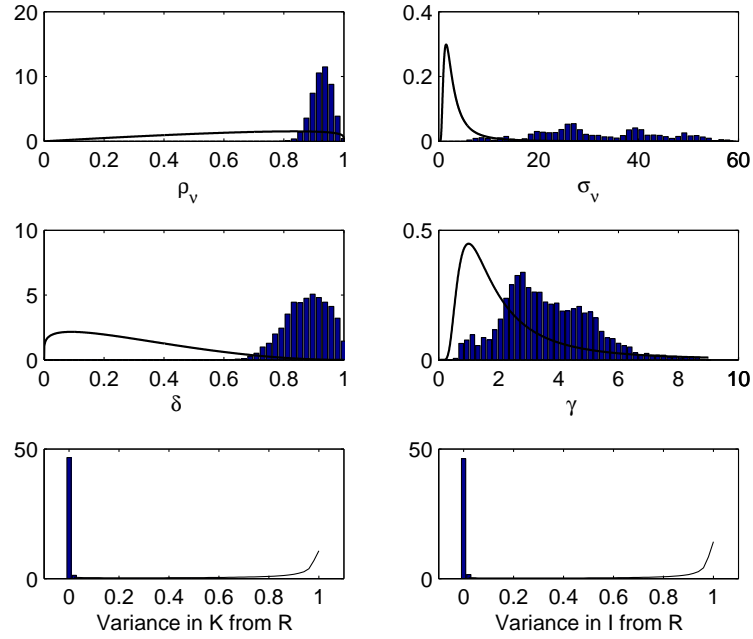
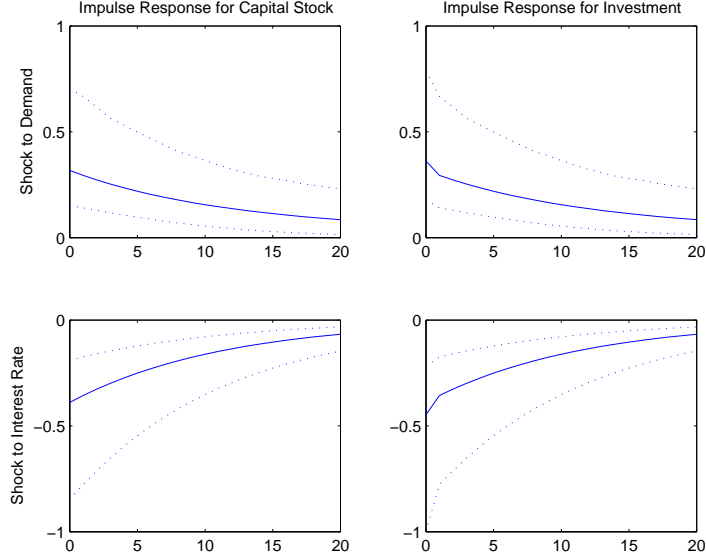


Table 4: Proportion of Variance in Investment due to Interest Rate

Sector	Mean	95th Percentile	99th Percentile
Engineering	0.0024	0.0081	0.0218
Food, Drink & Tobacco	0.0061	0.0371	0.0739
Textiles & Leather	0.0211	0.0714	0.1068
Fuels	0.0025	0.0096	0.0190
Chemicals	0.0041	0.0162	0.0318
Metals	0.0161	0.0627	0.0987

the different scales used for the two types of shock).

Figure 5: Impulse Responses for the Sector *Engineering*

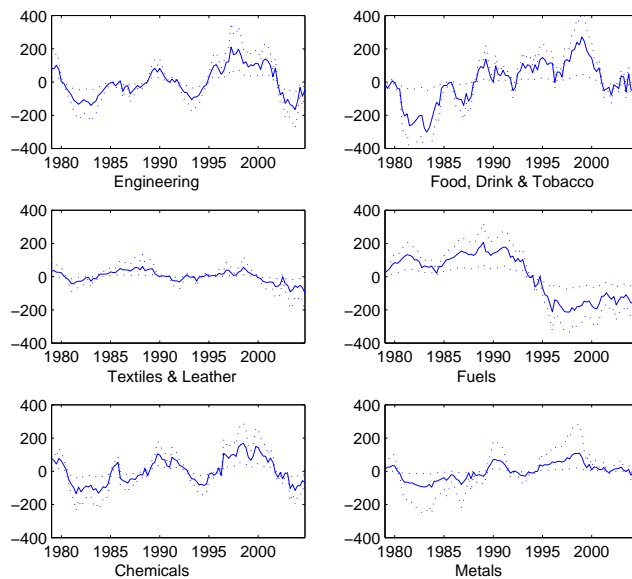


There are two other features of the results that draw our attention. First, the rather high estimates for the depreciation rate δ are surprising. This result hints at a misspecification issue here and suggests to consider other specifications for the investment process (e.g. lumpiness in investment) or the industry dynamics (e.g. market power). Testing such other models, possibly using a larger vector of industry data, is an interesting task for future research, but beyond the scope of the current paper.

The second salient feature is large posterior variance of the model parameters σ_ν and γ . It turns out that they are also highly correlated, which hints at an identification problem. Equation (6) reveals why this is the case: when removing interest-rate shocks from the model, it would be impossible to tell a high variance of demand shocks and a low elasticity apart. Since the interest rate is estimated to contribute very little to investment, the system is close to this non-identification case. Appendix A.5 shows that identification is not a problem when the contribution of interest rate shocks is large enough: no issue arises in estimation on simulated data. At any rate, the main results on the importance of the interest rate for investment are not affected by

weak identification of σ_ν and γ . The posterior covers a large range of possible values for the two parameters, but in all areas a low impact of interest rates on investment is found, as the posteriors for the variance decomposition in Table 4 show. Economically speaking, we cannot be sure if it is large shocks or inelastic demand that makes demand shocks matter so much, but whichever of the two is responsible we can be sure that interest-rate shocks are unimportant.

Figure 6: The Demand Shifter ν_t



The posterior distribution of the hidden process $\{\tilde{\nu}_t\}_{t=1}^{104}$ is depicted in Figure 6 for all sectors.⁸ Visual inspection suggests that the investment incentives faced by the firms in the different sectors are lowly correlated among each other. It seems that macroeconomic factors which affect all

⁸Note that these distributions mirror both the uncertainty about the deep model parameters remaining after the estimation and the uncertainty about the hidden state that remains after the filtering exercise. For this reason, the size of the confidence intervals is time-varying, which may be striking at first for the reader accustomed to the constant conditional variances that characterize the Kalman filter under parameter certainty. It is important to bear in mind the additional dimension of parameter uncertainty that arises in a Bayesian estimation framework.

sectors and are not captured in interest rates (e.g. multi-purpose technologies, common components in demand, government policies) play a minor role in determining investment in the different sectors. Further econometric analysis of the joint properties of these processes or a model encompassing more than one sector would be an interesting extension of this exercise.

5 Conclusions

This paper estimates a structural model for investment using a Bayesian likelihood approach. This approach has the advantage that it systematically takes into account all short-term variation in the data. The main result is that movements in the real interest rate accounted for less than 2 percent of the variance in investment in six industrial sectors in the UK over the last 26 years.

This statement can be made on a statistically sound basis in a Bayesian estimation framework. I argue that confidence intervals derived from first-order approximations employed in frequentist statistics are inferior to the Bayesian concept of the posterior distribution when this fraction is very close to zero. Moreover, the Bayesian approach offers the possibility to force model parameters into the economically sensible range and is very robust even when the dimensionality of the parameter space increases.

Furthermore, I find that the uncovered non-interest-rate investment incentives (demand shocks, productivity shocks etc.) in the different sectors have very little in common. This is surprising, since many macroeconomic conditions other than the interest rate should have a similar impact on all sectors. The results suggest that sector-specific conditions are dominate macroeconomic factors in their effect on investment on the sector level. An extension of this model to investigate this issue systematically would be an interesting exercise.

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A Details on the estimation procedure

A.1 Likelihood functions and the Kalman Filter

The likelihood of observing the data $\{\tilde{r}_{p,t}, \tilde{i}_t\}_{t=1}^{104}$ given a vector of parameters is evaluated applying the Kalman Filter to the state-space system described in (11). To obtain the series $\{\tilde{i}_t\}_{t=1}^{104}$, again I de-mean the logarithm of the investment time series in the respective sector, which is tantamount to estimating the model parameter C by a moment condition.

Since (11) contains a dynamic component, it is necessary to work with a time-varying system for a certain number of periods. For small values of δ , the matrices calculated for the Kalman Filter do not converge for a long time and sometimes the time-varying system has to be used until the end of the data series. In the other cases, the matrices from the doubling algorithm (I use a program that Ljungqvist & Sargent (2004) provide) of the limiting system are utilized after a number of periods applying a convergence criterion. For this stable system, the component \tilde{k}_0 is dropped from the hidden state, since no further information on \tilde{k}_0 is gained from new observations.

A.2 Metropolis-Hastings algorithm

As suggested by Johannes & Polson (2005), a fat-tailed distribution is used for the jump proposals in the Metropolis-Hastings algorithm. Specifically, I use a t -distribution with 5 degrees of freedom. In the estimations, it proved important to adjust the scaling of the jump-proposal density to the covariance of the parameters under the posterior. As Figure 8 in the appendix suggests, especially the covariance between the parameters γ and σ_ν is very high; in all sectors, their correlation coefficient under the posterior distribution exceeds 0.9. Implementing a well-scaled proposal density allowed me to increase the efficiency of the algorithm by using a relatively large variance for the jump proposals. The jump size was tuned such that the acceptance rate lay in the optimal range between 0.25 and 0.4.⁹ For each sector, I carried out 20,000 draws from the posterior distribution. For every tenth draw, an additional draw was taken from the process for the hidden state in (11).

⁹See Johannes & Polson (2005) for an overview of theoretical results on the optimal acceptance rate of MCMC algorithms.

A.3 Drawing from the hidden state

The technique I use to draw from the hidden state is inspired by the smoothing algorithm as described, for example, in Hamilton (1994a).¹⁰ To simplify notation, denote a generic state-space system (as the one in (11)) as follows:

$$\begin{aligned}\mathbf{x}_{t+1} &= \mathbf{A}\mathbf{x}_t + \mathbf{C}\boldsymbol{\varepsilon}_t \\ \mathbf{y}_t &= \mathbf{F}\mathbf{x}_t + \mathbf{G}\boldsymbol{\eta}_t,\end{aligned}$$

where \mathbf{x}_t is a vector of hidden state variables, \mathbf{y}_t is a vector of observed variables, $(\boldsymbol{\varepsilon}'_t, \boldsymbol{\eta}'_t)'$ is vector white noise and the matrices \mathbf{A} , \mathbf{C} , \mathbf{F} and \mathbf{G} are known at t and fulfill the obvious conformability conditions with the state and shock vectors. Note that the following derivation is valid for time-varying matrices \mathbf{A}_t , \mathbf{C}_t , \mathbf{F}_t and \mathbf{G}_t as long as they are known at t — the subscript is dropped for notational convenience only.

The following identity is at the heart of the algorithm:

$$E[\mathbf{x}_t | \mathbf{x}_{t+1}, \mathbf{y}^T] = E[\mathbf{x}_t | \mathbf{x}_{t+1}, \mathbf{y}^t],$$

where $\mathbf{y}^t \equiv (\mathbf{y}_0, \mathbf{y}_1, \dots, \mathbf{y}_t)$. This can easily be seen by decomposing \mathbf{y}_{t+j} into

$$\mathbf{y}_{t+j} = \mathbf{F} \left[\mathbf{A}^{j-1} \mathbf{x}_{t+1} + \sum_{k=0}^{j-1} \mathbf{A}^k \mathbf{C} \boldsymbol{\varepsilon}_{t+j-k} \right] + \mathbf{G} \boldsymbol{\eta}_{t+j}$$

and noting that the errors $\boldsymbol{\varepsilon}_{t+k}$ and $\boldsymbol{\eta}_{t+k}$ are uncorrelated with \mathbf{x}_t for $k > 0$ by assumption. To facilitate notation, introduce $\hat{\mathbf{x}}_{t|t} \equiv E[\mathbf{x}_t | \mathbf{y}^t]$, $\hat{\mathbf{x}}_{t+1|t} \equiv E[\mathbf{x}_{t+1} | \mathbf{y}^t]$ and $\hat{\mathbf{x}}_t^d \equiv E[\mathbf{x}_t | \mathbf{x}_{t+1}, \mathbf{y}^t]$, where the d in the superscript indicates that this value will be used for drawing from the posterior. Now, update the projection of \mathbf{x}_t on \mathbf{y}^t , which is a by-product of the Kalman Filter, with the information about \mathbf{x}_{t+1} . Make the “news” from \mathbf{x}_{t+1} orthogonal on \mathbf{y}^t by introducing the innovation $\mathbf{a}_{t+1} \equiv \mathbf{x}_{t+1} - \hat{\mathbf{x}}_{t+1|t}$ and update using the formula for updating a linear projection (as given in Hamilton (1994b), for example):

$$\hat{\mathbf{x}}_t^d = E[\mathbf{x}_t | \mathbf{x}_{t+1}, \mathbf{y}^t] = \hat{\mathbf{x}}_{t|t} + \underbrace{E[(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t}) \mathbf{a}'_{t+1}]}_{\equiv \boldsymbol{\Omega}_{xa}} \left\{ \underbrace{E[\mathbf{a}_{t+1} \mathbf{a}'_{t+1}]}_{\equiv \boldsymbol{\Omega}_{t+1|t}} \right\}^{-1} \mathbf{a}_{t+1} \quad (13)$$

¹⁰“Smoothing” describes a recursive procedure for obtaining the conditional expectation (or projection, in the non-Gaussian case) $E[x_t | y^T]$ with its associated conditional variance (or mean squared error). Note that the Kalman Filter only gives a recursive formula for finding $E[x_t | y^t]$ and $E[x_{t+1} | y^t]$ — it does not take into account future observations of y_t , which potentially contain useful information about the distribution of x_t .

Notice that $\Omega_{t+1|t}$ is also an ingredient of the Kalman Filter and hence does not require additional computations. As for Ω_{xa} , it is given by

$$\Omega_{xa} = E\left[(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t})\mathbf{a}'_{t+1}\right] = E\left[(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t})\left(\mathbf{A}(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t}) + \mathbf{C}\varepsilon_{t+1}\right)'\right] = \Omega_{t|t}\mathbf{A}',$$

where $\Omega_{t|t} \equiv E[(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t})(\mathbf{x}_t - \hat{\mathbf{x}}_{t|t})']$ is again an ingredient of the Kalman Filter.

The variance of the true state \mathbf{x}_t around $E[\mathbf{x}_t|\mathbf{x}_{t+1}, \mathbf{y}^t]$ is given by the usual formula for updating linear projections:

$$\Omega_t^d \equiv E[(\mathbf{x}_t - \hat{\mathbf{x}}_t^d)(\mathbf{x}_t - \hat{\mathbf{x}}_t^d)'] = \Omega_{t|t} - \Omega_{xa}\Omega_{t+1|t}^{-1}\Omega_{xa} \quad (14)$$

Since the variables $\{\mathbf{y}_t, \mathbf{x}_t\}_{t=1}^T$ are by assumption jointly normally distributed, the conditional variance $E[(\mathbf{x}_t - \hat{\mathbf{x}}_t^d)(\mathbf{x}_t - \hat{\mathbf{x}}_t^d)'|\mathbf{x}_{t+1}, \mathbf{y}^t]$ is equal to the variance Ω_t^d . Ω_t^d is a deterministic sequence, i.e. not conditioned on $\mathbf{x}_{t+1}, \mathbf{y}^t$.

The algorithm to draw a sequence $\{\mathbf{x}_t\}_{t=1}^T$ from its distribution conditional on a sequence $\{\mathbf{y}_t\}_{t=1}^T$ is as follows:

- Initialize by setting $t := T$, $\hat{\mathbf{x}}_t^d = \hat{\mathbf{x}}_{T|T}$ and $\Omega_t^d = \Omega_{T|T}$, which can both be obtained from the Kalman Filter.¹¹
- Draw $\mathbf{x}_t = \hat{\mathbf{x}}_t^d + [\Omega_t^d]^{-1/2}\boldsymbol{\chi}_t$, where $\boldsymbol{\chi}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$.
- Set $t := t - 1$. Stop if $t = 0$ is reached. If not, update $\hat{\mathbf{x}}_t^d$ according to (13) and Ω_t^d according to (14).

A.4 Parameter Paths in the MCMC Algorithm

Figures 7 and 8 show the path of the Markov chain for the four model parameters in the estimation for the *Engineering* sector. For the parameters ρ_ν and δ , the sensible range of parameter values is thoroughly explored — note that only 1,000 draws are shown in Figure 7, whereas all 20,000 draws are shown in Figure 8. For σ_ν and γ , however, the picture is different — it would be quite confident to assert that the chain has converged to a stationary distribution for *these* two parameters.

¹¹There were some computational difficulties involved in this step since the updated matrices lost the property of positive definiteness for some parameter draws. These irregularities occurred very rarely and were obviously due to computational inaccuracies when the vectors in Ω_t^d were close to collinear. The problem was fixed by adding very small numbers to the elements of the matrix to make it positive definite whenever this property was lost.

Figure 7: MCMC Path of ρ_ν and δ (Sector *Engineering*)

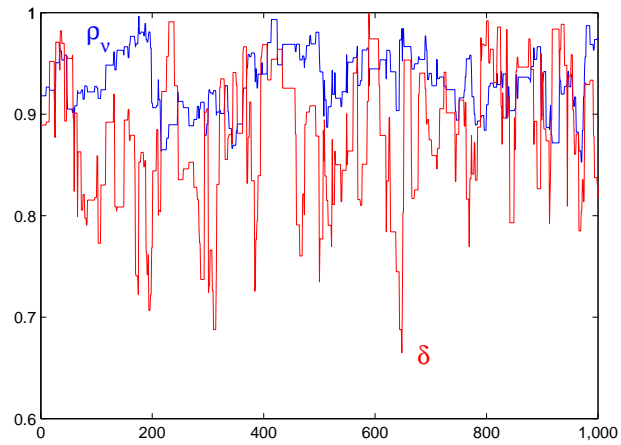
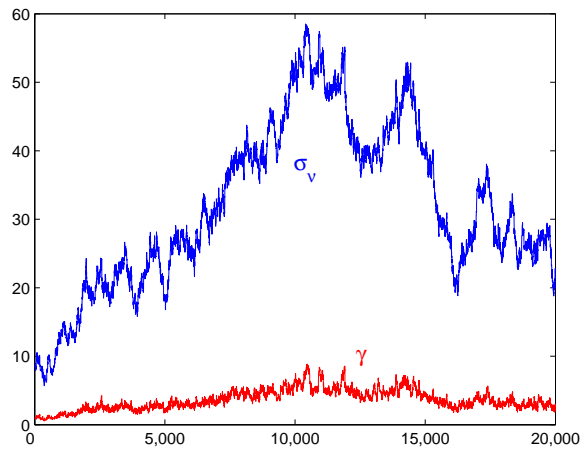


Figure 8: MCMC Path of σ_ν and γ (Sector *Engineering*)



Due to their high correlation, the ratio between σ_ν and γ stays in a relatively stable range, so that other statistics of interest (as impulse responses and variance decompositions) do not vary much along the chain. The system described in (11) seems to come close to non-identifiability when the influence of interest rates on investment goes close to zero; yet, the main conclusion of the exercise — interest rates plays a minor role in determining investment — is very robust.

A.5 Estimation with Simulated Data

The data in this simulation were generated by drawing 104 independent standard normal shock vectors $(\tilde{\varepsilon}_{\nu,t}, \tilde{\varepsilon}_{r,t}, \eta_t)'$ and feeding them into the dynamic linearized system described in (11). The initial state was drawn from the stationary distribution of the system. The parameters ρ_r , σ_r and σ_η were fixed at the values obtained in the first estimation stage. For the remaining parameters, the following values were chosen: $\rho_\nu = 0.9$, $\sigma_\nu = 2$, $\delta = 0.1$ and $\gamma = 1.5$. These true values are marked with a black diamond in Figure 9, which gives the results of an estimation that was carried out in exactly the same fashion as the estimation on the real data (described in Section 4). The estimation procedure yields reasonable results. The posterior distribution does not depart far from the true values and the variance of the parameters under the posterior is modest. This indicates strongly that the model does not suffer from an identification problem.

Figure 9: Posterior Distribution for Estimation on Simulated Data

