Uncertainty and Capital Accumulation: Empirical Evidence for African and Asian Firms

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Abstract

This paper presents estimates of the effects of uncertainty on both short run investment behaviour and long run capital accumulation for panels of African and Asian firms. We estimate structural investment models in which the level of uncertainty influences investment behaviour through different forms of adjustment costs: partial irreversibility, a fixed cost of undertaking any investment at all, and quadratic adjustment costs. Structural parameters are estimated by matching simulated model moments to empirical data for firms in China, India, Morocco and Ghana, using a simulated minimum distance estimator. The estimated models suggest that a lower level of uncertainty would have only modest effects on short run investment dynamics, but would result in much higher capital stocks.

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Key words: Uncertainty, investment, capital accumulation.

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1 Introduction

This paper presents estimates of the effects of uncertainty on both short run investment behaviour and long run capital accumulation for panels of African and Asian firms. We estimate structural investment models in which the level of uncertainty influences investment behaviour in both the short run and the long run as a result of different forms of adjustment costs: partial irreversibility, a fixed cost of undertaking any investment at all, and quadratic adjustment costs. Structural parameters are estimated by matching simulated model moments to empirical data for firms in China, India, Morocco and Ghana, using a simulated minimum distance estimator. The estimated models are used to investigate how these firms' investment behaviour would differ if they faced different levels of uncertainty. Counterfactual simulations indicate that investment would be more responsive to new information about demand if firms in these countries faced a lower level of uncertainty, although quantitatively the impact of uncertainty on short run investment dynamics is found to be modest. On average, however, we estimate that a lower level of uncertainty would induce firms to operate with substantially higher capital stocks.

The model of investment that we estimate is closely related to that analysed under complete irreversibility by Abel and Eberly (1999). Firms produce output using capital and flexible inputs according to a constant returns to scale Cobb-Douglas production function. Output is sold in imperfectly competitive markets, and each firm faces an isoelastic demand curve. Formally we model uncertainty in the level of demand, although broadly similar results would be expected for uncertainty in the level of total factor productivity. We generalise the Abel-Eberly model to allow for partial rather than complete irreversibility, and we introduce both fixed and quadratic components of adjustment costs. In line with Cooper and Haltiwanger (2006) and Bloom (2006), we find that a rich mix of adjustment costs is required to fit features of firm-level investment data.

We estimate this model using data for firms in China, India, Morocco and Ghana collected by the World Bank and the Centre for the Study of African Economies. Firm-level data for developing countries has two important advantages for this study. First, this allows us to consider investment behaviour in environments that have been much less stable than richer countries like the UK or the USA, and in which firms plausibly face much higher levels of uncertainty. Second, models with non-convex adjustment costs (fixed costs or partial irreversibility) predict an important region of inaction, in which firms prefer to undertake no investment rather than (potentially) costly upward or downward adjustments. Consistent with this, we see a substantial fraction of observations with zero annual investment in our samples. This varies from 67% for smaller firms in India to 18% for larger firms in China. In contrast, observations with zero investment expenditure are extremely rare in annual data for publicly traded US or UK firms.[1]

A less attractive feature of survey data for firms in developing countries is the possibility of significant measurement error in recorded investment and other variables. We recognise this by allowing for an unusually rich structure of measurement errors in our empirical specification, and we find that this is also needed to fit the sample data. We find important differences between the data for smaller and larger firms in each country, which we account for by estimating separate models. We also explore the robustness of our results to treating the data on larger firms as the outcome of aggregation over several smaller units.

The investment models that we consider do not have closed-form solutions but they can be solved and simulated numerically. We therefore apply a simulated minimum distance procedure to estimate the structural parameters by matching simulated moments, such as the correlation between investment rates and output growth, to their observed counterparts in our samples. We check that varying the parameters that we estimate generates useful variation in the set of moments we

[1] See Bloom (2006) and Bloom, Bond and Van Reenen (2007) for evidence for US and UK firms respectively.

use to estimate them, and that conditions for local identification are satisfied at our estimated parameter values.

The estimated models highlight the importance of adjustment frictions for firms in these countries. Investment responds much less to new information about demand than would be the case in the absence of adjustment costs, and average capital stock levels are much lower than they would be if firms did not face adjustment costs. Keeping the estimated adjustment cost parameters constant, counterfactual simulations show that the response of investment to demand shocks would be greater if firms faced a lower level of uncertainty. The sign of this relationship between uncertainty and the impact effect of demand shocks is consistent with that estimated by Bloom (2006) for US firms and Bloom, Bond and Van Reenen (2007) for UK firms. However the magnitude of this effect of uncertainty on short run investment dynamics is estimated to be quite modest for our samples of Asian and African firms.

In contrast, the most striking result of this study is that we find large effects of uncertainty on average capital stock levels. For example, we find that if the level of demand uncertainty could be permanently halved, then in the long run this would induce firms to increase their average capital stocks by about 10% for firms in Morocco or by about 20% for firms in China. This suggests a potentially important relationship between uncertainty and average capital stock levels.

Abel and Eberly (1999) emphasised that the sign of the relationship between uncertainty and average capital stock levels was ambiguous in their model in which the only adjustment friction was due to irreversibility. Higher uncertainty makes firms more reluctant to invest in response to good news about demand, but only because they may be stuck with more capital than they would like to have following the realization of negative demand shocks. In theory the latter effect may dominate, giving a positive relationship between uncertainty and average capital stock levels; and even if this is not the case, the net impact of the two opposing effects may be small. In a companion paper, Bond, Söderbom and Wu (2007),

we show that a negative relationship between uncertainty and average capital stock levels is more likely under either fixed or quadratic costs of adjustment, and that quantitatively this effect can be large. The strong negative relationship that we find in our counterfactual simulations thus reflects the relative importance of both fixed cost and quadratic cost components of our estimated adjustment cost functions.

The rest of the paper is organised as follows. Section 2 outlines the model of investment that we estimate, and illustrates differences in the implied investment behaviour under different forms of adjustment costs. Section 3 describes the firm-level datasets that we use in this study. Section 4 outlines the method we use to estimate the structural parameters of our model, and reports the empirical results. Section 5 presents counterfactual simulations that illustrate how short run investment dynamics and average capital stock levels would differ if firms faced different levels of demand uncertainty. Section 6 concludes.

2 Investment model

We assume that firms face isoelastic, downward-sloping, stochastic demand schedules of the form

$$Q_t = X_t P_t^{-\eta} \tag{1}$$

where Q_t is output, P_t is price and $-\eta < -1$ is the price elasticity of demand. The demand shift parameter X_t is stochastic and is the only source of uncertainty in the model. The log of this demand shift parameter follows a trend stationary process

$$\begin{aligned} x_t &= \ln X_t = x_0 + \mu t + z_t \qquad (2) \\ z_t &= \rho z_{t-1} + \varepsilon_t \\ \varepsilon_t &\sim \text{iid } N(0, \sigma^2) \end{aligned}$$

Demand shocks ε_t have effects that are persistent but not permanent, decaying at the rate $0 < \rho < 1$, and on average demand grows at the trend rate μ. Firms making decisions in period t know X_t and the parameters η, x_0, μ, ρ and σ^2, but are uncertain about future levels of demand which depend on future realizations of the demand shocks. The variance of these demand shocks σ^2 measures the level of uncertainty faced by firms in the model.

Output is produced using capital, labour and materials according to a constant returns to scale Cobb-Douglas production function

$$Q_t = A\widehat{K}_t^{\beta} L_t^{1-\alpha-\beta} M_t^{\alpha} \tag{3}$$

where $\widehat{K}_t = K_t + I_t$ and $K_{t+1} = (1-\delta)\widehat{K}_t$. New investment I_t contributes to productive capital $\widehat{K}_t$ immediately in period t, and productive capital depreciates at the known, constant rate δ at the end of each period. If the firm undertakes no investment, its productive capital stock thus decays at the rate δ. Adjusting the productive capital stock upwards or downwards from this path requires investment, which may be positive or negative, and incurs adjustment costs $G(I_t, K_t)$ that will be specified below. The parameters A, α and β are assumed constant and known to the firm.

The net revenue function in period t is given by

$$P_t Q_t - G(I_t, K_t) - p^I I_t - wL_t - p^M M_t \tag{4}$$

where units of capital are purchased at the price p^I,[2] units of labour are hired at the wage rate w and units of material inputs are purchased at the price p^M. These input prices are assumed constant and known to the firm.

The objective of the firm is to maximise the net present value of current and expected future net revenues. We eliminate the choice of the flexible inputs L_t and M_t from the dynamic optimisation problem as follows. First re-write the

[2]Partial irreversibility, which implies a difference between the price at which units of capital can be bought and sold, will be incorporated through the adjustment cost function.

production function as

$$Q_t = A\widehat{K}_t^{\beta} L_t^{1-\beta} \left(\frac{M_t}{L_t}\right)^{\alpha} \tag{5}$$

Constant prices for the flexible inputs imply that the ratio (M_t/L_t) will be constant. Choosing units for material inputs relative to labour inputs such that $A(M_t/L_t)^{\alpha} = 1$ then allows us to write the production function as

$$Q_t = \widehat{K}_t^{\beta} L_t^{1-\beta} \tag{6}$$

where we note that the parameter β still corresponds to the coefficient on productive capital in a three-factor Cobb-Douglas specification, as in (3). This choice of units also allows the net revenue function to be written as

$$P_t Q_t - G(I_t, K_t) - p^I I_t - \widehat{w} L_t \tag{7}$$

where $\widehat{w} = w(1 + \frac{\alpha}{1-\alpha-\beta})$ also reflects the cost of material inputs. Following Abel and Eberly (1999),[3] the optimal choice of labour inputs then implies that the net revenue function simplifies to

$$hX_t^{\gamma} \widehat{K}_t^{1-\gamma} - G(I_t, K_t) - p^I I_t$$

where

$$0 < \frac{1}{\eta} < \gamma = \frac{1}{1 + \beta(\eta - 1)} < 1 \tag{8}$$

and

$$h = \left(\frac{1}{\gamma\eta}\right)^{\gamma\eta} (\gamma\eta - 1)^{\gamma\eta - 1} \widehat{w}^{1-\gamma\eta} > 0$$

Finally choosing units of labour such that $h = 1$ gives the net revenue function

$$X_t^{\gamma} \widehat{K}_t^{1-\gamma} - G(I_t, K_t) - p^I I_t \tag{9}$$

where $X_t^{\gamma} \widehat{K}_t^{1-\gamma} = P_t Q_t - \widehat{w} L_t = P_t Q_t - wL_t - p^M M_t$ denotes operating profits.

[3] Specifically p.344.

2.1 Dynamic optimisation

The firm's investment behaviour depends on the forms of adjustment costs that it faces. We follow Cooper and Haltiwanger (2006) and Bloom (2006) in considering three forms of adjustment costs.

Partial irreversibility allows the price at which firms can sell units of capital to be below the price at which firms must buy units of capital, for example, as a result of asymmetric information in the market for second hand capital goods (Akerlof, 1970). If we define p^I to be the purchase price and p^S to be the sale price, the effect of positive or negative investment on net revenue can be written as

$$-p^I I_t 1_{[I_t \geqslant 0]} - p^S I_t 1_{[I_t < 0]}$$

where $1_{[I_t \geqslant 0]}$ is an indicator equal to one if investment is non-negative (and equal to zero otherwise), and $1_{[I_t<0]} = 1 - 1_{[I_t \geqslant 0]}$ is an indicator equal to one if investment is strictly negative. Alternatively this can be written as

$$-p^I I_t - (p^S - p^I) I_t 1_{[I_t<0]}$$

The adjustment cost function in this case has the form

$$G(I_t) = -b_i I_t 1_{[I_t<0]}$$

where $b_i = p^I - p^S \geqslant 0$. We normalise the purchase price p^I to one, so that the parameter b_i can be interpreted as the difference between the purchase price and the sale price expressed as a percentage of the purchase price. For example, $p^S = 0.8$ gives $b_i = 0.2$, indicating that the sale price is 20% lower than the purchase price. Letting p^S approach zero, or letting b_i approach one, ensures that the firm never chooses to sell units of capital, and mimics investment behaviour under a complete irreversibilty constraint.

Fixed adjustment costs reflect costs that are paid if any investment or disinvestment is undertaken, and that can be avoided by choosing zero investment.

We allow the level of these fixed adjustment costs to be proportional to the firm's operating profits, so that these costs do not become irrelevant as firms grow larger. The form of the adjustment cost function in this case is

$$\begin{aligned} G(I_t, K_t) &= b_f 1_{[I_t \neq 0]}(P_t Q_t - wL_t - p^M M_t) \\ &= b_f 1_{[I_t \neq 0]} X_t^{\gamma} \widehat{K}_t^{1-\gamma} \end{aligned}$$

where $1_{[I_t \neq 0]}$ is an indicator taking the value one if investment is non-zero. The parameter b_f is interpreted as the fraction of operating profits lost by undertaking any strictly positive level of investment or dis-investment.

Quadratic adjustment costs reflect costs that increase as the firm undertakes additional investment or dis-investment. We allow the level of these quadratic costs to be proportional to the firm's capital stock, so that a given investment rate imposes costs that increase with the size of the firm, and again do not become irrelevant as firms grow larger. The form of the adjustment cost function in this case is

$$G(I_t, K_t) = \frac{b_q}{2}\left(\frac{I_t}{K_t}\right)^2 K_t$$

where b_q measures the size of quadratic adjustment costs.

Our model allows for these three forms of adjustment costs, specifying the adjustment cost function to be

$$G(I_t, K_t) = -b_i I_t 1_{[I_t<0]} + b_f 1_{[I_t \neq 0]} X_t^{\gamma} \widehat{K}_t^{1-\gamma} + \frac{b_q}{2}\left(\frac{I_t}{K_t}\right)^2 K_t \tag{10}$$

The firm has a discount rate of r per period, or a discount factor of $\phi = \frac{1}{1+r}$. Investment in period t is chosen to maximise the present discounted value of current and expected future net revenues, where expectations are taken over the distribution of future demand shocks. This investment decision can be represented as the solution to a dynamic optimisation problem defined by the stochastic Bellman equation

$$V_t(X_t, K_t) = \max_{I_t} \Pi(X_t, K_t; I_t) + \phi E_t\left[V_{t+1}(X_{t+1}, K_{t+1})\right] \tag{11}$$

where V_t is the value of the firm in period t, $E_t[V_{t+1}]$ is the expected value of the firm in period $t+1$ conditional on information available in period t, and

$$\Pi(X_t, K_t; I_t) = X_t^{\gamma} \widehat{K}_t^{1-\gamma} - G(I_t, K_t) - I_t \tag{12}$$

is net revenue in period t, as in equation (9) above, with the purchase price of capital goods normalised to unity. The two state variables are the capital stock K_t and the level of demand X_t, with equations of motion defined in the previous section.

2.2 Investment decisions

Given the forms of adjustment costs that we consider in equation (10), there is no analytical solution that describes the optimal level of investment I_t as a function of the state variables K_t and X_t. However we can use numerical stochastic dynamic programming methods to simulate these optimal investment decisions. We use a form of value function iteration, with a discrete approximation to the stationary AR(1) process for z_t in (2) as suggested by Tauchen (1986), and allowing for the trends in X_t, K_t and I_t. Further details of the algorithm we use to generate the simulated investment data are provided in Appendix A.

Figures 1-3 illustrate the investment decision rules which relate the level of investment I_t to the levels of K_t and X_t. We plot the implied investment rates (I_t/K_t) against variation in the level of demand relative to the inherited capital stock (X_t/K_t), where these investment policies are drawn for a given level of the inherited capital stock. We show these decision rules separately for three special cases of the model, in which the only adjustment costs present are respectively partial irreversibility ($b_i = 0.05$) in Figure 1, fixed costs ($b_f = 0.05$) in Figure 2, and quadratic costs ($b_q = 0.5$) in Figure 3.[4]

[4]The values of the other parameters used to generate these policy functions are $r = 0.05, \mu = 0.029, \sigma = 0.2405, \gamma = 0.2519$ (these correspond to parameter values used in Abel and Eberly (1999)) $\rho = 0.9$ and $\delta = 0.05$ (Abel and Eberly (1999) consider a geometric Brownian motion process for demand and assume no depreciation). Here and throughout the paper we set $x_0 =$

Figure 1 illustrates the familiar region of inaction with zero investment that is part of the optimal investment policy under partial irreversibility. The level of demand is scaled so that a value of zero on the horizontal axis would be associated with zero investment, even in the absence of any adjustment costs.[5] The 45^o line here shows how investment rates would vary with the level of demand if adjustment of the capital stock was costless, with dis-investment occuring at all levels of demand below this threshold value. With partial irreversibility, no dis-investment occurs unless the level of demand falls to around 50% of this threshold value; and for lower levels of demand the rate of dis-investment that occurs is also much less than would be chosen in the absence of adjustment costs. Similarly there is no positive investment unless the level of demand reaches a level that is about 10% higher than the level needed to induce positive investment in the frictionless case; and for higher levels of demand the investment rate continues to be lower than would be chosen in the absence of adjustment costs. The asymmetry in the firm's willingness to undertake positive or negative investments reflects the asymmetry in the adjustment costs implied by partial irreversibility, as well as the presence of depreciation and an upward trend in the level of demand in this specification.

The region of inaction illustrated in Figure 1 becomes wider as the difference between the prices at which units of capital can be bought and sold increases. As the price at which capital can be sold approaches zero, the firm ceases to undertake any dis-investment, no matter how low is the level of demand relative to the inherited capital stock.

Figure 2 illustrates that a region of inaction also forms part of the optimal investment policy with fixed adjustment costs. Here dis-investment again occurs only if the level of demand reaches a level that is about 50% lower than the level which induces dis-investment in the frictionless case, while positive investment

$-0.5\sigma^2/(1-\rho^2)$, so that changing the variance of the demand shocks has no effect on the expected level of demand $E[X_t] = \mu t$ (i.e. we consider the effects of mean-preserving spreads).

[5] In this case the level of the capital stock would fall as a result of depreciation.

occurs only if the level of demand reaches a level that is about 60% higher. In this case the region of inaction is centred around levels of demand, relative to inherited capital, that would be associated with low rates of investment or dis-investment in the absence of adjustment costs. Outside this region of inaction, the optimal investment decisions are quite different to those under partial irreversibility. Small adjustments to the capital stock do not generate benefits that are sufficiently high to warrant paying a fixed cost to implement them. Low rates of investment or dis-investment are therefore not part of the optimal investment policy, and the capital stock adjusts to new information about demand through infrequent, large adjustments. When the imbalance between the current level of demand and the inherited level of the capital stock reaches a level that justifies either positive or negative investment, the optimal investment policy jumps discontinuously to rates of investment or dis-investment that are similar to those that would be chosen in the frictionless case.

Figure 3 illustrates the optimal investment policy with quadratic adjustment costs only. In this case there is no region of inaction. Increasing marginal adjustment costs penalise high rates of investment or dis-investment. In this case the capital stock adjusts to new information about demand through a series of smaller, gradual adjustments.

These differences in the nature of optimal investment decisions allow the importance of these different forms of adjustment costs to be estimated by matching features of the distribution of investment rates in simulated data to corresponding features of empirical datasets. For example, observing a mass of observations with zero investment would suggest the importance of either fixed costs or irreversibility. Observing relatively few observations with negative investment would suggest an important role for irreversibility, while observing few observations with low rates of investment or dis-investment would suggest that fixed costs are likely to be important. Additional information comes from matching the relationship between investment rates and proxies for either demand shocks (such as sales growth) or

the imbalance between demand and inherited capital (such as the ratio of sales to lagged capital); and from matching the serial correlation properties of observed investment rates. For example, observing low correlation between investment rates and current sales growth and positive serial correlation in investment rates would be consistent with the pattern of gradual adjustment over time to new information about demand associated with quadratic adjustment costs.

2.3 Uncertainty and investment

The level of uncertainty about demand (i.e. the variance (σ^2) of the demand shocks) influences both the way in which investment responds to new information about demand, and the capital stock levels that firms choose to accumulate.

2.3.1 Short run adjustment

We illustrate the effect of uncertainty on capital stock adjustment behaviour by considering the impact effect of demand shocks (ε_t) on expected growth rates of the capital stock ($\Delta \ln K_t$) in the same period. A weaker impact effect indicates that the capital stock adjusts more slowly to new information about the level of demand.

Figures 4-6 illustrate how the level of uncertainty affects this impact effect of demand shocks on current investment rates in each of the three special cases of our model considered in the previous section. Figure 4 considers investment behaviour under partial irreversibility. The dashed 45^o line again shows that capital stock growth simply follows current demand growth in the absence of adjustment costs. The darker solid line illustrates how expected capital stock growth varies with current demand growth in our specification with partial irreversibility only ($b_i = 0.05$), at our reference level of uncertainty ($\sigma = 0.2405$). This relationship is estimated by fitting a non-parametric regression to data on simulated capital stock growth rates for a generated sample of 10,000 firms in a typical year. The simulated investment rate for each firm varies not only with the current realisation of the

demand shock but also with the history of past shocks. The non-parametric regression line thus presents a smoothed average of these simulated capital stock growth rates at each level of the current demand shock.[6]

As expected from the investment decision rule shown in Figure 1, the impact effect of positive demand growth on capital stock growth is weaker under partial irreversibility than in the frictionless case. Whereas all firms adjust immediately and fully to new information about demand in the frictionless case, some firms do not adjust at all in the current period under partial irreversibility (i.e. those for whom the demand shock leaves them within their region of inaction), and even those firms that do some adjustment in the current period do less investment than they would in the absence of adjustment costs. Also as expected, the impact effect of negative demand growth on capital stock growth is very much weaker under partial irreversibility, reflecting the greater reluctance of firms to undertake dis-investment.

The lighter solid line shown in Figure 4 illustrates how expected capital stock growth varies with demand growth under the same degree of partial irreversibility in a case where firms face a lower level of uncertainty. In this case, the standard deviation of the demand shocks is set to half our reference value (i.e. $\sigma = 0.12025$), and the simulated capital stock growth rates reflect the optimal investment decisions for firms facing this lower level of uncertainty. All other parameter values, including the 5% difference between the sale price and the purchase price for units of capital ($b_i = 0.05$), are left unchanged. The impact effect of positive demand growth on capital stock growth is noticeably stronger when firms subject to partial irreversibility operate in a less uncertain environment, although the expected response to negative demand growth is almost indistinguishable. This illustrates the effect of uncertainty on short run investment dynamics under partial irreversibility

[6] These non-parametric regressions are obtained by Lowess smoothing, using the curve fitting toolbox in Matlab. Demand shocks are drawn from a discrete distribution with 200 points of support in these simulations.

that was emphasised by Bloom et al. (2007).

Figure 5 illustrates that with fixed adjustment costs, at least for the parameter values used here, we find a similar pattern. The impact effect of positive demand growth on capital stock growth decreases with the level of uncertainty. Again there is relatively little effect of uncertainty on the relationship between demand growth and capital stock growth over the region where demand growth is negative. Figure 6 shows that with quadratic adjustment costs, the impact effect of demand shocks on expected growth rates of the capital stock is insensitive to the level of uncertainty over the whole range of demand shocks.

2.3.2 Capital accumulation

While there is some interest in the speed of capital stock adjustment, for development policy it is arguably more important to consider how expected capital stock levels vary with the level of uncertainty. Abel and Eberly (1999) emphasised that this effect is theoretically ambiguous in a model with complete irreversibility and no other forms of adjustment costs. At a higher level of uncertainty, firms are more cautious about investing in response to good news about demand (as illustrated for the case of partial irreversibity in Figure 4). This 'user cost' effect tends to lower the expected capital stock at higher levels of uncertainty. However this reluctance to invest reflects the risk of getting stuck with more capital than firms would like to have following the later realisation of negative demand shocks. This *ex post* 'hangover' effect tends to increase the expected capital stock, and is also increasing in the level of uncertainty. The net effect of uncertainty on the expected level of the capital stock depends on the balance of these opposing forces, and is theoretically unclear. Calculations of this net effect reported in Abel and Eberly (1999) for their model also suggest that the net effect may be small. In their Figures 1-3, for example, the expected level of the capital stock varies by only about 1 per cent over the entire range of values considered for the level of the uncertainty parameter (σ).

In Bond, Söderbom and Wu (2007) we simulate data for an investment model that is very similar to that analysed by Abel and Eberly (1999), except that we allow for richer forms of adjustment costs.[7] For the special case with complete irreversibility and no other adjustment costs, we replicate their analytical results. However for versions of the model with fixed or quadratic adjustment costs, we find that a higher level of uncertainty tends to reduce the expected level of the capital stock. We also find that this effect can be quantitatively significant, particularly for the case of quadratic adjustment costs.

The model we estimate in this paper differs from that considered in Bond, Söderbom and Wu (2007) in two respects. Here we specify the level of demand to follow the trend stationary process outlined in (2), and we allow for depreciation of the capital stock. Figures 7-9 illustrate how the expected level of the capital stock varies with the level of uncertainty in the three special cases of this model considered previously, using the same parameter values as in section 2.2.

Figure 7 considers a specification with partial irreversibility only. For each level of uncertainty shown on the horizontal axis, ranging between $\sigma = 0.0245$ and $\sigma = 0.2405$, the dashed line shows the average level of the capital stock calculated from simulated data for a sample of 10,000 firms.[8] These average capital stock levels are scaled by the average capital stock level in the simulation using our reference level of uncertainty ($\sigma = 0.2405$), so that the values on the vertical axis can be read as percentage increases in the expected capital stock level as we reduce the level of uncertainty below this reference value.[9] For example, these simulations suggest that halving the level of uncertainty, from $\sigma = 0.2405$ to

[7] Our simulation model there specifies the demand process to be a discrete-time random walk with drift, rather than the geometric Brownian motion considered by Abel and Eberly (1999). Our model also allows investment in period t to contribute immediately to the productive capital stock.

[8] The average capital stock level is measured for a single reference year, chosen so that the results are insensitive to the initialisation of the simulation, which is discussed further in Appendix A. In Figure 7, for example, results are presented for $t = 88$.

[9] Recall that the value of x_0 in (2) is set so that the expected level of demand is $E[X_t] = \mu t$, independent of σ. In our model this implies that the expected level of the capital stock in the absence of adjustment costs would not depend on the level of uncertainty.

$\sigma = 0.12025$, increases the expected level of the capital stock by about 2 per cent. The solid line fits a simple polynomial regression through these points to illustrate the general pattern. This suggests that the expected level of the capital stock decreases as we consider higher levels of uncertainty over most of this range.

Figure 8 finds a broadly similar pattern in a specification with fixed adjustment costs only. Here the effect of halving the level of uncertainty is smaller, increasing the expected level of the capital stock by about 1 per cent.

Figure 9 confirms that much larger effects are possible in a specification with quadratic adjustment costs only. Here we find that halving the level of uncertainty increases the expected level of the capital stock by about 6 per cent. While this particular effect is certainly sensitive to the value of the quadratic adjustment cost parameter b_q, the point here is that we do not find effects of this magnitude in models with either partial irreversibility or fixed costs alone, for any values of b_i or b_f.[10] For example, increasing b_i from 0.05 (as in Figure 7) to 1 (i.e. complete irreversibility) has almost no effect on the relationship between the level of uncertainty and the expected level of the capital stock illustrated in Figure 7.

As we discuss further in Bond, Söderbom and Wu (2007), the reason for this monotonic and potentially large negative relationship between the level of uncertainty and the expected level of the capital stock in the model with quadratic adjustment costs only is that, when the level of demand is uncertain and fluctuating, quadratic adjustment costs impose a cost associated with using capital that can be reduced by substituting away from capital towards the flexible inputs. The expected level of this cost increases as the demand process becomes more variable. The firm operating in an environment with higher uncertainty anticipates that larger future adjustments of its capital stock may be required, imposing higher adjustment costs. Its optimal response implies substitution away from capital towards labour and materials (inputs which can be adjusted in response to future demand fluctuations at lower cost), and so implies a smaller

[10] Holding constant the values of all the remaining parameters in the model.

expected capital stock.

Our aim in this paper is to estimate the relative importance of these different forms of adjustment costs for firms in China, India, Morocco and Ghana. The results are important for understanding how uncertainty influences short run adjustment dynamics and long run capital accumulation. To anticipate, one of our main findings is that quadratic adjustment costs have an important role in explaining these firms' investment behaviour, notwithstanding the proportion of firms reporting zero investment spending in these countries. As a result, we estimate that lower levels of uncertainty could be a significant factor in stimulating capital accumulation by firms in these countries, for the reasons discussed and illustrated in this section.

3 Data

This section describes the datasets used in our empirical analysis, and the specific features of these datasets that we use to estimate the structural parameters of our investment model.

3.1 Samples

Our data on firms in China and India come from the World Bank's Investment Climate Surveys, conducted in 2002, providing annual observations for up to 3 years in the period 1998-2000 for China and 1999-2001 for India.

The survey for China provides data for 1,548 firms, with approximately 300 firms in each of 5 main cities: Beijing, Chengdu, Guangzhou, Shanghai and Tianjin. The survey covered both manufacturing and service sector firms, and covered state-owned as well as private sector enterprises. We focus on a sub-sample of 604 manufacturing firms with majority private ownership.

The survey for India provides data for 1,860 manufacturing firms, sampled from 40 cities in 12 of India's 14 major states, and covering 8 manufacturing sectors.

Our data on firms in Morocco comes from the World Bank's Firm Analysis and Competitiveness Survey, conducted jointly with the Ministry of Commerce and Industry in 2000, and providing annual observations for up to 3 years in the period 1996-98. This provides data for a sample of 859 firms in 7 manufacturing sectors.

Our data on firms in Ghana comes from manufacturing enterprise surveys organised by Oxford University's Centre for the Study of African Economies. This covers a smaller panel of firms over a longer time period, 1992-2000. Each wave covers about 200 firms.

From each of these samples we obtain measures of annual investment expenditure (net of asset sales) on machinery, equipment and vehicles; end of period net book values of machinery, equipment and vehicles; and total sales. These financial variables, measured in current prices in local currencies, are converted into constant price US dollars.

We focus on firms with between 10 and 1000 employees, and sub-divide these into samples of smaller firms (10-75 employees) and larger firms (76-1000 employees) within each country. The construction of other variables used in the analysis, additional criteria for excluding observations from our samples, and some basic descriptive statistics are provided in the Data Appendix. It should be noted that the median levels of employment in our samples of smaller firms for India and Ghana are less than half of the median level of employment in our sample of smaller firms for China, while the median level of employment in our sample of larger firms for China is also considerably higher than in any of the other countries. Morocco and China have higher per capita incomes than Ghana and India, and this is reflected in differences in average levels of value-added per employee in our samples of manufacturing firms. China experienced much faster growth rates of real GDP and had a higher share of investment in GDP during our sample periods. This is reflected in a faster average growth rate of real sales and a higher average investment rate in our firm-level datasets.

3.2 Moments

Table 1 reports the moments that we use in our estimation procedure, separately for the samples of smaller and larger firms in each of these four countries. As we noted in the Introduction, zero investment is reported for machinery, equipment and vehicles in a high proportion of the firm-year observations. This varies between 18% for our samples of larger firms in China and Morocco and 67% for our sample of smaller firms in India. Within each country, the fraction of observations with zero investment is noticeably lower for the sub-sample of larger firms. One possible explanation is that annual investment spending for larger firms may reflect aggregation over investment decisions in more types of capital or at more production units. We will explore whether our results are sensitive to treating the data on larger firms as the result of aggregation over two or more production units.

Means and standard deviations of investment rates (annual investment divided by end-of-period capital stocks) are calculated separately using all observations and using only observations with strictly positive investment spending. Overall mean investment rates are notably higher in China than in the other three countries. Among smaller firms, this remains the case if we focus on sub-samples with positive investment; although the relatively small fraction of larger firms in India that report positive investment have similar investment rates to those observed for larger Chinese firms. Both the standard deviation of these investment rates, and the fraction of observations with investment rates above 20%, are also much higher in China than in the other three countries.

These investment rates display positive serial correlation in all the samples, and this remains the case even if we exclude any observations with zero investment from the calculation (i.e. the positive serial correlation is not simply explained by sequences of observations with zero investment). This suggests a potentially important role for quadratic adjustment costs, although one or both of partial

irreversibility and fixed adjustment costs will also be required to account for the bunching of observations at zero investment.

The correlation between investment rates and current real sales growth is generally positive but typically low, and is essentially zero in our sample of large firms in Ghana. The correlation between investment rates and the lagged ratio of real sales to capital is also positive and generally higher, although there are exceptions to this pattern.[11] These moments are expected to reflect the relationship between the growth of the capital stock and demand, which drives the investment decisions in our structural model.

Other moments are considered that are useful for identifying the other structural parameters that we estimate. The average growth rate of real sales is higher in our Chinese samples than in the other countries; this moment is useful for estimating the trend growth rate of demand (μ). The standard deviation of real sales growth rates is higher in China than in India or Morocco, but is even higher in our samples of firms in Ghana; this moment is useful for estimating the standard deviation of the demand shocks (σ). Finally there is variation across the samples in both the mean and the standard deviation of the ratio of real sales to the end-of-period capital stock; these moments are useful for estimating the elasticity of operating profits with respect to the capital stock (i.e. $1-\gamma$; see equation (9)), which in turn reflects the capital share in total output and the price elasticity of demand.

4 Estimation and results

This section outlines the simulated method of moments procedure that we use to estimate the structural parameters of our investment model, and presents the estimated parameters that we obtain for each of the samples described in the previous section.

[11] Specifically for smaller firms in Ghana and for larger firms in Morocco.

4.1 Simulated method of moments

We use a simulated method of moments estimator to estimate the adjustment cost parameters and several other parameters of the investment model described in section 2. The model is fully parametric: once we specify the parameters of the demand process given in equation (2) (i.e. x_0, ρ, μ and σ), the parameters of the adjustment cost function given in equation (10) (i.e. b_i, b_f and b_q), the elasticity of operating profits with respect to the capital stock $(1-\gamma)$, the discount rate (r) and the depreciation rate (δ), we can use the numerical solution to the investment decision problem outlined in section 2.2 and Appendix A to generate simulated data on investment, end-of-period capital stocks and sales revenue for hypothetical panels of firms. We simply draw different histories of the demand shocks (ε_t) from the distribution specified in (2), and track each firm's optimal investment decisions in response to these realisations of the stochastic demand process. We used particular examples of these simulated datasets in section 2.3 to illustrate the relationship between investment rates and current demand shocks, and the relationship between average capital stock levels and the level of uncertainty (σ).

Estimation of the structural parameters of the model exploits the fact that different values of these parameters generate different patterns in the simulated datasets. For example, a higher degree of irreversibility or higher fixed adjustment costs will generate more observations with zero investment, and higher quadratic adjustment costs will generate more positive serial correlation in investment rates. Higher values of each of these adjustment cost parameters will generate lower correlation between investment rates and current sales growth. A higher trend growth rate of demand will generate higher mean investment rates and sales growth rates, and a higher variance of the demand shocks will generate higher standard deviations of investment rates and sales growth rates.

The basic idea of simulated method of moments estimation is to find the parameter values which provide the best match between these features of the simulated

datasets and the corresponding moments in our empirical datasets. More precisely, we find the parameter vector that minimises the discrepancy between the vector of empirical moments and the vector of simulated moments, in a weighted quadratic distance sense. Our implementation uses an estimate of the optimal weight matrix based on the covariance matrix of the empirical moments, and a robust simulated annealing algorithm to find the global minimum of this criterion function. Further details are given in Appendix B.

4.2 Empirical specification

In line with most related papers in the recent literature on investment,[12] we do not attempt to estimate the complete set of structural parameters. We impose a depreciation rate of 5% per annum for all samples, and discount rates of 10% per annum for larger firms and 20% per annum for smaller firms in all four countries. This accounts in a very simple way for the possibility that smaller firms may face a higher cost of capital, for example as the result of less diversified owners bearing greater idiosyncratic risk, or having less favorable access to formal capital markets. As noted earlier, we impose the restriction $x_0 = -0.5\sigma^2/(1-\rho^2)$ throughout this paper, so that the expected level of demand $E[X_t] = \mu t$ is independent of the variance of the demand shocks (σ^2). We also impose the persistence parameter in the demand process to be $\rho = 0.9$ in all samples. The discrete approximation to the AR(1) process for z_t in (2) that we use in our numerical solution cannot handle the case of $\rho = 1$, and is not expected to provide an accurate approximation for values of ρ that are very close to one.[13] Preliminary attempts to estimate ρ suggested very high values, typically around 0.95. The choice to impose $\rho = 0.9$ reflects a compromise between the need for numerical accuracy and this indication of a high degree of persistence in the underlying stochastic demand processes.

This leaves six structural parameters that we estimate by matching simulated

[12] Notably Bloom (2006) and Cooper and Haltiwanger (2006).

[13] Tauchen (1986) remarks that "experimentation showed that the quality of the approximation remains good except when λ [the AR(1) parameter] is very close to unity" (p.179).

moments to corresponding features of the empirical datasets: the three adjustment cost parameters (b_i, b_f and b_q), the trend growth rate of demand (μ), the standard deviation of the demand shocks (σ), and the elasticity of operating profits with respect to capital ($1-\gamma$). Our empirical specification also allows for the possibility of measurement error in the data on both sales and investment. If we do not allow for such measurement error, we find it difficult to match some features of the empirical data using our structural model at reasonable values of these parameters. In particular, the low correlations between investment rates and real sales growth that we report in Table 1 are difficult to match in a model where demand shocks are the main driver of investment decisions. Measurement error in either investment or real sales could potentially account for these low correlations.

We adopt a standard additive structure for measurement error in the log of real sales, specifying

$$\ln Y_{it} = \ln Y_{it}^{*} + m_{it}^{Y}$$

where Y_{it} denotes the observed level of real sales, Y_{it}^{*} denotes the true underlying level of real sales which is not measured accurately in the data, and the measurement error m_{it}^{Y} has both permanent and transitory components

$$m_{it}^{Y} = f_{i}^{Y} + e_{it}^{Y}$$

with

$$f_{i}^{Y} \sim \text{iid } N(0, \sigma_{YP}^{2}), \;\; e_{it}^{Y} \sim \text{iid } N(0, \sigma_{YT}^{2})$$

We cannot use exactly this form for measurement error in the investment data, partly because measured investment may be zero or negative, but more fundamentally because we take seriously the evidence that investment spending is zero for substantial fractions of the manufacturing firms in these datasets for developing countries. Instead we use a multiplicative specification for measurement error in the level of investment

$$I_{it} = I_{it}^{*} \exp(m_{it}^{I})$$

where the measurement error m_{it}^I again has permanent and transitory components

$$m_{it}^I = f_i^I + e_{it}^I$$

and

$$f_i^I \sim \text{iid } N(0, \sigma_{IP}^2), \quad e_{it}^I \sim \text{iid } N(0, \sigma_{IT}^2)$$

This specification has the property that the sign of recorded investment is not affected by measurement error, and treats observations with zero investment in the data as true zeros.

One further advantage of allowing for permanent components of measurement errors in the data on real sales and investment is that this accounts in a computationally tractable way for persistent differences between firms in investment rates and capital-output ratios. We expect such 'unobserved heterogeneity' to be an important feature of any data on firms, and we prefer to allow for it in this rather crude way than to ignore it completely in our empirical analysis. This is particularly important in this application where, for example, we are using serial correlation in the level of investment rates to make inferences about the magnitude of adjustment cost parameters.

4.3 Empirical results

Table 2 presents our simulated method of moments estimates of the parameters of our investment model and the standard deviations of the measurement error components introduced in our empirical specification. Identification of these parameters requires that the simulated moments vary significantly with changes in the parameter values. Figure 10 illustrates how, for example, the proportion of firms choosing zero investment varies with the fixed adjustment costs parameter (b_f) in one of our simulated datasets. Figure 11 illustrates how the correlation between investment rates and current sales growth varies with the quadratic adjustment costs parameter (b_q).[14] While such variation in individual moments is necessary

[14] All other parameter values used to generate the simulated moments shown in Figures 10 and 11 are held fixed at the values we estimate for our sample of larger firms in China, as reported

to identify these parameters, it is not sufficient. A sufficient condition for local identification of the vector of estimated parameters is that the Jacobian matrix of partial derivatives of each of the simulated moments with respect to each of the parameters is of full rank. We compute an estimate of this matrix of partial derivatives and check that this condition for local identification is satisfied at the parameter values we estimate for each of the samples.

The estimated values of the adjustment cost parameters suggest that both convex and non-convex forms of adustment costs play an important role in explaining the patterns of investment that we see in all these samples, with the possible exception of small firms in Ghana, where quadratic adjustment costs are found to be relatively unimportant. This reflects the combination of both high serial correlation in investment rates and the bunching of observations with zero investment that we noted in the empirical moments shown in Table 1.[15] The capital stock adjustment behaviour that generates these moments in our firm-level datasets appears too subtle to be described by a simple specification with just one of these forms of adjustment costs. Similar findings are reported for samples of US firms and US establishments by Bloom (2006) and Cooper and Haltiwanger (2006) respectively.

The estimated elasticities of operating profits with respect to capital vary considerably across the samples, and inversely with the observed variation in the mean ratio of real sales to capital reported in Table 1. Given our assumptions of consant returns to scale in the production function and flexible labour and material inputs, we can identify the coefficient on capital in the production function, as well as the mark-up, by combining the estimates of this capital elasticity with observed cost shares for labour and material inputs (see equation (8)). Our implied estimates

in Table 2.

[15] The relatively low estimate of the quadratic adjustment cost parameter and the relatively high estimate of the degree of irreversibility that we find for small firms in Ghana are consistent with the low level of serial correlation in investment rates and the high proportion of firms reporting zero investment that we observe in that sample.

of the coefficient on capital in the production function range between 0.14 (for larger firms in India) and 0.38 (for smaller firms in Ghana), broadly in line with previous estimates of production function parameters (e.g. Söderbom and Teal (2004)). The implied mark-ups are higher in India than in the other countries.

The estimated values of the trend rate of growth of demand vary across the samples in line with the mean growth rates of real sales and the mean investment rates that we presented in Table 1. The highest estimates are found for our samples of firms in China, and negative values are estimated for our samples of firms in Ghana. Similarly the estimated values of the standard deviation of the demand shocks vary in line with differences in the standard deviations of real sales growth and investment rates. The highest estimates are found for Chinese firms and for large firms in Ghana, and the lowest estimates are found for our samples of firms in India. Both permanent and transitory measurement errors appear to be important features of the investment data for all these samples, while permanent measurement errors appear to be relatively important in the data on real sales.[16]

Table 3 reports the simulated moments generated by our model at each of these sets of estimated parameters. Comparison with the empirical moments reported in Table 1 shows that the model does relatively well in matching the observed distributions of investment rates. Features such as the proportion of firms with zero investment and the proportion of investment spikes are more or less replicated in the simulated datasets. The model does less well in matching the serial correlation in these investment rates, particularly in the samples for India and Morocco. The model is much less successful at matching the correlations between investment rates and current sales growth (which tend to be too high in the simulated datasets), and the correlations between investment rates and the lagged sales-capital ratio (which tend to be too low in the simulated datasets).

[16] The importance of these measurement error components of our empirical specification could reflect a host of factors in addition to pure recording errors in the survey data. For example, our model equates real sales with the value of production, taking no account of inventories, and assumes that depreciation rates are common to all firms in each sample.

Since we use 14 moments to estimate 10 parameters, the minimised values of the simulated method of moments criterion functions used to obtain these estimated parameters provide a test of the overall fit of the models, based on the four over-identifying restrictions. These tests are reported together with the parameter estimates and sample sizes in Table 2. Not surprisingly, the validity of these over-identifying restrictions is formally rejected, except in the samples for Ghana, where we have relatively small numbers of firms. This result is commonly found in the related literature. It would be rather extraordinary if we could fully account for the potentially diverse investment behaviour of any sample of several hundred firms using a simple first-order Markov decision problem with so few parameters, all of which are assumed to be common to all firms in the sample. Indeed it is noticeable that the minimised values of the criterion functions vary across the samples in line with the number of firms: the highest values are found for our samples of smaller firms in India and larger firms in China, where we have 1016 and 454 firms respectively; the smallest values are found for our samples of smaller firms in China and both size categories in Ghana, where we have 150 or fewer firms in each case.

Given this, we do not report standard errors for the estimated parameters, which would be unreliable. Imposing the restriction that either the quadratic adjustment cost parameter (b_q) is zero, or that both the non-convex adjustment cost parameters (b_i and b_f) are zero, resulted in large increases in the minimised values of the criterion functions, suggesting that neither of these restrictions is consistent with the data. Similarly imposing the restriction that the variance of the measurement error components are all zero resulted in a large deterioration in the fit of the models.

In the next section we report the results of counterfactual simulations using these estimated models, exploring the effects of variation in the level of uncertainty on short run investment behaviour and long run capital accumulation. Clearly the precise estimates that we report should not be taken too seriously, given the lim-

itations of the structural model in accounting for some features of the investment data. Our aim is rather to provide an indication of the likely order of magnitude of these effects, and the extent to which any changes in behaviour are likely to be similar or different across firms in these four countries.

5 Simulating the effects of uncertainty on investment behaviour

5.1 Short run adjustment

Figures 12-15 illustrate how short run investment behaviour varies with the level of uncertainty in our simulated data, using the parameter values that we have estimated for each of the empirical samples. These plots show the relationship between demand shocks (ε_t) and expected capital stock growth rates, and are constructed in the same way as Figures 4-6, that we used in section 2.3.1 to illustrate adjustment behaviour in special cases of our general model. The darker curve in Figure 12(a), for example, shows the estimated impact effect of demand shocks on capital stock growth rates using our estimated parameters for the sample of smaller firms in China. The lighter curve shows the impact effect predicted by our estimated model if the level of demand uncertainty estimated for this sample was permanently reduced, from the estimated value ($\widehat{\sigma} = 0.463$) to half the estimated value ($\sigma = 0.2315$). In samples where we have estimated much lower levels of demand uncertainty,[17] we illustrate the effects of a permanent increase in the level of σ. The adjustment cost parameters and all other parameters of the model are kept constant at their estimated values in these simulations.

These simulations show the important role played by adjustment costs in slowing down adjustment of capital stocks to new information about demand, relative to a frictionless benchmark (indicated by the 45^o lines), in each of these samples. In most cases we find that a higher level of uncertainty tends to result in a weaker

[17] i.e. for smaller and larger firms in India, larger firms in Morocco and smaller firms in Ghana. In each case the estimated values of σ are reported in Table 2.

impact effect of positive demand shocks on investment rates, implying slower adjustment of capital stocks to new information about demand. This is the effect of uncertainty on short run investment dynamics emphasised under irreversibility by Bloom et al. (2007), and is consistent with an important role for either partial irreversibility or fixed adjustment costs in our estimated models. This effect of uncertainty on the speed of adjustment is estimated to be quite small, however, except in our sample of smaller firms in India, where the level of the fixed adjustment cost parameter (b_f) is estimated to be relatively high. This generally modest impact of uncertainty on short run investment dynamics is also consistent with the relatively important role that we estimate for quadratic adjustment costs.

5.2 Capital accumulation

Figures 16-19 illustrate how the level of uncertainty affects expected capital stock levels in our simulated data, using the estimated parameter values for these samples. These plots show the relationship between the standard deviation of the demand shocks (σ) and the average level of capital stocks, and are constructed in the same way as Figures 7-9 in section 2.3.2. The dashed line in Figure 16(a), for example, shows how the average level of capital stocks varies in simulations where we vary the level of uncertainty, using the estimated parameters for our sample of smaller firms in China. Here we consider levels of uncertainty that are below the estimated level for this sample ($\widehat{\sigma} = 0.463$). In the counterfactual simulations reported for other samples we consider ranges for σ that are both above and below the estimated level. In all cases the average level of the capital stock in each simulation is scaled by the average level found for that sample at the estimated value of σ, so that the values on the vertical axis show percentage increases or decreases in the expected level of the capital stock as we vary the level of uncertainty away from that benchmark level. The values of all other parameters are held constant at their estimated levels as we vary the level of uncertainty in these simulations. Recall that the expected level of the demand process in our specification does not

depend on the variance of the demand shocks, so that these simulations illustrate the effects of mean-preserving spreads in the distribution of demand.

The main result of these counterfactual simulations is that, except for the samples of larger firms in India and smaller firms in Ghana, we estimate quite large effects of uncertainty on expected capital stock levels. A permanent reduction in the level of demand uncertainty by 50% is estimated to increase average capital stock levels by about 10% for firms in Morocco and by about 20% for firms in China. For smaller firms in India, our model suggests large effects of reducing the level of uncertainty, but small effects of increasing the level of uncertainty. For larger firms in India and smaller firms in Ghana, we estimate much smaller effects of any variation in the level of uncertainty.

These findings are broadly consistent with the important role attributed to quadratic costs in our estimated adjustment costs functions. As we discussed in section 2.3.2, potentially large negative effects of uncertainty on expected capital stock levels are found primarily in specifications with quadratic adjustment costs. Firms operating in more volatile environments tend to substitute away from capital towards inputs that are less costly to adjust in specifications where quadratic adjustment costs are important. The distinctive relationship between uncertainty and expected capital stock levels that we find using our estimated parameters for the sample of smaller firms in Ghana is consistent with the much lower value of the quadratic adjustment cost parameter that we estimate for that sample.

5.3 Aggregation

One potential concern is that we may have over-estimated the importance of quadratic adjustment costs by treating the firm-level investment data as the outcome of a single investment decision in each period. It is well known that aggregation over investment decisions in several types of capital or at several production units may produce a smoother series for aggregate investment, for example if discrete adjustments to the underlying capital stocks occur at different points in time.

The aggregate series may then appear to be consistent with the smooth, gradual adjustments that are characteristic of strictly convex adjustment costs, when the underlying decisions are shaped by irreversibility or fixed costs. It is noticeable that our estimated values for the quadratic adjustment costs parameter are higher for the sub-sample of larger firms than for the sub-sample of smaller firms within each country, reflecting the higher serial correlation in investment rates reported in Table 1. It is also plausible that the data for larger firms is more likely to be affected by aggregation over multiple investment decisions.

To explore the robustness of our results to this possibility, we re-estimated the parameters for each sub-sample of larger firms, treating the data on larger firms as the result of aggregation over two or more production units. For example, to simulate data for a sample of N firms, we generate data for a sample of $2N$ establishments, and construct firm-level data by aggregating the series for pairs of independent production units. This produces lower estimates of the quadratic adjustment costs parameter (b_q), and higher estimates of one or both of the irreversibility (b_i) or fixed costs (b_f) parameters. In our sample of larger firms in China, for example, we obtain estimates of $b_q = 2.897, b_i = 0.076$ and $b_f = 0.084$, compared to the values reported in Table 2 when we treat each firm as a single production unit. The estimated values of the remaining parameters in the model are generally similar to those obtained when we treat each firm as having a single production unit.

However this has relatively little impact on the estimated relationship between uncertainty and expected capital stock levels. As in Figure 16(b), simulating the effect of permanently halving the level of demand uncertainty for the sample of larger firms in China again suggests that this would increase average capital stock levels by about 20%. Similar results to those presented in Figures 17(b)-19(b) are also found for the remaining countries. Broadly similar results were found when treating the data for larger firms as the result of aggregation over more than two production units, and the fit of the estimated models appears to deteriorate

as we consider aggregation over more units. We conclude that the quantitatively significant effects of uncertainty on average capital stock levels that we presented in section 5.2 are not simply due to neglecting the potential importance of aggregation over multiple investment decisions.

6 Conclusions

This paper presents estimates of the effects of uncertainty on both short run investment behaviour and long run capital accumulation for panels of African and Asian firms. We estimate structural investment models in which the level of uncertainty influences investment behaviour in both the short run and the long run as a result of different forms of adjustment costs: partial irreversibility, a fixed cost of undertaking any investment at all, and quadratic adjustment costs. Structural parameters are estimated by matching simulated model moments to empirical data for firms in China, India, Morocco and Ghana, using a simulated minimum distance estimator.

The estimated models are used to investigate how these firms' investment behaviour would differ if they faced different levels of uncertainty. Counterfactual simulations indicate that investment would be more responsive to new information about demand if firms in these countries faced a lower level of uncertainty, although quantitatively the impact of uncertainty on short run investment dynamics is found to be modest. On average, however, we estimate that a lower level of uncertainty would induce firms to operate with substantially higher capital stocks. For example, we find that if the level of demand uncertainty could be permanently halved, then in the long run this would induce firms to increase their average capital stock levels by about 10% for firms in Morocco or by about 20% for firms in China.

These findings that uncertainty has a modest impact on short run adjustment behaviour but a potentially large effect on long run capital accumulation are pri-

marily explained by the important role that we estimate for quadratic adjustment costs in explaining the investment behaviour of the firms in these countries. While much of the recent literature on uncertainty and investment has emphasised the role of non-convex forms of adjustment costs, we find that it is the presence of a significant convex component in our estimated adjustment cost functions that suggests a potentially important relationship between uncertainty and average capital stock levels.

References

[1] Abel, Andrew B. and Janice C. Eberly, 1999, "The effects of irreversibility and uncertainty on capital accumulation", *Journal of Monetary Economics*, vol. 44, no. 3, pp. 339-377.

[2] Akerlof, George A., 1970, "The market for 'lemons': quality uncertainty and the market mechanism", *The Quarterly Journal of Economics*, vol. 84, no. 3, pp. 488-500.

[3] Bloom, Nick, 2006, "The impact of uncertainty shocks: firm level estimation and a 9/11 simulation", Mimeo, Department of Economics, Stanford University.

[4] Bloom, Nick, Stephen R. Bond and John Van Reenen, 2007, "Uncertainty and investment dynamics", *Review of Economic Studies*, vol. 74, pp. 391-415.

[5] Bond, Stephen R., Måns Söderbom and Guiying Wu, 2007, "Pursuing the wrong options? Adjustment costs and the relationship between uncertainty and capital accumulation", Mimeo, Department of Economics, University of Oxford.

[6] Cooper, Russell W., and John Haltiwanger, 2006, "On the nature of capital adjustment costs", *Review of Economic Studies*, vol. 73, pp. 611-634.

[7] Goffe, William L., Gary D. Ferrier and John Rogers, 1994, "Global optimization of statistical functions with simulated annealing", *Journal of Econometrics*, vol. 60, nos. 1-2, pp. 65-99.

[8] Gouriéroux, Christian and Alain Monfort, 1996, *Simulation-Based Econometric Methods*, Oxford University Press.

[9] Söderbom, Måns, and Francis Teal, 2004, "Size and efficiency in African manufacturing firms: evidence from firm-level panel data", *Journal of Development Economics*, vol. 73, pp. 369-394.

[10] Tauchen, George, 1986, "Finite state Markov-chain approximations to univariate and vector autoregressions", *Economics Letters*, vol. 20, no. 2, pp. 177-181.

Appendix A: Algorithm

This appendix describes the numerical optimisation procedures used to solve the model and generate the simulated investment data.

The value of the firm is given by the Bellman equation

$$V_t(X_t, K_t) = \max_{I_t} \Pi(X_t, K_t; I_t) + \phi E_t \left[V_{t+1}(X_{t+1}, K_{t+1}) \right] \tag{A1}$$

subject to the capital evolution constraint

$$K_{t+1} = (1 - \delta)(I_t + K_t), \tag{A2}$$

and law of motion for demand

$$\begin{aligned} x_t &= \ln X_t = x_0 + \mu t + z_t \\ z_t &= \rho z_{t-1} + \varepsilon_t \\ \varepsilon_t &\sim \text{iid } N(0, \sigma^2) \end{aligned} \tag{A3}$$

where $x_0 = -0.5\sigma^2/(1-\rho^2)$, so that $E[X_t] = \exp(\mu t)$.

We solve this dynamic program numerically using value function iteration. Demand X_t and the beginning-of-period capital stock K_t are the state variables. Investment I_t, or equivalently the end-of-period capital stock $K_t + I_t$, is the control variable. In order to use value function iteration, these state and control variables must be stationary. Since demand is a trend stationary process, we first detrend by defining $\Psi_t = \exp(\mu t)$ and dividing the control and state variables by Ψ_t

$$\begin{aligned} V(\frac{X_t}{\Psi_t}, \frac{K_t}{\Psi_t}) = \max_{I_t/\Psi_t} & \left\{ \left(\frac{X_t}{\Psi_t} \right)^{\gamma} \left(\frac{K_t + I_t}{\Psi_t} \right)^{1-\gamma} - \frac{I_t}{\Psi_t} - \frac{G(I_t, K_t)}{\Psi_t} \right\} \\ & + \phi \exp(\mu) E_t \left[V \left(\frac{X_{t+1}}{\Psi_{t+1}}, \frac{K_{t+1}}{\Psi_{t+1}} \right) \right] \end{aligned}$$

where we have used the fact that $\Psi_{t+1}/\Psi_t = \exp(\mu)$. Hence, at time t, X_t/Ψ_t and K_t/Ψ_t are the two state variables, and I_t/Ψ_t is the control variable in the scaled problem. Now define

$$\begin{aligned} \widetilde{X_t} &= \frac{X_t}{\Psi_t} = \frac{\exp(x_t)}{\Psi_t} = \exp(x_0)\exp(z_t), \quad \text{(state variable)} \\ \widetilde{K_t} &= \frac{K_t}{\Psi_t}, \quad \text{(state variable)} \\ \widetilde{I_t} &= \frac{I_t}{\Psi_t}, \quad \text{(control variable)} \end{aligned}$$

which are all stationary, so that we can apply value function iteration to the normalised Bellman equation

$$V_t(\widetilde{X_t}, \widetilde{K_t}) = \max_{\tilde{I}_t} \{ \Pi(\widetilde{X_t}, \widetilde{K_t}; \widetilde{I_t}) \} + \phi \exp(\mu) E_t \left[V_{t+1}(\widetilde{X}_{t+1}, \widetilde{K}_{t+1}) \right] \tag{A4}$$

Notice the capital accumulation formula implies

$$\widetilde{K}_{t+1} = \exp(-\mu)\,(1-\delta)\left(\widetilde{I}_t + \widetilde{K}_t\right) \tag{A5}$$

We also have $\widetilde{I}_t/\widetilde{K}_t = I_t/K_t$, which is convenient.

Since conditional expectations need to be formed based on $\widetilde{X}_t$, we use the approximation method in Tauchen (1986) to discretise the continuous AR(1) process for z_t in (A3) into a 9 state Markov process for given parameters ρ and σ. Then we get $\widetilde{X}_t(i)$ by multiplying $\exp(z_t(i))$ with the constant $\exp(x_0)$, where $i = 1, 2, ..., 9$.

In the absence of adjustment costs, we can derive an analytical solution to (A1), which implies the frictionless optimal capital stock would be

$$K_t^* = cX_t$$

or equivalently

$$\widetilde{K}_t^* = c\widetilde{X}_t \tag{A6}$$

where $c = (1-\delta)\left[(1-\gamma)/(1-\phi(1-\delta))\right]^{1/\gamma}/\exp(\mu)$. Given this, we define the support of $\widetilde{K}_t$ as $\left[c\widetilde{X}_t(1),\ c\widetilde{X}_t(9)\right]$, and we discretise this state space with 200 grid points.

Since the (normalised) net revenue function is strictly concave in $\widetilde{K}_t$ for any $0 < \gamma < 1$, and the set of constraints (A3) and (A5) is compact and convex, there must exist a unique solution to the dynamic program (A4). To begin the value function iteration, we begin with an arbitrary initial guess $V(\widetilde{X}_t, \widetilde{K}_t)_{[0]}$. For each combination of $(\widetilde{X}_t, \widetilde{K}_t)$, we search along the state space of the capital stock for the optimal policy rule $\widetilde{K}_t + \widetilde{I}_t$, or equivalently $\widetilde{I}_t$, which would maximise the value of the firm $V(\widetilde{X}_t, \widetilde{K}_t)_{[1]}$. We then use $V(\widetilde{X}_t, \widetilde{K}_t)_{[1]}$ to update $V(\widetilde{X}_t, \widetilde{K}_t)_{[0]}$ and repeat this procedure until the difference between $V(\widetilde{X}_t, \widetilde{K}_t)_{[j-1]}$ and $V(\widetilde{X}_t, \widetilde{K}_t)_{[j]}$ is within our tolerance $1e-8$. At this point, there is convergence and we have found the optimal solution $\widetilde{I}_t^* = f(\widetilde{X}_t, \widetilde{K}_t)$. Then we interpolate so that the final state space for $\widetilde{X}_t$ has 200 grid points, that for $\widetilde{K}_t$ has 2000 grid points, and the final policy space for I_t^* has the dimension of 200×2000.

We use this numerical solution to the model to generate simulated panel data. We endow all simulated firms with the initial condition $z_0 = -\sqrt{\sigma^2/(1-\rho^2)}$ and the corresponding frictionless optimal capital stock $\widetilde{K}_0 = c\widetilde{X}_0 = c\exp(x_0 + z_0)$. For all subsequent periods, we randomly draw demand shocks ε_{it} for each firm i at each time t. Given the realization of $\widetilde{X}_{it}$ and the inherited $\widetilde{K}_{it}$, we find the discrete approximation to the optimal investment $\widetilde{I}_{it}$ using the policy rule derived above. Then $\widetilde{X}_{it}$ or equivalently z_{it} evolves exogenously according to (A3), $\widetilde{K}_{i,t+1}$ evolves endogenously according to (A5), and the control variable in this period becomes the state variable in next period.

The last step is to recover the time trend in the variables of the original model. Given our normalisation, we know that at time t, the actual demand shock for firm

i is $X_{it} = \widetilde{X}_{it} \exp(\mu t)$, and the actual investment and capital stock are therefore $I_{it} = \widetilde{I}_{it} \exp(\mu t)$ and $K_{it} = \widetilde{K}_{it} \exp(\mu t)$.

To obtain the simulated moments that we match to the empirical moments shown in Table 1, we use I_{it} as the measure of investment for firm i in period t. We use $K_{it}+I_{it}$ as the measure of the end-of-period capital stock. We derive a measure of real sales during period t using $Y_{it} = \left[X_{it}^{\gamma} \left(K_{it} + I_{it}\right)^{1-\gamma}\right] / \left(1 - \alpha_L - \alpha_M\right)$, where α_L and α_M are cost shares of labour and material inputs.

Appendix B: Simulated Method of Moments

The basic idea of simulated method of moments (SMM, hereafter) can be described in Figure B1. It aims at estimating a vector of unknown parameters Θ, by matching a set of simulated moments $\widehat{\Phi}^S(\Theta)$ with the corresponding empirical moments $\widehat{\Phi}^D$ from the real data. The structural model in this paper is the dynamic program for optimal investment with three types of adjustment costs. This model has a vector of structural parameters Θ, for example, the adjustment cost parameters and the demand process parameters. Using the algorithm described in Appendix A, we solve this model numerically for a given parameter vector Θ, and generate H datasets, each of which has approximately the same number of firms N and number of years T as those in the corresponding empirical dataset. We compare a set of empirical moments $\widehat{\Phi}^D$ obtained from the real data, and the average of the corresponding simulated moments $\frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)$ from the H panels of simulated data. The crucial point is that $\widehat{\Phi}_h^S(\Theta)$ is a function of Θ, which is utilized in that particular round of simulations. If the averaged simulated moments are far away from the empirical moments, we know the current guess for the parameter vector is far away from its true value. Then we update our guess for the parameter vector using a simulated annealing algorithm due to Goffe, Ferrier and Rogers (1994). We repeat this procedure until at a particular Θ^*, the averaged simulated moments $\frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)$ match the empirical moments $\widehat{\Phi}^D$ in a weighted quadratic distance sense.

More formally, the SMM estimator Θ^* solves

$$\widehat{\Theta} = \arg\min_{\theta}\left(\widehat{\Phi}^D - \frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)\right)' \Omega \left(\widehat{\Phi}^D - \frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)\right) \tag{B1}$$

where Ω could be any positive definite matrix. We use the optimal weighting matrix given by a bootstrap estimate of the inverse of the variance-covariance matrix of the empirical moments, i.e.

$$\Omega = \left[Nvar\left(\widehat{\Phi}^D\right)\right]^{-1}$$

The SMM estimator is asympototically normal for fixed H and $N \to \infty$

$$\sqrt{N}\left(\widehat{\Theta} - \Theta^*\right) \xrightarrow{D} N\left(0, W\left(H, \Omega\right)\right) \tag{B2}$$

where

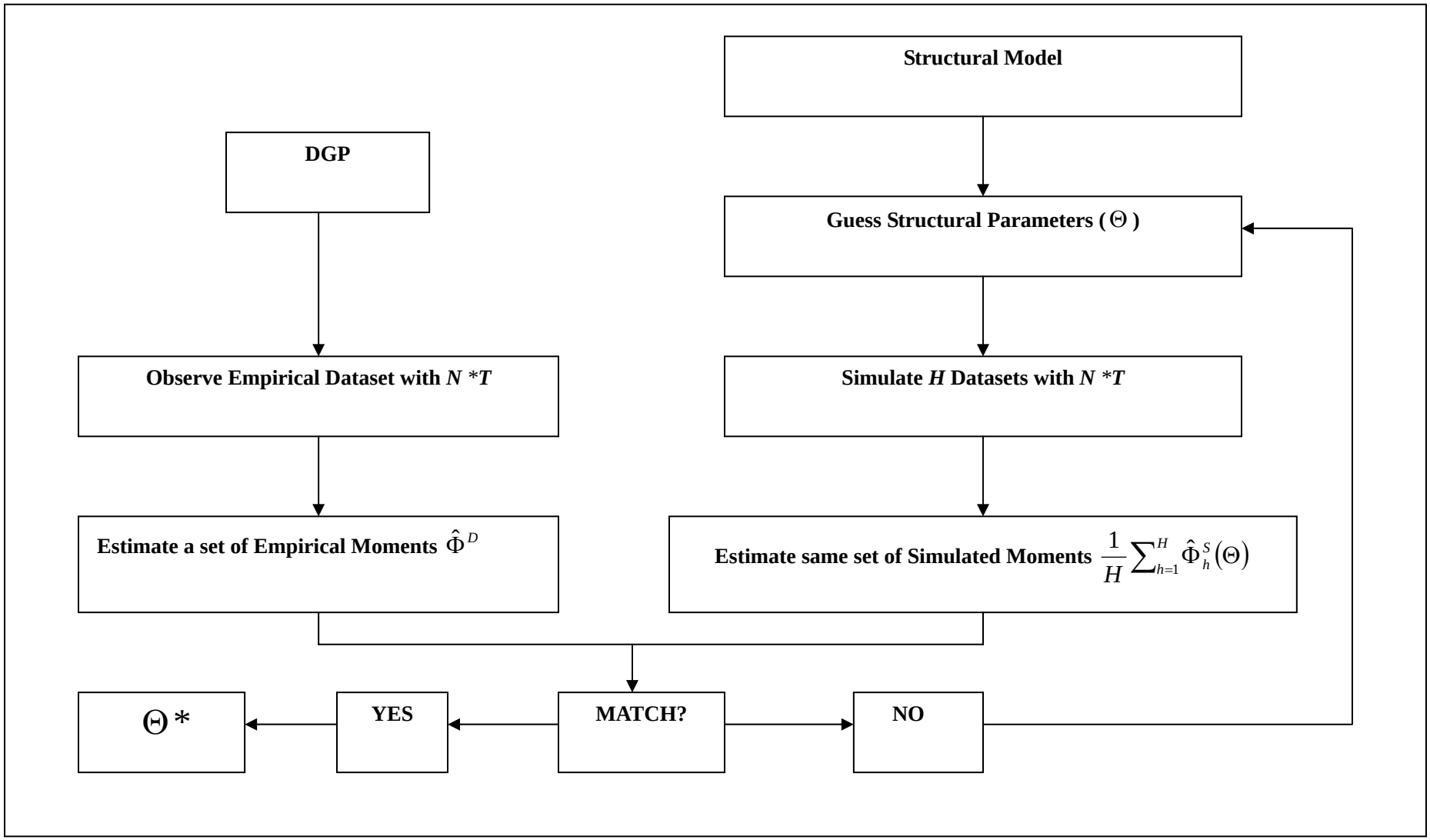
$$W\left(H, \Omega\right) = \left(1 + \frac{1}{H}\right)\left(\frac{\partial \widehat{\Phi}^{S\prime}\left(\widehat{\Theta}\right)}{\partial \Theta}\Omega\frac{\partial \widehat{\Phi}^{S}\left(\widehat{\Theta}\right)}{\partial \Theta'}\right)^{-1}$$

We use the simulated annealing algorithm described in (Goffe, Ferrier and Rogers, 1994) to avoid local minima in solving the minimisation problem (B1).

This SMM procedure provides a global specification test of the overidentifying restrictions of the model, i.e. if the model is well-specified, we have

$$\begin{aligned} OI &= \frac{NH}{1+H}\left(\widehat{\Phi}^D - \frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)\right)' \Omega \left(\widehat{\Phi}^D - \frac{1}{H}\sum_{h=1}^{H}\widehat{\Phi}_h^S(\Theta)\right) \\ &\sim \chi^2\left[\dim\left(\widehat{\Phi}\right) - \dim(\Theta)\right]. \end{aligned} \tag{B3}$$

Figure B1: Illustration of Simulated Method of Moments



Appendix C: Data

(1) Sampling

Original dataset is downloadable from http://www.enterprisesurveys.org/Portal after registration for China and India.

- **China**

World Bank investment climate dataset collected in 2002. Covered 1,548 firms and about 300 in each of five cities--Beijing, Chengdu, Guangzhou, Shanghai, and Tianjin. The sample consists of both manufacturing and service firms.

- **India**

World Bank investment climate dataset collected in 2002.Covered a random election of 1,860 firms sampled from 40 cities in 12 India's 14 major states and 8 manufacturing sectors.

- **Morocco**

World Bank Firm Analysis and Competitiveness Surveys collected in 2000. Covered a random of sample 859 firms in 7 manufacturing sectors.

- **Ghana**

CSAE, Oxford, have organized manufacturing enterprise surveys since 1992, yielding a relatively long panel of firms. Each wave covers about 200 firms.

(2) Definition of Variables

- Define I = investment-disinvestment in machinery, equipment and vehicles.
- Define K= net book value of machinery, equipment and vehicles.
- Define Y = total sales.
- Define L = number of (permanent) employees.
- Define wage = total wage bill or manpower cost.
- Define rawmat = value of raw materials used.
- Define totic=value of total indirect costs (consumption of energy + other costs).
- Define vademp=(Y-rawmat-totic)/L, value-added per employee.
- Define α_L=wage/Y, share of labour cost.
- Define α_M=(rawmat+totic)/Y, share of material cost.

(3) Cleaning Rules

- Translate all financial variables into constant USD in 2000.
- Drop non-manufacturing firms.
- Drop state-owned firms--government ownership more than 50%.
- Drop firms with employment less than 10 or larger than 1000.
- Drop firms with less than two consecutive observations for I/K.
- Rule out Investment Rate less than -1 or larger than 1.
- Rule out top and bottom 5% observations for Y/K and $\Delta \ln Y$.
- Rule out α_L and α_M less than 0.2 or larger than 0.8.
- Divide each sample into small firms (L<=75) and large firms (L>75).

(4) Sample Structure

	China Small	China Large	India Small	India Large	Morocco Small	Morocco Large	Ghana Small	Ghana Large
years	1998-2000		1999-2001		1996-1998		1992-2000	
# of Firms	150	454	1016	244	413	346	116	50
median L	45	257	18	170	28	180	22	160

(5) Macro and Micro Comparison

China

Macro		**Micro**	mean	median
GDP annual growth rate (%)	8.0	sales growth rate (%)	13.1	11.1
GDP per capita (USD)	886	value-added per employer (USD)	6354	3331
Gross fixed capital formation (%)	10.3	net investment rate (%)	14.3	4.2

India

Macro		**Micro**	mean	median
GDP annual growth rate (%)	5.3	sales growth rate (%)	8.0	3.8
GDP per capita (USD)	455	value-added per employer (USD)	3801	3241
Gross fixed capital formation (%)	4.7	net investment rate (%)	6.2	0.0

Morocco

Macro		**Micro**	mean	median
GDP annual growth rate (%)	6.0	sales growth rate (%)	0.0	0.0
GDP per capita (USD)	1162	value-added per employer (USD)	5359	4030
Gross fixed capital formation (%)	7.7	net investment rate (%)	5.8	1.6

Ghana

Macro		**Micro**	mean	median
GDP annual growth rate (%)	3.8	sales growth rate (%)	1.5	0.0
GDP per capita (USD)	233	value-added per employer (USD)	2121	1325
Gross fixed capital formation (%)	--	net investment rate (%)	5.6	0.0

Note: macro data comes from World Development Indicator Database, the World Bank.

Figure 1: Policy Function for Investment Rate: Partial Irreversibility Only

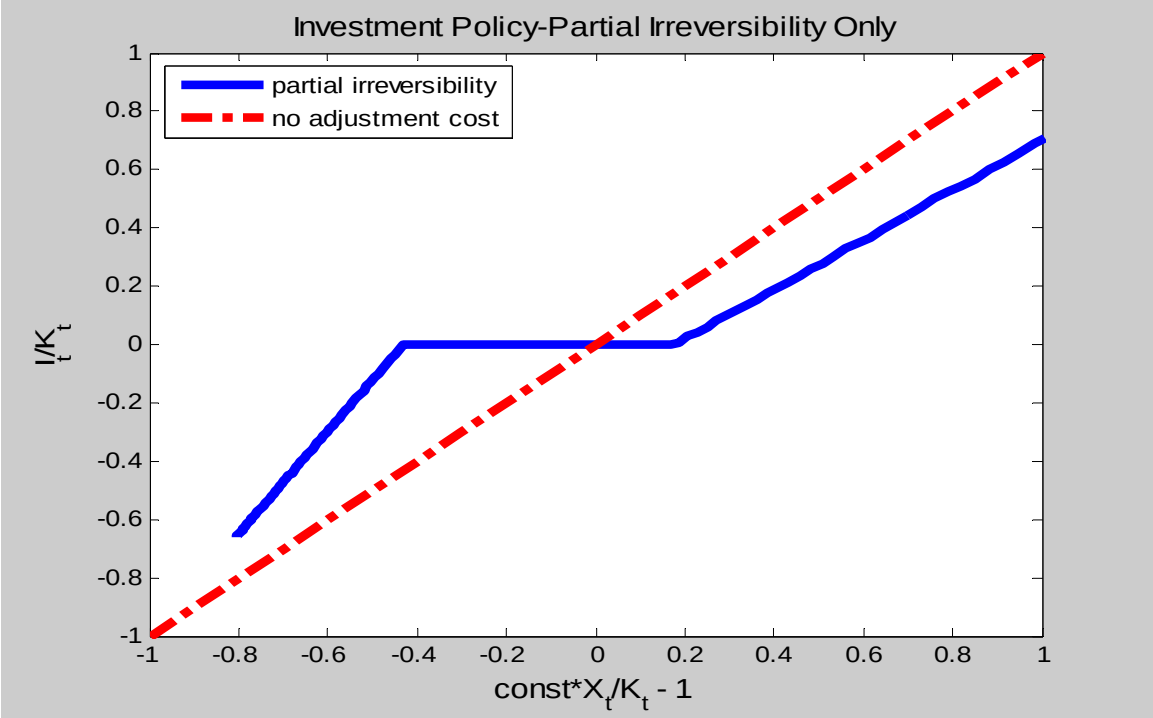


Figure 2: Policy Function for Investment Rate: Fixed Costs Only

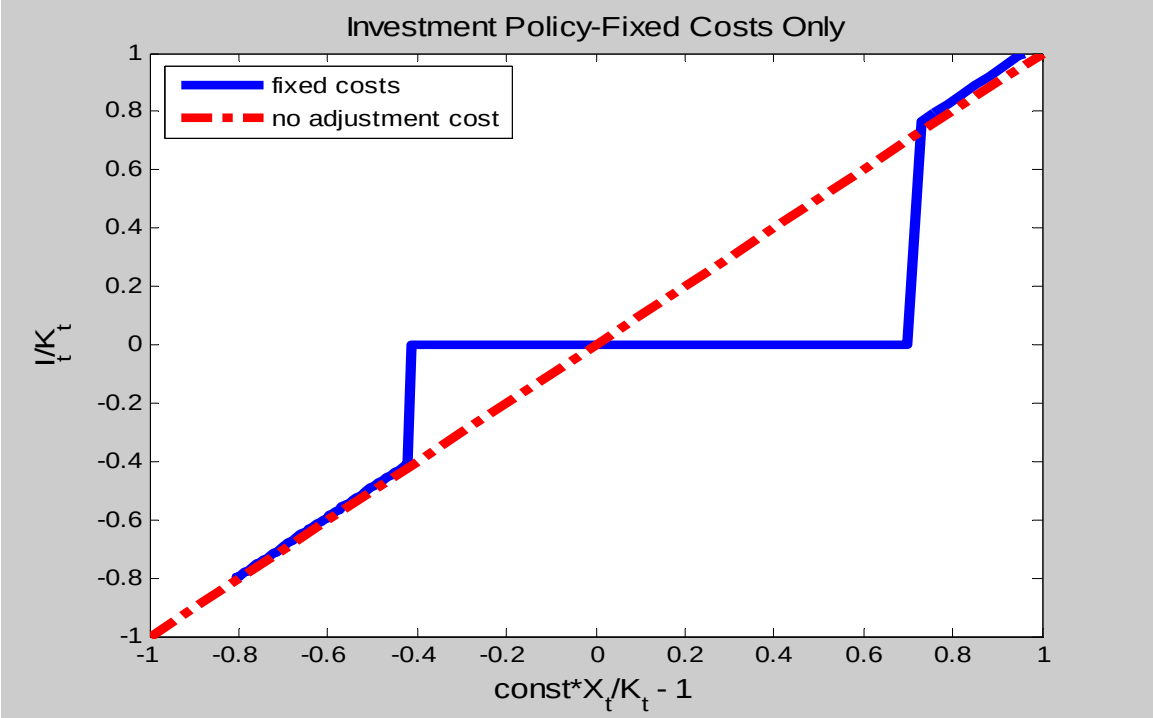


Figure 3: Policy Function for Investment Rate: Quadratic Costs Only

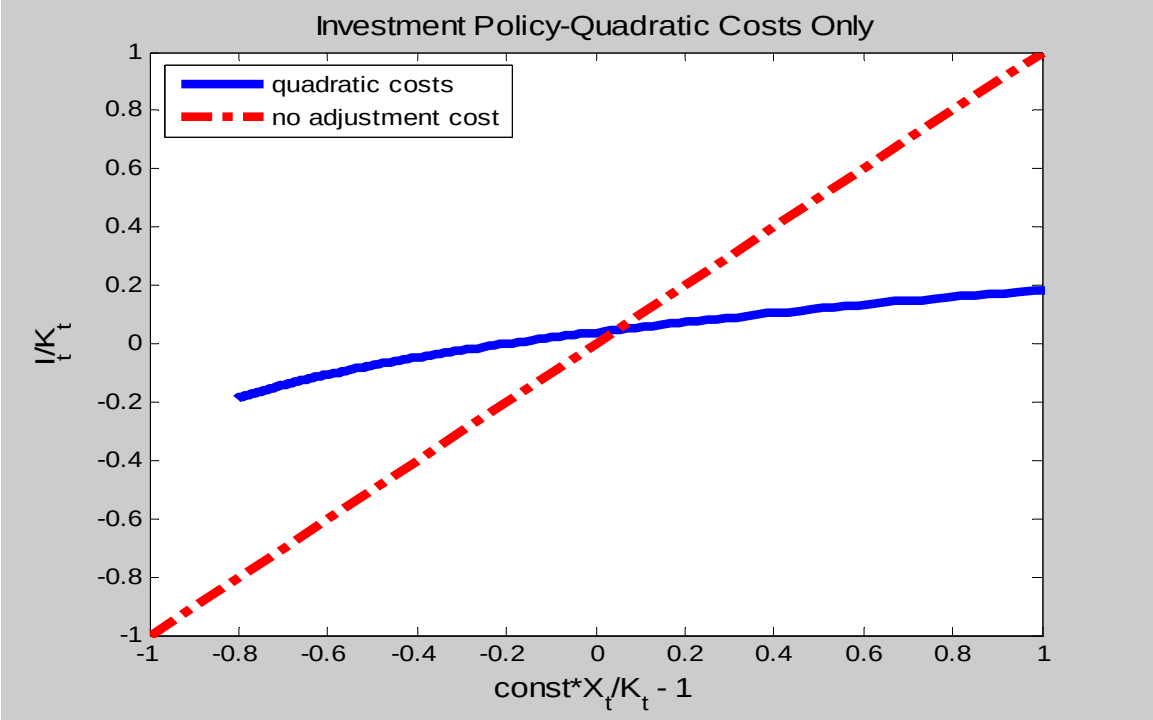


Figure 4: Effects of Demand Shocks on Investment under High and Low Levels of Uncertainty: Partial Irreversibility Only (Illustration)

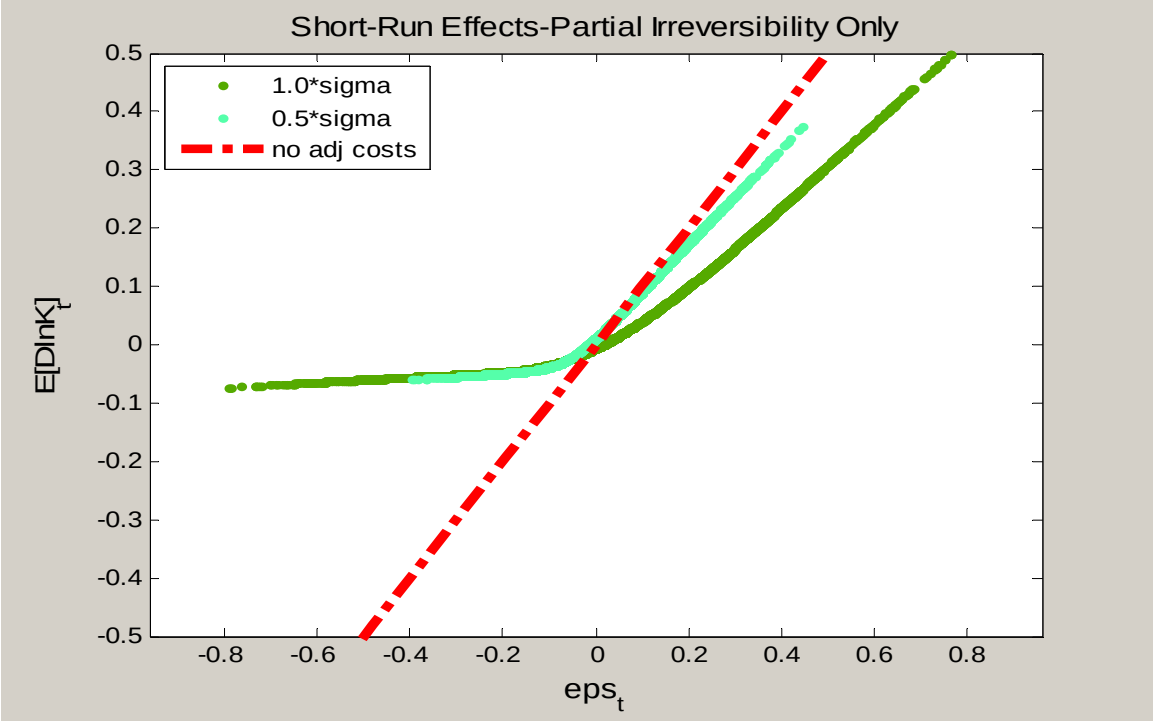


Figure 5: Effects of Demand Shocks on Investment under High and Low Levels of Uncertainty: Fixed Costs Only (Illustration)

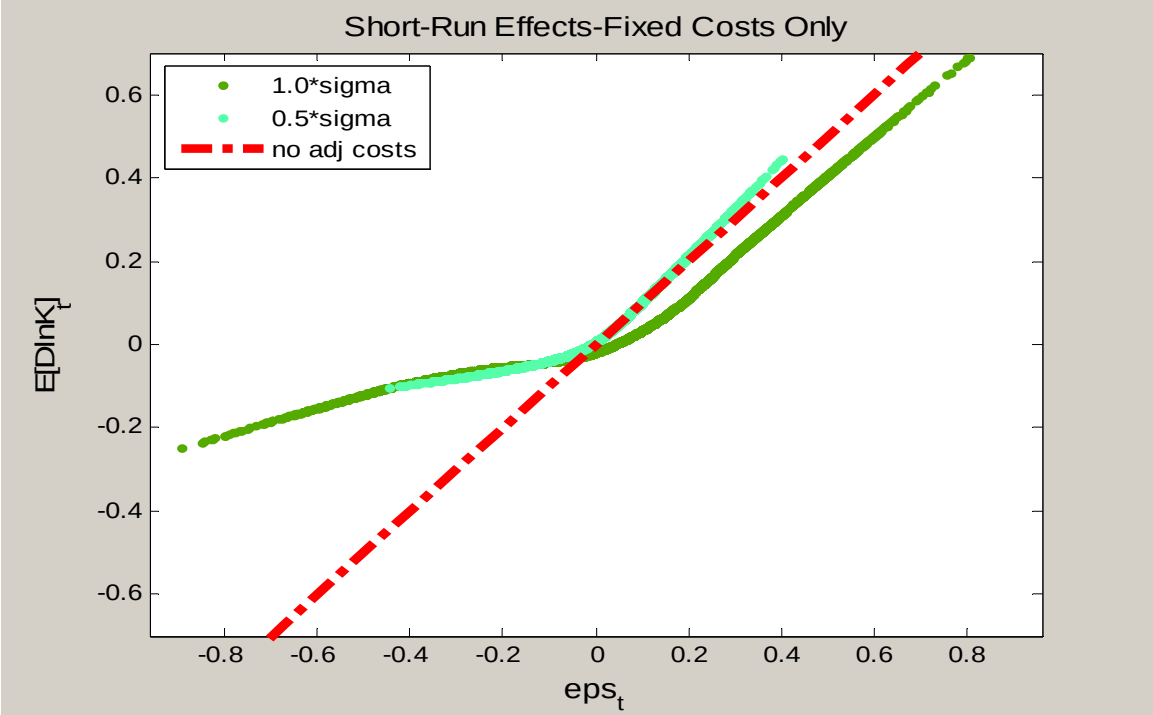


Figure 6: Effects of Demand Shocks on Investment under High and Low Levels of Uncertainty: Quadratic Costs Only (Illustration)

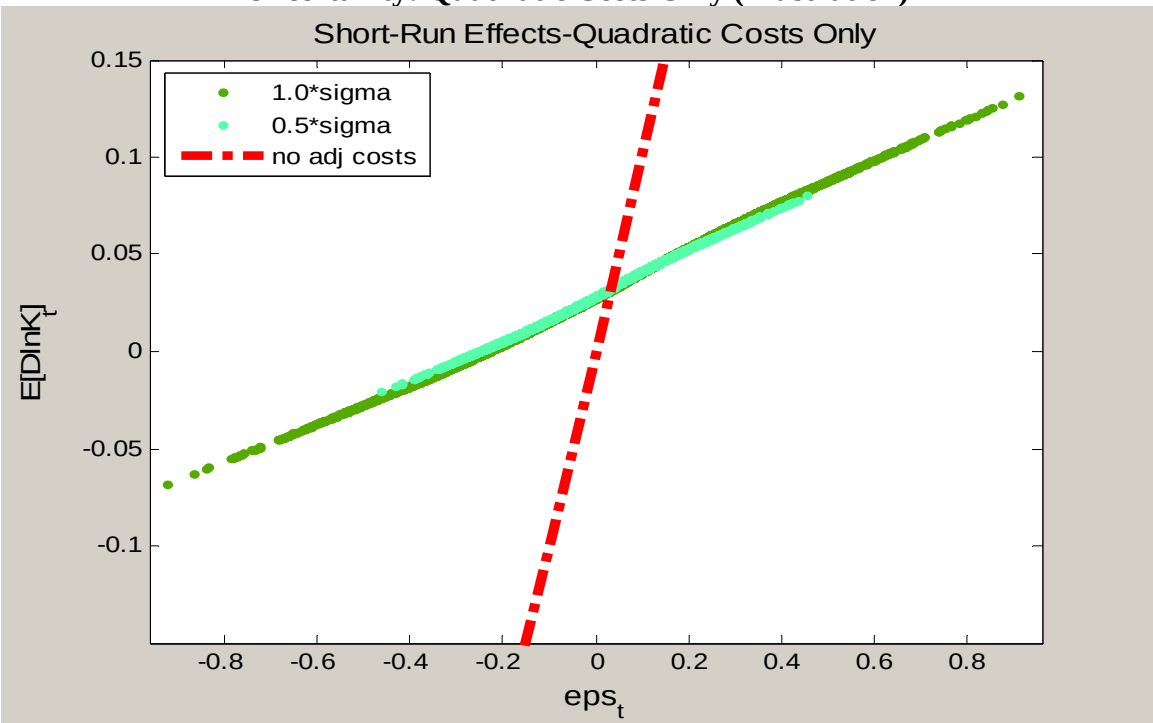
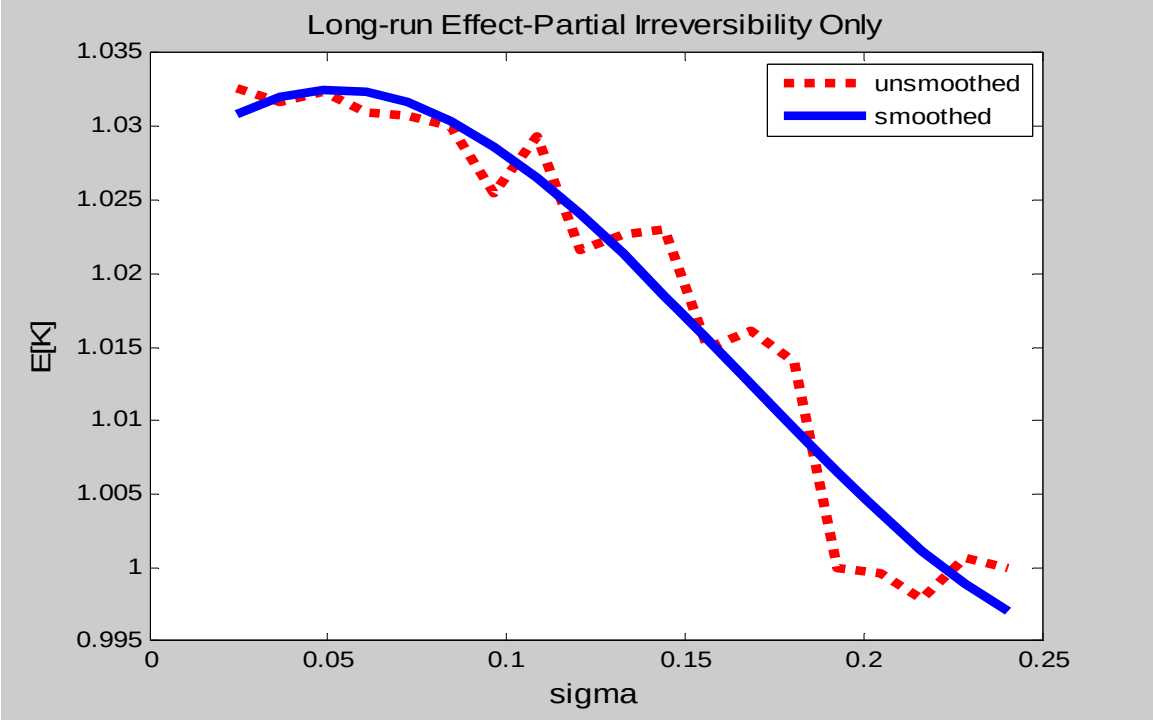


Figure 7: The Long Run Effect of Uncertainty on Average Capital Stock Levels: Partial Irreversibility Only (Illustration)



Note: We normalize the simulations so that the expected value of capital is equal to 1 at the highest level of uncertainty considered.

Figure 8: The Long Run Effect of Uncertainty on Average Capital Stock Levels: Fixed Costs Only (Illustration)

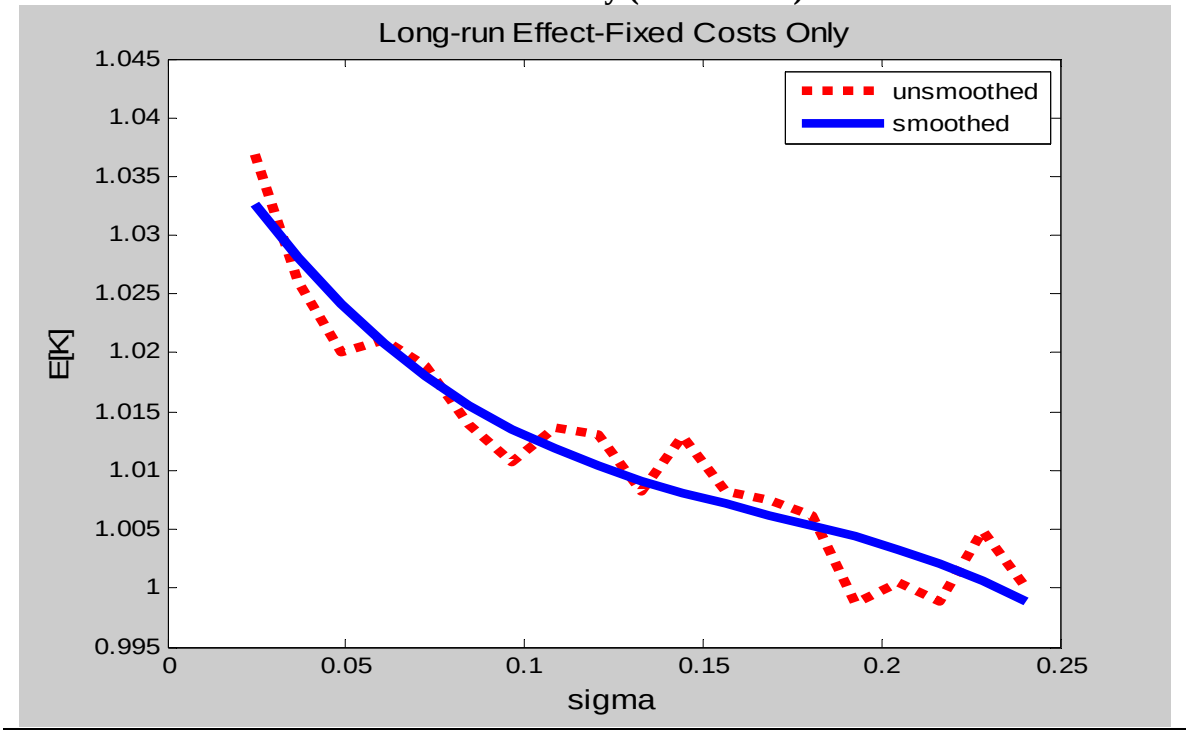


Figure 9: The Long Run Effect of Uncertainty on Average Capital Stock Levels: Quadratic Costs Only (Illustration)

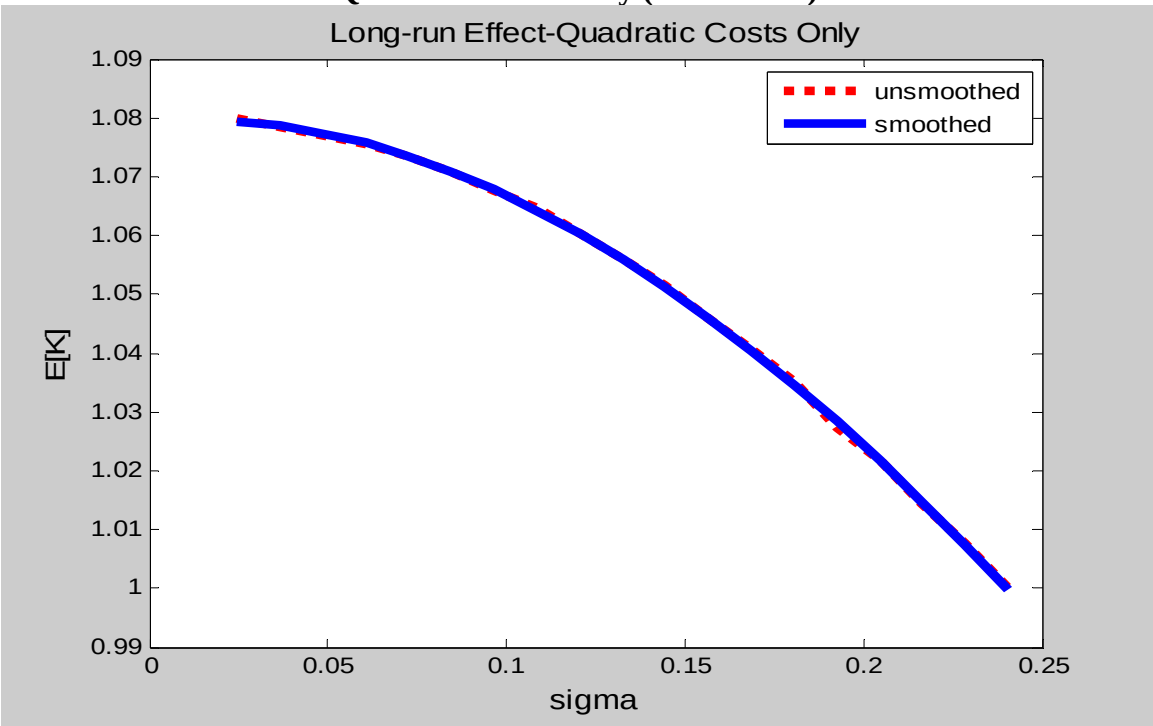


Figure 10: The Effect of Varying b_f on the Proportion with Zero Investment

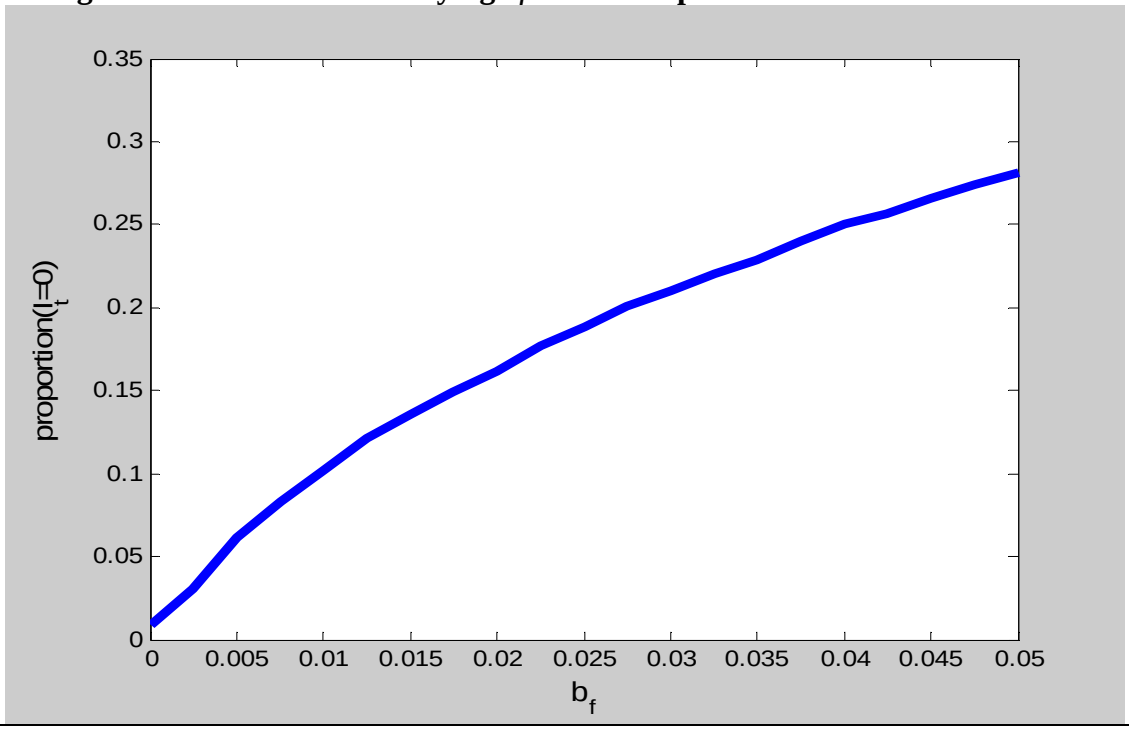


Figure 11: The Effect of Varying b_q on the Correlation between Investment Rates and Sales Growth

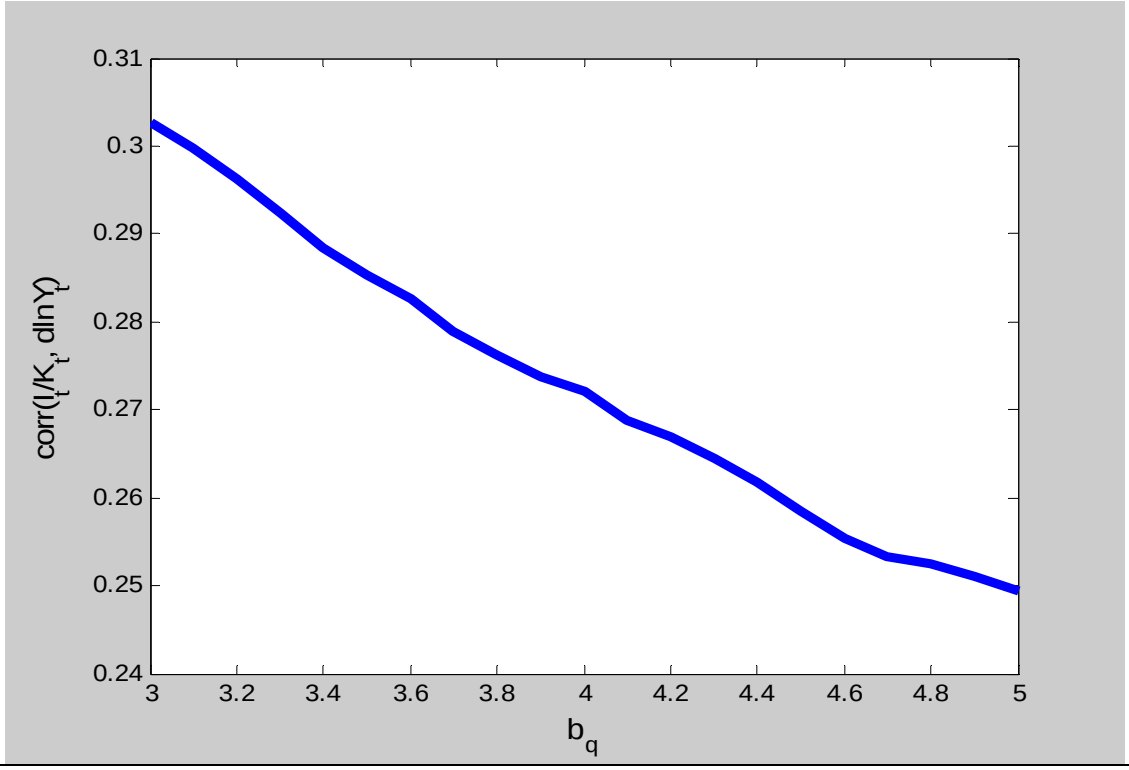
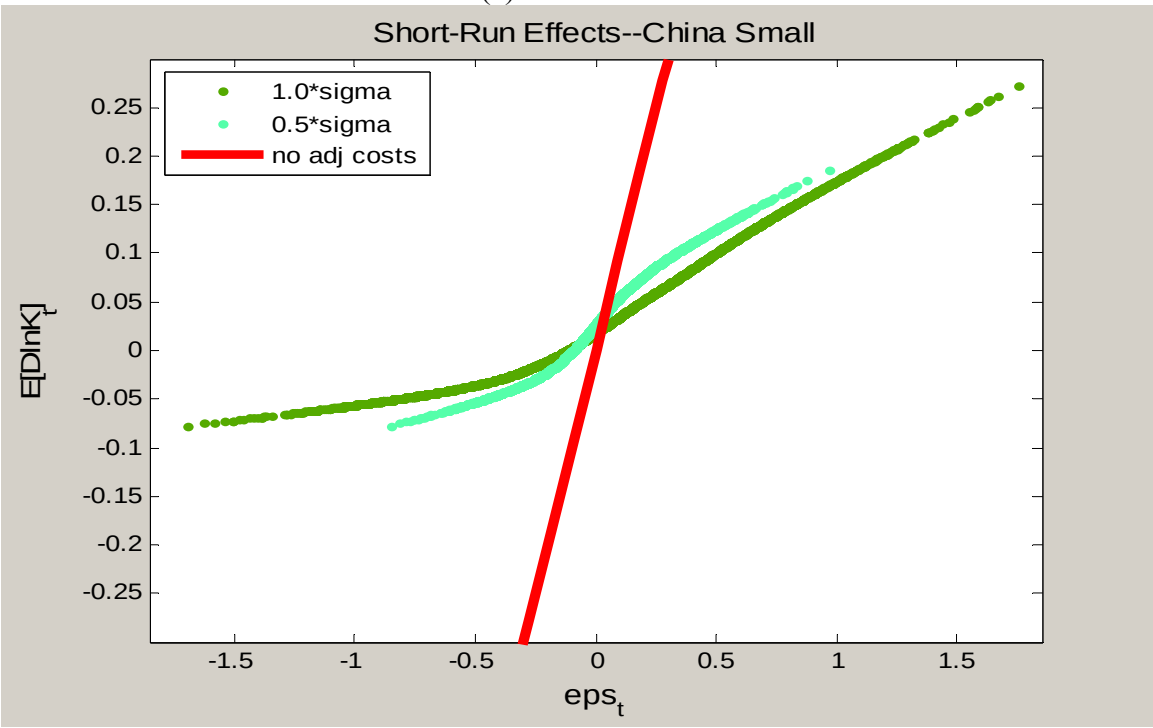


Figure 12: Demand Shocks and Investment: China

(a) Small firms



(b) Large firms

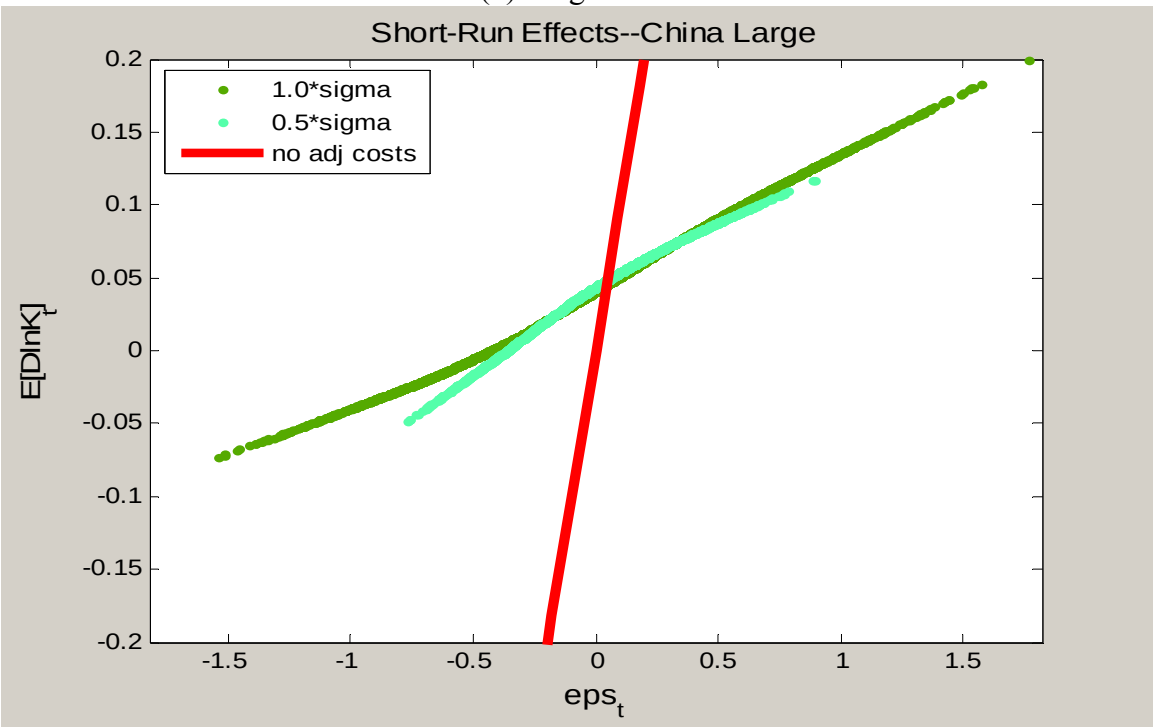
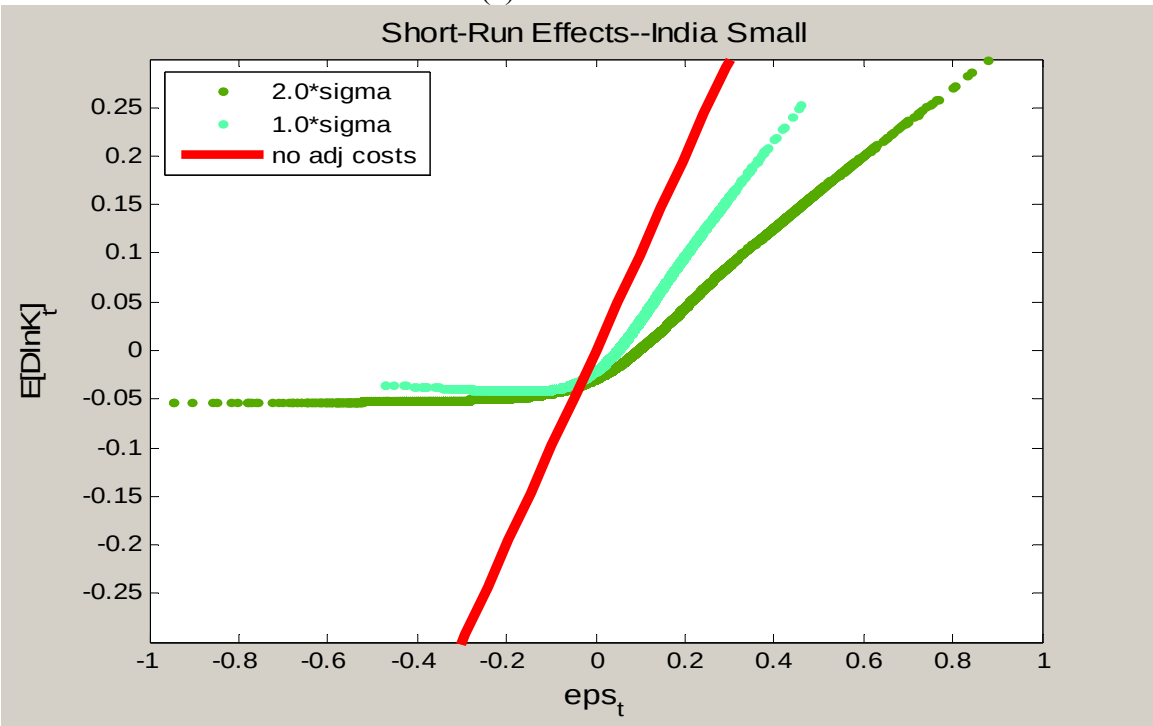


Figure 13: Demand Shocks and Investment: India

(a) Small firms



(b) Large firms

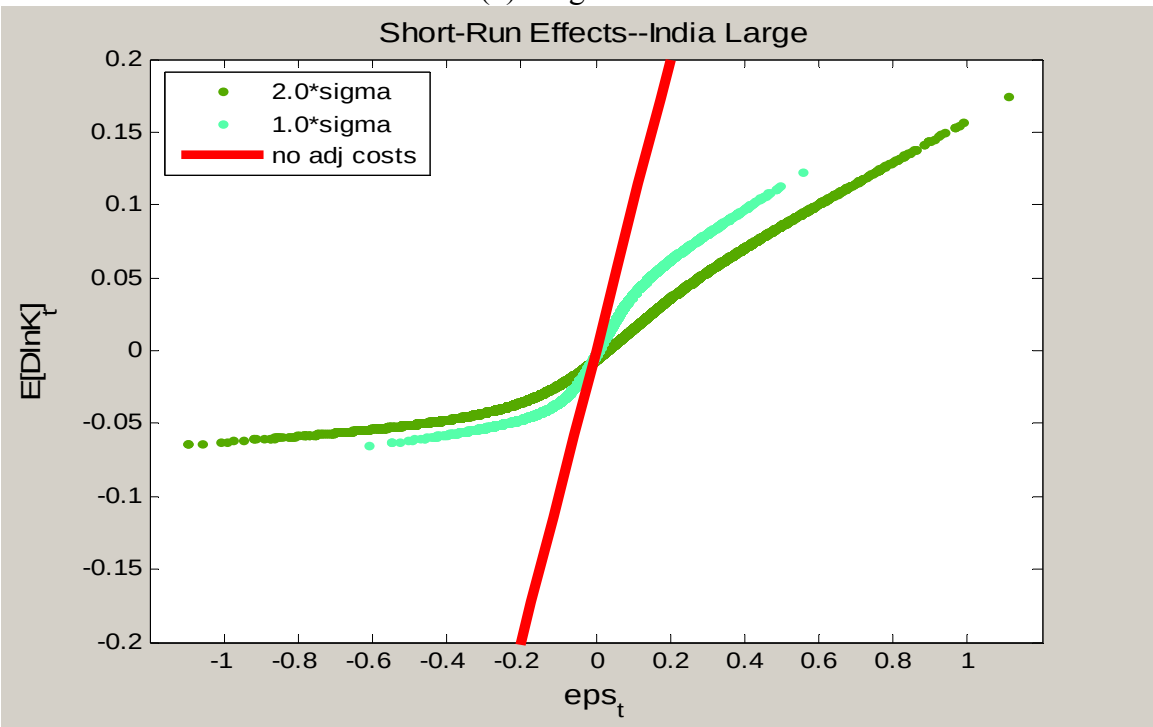
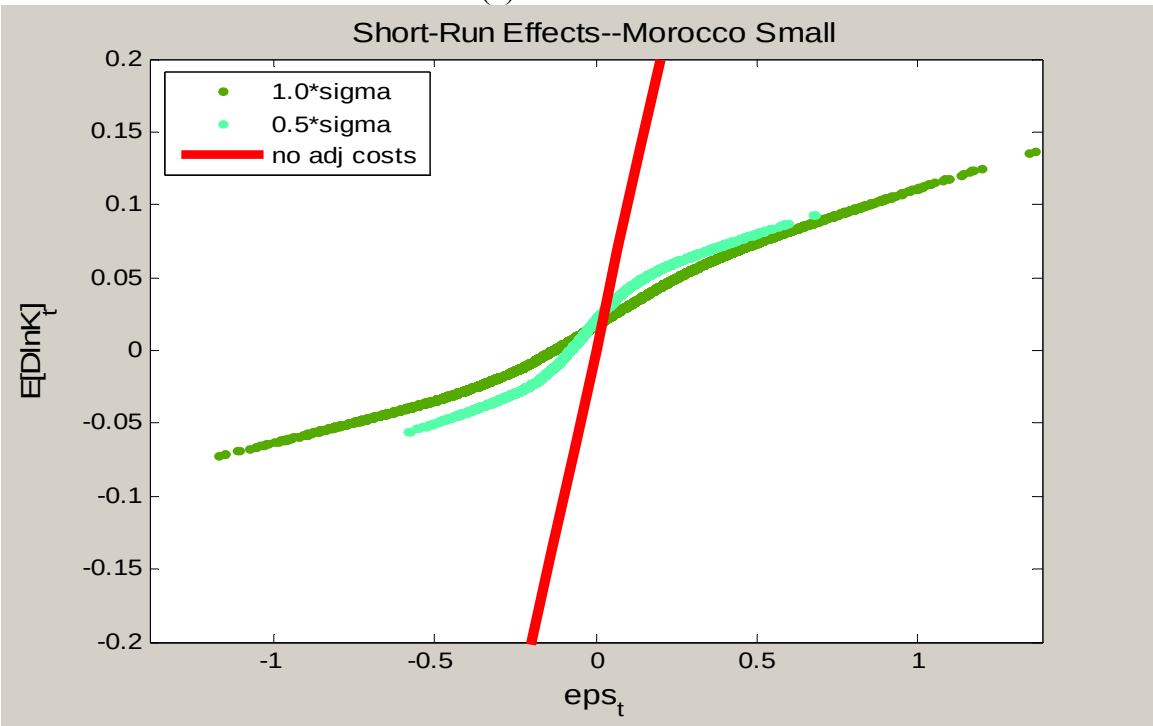


Figure 14: Demand Shocks and Investment: Morocco

(a) Small firms



(b) Large firms

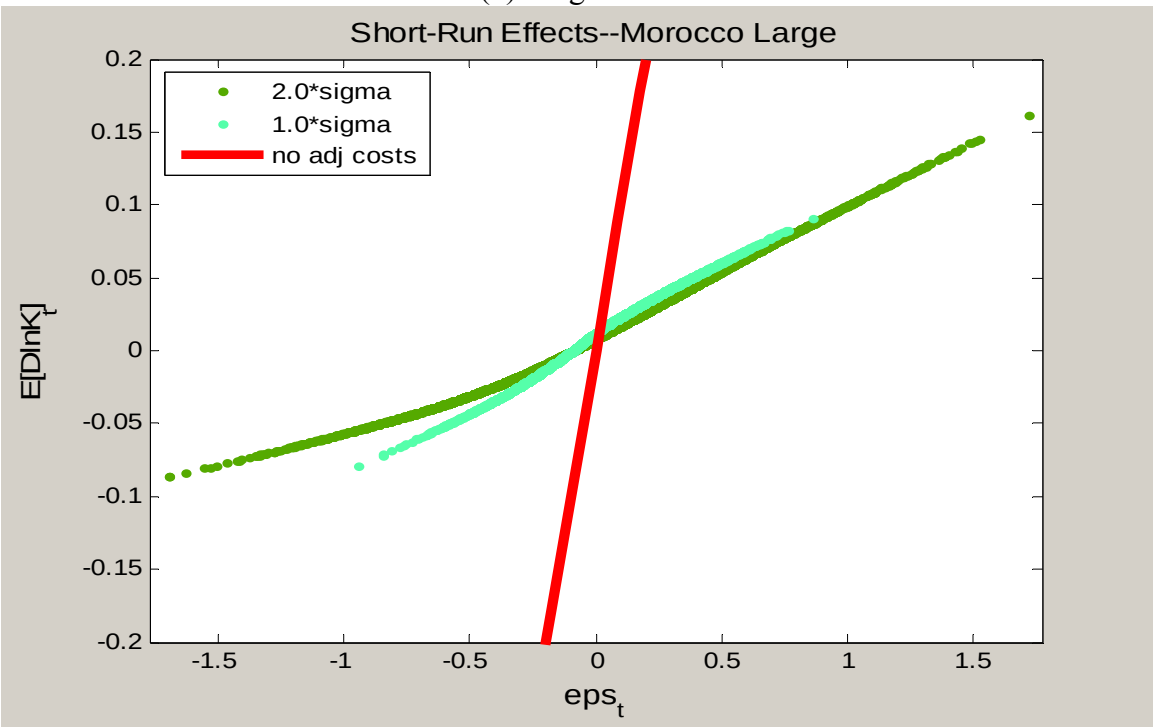
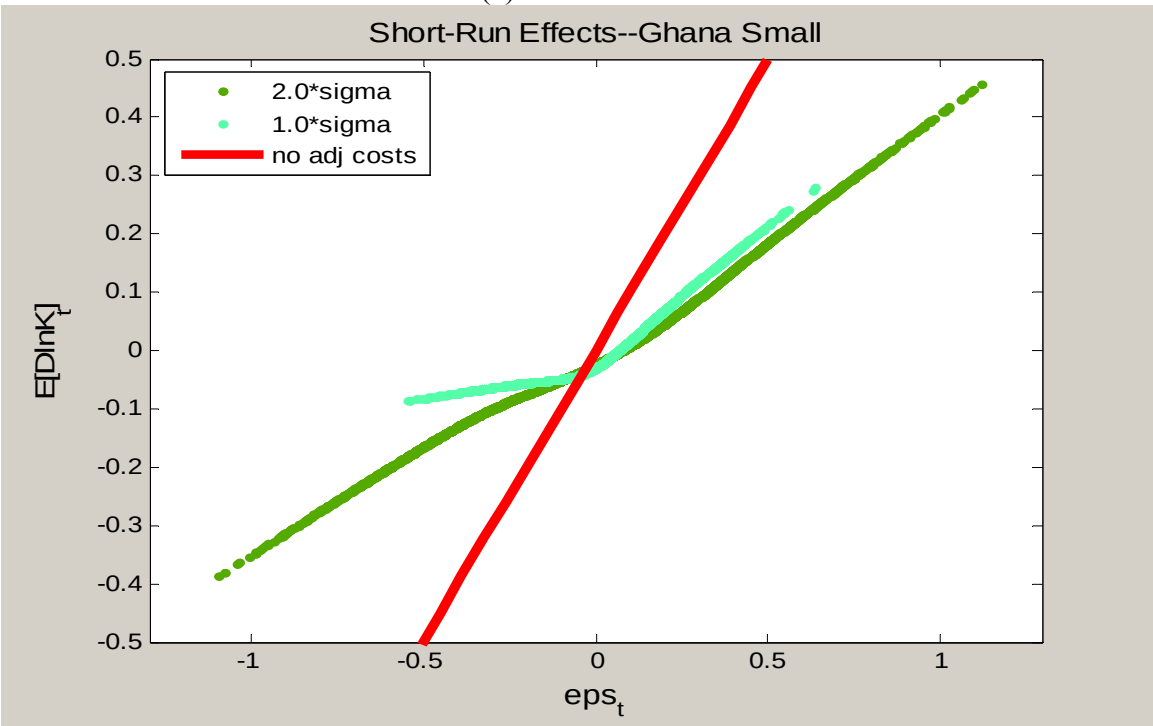


Figure 15: Demand Shocks and Investment: Ghana

(a) Small firms



(b) Large firms

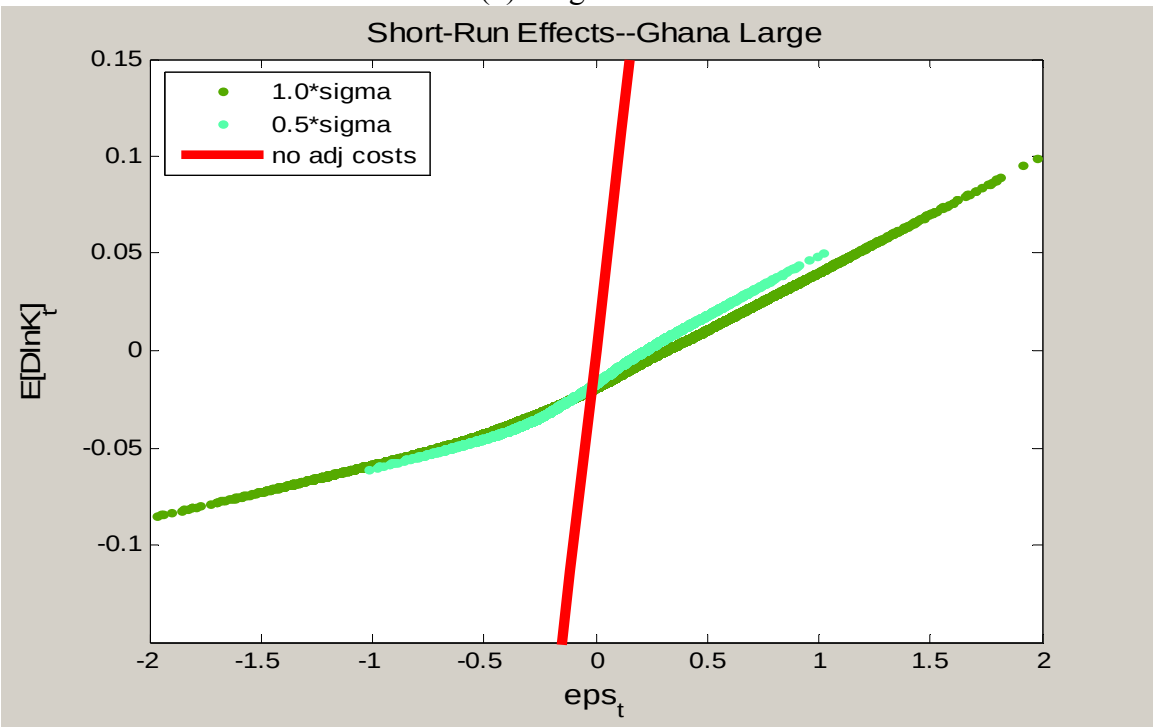
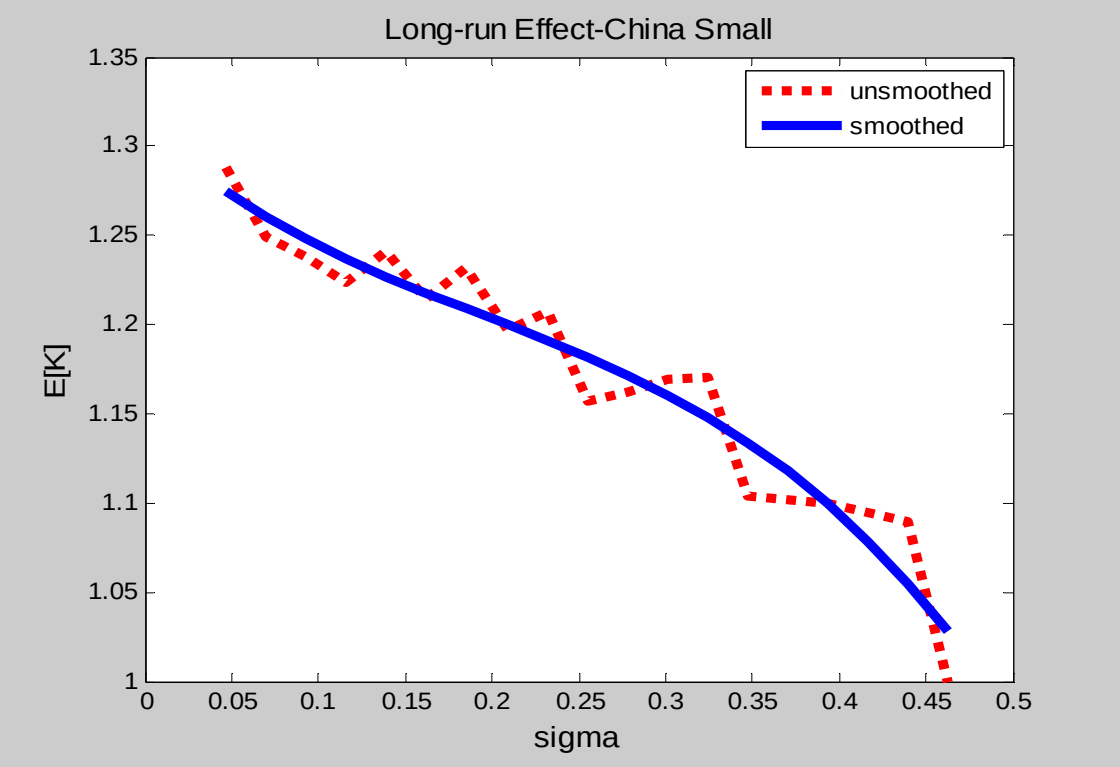


Figure 16: The Long Run Effect of Uncertainty on Average Capital Stocks: China

(a) Small firms



(b) Large firms

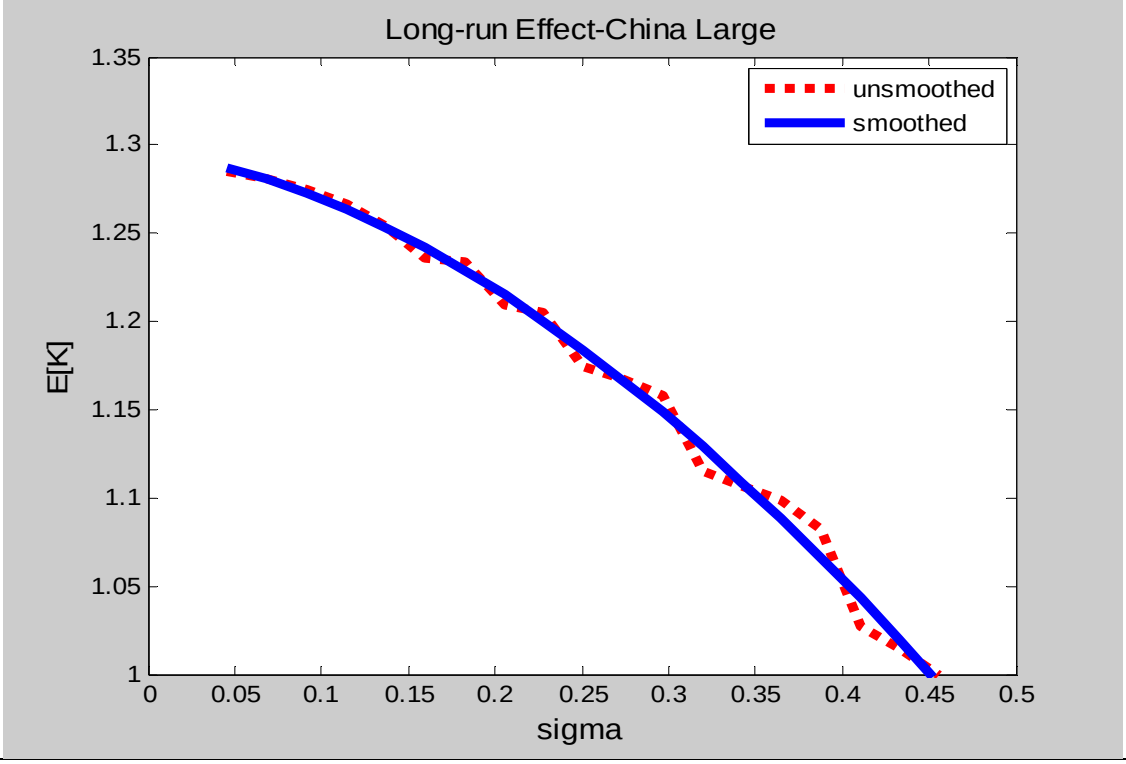
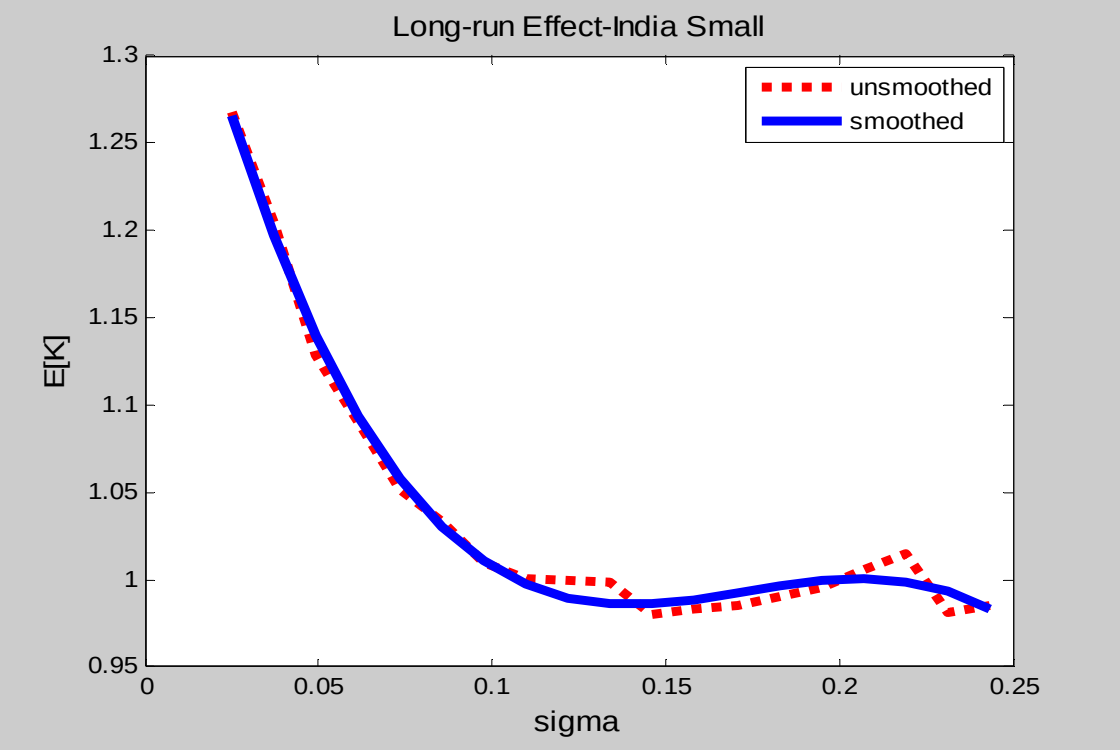


Figure 17: The Long Run Effect of Uncertainty on Average Capital Stocks: India

(a) Small firms



(b) Large firms

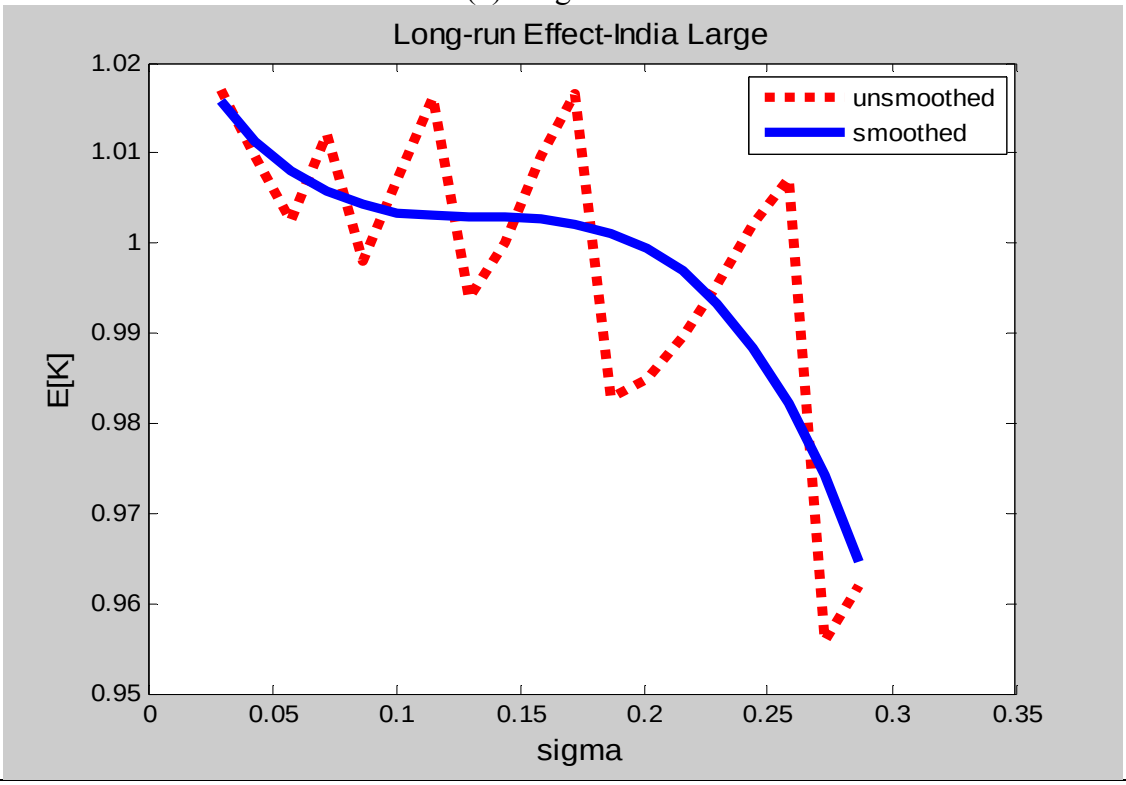
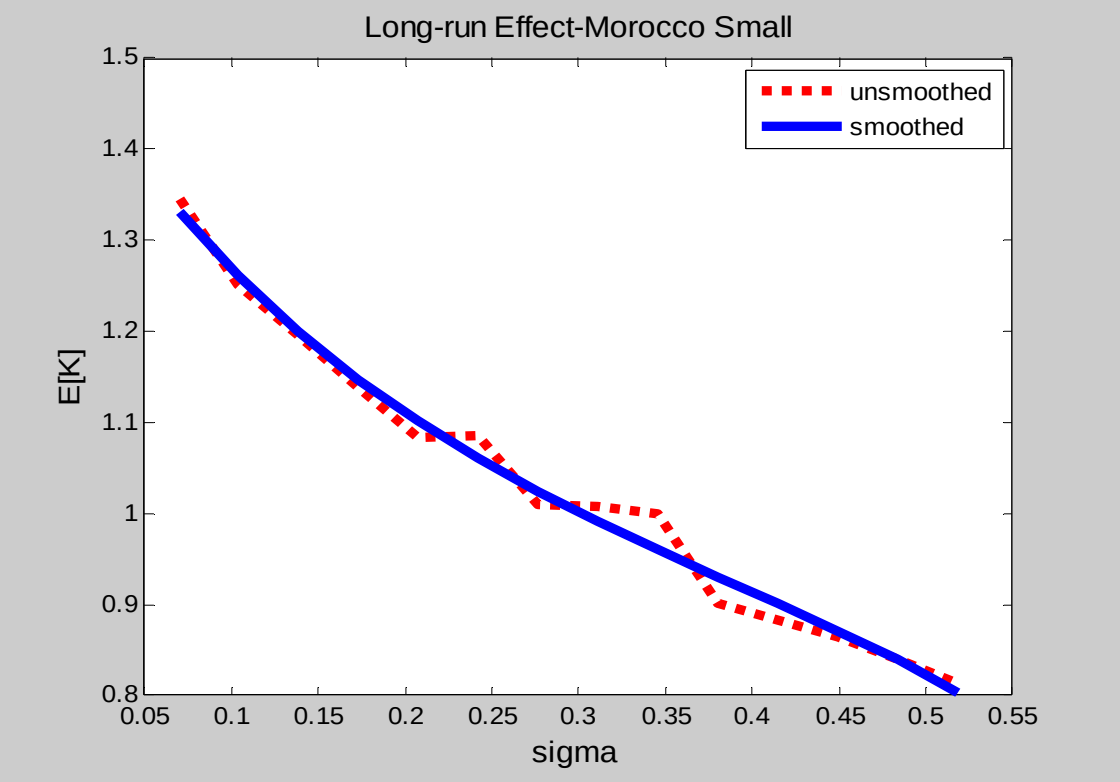


Figure 18:The Long Run Effect of Uncertainty on Average Capital Stocks: Morocco

(a) Small firms



(b) Large firms

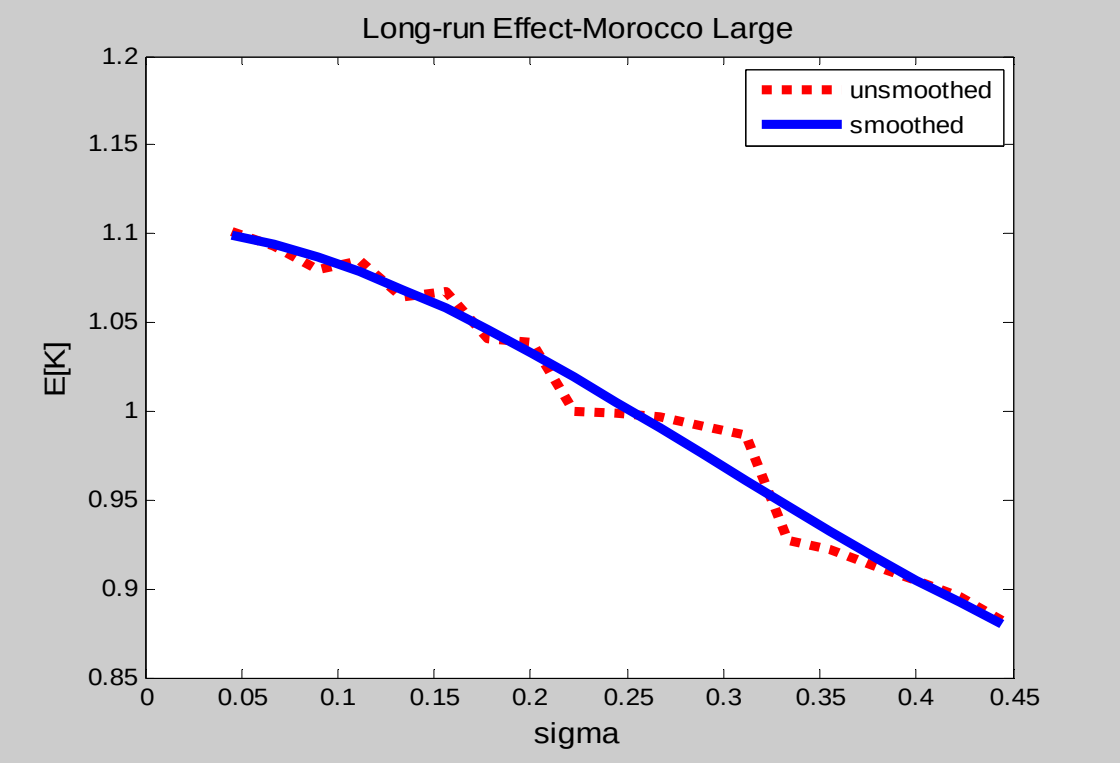
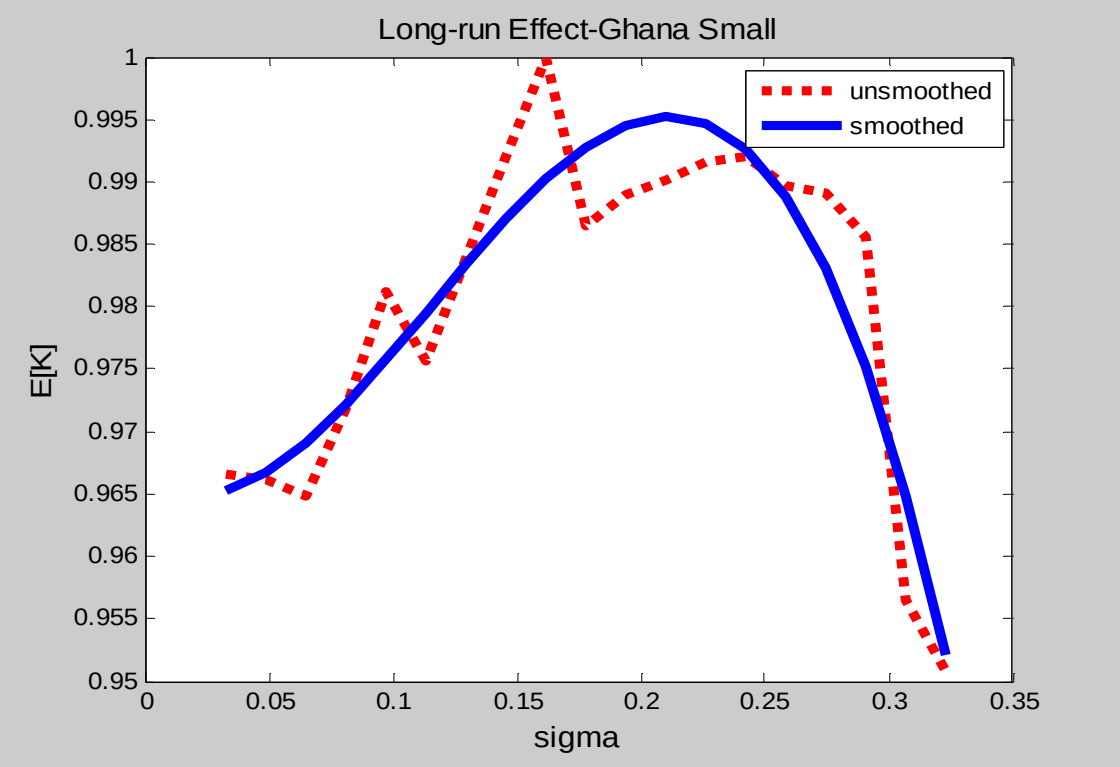


Figure 19: The Long Run Effect of Uncertainty on Average Capital Stocks: Ghana

(a) Small firms



(b) Large firms

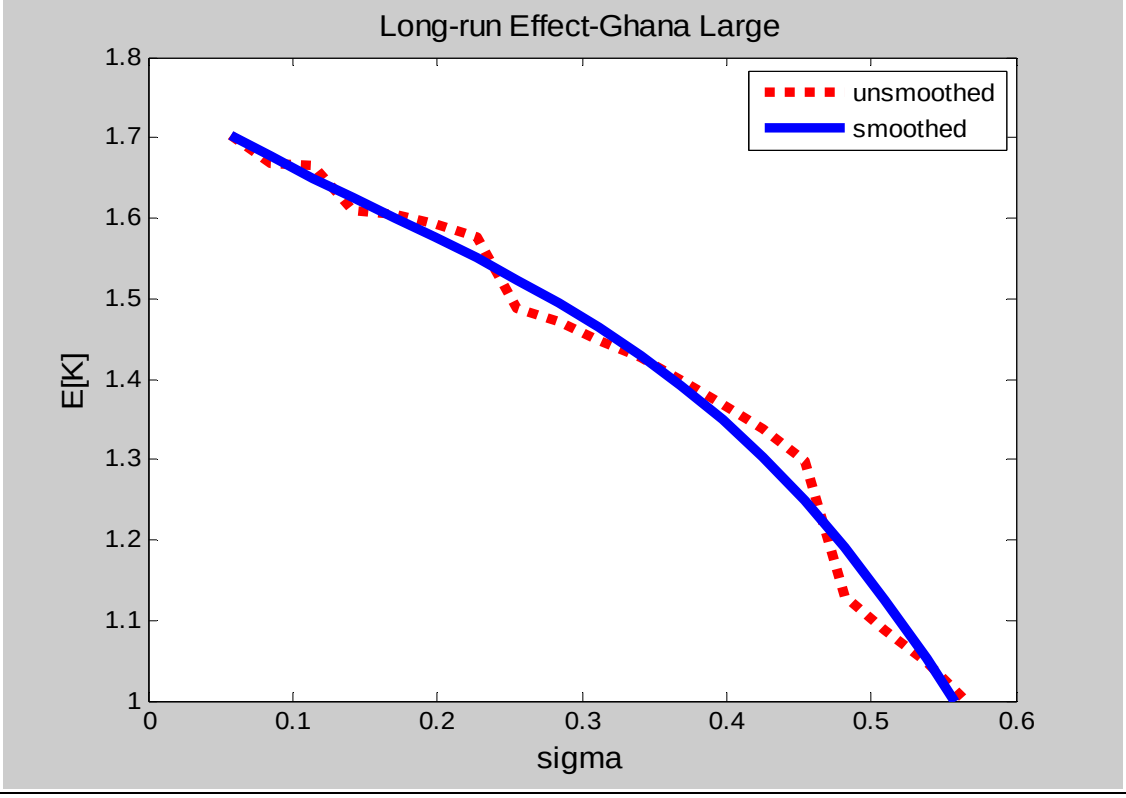


Table 1: Empirical Moments: by Country and by Firm Size

		China		India		Morocco		Ghana	
	Moments	Small	Large	Small	Large	Small	Large	Small	Large
1)	$corr\left(I_t/K_t, I_{t-1}/K_{t-1}\right)$	0.448	0.456	0.262	0.305	0.498	0.621	0.159	0.245
2)	$corr\left(I_t/K_t, I_{t-1}/K_{t-1}\right)_{1[I_t>0,\, I_{t-1}>0]}$	0.503	0.472	0.347	0.372	0.292	0.447	0.201	0.220
3)	$corr\left(I_t/K_t, \ln\left(Y_{t-1}/K_{t-1}\right)\right)$	0.182	0.324	0.151	0.216	0.134	0.059	0.089	0.200
4)	$corr\left(I_t/K_t, \Delta \ln Y_t\right)$	0.068	0.199	0.086	0.041	0.064	0.104	0.100	-0.009
5)	$\Pr\left(I_t = 0\right)$	0.407	0.181	0.667	0.458	0.340	0.183	0.568	0.341
6)	$\Pr\left(I_t/K_t > 0.2\right)$	0.213	0.208	0.095	0.149	0.148	0.151	0.089	0.114
7)	$mean\left(I_t/K_t\right)$	0.164	0.135	0.055	0.087	0.056	0.062	0.055	0.069
8)	$std\ dev\left(I_t/K_t\right)$	0.298	0.213	0.150	0.166	0.275	0.226	0.148	0.136
9)	$mean\left(I_t/K_t\right)_{1[I_t>0]}$	0.277	0.166	0.181	0.172	0.183	0.135	0.138	0.110
10)	$std\ dev\left(I_t/K_t\right)_{1[I_t>0]}$	0.344	0.225	0.206	0.194	0.250	0.182	0.192	0.154
11)	$mean\left(\ln\left(Y_t/K_t\right)\right)$	1.401	1.124	1.546	1.778	0.827	0.886	1.095	0.134
12)	$std\ dev\left(\ln\left(Y_t/K_t\right)\right)$	1.114	1.081	0.784	0.891	0.815	0.732	1.447	1.128
13)	$mean\left(\Delta \ln Y_t\right)$	0.070	0.119	0.008	0.015	-0.008	-0.002	0.026	-0.008
14)	$std\ dev\left(\Delta \ln Y_t\right)$	0.357	0.326	0.129	0.176	0.268	0.250	0.424	0.339

Table 2: SMM Estimates of Structural Parameters

	(1) China		(2) India		(3) Morocco		(4) Ghana	
	(a) Small firms	(b) Large firms	(a) Small firms	(b) Large firms	(a) Small firms	(b) Large firms	(a) Small firms	(b) Large firms
Adj cost function:								
b_i	0.005	0.044	0.000	0.000	0.000	0.000	0.104	0.082
b_f	0.046	0.026	0.069	0.022	0.032	0.017	0.003	0.004
b_q	3.133	3.934	2.651	3.575	1.602	2.997	0.138	1.356
Rev. process:								
μ	0.029	0.042	-0.003	0.003	0.019	0.011	-0.010	-0.016
σ	0.463	0.456	0.122	0.144	0.346	0.222	0.162	0.567
Rev. function (capital):								
$1-\gamma$	0.414	0.327	0.227	0.153	0.812	0.418	0.267	0.789
Measurement errors (sdev):								
σ_{YP}	1.042	0.966	0.739	0.855	0.788	0.697	1.431	1.079
σ_{YT}	0.128	0.000	0.052	0.087	0.184	0.148	0.291	0.221
σ_{IP}	0.732	0.744	0.344	0.720	0.573	0.688	0.290	0.335
σ_{IT}	0.563	0.552	0.718	0.606	0.740	0.694	0.772	0.991
Criterion value	21.1	84.9	142.2	52.8	53.3	36.5	8.7	7.8
Over-ID restrictions	4	4	4	4	4	4	4	4
Firms	150	454	1016	244	413	346	116	50
Time periods	3	3	3	3	3	3	6	6

Table 3: Simulated Moments: by Country and by Firm Size

		China		India		Morocco		Ghana	
	Moments	Small	Large	Small	Large	Small	Large	Small	Large
1)	$corr\left(I_t/K_t, I_{t-1}/K_{t-1}\right)$	0.442	0.480	-0.145	0.218	0.309	0.400	0.117	0.272
2)	$corr\left(I_t/K_t, I_{t-1}/K_{t-1}\right)_{1[I_t>0, I_{t-1}>0]}$	0.463	0.477	0.078	0.384	0.270	0.389	0.069	0.164
3)	$corr\left(I_t/K_t, \ln\left(Y_{t-1}/K_{t-1}\right)\right)$	0.080	0.096	0.016	0.015	0.022	0.065	0.004	0.097
4)	$corr\left(I_t/K_t, \Delta \ln Y_t\right)$	0.301	0.273	0.117	0.245	0.149	0.138	0.144	0.114
5)	$\Pr\left(I_t = 0\right)$	0.441	0.193	0.641	0.420	0.370	0.199	0.565	0.377
6)	$\Pr\left(I_t/K_t > 0.2\right)$	0.188	0.202	0.098	0.122	0.152	0.138	0.093	0.090
7)	$mean\left(I_t/K_t\right)$	0.126	0.137	0.062	0.081	0.102	0.100	0.059	0.061
8)	$std\ dev\left(I_t/K_t\right)$	0.257	0.220	0.143	0.157	0.200	0.161	0.149	0.133
9)	$mean\left(I_t/K_t\right)_{1[I_t>0]}$	0.228	0.170	0.172	0.141	0.162	0.125	0.141	0.108
10)	$std\ dev\left(I_t/K_t\right)_{1[I_t>0]}$	0.309	0.233	0.195	0.185	0.230	0.171	0.198	0.155
11)	$mean\left(\ln\left(Y_t/K_t\right)\right)$	1.376	1.084	1.526	1.710	0.842	0.892	1.145	0.144
12)	$std\ dev\left(\ln\left(Y_t/K_t\right)\right)$	1.112	1.045	0.761	0.863	0.808	0.731	1.459	1.124
13)	$mean\left(\Delta \ln Y_t\right)$	0.028	0.038	-0.004	-0.001	0.012	0.011	-0.009	-0.010
14)	$std\ dev\left(\Delta \ln Y_t\right)$	0.351	0.320	0.122	0.176	0.277	0.252	0.435	0.346