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The Role of Financial Constraints on Firm Investment in Developing Countries: The Case of Ethiopian Manufacturing

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Abstract

A question of considerable interest in the literature of firm investment is if financial factors inhibit investment. Several studies that use both q-theoretic and Euler equation approaches report that investment is more sensitive to financial factors among firms that are more likely to face financing constraints. However, there is no consensus if these results can be interpreted as indicative of the presence of financial constraints. One major reason for this is the difficulty to isolate the effects of financial and fundamental factors since the two factors not only affect each other, but are also in return affected by investment. This paper uses panel VAR methodology to explicitly model the dynamics between firm investment, and its fundamental and financial determinants. The marginal product of capital and cash flow are used to measure fundamental and financial factors respectively. Analysis using a unique census-based dataset of Ethiopian manufacturing establishments shows that cash flow is an important determinant of investment. Orthogonalized impulse response shocks of cash flow elicit much larger investment response among small and privately owned firms compared respectively to larger plants and state-owned enterprises. I find that financial liberalization in more recent years has eased the cash flow sensitivity of investment, especially for financially more constrained small and privately owned firms.

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1. Introduction

Small and medium-sized enterprises form the backbone of most advanced economies, contributing significantly towards employment and income growth. In many developing countries, however, the distribution of firms tends to be dominated by microenterprises and large-sized firms (Sleuwaegen and Goedhuys, 2002). This phenomenon, dubbed “the missing middle” in the literature, has initiated an unsettled debate as to what drives firm growth and investment in developing countries.

Severe financial constraints are arguably one of the most serious obstacles for firm investment. Due to low level of financial development, firms in developing countries have limited access to external financing which hampers their ability to invest in physical capital and grow (Love and Zicchino, 2006). This can also lead to lower productivity since inability to invest in new physical capital could mean failure to acquire new technologies that are embedded in them.

The presence of information asymmetry between lenders and borrowers is a major factor that can make external financing more expensive (Greenwald *et al*., 1984). Further, costly monitoring, contract enforcement and incentive problems contribute toward making uncollateralized external financing more expensive (Schiantarelli, 1995). The implication is that small firms that have limited net worth to use as collateral will be more financially constrained (Beck *et al*., 2007; Dinh *et al*., 2010; Beck and Demirguc-Kunt, 2006). In some developing countries like Ethiopia where the government owns important banks, private firms can also be more subject to financial constraints compared to state owned enterprises (SOEs).

The empirical approach for testing the effect of financial constraints on investment often involves testing for potential departures from standard neoclassical investment models. The most widely employed investment model in the empirical research is the q-theoretic model which contends that the marginal profitability of capital (marginal q) is a sufficient statistics for explaining investment (Hayashi, 1982). However, studies reveal that augmenting the q-theoretic investment model by including different proxies of net worth improves the fit of the model (Fazzari *et al*., 1988; Hubbard, 1998). This literature also finds that variables such as cash flow that proxy net worth have a larger effect in subsamples of firms that are considered more likely to face financing constraints.

In general, the q-theoretic model has been found unsatisfactory because the average q has poor explanatory power on the rate of investment. Another strand of this literature employs the Euler equation investment model which relies on an alternative formulation of the solutions for the investment optimization problem. The presence of financial constraints in this framework is also tested by looking at the significance of financial variables that can proxy net worth. The null hypothesis of perfect capital markets is rejected if these variables appear with significant coefficients, and if the coefficients appear larger in subsamples that are classified a priori as financially constrained.

However, the plausibility of including proxies for net worth such as cash flow to capture the effect of financial constraints in both strands of literature is a subject of dispute (Hubbard, 1998; Gilchrist and Himmelberg, 1998). A central critique on this approach is that cash flow can carry substantial information about future profitability, and its positive effect on investment could be merely reflecting the unmeasured effect of future profitability. Another failing of this approach is that it is an incomplete representation of the data since it disregards the fact that the relationship between investment, future profitability of cash flow is not necessarily one way.

This paper uses an alternative approach of panel Vector Autoregressive (VAR) modeling that explicitly represents the complex dynamics between investment, future profitability and cash flow. This approach offers an alternative approach for testing the sensitivity of investment for cash flow given the level of future profitability. A unique advantage of using panel VAR approach is that it recognizes the fact that cash flows and measures of future profitability not only affect investment, but are also in return affected by investment. Thus, we are able to measure the direct effect of cash flow on investment, as well as its indirect effect through its effect on future profitability and on the lags of investment. This can be done by computing the impulse responses of investment for orthogonalized shocks on the innovations of cash flow.

Panel VAR techniques were pioneered by Holtz-Eakin *et al.*(1988) and have been employed to overcome identification problems in investment analysis in recent studies. Gilchrist *et al.* (1995) and Gilchrist and Himmelberg (1998) study the relationship between cash flow, future profitability and investment among US manufacturing firms. They find that shocks in lagged values of cash flow can elicit a response from investment over a three-year period, suggesting that cash flow matters above and beyond its ability to predict investment fundamentals. Love and Zicchino (2006) use firm-level data across several countries to test if financial development reduces the sensitivity of investment for cash flow shocks in a panel VAR setting. They conclude that the impact of financial factors on investment is significantly larger in countries with less developed financial systems.

However, the few studies that employ panel VAR techniques to understand the role of financial constraints on investment are exclusively based on very large stock listed firms which are unrepresentative of the rest of the population of firms. This is largely due to lack of balance sheet data on cash flow for smaller private firms. There is particularly no evidence in this literature for developing country firms where the effect of financial constraints is presumably stronger. This paper investigates the cash flow sensitivity of investment using the Ethiopian Manufacturing Industries Survey dataset which is longitudinal firm-level dataset that covers the years 1996-2010.

The analysis mainly involves using impulse responses to test if shocks in orthogonalized innovations of cash flow elicit response in investment. Since cash flow is strongly correlated with future profitability, it could capture the effects of future profitability if the later is measured with error. Thus it is difficult to interpret significant coefficients for cash flow as indicative of financial constraints. Panel VARs, like other techniques of panel data analysis, allow us to partially address this issue by controlling for individual effects which might constitute a large part of the correlation between the two factors. Since this might not be sufficient to eliminate the correlation, it is useful to follow the standard approach of testing if investment by firms with higher likelihood of facing financial constraints displays excess sensitivity for cash flow. Therefore, I compare the magnitude of sensitivity to cash flow among small and large establishments, as well as between private and state owned enterprises (SOEs). Furthermore, I conduct variance decomposition to find out if the relative magnitude of cash flow to the forecast error of investment is larger among small and private firms.

While size is widely used as a criterion for classifying the level of financial constraints firms face, the private vs. SOE dichotomy is not emphasized in the investment literature. Since studies suggest that state owned enterprises face soft budget constraints (Lízal and Svejnar, 2002), type of ownership can provide a useful alternative for exploring the relevance of financial constraints. Our dataset is particularly suitable for applying ownership criteria because of the importance of SOEs and public banks in Ethiopia.

The Ethiopian economy used to be centrally planned and no private banks were allowed to operate until the country embarked on transition to market economy in 1991. However, there have been significant changes in the banking sector since the entry of the first private banks in 1995. Once non-existent, the share of private banks in total domestic borrowing rose to 52% by 2010. The process of liberalization in the banking sector thus provides us with an excellent opportunity to investigate if financial constraints have been relaxed.[1]

The results show that investment is more sensitive to cash flow among small and privately-owned plants compared to large plants and SOEs respectively. Both orthogonalized impulse response analysis as well as variance decompositions highlight the relative importance of cash flow among small and private firm, as well as among non-exporting and single unit establishments. Comparing the cash flow sensitivity of investment among these samples in the early and later years of liberalization, I find that the sensitivity of investment to cash flow has been substantially reduced in later years. This effect is true across all firm classes, although it is more pronounced for small and privately owned (as well as single unit and non-exporting) plants that are more likely to face financing constraints.

The rest of the paper is organized as follows. Section 2 sketches the VAR methodology used for analysis as well as estimation. Section 3 describes the data and presents summary statistics. Section 4 provides results and section 5 concludes.

[1] There has been no privatization of banks in Ethiopia, and all private banks are newly established ones. However, there has been significant privatization of SOEs in the manufacturing sector. The percentage of state-owned enterprises (SOEs) in our dataset constituted 25% of all observations in 1996; but this fell to less than 6% of the sample in 2010, driven partly by privatization and partly by increases in the entry of private enterprises.

Although a number of studies have examined the effects of liberalization in developing countries, none have done so in a manner that addresses the dynamic relationship between financial and fundamental determinants of investment. Some of these studies include Koo and Maeng (2005) who report that financial liberalization in Korea reduced the sensitivity of investment to cash flow among small and independent (non-chaebol) firms. This implies that large and chaebol firms lost their relative advantage of financial access following liberalization. Similarly, Gelos and Werner (2002) find that financial liberalization in Mexico eased the cash flow sensitivity of investment for small firms (though not for large firms).

2. Methodology

2.1 Impulse response analysis

A VAR provides a statistical description of the dynamic interrelation between *N* different variables contained in the vector y:

$$(1) \quad y_{it} = \mathrm{A}_1 y_{it-1} + \cdots + \mathrm{A}_L y_{it-L} + \varepsilon_{it}$$

E(ε_{it})=0

E($\varepsilon_{it}\varepsilon_{it}'$) = Σ_ε

where A_l are NxN matrices of coefficients, and ε_{it} is Nx1 vector of disturbances. For our analysis, y includes three variables: the marginal product of capital (MPK), the cash flow - capital ratio (CFK) and the rate of investment (IK). The matrix $\Sigma_\varepsilon$it the variance-covariance matrix of NxN dimensions. Assuming all variables in the system are endogenous, the dynamics of the jth variable is given as follows:

$$(2) \quad y_{j,it} = \sum_{n=1}^{N} \sum_{l=1}^{L} \alpha_{nl} y_{n,it-1} + \varepsilon_{j,it} \; .$$

where *l* represents the lag length and L is the maximum lag length; n represents the variables and N is the total number of variables in the VAR. The coefficient α in this case is the jth row of the A_l matrices of Equation (1).

The representation given in (2) assumes a common mean for all cross-sections, which is likely to be violated in firm level data where there is substantial heterogeneity. It is thus necessary to allow for differences in the means of the variables across cross-sections. This can be done by allowing for a firm-specific error term in the specification. Likewise, time effects can be included to accommodate macro-economic and other shocks common for all firms:

$$(3) \quad y_{j,it} = \sum_{n=1}^{N} \sum_{l=1}^{L} \alpha_{nl} y_{n,it-1} + \eta_i + \lambda_t + \varepsilon_{it} \; .$$

Although the panel VAR of (3) assumes that all individual time series have the same coefficients, the inclusion of fixed individual effects allows for varying unconditional means of y. The ability to control for cross-section heterogeneity is one of the unique advantages of panel VARs over time series VARs. Since the sampling properties of panel VARs are based on the number of cross-sections (i) and not on the number of years (t), panel VARs can also be estimated using relatively short panels (Holtz-Eakin *et al.*, 1988). Further, differences in the variances of the variables can be accounted for using appropriate estimators with heteroskedasticity robust standard errors (Holtz-Eakin *et al.*, 1988).

Our interest lies in measuring the direct and indirect effects of a change in one of the variables in the system upon others. This is readily done through impulse response analysis using the moving average

(MA) representation of the VAR model. Since every stable and stationary VAR has a VMA(∞) representation, Equation (1) is summarized as an infinite summation of error terms:

$$(4) \quad y_t = \sum_{l=0}^{\infty} \Phi_l \varepsilon_{t-l}$$

where

$$\Phi_l = \begin{cases} I_N & \text{if } l = 0 \\ \sum_{r=1}^{l} \Phi_{l-r} A_r & \text{if } l > 0 \end{cases}$$

The firm-identifier is supressed here since it is not relevant for the impulse response analysis, and the constant is assumed to be zero since the interest is not on the average value of the variables but on variations around the average. The matrix Φ_l gives the impulse response coefficients. The rnth element of Φ_l gives the response of the rth variable to a unit shock in the innovations of the nth variable *l* time periods after the impulse.

These impulse responses, however, are difficult to give causal interpretation because in the presence of contemporaneous correlations among ε_t, the off-diagonal elements of the co-variance matrix of the error terms Σ_ε will have non-zero values. Thus a shock in the innovation of one variable also induces shocks in other variables. To overcome this, it is necessary to decompose the values of $\varepsilon_t$into components that are orthogonal to each other. This can be done using the Cholesky factorization of the error variance-covariance matrix using matrix P which gives $PP' = \Sigma_\varepsilon$ (See Lütkepohl, 2005).

Using the matrix P^{-1}, we can construct Nx1 vector of u_t as follows:

$u_t = P^{-1}\varepsilon_t$ which implies $\varepsilon_t = Pu_t$.

By construction, the variance of the error terms $\Sigma_u = E(u_t u_t') = [P^{-1}]E(\varepsilon_t \varepsilon_t')[P^{-1}]' = I$ is an identity matrix. Thus the error terms u_t are mutually uncorrelated. The VMA representation given by (4) can be re-written as follows:

$$(5) \quad y_t = \sum_{l=0}^{\infty} \Phi_l P u_{t-l}$$

$$= \sum_{l=0}^{\infty} \Theta_l u_{t-l}$$

where $\Theta_l = \Phi_l P$.

Components of the modified error term u_t are uncorrelated since the covariance of the error terms is zero. The rnth elements of Θ_l give effects of orthogonalized shocks in the innovations of variable *n* on variable *r* after time j. Since the variance-covariance matrix of the error terms Σ_u is an identity matrix, the the error terms have unit variances. A unit shock in the levels of the transformed error term is thus equivalent to a unit shock in the standard deviation of the untransformed error terms. Therefore elements of Θ_l give impulse responses for orthogonalized shock of one standard deviations ($\Theta_{l=} \, {\partial y_{t+l}}/{\partial se(v_t)}$).

To show the effect of decomposing the error terms in the VAR representation, it is more convenient to take the following triangular factorization of the original error term ε_t: $\Sigma_\varepsilon = PP' = W\Sigma_v W'$, where $\mathrm{W} := P\,D^{-1}$. The covariance matrix $\Sigma_v = DD'$ is a diagonal matrix with positive elements on the main diagonal.

Pre-multiplying Equation (1) with W^{-1}, we get the corresponding VAR representation:

(6) $$W^{-1}y_t = A_L^* y_{t-1} + \cdots + A_L^* y_{t-L} + v_t$$

where $A_l^* = W^{-1}\mathrm{A}_l$ and $v_t = \mathrm{W}^{-1}\varepsilon_t$

Solving for y_t, we get

$$y_t = WA_L^* y_{t-1} + \cdots + WA_L^* y_{t-L} + Wv_t$$

Since $W = \mathrm{P}D^{-1}$, substitution gives us:

$$y_t = \mathrm{P}D^{-1}A_L^* y_{t-1} + \cdots + \mathrm{P}D^{-1}A_L^* y_{t-L} + \mathrm{P}D^{-1}v_t$$

$$y_t = B_1 y_{t-1} + \cdots + B_2 y_{t-L} + \varepsilon_t$$

Thus the instantaneous effect on y_t of a unit shock in v_t is $\mathrm{P}D^{-1}$. Noting that D is a diagonal matrix with the standard deviations of v_t on its main diagonal, the instantaneous effect of a one standard deviation increase of v_t is given by $(\mathrm{P}D^{-1})D = P = \Theta_0$. If some of the off-diagonal elements of P are non-zero, the same will be true of Θ_0. Unlike in the reduced VAR of Equation (1), instantaneous shocks of innovations in one variable could have non-zero effect on another variable in this structural VAR. If (6) is VAR(1) process, the impulse response matrix could be given by $\Theta_l = B_i^l$ so that $\Theta_1 = B_1$; $\Theta_2 = B_1^2$ etc.

Equation 6 thus shows that decomposing the error term into uncorrelated terms is done by pre-multiplying the left hand term with W^{-1}. Let $A_0 = W^{-1} = P^{-1}D$. Since P is lower triangular and D is diagonal, A_0 as well as its inverse W are lower triangular.

We consider the following VAR(1) process in which the variables relevant for our analysis as well as individual and time effects are explicitly mentioned while firm identifiers are also used:

(7) $$A_0 \begin{bmatrix} MPK_{it} \\ CFK_{it} \\ IK_{it} \end{bmatrix} = A_1^* \begin{bmatrix} MPK_{it-1} \\ CFK_{it-1} \\ IK_{it-1} \end{bmatrix} + \begin{bmatrix} \eta_i^1 \\ \eta_i^2 \\ \eta_i^3 \end{bmatrix} + \begin{bmatrix} \lambda_t^1 \\ \lambda_t^2 \\ \lambda_t^3 \end{bmatrix} + \begin{bmatrix} v_{it}^1 \\ v_{it}^2 \\ v_{it}^3 \end{bmatrix}.$$

where MPK is the marginal product of capital, CFK is cash flow- capital ratio, and IK is the rate of investment, and η_i and λ_t are the individual- and year-effects.

Pre-multiplication by A_0 as in (7) is equivalent to assuming a recursive ordering of the variables in the VAR. We assume that all of the elements of A_0 below the diagonal are non-zero:

$$A_0 = \begin{pmatrix} \alpha_{11} & 0 & 0 \\ -\alpha_{21} & \alpha_{22} & 0 \\ -\alpha_{31} & -\alpha_{32} & \alpha_{33} \end{pmatrix}$$

The diagonal elements of A_0 are positive because they are the variances of the error terms.

The recursive ordering implied by A_0 assumes that some variables depend on the current values of others but not all of them. From the recursive matrix structure above, the variables have the following order (1) the marginal product of capital (2) cash flow and (3) investment rate. Thus current values of cash flow and the marginal product of capital affect the rate of investment, but not vice versa. The assumption that investment affects the marginal product of capital and cash flow only with a lag is motivated by the widespread empirical evidence that new investments take time to be operational due to time lags for installing and commissioning physical assets. Similarly, current values of the marginal product of capital affect cash flow, but the opposite is not true. The marginal product of capital affects cash flow contemporaneously because high marginal productivity is likely to translate to high cash flow. The marginal product of capital, on the other hand, is not to contemporaneously affected by any of the other two variables. This can be justified by the fact that, since sales are largely demand driven, they are less likely to be affected by current values in the system than outside it.

Therefore, the innovations of the last variable, IK, have instantaneous effect on all variables, whereas those of the second, CFK, can have instantaneous affect only on itself and on MPK. Since MPK is the first variable, a shock on its innovation has no instantaneous effect on any of the variables other than itself.

2.2 Variance Decomposition

The VMA representation given by Equation 5 is used to forecast outcomes of a shock in the error terms of variables in the system. In many instances, decomposing the variance of the forecast error can give useful insights regarding the relative importance of shocks of different variables. In our investment model this approach is useful to compare the contributions of shocks between MPK and CFK in the forecast error of investment rate (IK). In addition, variance decomposition helps us compare the contributions of cash flow to the forecast errors of investment between small and large plants, and between private plants and SOEs.

If $y_t(h)$ is the optimal h-time ahead forecast of y, and y_{t+h} are the realized values, the prediction error is given as follows:

$$(8)\ \ y_{t+h} - y_t(h) = \sum_{l=0}^{h-1} \Theta_l u_{t-l}$$

If y_j is one of the N variables in the system, and $\theta_{jn,l}$ is the jnth element of the matrix Θ_l, the forecast error of y_j for period h is given by the summation of θu across all variables and time periods until h-1:

$$(9)\ \ y_{j,t+h} - y_{j,t}(h) = \sum_{n=1}^{N} \sum_{l=0}^{h-1} \left(\theta_{jn,l} u_{t-l}\right)$$

The fact that u_t are uncorrelated and with unit variances allows us to write the mean square error of the prediction as a function of θ.

(10) $\left(y_{j,t+h} - y_{j,t}(h)\right)^2 = \sum_{n=1}^{N}\sum_{l=0}^{h-1}\left(\theta_{jn,l}\right)^2 = \sum_{n=1}^{N}\omega_{jn}$ where $\omega_{jn} = \sum_{l=0}^{h-1}\left(\theta_{jn,l}\right)^2$

Therefore, the total mean square forecast error of variable y_j can be decomposed into the sum of the contributions of other variables. The value of ω_{jn} measures the contribution of variable j, and expressing it as percentage of the total mean square error, we get the proportional contribution of this variable. This provides useful information on the relative magnitude of the accumulated effects of a shock in one variable over another.

2.3 Estimation

We proceed to estimate the reduced form Equation (1) and then use the Cholesky decomposition of the variance-covariance matrix of the error terms to find matrix A_0. Since all explanatory variables are potentially correlated with the unobserved individual effect η_i, a consistent estimator for the coefficients can be found only using deviations from individual means.

It is well known that the standard fixed effects estimator introduces endogeneity into the error terms of dynamic models. Alternatively, the first differences estimator can be used, though this approach could have poor precision when individual heterogeneity is large (Blundell and Bond, 1998). In this paper, I remove the individual effects using Helmert transformation procedure which is a convenient approach when the variables in the model are pre-determined (See Arellano and Bover, 1995). When the variables are pre-determined, a shock in error terms v_{it} can not affect current (and past) values of the variables, although it could affect their future values (i.e. $E(v_t|y_{it}, \eta_i, \lambda_t, v_{it}) = 0$). This allows to apply Helmert transformation which removes the individual effects from data at time t by deducting the individual average for all subsequent periods t+1, t+2… T.

If v_{it} are serially uncorrelated and have constant variance, the Helmert transformed error terms will also have the same properties, thus keeping the orthogonality condition intact.[2] In dynamic models like Equation 1, however, the transformation leads to correlation between the error terms and the lagged dependent variables, thus requiring instrumental variable estimation.[3]

Once time and fixed effects are removed prior to estimation, the coefficients are estimated as a system using the GMM procedure of Arellano and Bover (1995). Following the standard approach in the investment literature (Gilchrist and Himmelberg, 1995; Love and Zicchino, 2006; Gelos and Werner,

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[2] Specifically, Helmert transformation produces deviations from forward means as follows: $\mathrm{y}_{\mathrm{it}}^{*} = \mathrm{y}_{\mathrm{t}} - \mathrm{c}_{\mathrm{t}}\left[\frac{1}{\mathrm{T-t}}(\mathrm{y}_{\mathrm{t+1}} + \cdots + y_{\mathrm{T}})\right]$ for t = 1, 2, … , T-1. This transformation cannot be calculated for the last year of data for each firm since forward means are not available for them. The weighting term $\mathrm{c}_{\mathrm{t}} = \sqrt{(T-t)/(T-t+1)}$ corrects for differences in variances introduced by using different number of observations for calculating forward means in different time periods.

[3] Note that the transformed dependent variable y_{it}^{*} is forward differenced using averages of $y_{t+1} \ldots y_T$ and its lag using averages of y_t, $y_{t+1} \ldots y_T$. Since values of $y_{t+1} \ldots y_T$ are used for transforming both the dependent variable and its lag, there will be endogeneity in the error term (i.e. the transformed error term v_{it}^{*} will be correlated with the transformed explanatory variable y_{it-1}^{*} since, due to the transformation, both depend on $v_{t+1} \ldots v_T$.) If Y_t is predetermined, the untransformed levels of y_{t-1} as well as its lags can be used as instruments for y_{it-1}^{*}.

2002), I assume that all variables in the model are pre-determined so that Helmert transformed explanatory variables are instrumented with their own untransformed values in levels.[4] Although the lags of the levels could also be used as instruments, I use only current values since the levels instruments have strong autocorrelation with the Helmert transformed explanatory variables (The R-square values of the first stage regressions range between 30-80%, showing that the instruments explain a large portion of the total variation). Since the error terms of the reduced model are correlated with each other when the structural VAR is recursive structure as in Equation (7), the model is estimated as a system to get more efficient estimates. Equation by equation GMM (2sls) would also give the same results as system GMM since the model is just identified.

To test the significance of the impulse responses, 95% confidence interval is generated for the coefficients using Monte-Carlo simulations (see Love and Zicchino, 2006). The simulations are conducted using repeated, random draws of the coefficients of the VAR model with replacement, which are used to re-calculate the impulse responses. The 5th and 95th percentiles of the generated impulse responses from 1000 draws are then used to construct the confidence interval bands.

3. Data and Measurement

3.1 Data description

The analysis in this article is based on the Ethiopian Manufacturing Establishments Survey dataset, which is a census-based survey dataset that covers all manufacturing establishments in Ethiopia with at least 10 employees.[5] The data is collected by the Central Statistics Agency of Ethiopia and, is very structured and contains detailed information on production, sales and other variables. Below is a description of the coverage of the dataset and the measurement of variables.

Data is available for the 15 years from 1996-2010, and the number of observations ranges from below 700 in earlier years to around 2000 in the last year. After dropping missing observations as well as the top and bottom percentiles of MPK, CFK and IK, which are likely to have been measured with error, 14,400 valid observations remain in the dataset. Since some observations appear only for one year, the final data used for analysis consists of 12,300 observations for 2,275 firms (each firm appearing for an average of 5.4 years). The Helmert transformation for removing individual effects leads to loss the last year of data for each firm. This leaves us with about 10,000 observations for the final analysis. However, a large number of firms appear for two or three years, mainly because the dataset includes many new observations in the last years due to the growth in the sector. In addition, many firms appear and

[4] That is, I use the moment condition that $\mathrm{E}(\mathrm{v}_{\mathrm{it}}^{*}|y_{it}) = 0$ to use y_{it-1} as an instrument for its transformed value $\mathrm{y}_{\mathrm{it-1}}^{*}$. The model could also be estimated under a more restrictive assumption that all variables are endogenous so that they are correlated with current error terms. In this case we can use all lags of y_{it} as instruments using the moment conditions that $\mathrm{E}(\mathrm{v}_{\mathrm{it}}^{*}|y_{it-s}) = 0$ for s >0. This however requires the use of more than one lags of y_{it} to compensate for the fact that lags could be poor predictors of current levels, which can introduce finite sample bias.

[5] However, the dataset also includes a large number of observations with fewer than 10 employees due to firms which had employed 10 or more employees during entry, but shrank in size in subsequent years while still staying in the census.

disappear in consecutive years, making the dataset very unbalanced and with many gaps. Due to the resulting missing lag variables, the number of valid observations that can be used in a VAR(1) model falls to less than 7000.

The census uses ISIC classifications to identify the industrial group of firms. It includes all industrial groups classified under manufacturing in the classification ISIC 3rd revision. Appendix 1 shows the number of observations by 2 digit industrial group for the cleaned dataset. The most important industry with regard to both the number of firms and total sales is the food products and beverages industry (ISIC code 15). This industry contributes to nearly 30% of all observations and 40% of total sales in the manufacturing sector.

3.2 Measurement of variables

Three key variables are used for the analysis in this paper: the Investment rate (IK), the cash flow- capital stock ratio (CFK) and the marginal profit of capital (MPK). IK is calculated as net investment, defined as total expenditure on capital items less income from sale of capital items, divided by the beginning year capital stock. CFK is calculated as cash flow, defined as profits after interest and total tax payments plus benefits and subsidies, divided by capital stock at beginning of year.

In order to measure the marginal profit of capital, it is necessary to make assumptions regarding the technology and the demand curve the firm faces. I assume firms operate in an imperfectly competitive output market, and thus face a negative sloped demand curve. Assuming Cobb-Douglas technology, the marginal profitability of fixed capital is given by

$$(11) \quad MPK = \frac{\partial \pi}{\partial k} = (1 + \sigma^{-1})\alpha_k \frac{py}{k}$$

where $\sigma = (\partial q/\partial p)p/q < -1$ is the price elasticity of demand; α_k is the output elasticity of capital; and py is sales (See Gilchrist and Himmelberg, 1998).

If the elasticity of demand and the output elasticity of capital are constant, the marginal product of capital is proportional with the sales to capital ratio. However, it is unreasonable to assume that these parameters are the same across industries. Thus, I calculate MPK using industry specific parameters.

Rewriting (11), we get

$$(12) \quad MPK = \frac{\alpha_k}{u}\frac{py}{k}$$

where $u = \sigma/(\sigma + 1)$ is the mark up term. I estimate a production function at industry level to identify the output elasticity of capital.[6] Having derived the returns to scale parameter from the production

[6] The production function includes four inputs: capital, labor, energy and raw materials. Output is measured with total revenues deflated with Laspyres-type fixed-weight price indices that measure price changes at firm-level. Labor is measured with employment, and capital with capital stock in constant prices. Energy and materials are measured with energy and material costs deflated with Laspyres-type fixed-weight price indices for energy and materials respectively. The regression estimated applies frontier regression technique to isolate positive values of

function, I compute the mark up using the relationship that the mark-up to return to scale ratio is equal to the revenue-cost ratio (Basu and Fernald, 1995):

$$(13) \quad u = \gamma(Revenues/Costs),$$

where γ is the returns to scale of the technology in the industry, and revenue and costs are aggregate industry-level revenues and costs.[7] Since revenues and costs are aggregated for each year, mark-ups vary across time.

Equation 2 needs one final correction. Apart from technology and demand differences, corporate tax rates could also vary across different industries due to varying tax privileges. I thus correct the marginal profit of capital using the average industry-level corporate tax rate τ:

$$(14) \quad MPK = (1-\tau)\frac{\alpha_k}{u}\frac{py}{k} .$$

The industry-level corporate tax rate is calculated as the average of the income tax payment rate reported by establishments.[8] As shown in Table 1, there is large difference in the correction parameters across industries.

Table 1: Industry-level MPK correction parameters

ISIC	Obs	Correction term $(1-\tau)\,\alpha_k/u$	Corp tax rate (τ)	Capital elas. (α_k)	Mark-up (u)	Ret Scale (γ)
15&16	3529	0.121	0.099	0.300	2.259	1.468
17	447	0.046	0.093	0.058	1.142	1.030
18	361	0.061	0.058	0.097	1.504	1.328
19	794	0.152	0.075	0.236	1.441	1.309
20	268	0.081	0.146	0.120	1.282	0.884
21	139	0.170	0.123	0.305	1.597	1.235
22	829	0.152	0.154	0.305	1.698	1.235
24	647	0.053	0.137	0.092	1.513	1.189
25	637	0.210	0.087	0.328	1.436	1.109
26	1696	0.033	0.188	0.066	1.685	1.137
27	140	0.319	0.115	0.569	1.583	1.256
28	744	0.058	0.106	0.124	1.907	1.548
29&34	242	0.074	0.137	0.107	1.252	1.041
36	1837	0.078	0.090	0.120	1.410	1.124

efficiency from zero-meaned error terms in the total residual of the production function assuming constant efficiency over time.

[7] Total costs include costs for labor, materials, energy, other services and the flow of capital services. Flow of capital services is calculated for each firm using the standard Jorgensenian approach by summing up the services from different asset type which are imputed as a product of the user cost and the capital stock. The user cost is calculated by assuming asset-specific depreciation rates and a constant rate of return of 6%.

[8] It is also possible to use establishment level corporate tax rate, but this is impractical due to the large number of firms reporting negative profits (about 25% of the total). Furthermore, there are no grounds to expect that firms in the same industry pay different tax rates.

3.3 Descriptive statistics

Table 2 provides summary statistics of key variables for the whole sample as well as different subsamples used in the analysis. The first two rows summarize the subsample of small and large firms. Firms are classified as small or large based on the level of capital stock, since size in our context is taken as a proxy for net worth. I classify establishments as small when their capital stock in 1996 prices is less than 500,000 Birr (equivalent to 79,000 USD at the exchange rate of that year). Accordingly, slightly more than half (54%) of all observations are classified small.[9] As shown in Table 2, small firms have an average employment of just 24 persons (and a median employment of 16 persons) compared to large firms which have an average employment of 214 persons (and a median employment of 71 workers). The difference between the two subsamples seems even more pronounced when we compare their capital stock: the average and median values indicate that the capital stock of large firms is 30-100 times as large as that of small firms.

The two subsamples also differ substantially in terms of their marginal product of capital (MPK), their cash flow (CFK) and investment rates (IK). Small firms appear to have much larger marginal product of capital and cash flow, but significantly smaller investment rates. Previous studies also reported that financially constrained firms have higher marginal products and cash flow.[10] The high marginal product could suggest inability to invest and lower their marginal products. Given the strong correlation between them, the high cash flow ratio of these firms could reflect their high MPK. The last column of Table 2 shows that 31% of small firms report shortage of working capital as one of their top challenges, which is somewhat higher than the 28% response among large firms.

Type of ownership is the second criteria used for classifying the level of financial constraints firms face. With 1,779 observations and 226 firms, state owned enterprises (SOEs) constitute only 14.5% of our sample. The Table also reveals that SOEs are much larger than private establishments. In contrast to what the size comparison revealed, private firms which we expect to be more financially constrained, have significantly lower values of MPK and slightly lower values of CFK than SOEs. Their rate of investment, however, is not different from that of SOEs. The last column suggests that private firms face more working capital shortages than SOEs.

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[9] Employment refers to number of all workers including full-time equivalent of temporary workers. As is typical among developing countries, most firms in our sample are very small in size, with median employment of just 20 workers. More than 64% of the establishments in the dataset employ 50 or fewer workers.

[10] Devereux and Schiantarelli (1990) and Guariglia *et al*.(2011) find that firms that are likely to be financially constrained (younger and smaller firms in the first case; private firms in the second case) seemed to have higher cash flow and marginal products. Similarly, Schaller (1993) reports that younger firms, although more financially constrained, have higher cash flow as well as larger values of Tobin's q. Similarly, Fazzari *et al*.(1988) also report that firms that are likely to be financially constrained (from their low dividend payout ratio) have larger values of cash flow and Tobin's q.

Table 2: Summary statistics

		Obs	Employment	Capital Stock	MPK	CFK	IK	Work. Cap. Const.
Size	Small	5,604	24(16)	144(94)	0.663(0.252)	1.821(0.371)	0.108(0)	31
	Large	6,648	214(71)	14,400(3,554)	0.372(0.16)	0.385(0.156)	0.152(0.011)	28
Ownership	Private	10,531	66(24)	5,347(467)	0.484(0.184)	1.045(0.204)	0.132(0)	30
	SOE	1,779	483(263)	22,900(5,679)	0.632(0.295)	1.093(0.38)	0.131(0.024)	26
No of Units	Single	11,502	121(28)	7,484(587)	0.508(0.196)	1.07(0.22)	0.131(0)	29
	Multiple	808	203(67)	13,600(2,647)	0.479(0.204)	0.794(0.244)	0.137(0.003)	30
Exp. Status	Non-exporting	11,705	103(28)	6,460(572)	0.505(0.194)	1.071(0.224)	0.13(0)	29
	Exporting	605	595(291)	35,400(11,600)	0.512(0.275)	0.671(0.164)	0.16(0.034)	27
Total		12,302	127(30)	7,890(661)	0.506(0.197)	1.052(0.222)	0.132(0)	29

Notes: The numbers in brackets indicate median values. Capital is measured in thousands of Birr in 1996 price. MPK is calculated using Equation (14) with beginning of year capital stock. CFK and IK are calculated as ratios of net investment and net profits, respectively, to beginning of year capital stock. The last column gives the percentage of firms that reported shortage of working capital is one of their top 3 difficulties. The median values are not given for this variable because in all subsamples its value is zero. Firms are classified as multiple units when they have more than one plant within the country our are branches of foreign firms.

Table 2 provides summary statistics for subsamples classified based on two additional criteria that are likely to affect firms' financial access. These are whether or not the establishment belongs to a multiple unit firm, and its exporting status.[11] Studies have shown that firms belonging to a larger business group can be less financially constrained. Among other reasons, this is because firm groups create a mechanism of pooling and allocating funds across establishments. In addition belonging to multiple plant firms can increase creditworthiness and facilitate bank financing. In developing countries, public banks also try to encourage exporting by facilitating financing for firms engaged in exporting.

Table 2 reveals that the number of plants belonging to multiple unit firms (including foreign establishments) is very small, consisting of just 300 firms or 800 observations. In conformity with the previous results, single unit plants that are likely to be financially constrained have significantly higher values of MPK and CFK, and marginally lower values of investment.

The last rows of the Table also indicate that the number of establishments that engage in exporting is extremely small (158 firms). Non-exporting firms, which we expect to be discriminated against by (public) banks, have almost equal MPK as non-exporting firms. However, they have significantly higher cash flow and somewhat smaller investment rate.

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[11] In general, there is strong evidence that membership to business groups, can reduce the sensitivity of investment for cash flow. A more commonly studied aspect of business groups in the literature is the financing advantage firms belonging to some business groups gain in certain Asian countries such as *keitsu* membership in Japan, and *chaebol* membership in Korea Koo and Maeng, 2005).

From the last row of Table 2, the average rate of investment for the whole sample is 13%. This is only marginally higher than the replacement rate of investment which is could be as high as 10%. The median investment rate is zero since only 45% of the observations report positive investment. Although not apparent from Table 2, about a quarter of all observations also report negative net profit. The average cash flow ratio of 1.1 thus masks the huge disparity among firms in terms of profitability, as can be seen from the much lower median value of 22%.

4. Results

4.1 Full sample results

I estimate the VAR(1) model because it maximizes use of available data while also providing reasonably robust results that are similar to those with higher order processes. A VAR of order 1 has also been found to be a reasonable representation of investment models estimated on short panel datasets in previous studies (Love and Zicchino, 2006).

Table 3 provides the regression results for the full sample. The first column gives the coefficients for the first model in the system where MPK is the dependent variable. The results show that lagged values of MPK are important predicators of its current value, with a strong positive effect. Lagged values of investment have also a significant negative effect, but the effect of cash flow is insignificant. The last two columns reveal that lagged values of CFK and IK are the only significant predictors of their current values.

Table 3: Three equation VAR(1) regression results for the full sample

	Dependent variables		
	(1)	(2)	(3)
	MPK(t)	CFK(t)	IK(t)
MPK(t-1)	0.478***	-0.038	0.010
	(0.058)	(0.198)	(0.019)
CFK(t-1)	-0.007	0.138***	0.003
	(0.007)	(0.039)	(0.003)
IK(t-1)	-0.124***	-0.003	0.043***
	(0.021)	(0.081)	(0.012)
Obs	6,829	6,829	6,829

Notes: Each column gives the results for separate regressions in the system, where the dependent variables are MPK, CFK and IK respectively. Robust standard errors are given in parenthesis. Definition of variables is reported in Table 2.

The neoclassical investment model indicates that MPK, being the fundamental determinant of investment, should be a sufficient statistics to explain investment, whereas recent models with market imperfection suggest a role for financial variables. None of these positions seem to hold from the VAR regression results, since both MPK and CFK have insignificant coefficients in the investment model. However, an important prediction of models with imperfect capital markets is that the relevance of financial factors could be heterogeneous across firms. This is the reason why it is often deemed necessary to split the sample into groups of firms that are likely to face different levels of financial constraints. Splitting the sample allows us to see if investment among certain classes of firms displays 'excess sensitivity' to cash flow compared to classes of firms. For this reason, the next sub-section will give results by splitting the sample in sample into groups of firms that are expected to face different levels of financial constraints.

The coefficients of the VAR regressions are difficult to interpret because a change in one of the variables is likely to induce changes in others. As discussed in the methodology section, impulse response analysis provides a useful way of addressing this by orthogonlazing the error terms so that a change in the innovations of one variable will not affect variables in other equations. Figure 1 gives results of the orthogonalized impulse responses as well as the bootstrap confidence intervals using the full sample in the dataset.

Firstly, all of the impulse response graphs show that the responses to a onetime shock in the innovations go to zero as time increases, showing that the VAR is stable and stationary. The first panel of the graph depicts the response of MPK to one standard deviation shocks in the errors of MPK, CFK and IK. MPK responds positively for a shock in its own innovation. But its responses for shocks in the innovations of CFK and IK are negative, though it is significant only for the later. Thus positive investment elicits a significant fall in MPK, which is in line with law of diminishing marginal returns.

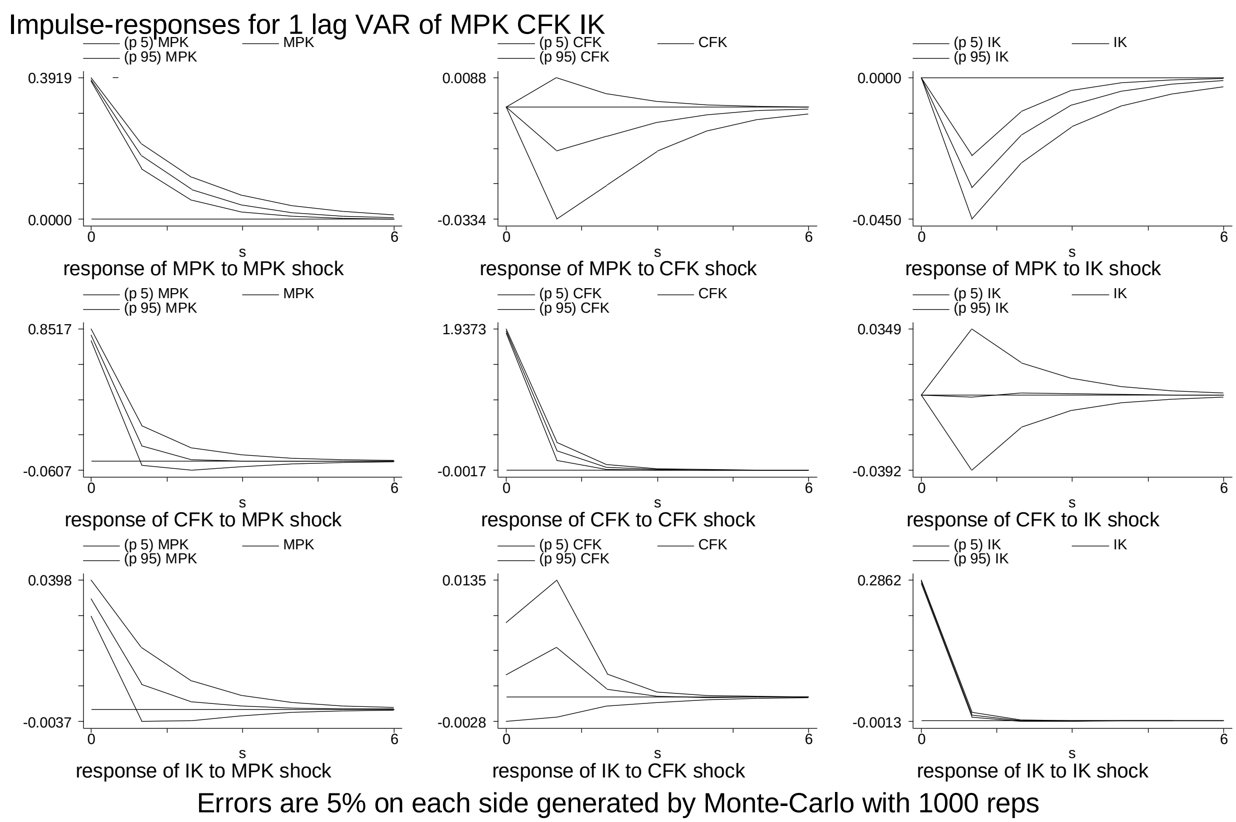

Figure 1: Orthogonalized impulse-responses for VAR(1) using the full sample

As is seen from the second panel, CFK responds positively to shocks in its own innovations and those of MPK. But the response is large and significant only for one period, after which it fades away. CFK shows a very small and insignificant response to a shock in investment. The last panel reveals that investment responds positively to orthogonalized shocks in the innovations of MPK and CFK, suggesting that both fundamental and financial factors play a role. However, its response for CFK shocks is much smaller than that at of MPK, and the effect is not significant. The effects of both MPK and CFK shocks drop off to zero after maximum of two periods. Investment also seems to have strong path dependence, with past shocks having a very strong positive effect on current investment. The fact that the lag of investment is the best predictor of current investment rather than cash flow of MPK has also been documented in previous studies (Eberly *et al*., 2011).

The variance decompositions for the 10 year ahead forecasts of each variable, given in Table 4, indicate the contribution of each variable in the system in the of mean square forecast error of other variables. It appears that a significantly large percentage of the total forecast mean square error for each variable is explained by shocks in its own innovations.

Table 4: Variance decomposition for 10-year-ahead forecasts, full sample

	MPK	CFK	IK
MPK	0.99	0.153	0.015
CFK	0.001	0.847	0.000
IK	0.009	0.000	0.985

Note: Values of each column show the percentage of variation in the column variable explained by shocks of the row variable.

4.2 Results by size and ownership

While the results for the full sample discussed above could be informative, they are likely to suffer from misspecification problems since they fail to handle the potential heterogeneity among firms. Since the effect of both MPK and CFK on investment could vary across firms with different levels of financial constraints, it is instrumental re-estimate the model by splitting the sample accordingly. Table 5 reports the VAR(1) regression results for different size and ownership subsamples of firms. Although all the three variables are included in the VAR, only the regression results for IK are reported to conserve space.

The results from the investment equation indicate different roles form MPK and CFK across subsamples. Conditional on CFK and IK, MPK seems to have a negative effect among small firms, buts its effect is strong and positive among large firms. In contrast, CFK has a strong positive effect among small firms, whereas its effect is zero among large firms. This supports the hypothesis that investment is more sensitive for cash flow among small plants. In both subsamples, lags of investment have significant positive effect on current investment. Comparing SOEs and private establishments leads to similar conclusions. MPK has a strong positive effect on investment among publicly owned firms, but CFK is much more important among private firms. Again, this is supportive of the hypothesis that investment is sensitive to cash flow among private firms due to the financial constraints they face.

Table 5: Regression results for the investment equation using subsamples classified by size and ownership.

	Dependent variable: IK(t)			
	(1)	(2)	(3)	(4)
	Small	Large	Private	SOE
MPK(t-1)	-0.073***	0.089***	-0.03	0.081**
	(0.028)	(0.030)	(0.025)	(0.032)
CFK(t-1)	0.012***	-0.001	0.008**	0.001
	(0.004)	(0.005)	(0.004)	(0.002)
IK(t-1)	0.041***	0.092***	0.047***	0.093**
	(0.016)	(0.024)	(0.013)	(0.045)
Obs	2,390	2,787	5,412	1,328

Figures 2a and 2b give the orthogonalized impulse responses for the subsamples of small and large establishments respectively. In both samples, all impulse responses lapse to zero as time goes, indicating the stationarity of the processes. The most important part of our analysis lies in the third panel of both graphs where the responses of investment are given. IK responds for CFK shocks in very different ways between the two samples. Among small firms, a one standard deviation shock in CFK elicits zero investment response contemporaneously, but positive and significant responses of 0.023 and 0.006 respectively in the first and second years, before returning to zero in the third year. In contrast, a shock of CFK among large firms elicits an insignificant response of 0.009 on IK contemporaneously, and it elicits zero responses during and after the first year.

The responses for the shocks in MPK are equally different between the two subsamples. Among small firms, IK responds contemporaneously by a very large amount (0.057) for a one standard deviation shock of MPK. After one year, the response is a much smaller negative and significant amount (-0.03), and this effect approaches zero from the third year onwards. Among large firms, on the other hand, MPK elicits a large and significant response (0.025) on IK in the current and in the first years, which falls slowly until it vanishes in the fourth year. Overall, these results suggest that small firms are very sensitive to the availability of cash for investment financing, whereas marginal profitability plays a much bigger role among large firms.

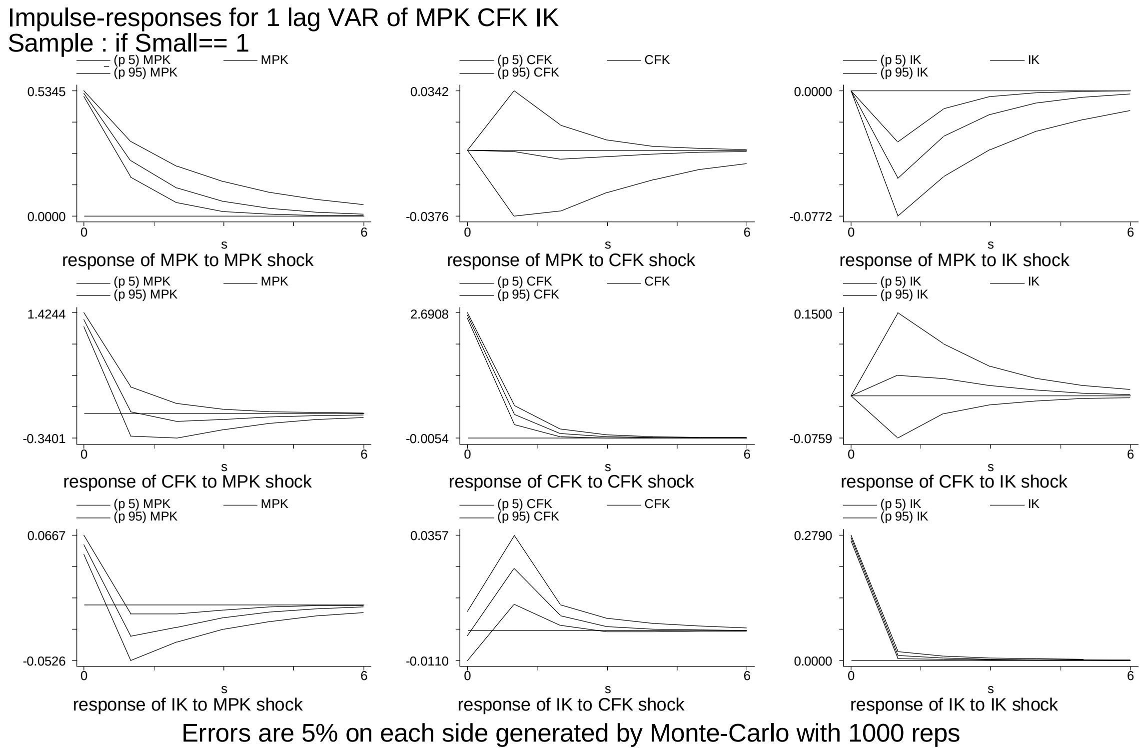

Fig 2a: Orthogonalized impulse responses for small firms.

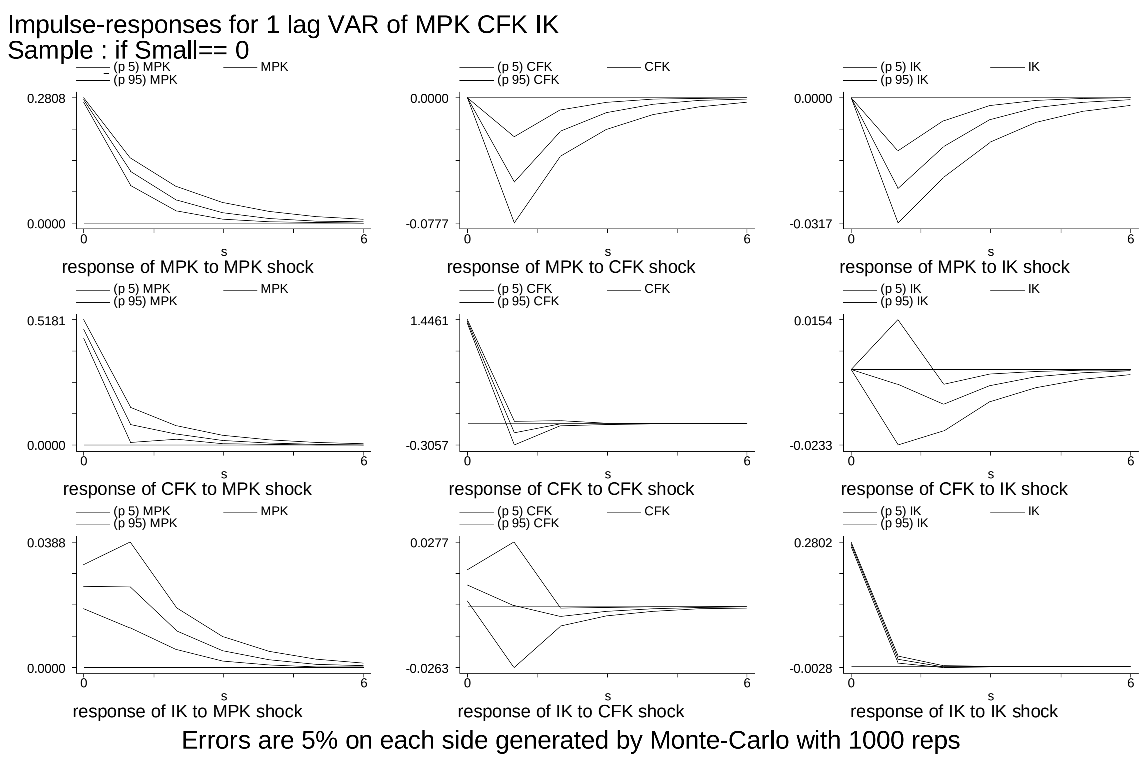

Fig 2b: Orthogonalized impulse responses for large firms.

The first panels of Figure 2a and 2b report how MPK responds to shocks on the innovations of the variables in the system. Both pictures reveal results that are in general the same as for the whole sample. MPK responds positively to its own shock, and negatively to investment shocks. The response of MPK to CFK shocks vary between the two subsamples: whereas CFK elicits no response on MPK among small firms, it has a negative effect among large firms. The responses of CFK are depicted in the second panel of both figures. For both subsamples, CFK responds positively to shocks in MPK and its own innovations. These effects last for a maximum of two years. However, the effects of IK shocks on CFK are not significant in both subsamples.

Comparisons between the impulse response of private firms and SOEs also confirm the hypothesis that investment among private firms is more sensitive to cash flow. As is seen in the third panel of Figure 3a, investment responds positively and significantly for cash flow shocks among private firms in the current period, as well as after 1 and 2 years with values of 0.003, 0.013 and 0.003, respectively. However, as Figure 3b shows, the response of IK for CFK shocks for the same periods among SOEs are insignificant and smaller values of 0.003, 0.002 and 0.002 respectively. On the other hand, while investment among private firms responds positively only contemporaneously for MPK shocks, the response of investment among SOEs is positive and more persistent lasting for more than four years. This confirms that financially constrained private firms respond more to cash flow than to marginal product shocks, whereas the opposite is true for less financially constrained SOEs.

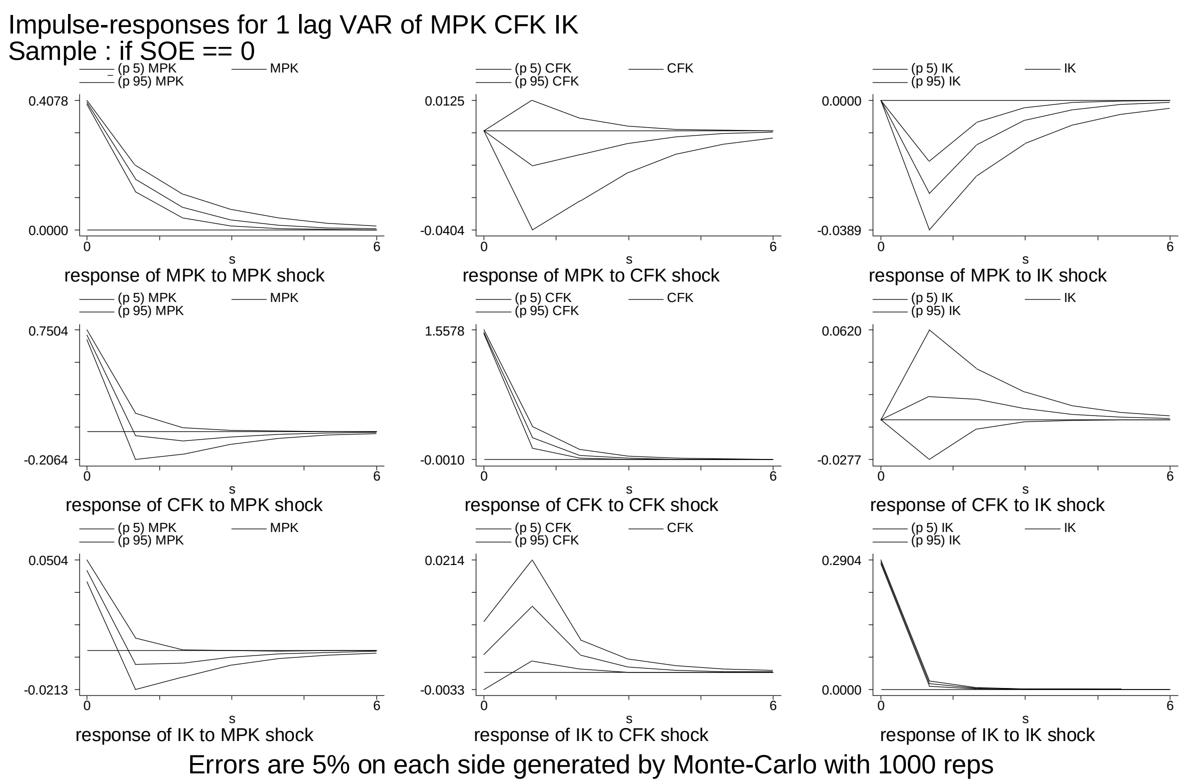

Fig 3a: Orthogonalized impulse responses for private firms.

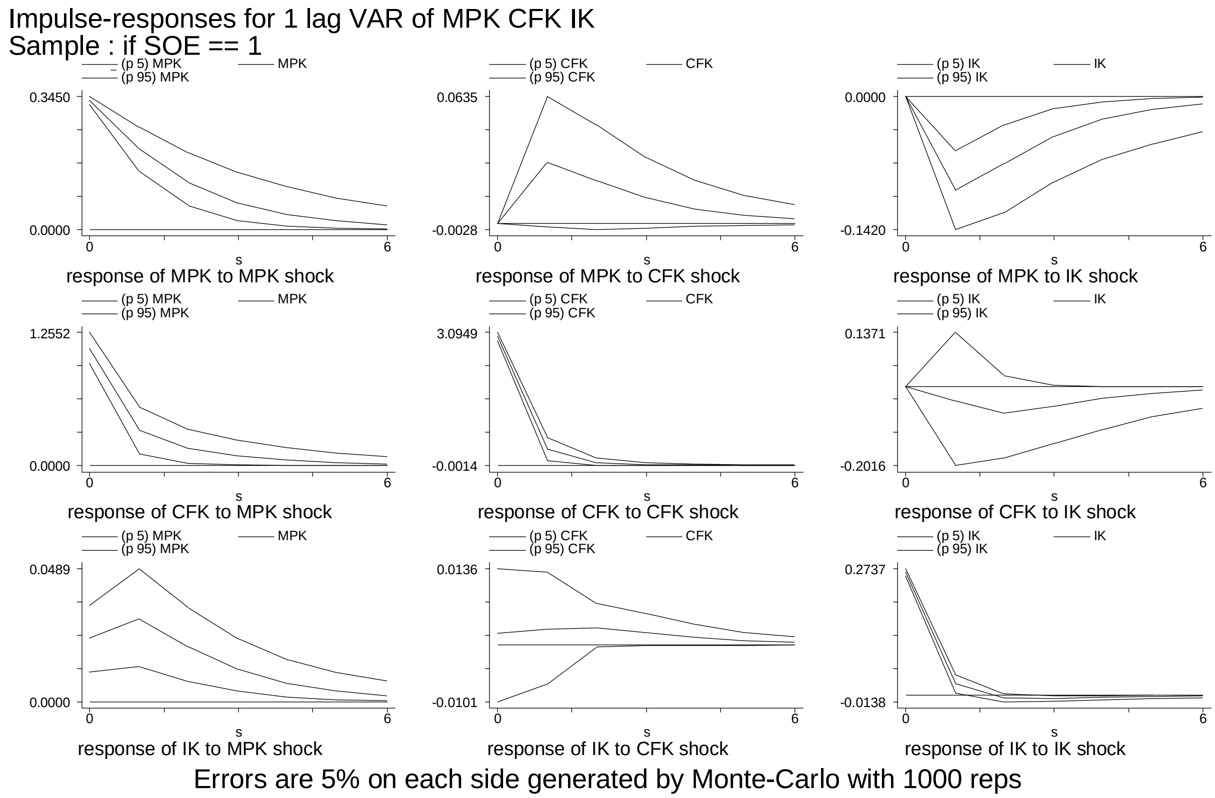

Fig 3b: Orthogonalized impulse responses for state-owned enterprises (SOEs).

As highlighted in Table 2, the level of financial constraints of a plant can also depend on factors such as whether or not it belongs to multiple units, and whether or not it engages in exporting. Therefore, these aspects can serve as alternative criteria for splitting the sample to compare their sensitivity to cash flow. Unfortunately, the number of multiple unit establishments and exporting firms in the sample is too small to allow meaningful comparison across samples. Instead of creating separate subsamples based on these criteria, I combine them with type of ownership to classify the sample into two classes. The first class of establishments comprises potentially financially constrained plants that fulfill all the three conditions of being: i) privately owned ii) single unit and iii) non-exporting. About 1,950 observations (360 firms) are used in the VAR model for this subsample. The second class consists of all remaining plants that are either state owned enterprises (SOEs), part of multiple unit plants, or plants that engage in exporting. The sample size of this group is about 4,650 observations (1,380 firms).

To conserve space, Figure 4 reports only the impulse response of IK for CFK shocks, which is the most relevant part for the comparison between the two subsamples. The most apparent difference between the two graphs is that the responses are significant only for the first class of firms (i.e. single unit, non-exporting, private firms). The size of the responses is also substantially different between the two subsamples. Contemporaneously, CFK shocks have more or less the same effect of about 0.005 in both subsamples. One year later, however, this shock elicits a response of 0.016 among the first class of firms whereas its effect is almost zero among the second class. The effect declines sharply in the second year, although its size is still relatively larger among more financially constrained private, single unit, non-exporting plants. The excess sensitivity to cash flow among this group of firms is also somewhat larger than that of private firms only (i.e. those reported in Figure 3a). The response of IK one year after the CFK shock, for example, is 0.013 among privately owned firms, compared to 0.016 among privately owned, single unit non-exporting firms. This suggests the later classification is more refined at grouping firms based on their financial constraints.

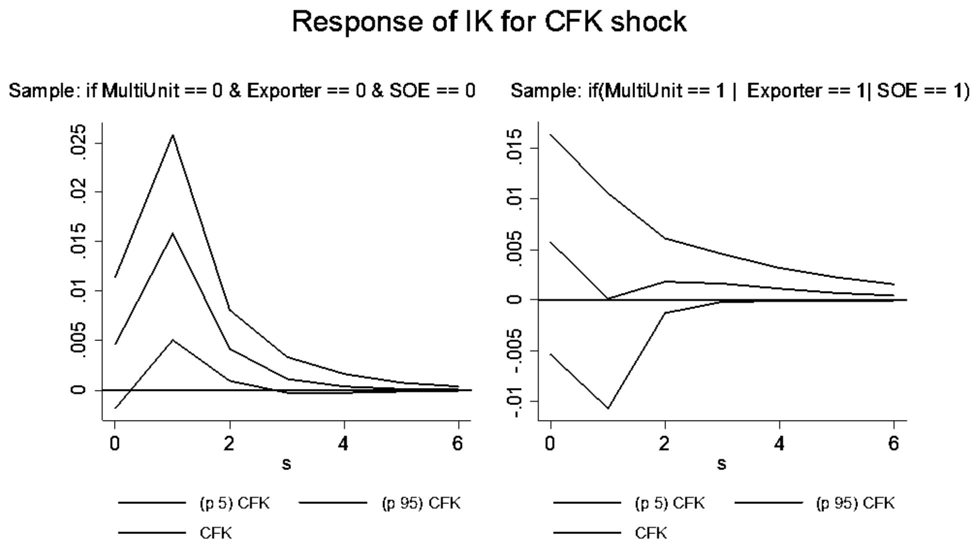

Fig 4: Orthogonalized impulse responses of IK for CFK shocks.

The variance decomposition for the 10-year-ahead forecast error of IK is given in Table 6 for different subsamples. The bottom row of the Table again indicates that much of the forecast error in investment is attributable to its own shocks, which is in conformity with findings in other studies (Eberly *et al.*, 2011; Love and Zicchino, 2006). The first two rows show that, although the contributions of MPK and CFK are much smaller, they vary greatly among subsamples. For example, the contribution of cash flow shocks is seven times higher among small firms than large firms (0.7% vs. 0.1%). Similarly, the proportion of forecast error due to cash flow shocks is more than 5 times higher for private establishments than for SOEs (0.21% vs. 0.04%). Likewise, CFK explains a larger share of the error variance of IK among Class 1 firms than among Class 2 firms. These results confirm that cash flow has a much larger effect on investment among small and private firms.

Table 6: Variance decomposition for 10 year ahead forecasts by subsample

	Small	Large	Private	SOEs	Class 1	Class 2
MPK	0.060	0.018	0.025	0.028	0.037	0.028
CFK	0.007	0.001	0.002	0.000	0.003	0.001
IK	0.933	0.980	0.973	0.971	0.960	0.971

Notes: Values of each column show the percent of variation in IK explained by shocks of the row variable. Class 1 consists of all private, single unit, and non-exporting plants whereas Class 2 consists of establishments that are either SOEs, that have multiple units or that engage in exporting.

4.3 Financial liberalization and the cash flow sensitivity of investment

Results from the previous section suggest that investment among small firms as well as among private, non-exporting, and single unit firms shows excess sensitivity to the availability of cash flow. This section tries to answer if the cash flow sensitivity of investment has slackened over time following the liberalization of the financial sector. Although financial liberalization is by no means a completed process in Ethiopia, there has been significant expansion of the banking sector, and thus the availability of bank credit in the 15 years our dataset covers (1996-2010). This invites the question of whether or not the liberalization of the banking sector has benefited small and private establishments.

While maintaining the earlier approach of splitting the sample into two groups, I will also divide the time period into two and estimate the model for each subsample twice. Specifically, I will classify the sample period into two parts: from 1996-2004, and from 2005-2010. While the choice of the specific year is admittedly arbitrary, there are significant changes in the banking sector in the earlier and later phases of liberalization. For example, the percentage of firms that report that working capital shortages are among their most challenging constraints fell from more than 34% in earlier period to 26% in the later period. Similarly, a large expansion of the banking sector is evident at macro-level.[12]

Figure 5a and Figure 5b report the response of IK for CFK shocks in different subsamples during the earlier and later stages of liberalization. The top panel of Figure 5a compares the impulse response for small plants before and after 2005. It is evident that impulse response of IK for CFK shocks are only large and significant in the earlier periods of liberalization. Whereas IK responds by as much as 0.07 one year after the impulse in the early liberalization period, the response is practically zero in the later period. It thus appears that in later days of liberalization investment among small firms is not sensitive to cash flow shocks. The second panel of Figure 5a compares the impulse responses of large firms. The graph in the bottom left section indicates that, in the earlier periods of liberalization, even investment among large firms showed significant contemporaneous response to CFK shocks (although by a small amount of 0.02). This effect seems to have disappeared in the years since 2005. In general, this suggests that large firms have also benefited from expansions in banking activities, although the changes seem marginal compared to small firms.

Figure 5b compares the impulse responses of Class 1 and Class 2 firms (where the first class includes private, single unit, non-exporting plants, and Class 2 to includes all the remaining plants). The top panel of the Figure compares the impulse responses of Class 1 firms in the earlier and later periods of liberalization. The results are again very clear: in the earlier period, investment among Class 1 firms shows large and significant sensitivity to cash flow shocks, but not in the later periods of liberalization. As an example, one standard deviation shock in CFK induced a response of 0.04 a year later in the earlier period of liberalization, but the response during the later period for the same shock is practically zero.

[12] The number of commercial bank branches per 100,000 adults has more than doubled from around 0.70 in the early 2000's to 1.76 by the year 2010. Similarly, the share of private banks in total domestic borrowing in Ethiopia has risen from nearly nil in the late 90's to 52% by 2010. Since public banks have also expanded their operation, these figures suggest that domestic borrowing has grown multiple times between the years 1996-2010.

Thus liberalization seems to have reduced the cash flow sensitivity of investment among private, single unit, non-exporting firms.

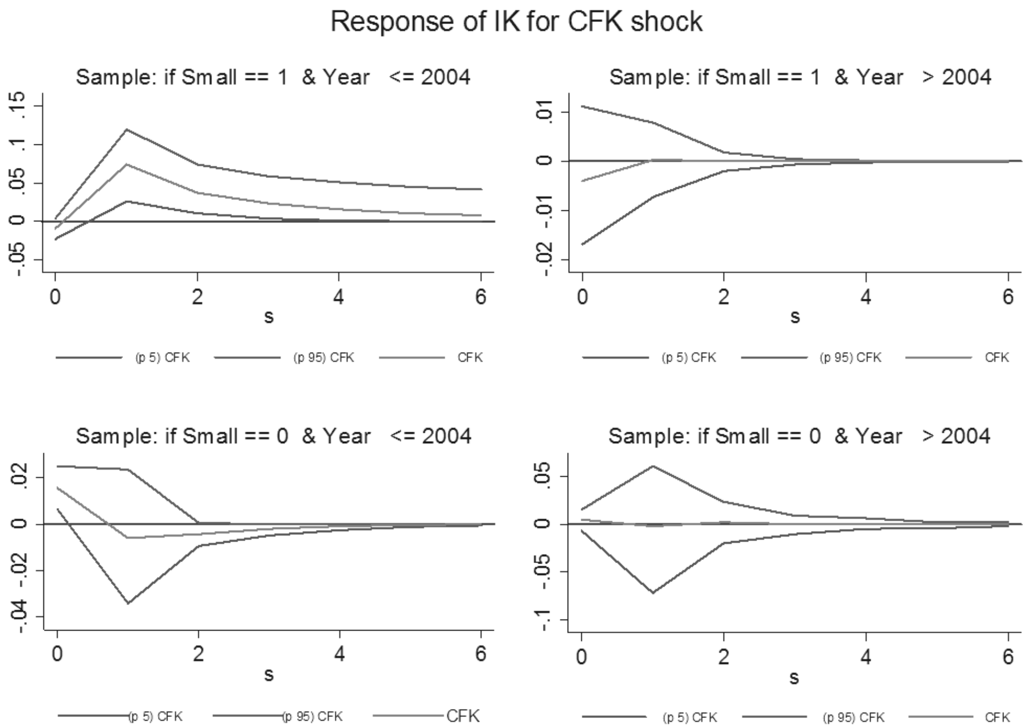

Fig 5a: Orthogonalized impulse responses of IK for CFK shocks for small and large firms during earlier and later stages of liberalization.

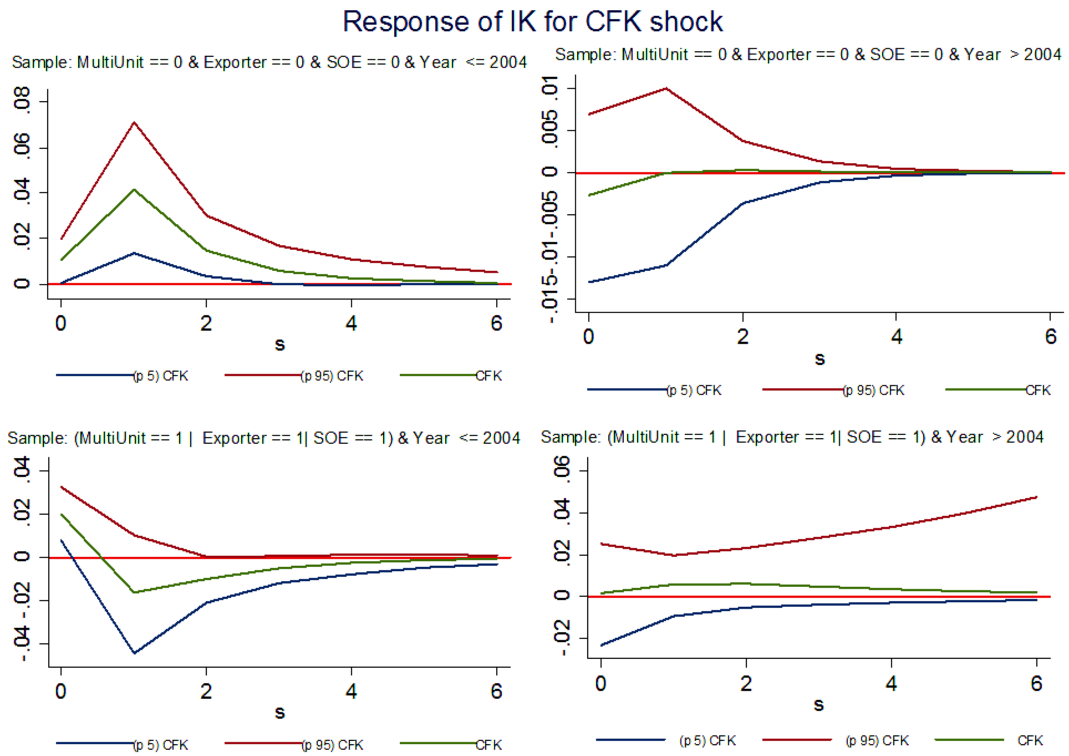

Fig 5b: Orthogonalized impulse responses of IK for CFK shocks for Class 1 and Class 2 establishments during earlier and later stages of liberalization.

The second panel of Figure 5b, which compares impulse responses of Class 2 firms, leads to the same conclusion. As the bottom left graph shows, cash flow shocks induced significant investment response contemporaneously even among Class 1 firms in the years until 2004 (by an amount of 0.02). In the later years, however, the response of investment for cash flow shocks is thoroughly very small and insignificant.[13] In general, these results suggest that liberalization in the years since 2005 has reduced the cash flow sensitivity of all types of firms, although the reduction seems larger among Class 1 firms.

5. Conclusion

Developing countries are characterized by the lack of medium-sized firms that are critical for dynamic growth and employment creation. This paper investigates the potential role of financial constraints on

[13] Another note is that the relatively small number of observations leads to large and diverging bootstrap standard errors in the right bottom graph. The number of observations in this group is indeed a very small number of 488 plants.

the ability of small and private firms to invest and grow in a developing country. In the presence of information asymmetries and other market imperfections external financing can be more expensive than internal sources of financing. Thus, small firms with limited net worth can face financing constraints that limit their ability to invest and grow. A large empirical literature contends that the sensitivity of investment to variables that measure net worth such as cash flow is especially higher among small and young firms that are more likely to face financing constraints (Fazzari *et al*., 1988; Hubbard, 1998).

It is, however, contentious if these results confirm the presence of financial constraints since cash flow variables that are used to proxy net worth are strongly correlated with future profitability. Furthermore, both financial and fundamental factors are affected by investment, and this dynamic effect is often neglected. The focus of this literature is also limited to large and publicly listed firms in developed countries.

This paper seeks to address these gaps by analyzing the dynamic relationship between investment and its determinants in a panel VAR setting. For this purpose, I use a unique census-based establishment level dataset of manufacturing firms in Ethiopia. This dataset is suitable for our application because, in addition to its large coverage of small firms, it comes from a developing country where financing constraints can be very binding.

I estimate a vector autoregressive model to explain investment with its own lags and the lags of cash flow and the marginal product of capital. Impulse response analysis is conducted by orthogonalizing the error terms by assuming a recursive structure in the VAR. Comparing the response of investment to cash flow shocks between different subsamples, I find that the response is much larger among small and private plants than among large plants and SOEs respectively. Results from variance decomposition also show that cash flow plays a much larger role in explaining forecast errors of investment among small and private plants than among large and SOEs respectively. These results confirm that financing constraints affect the investment of small firms, potentially due to their limited net worth, and that of private firms, possibly because of their limited ability to secure financing from government banks.

Since Ethiopia started transition towards a market economy in the early 1990's, the banking sector has been liberalized allowing the entry of private banks. The liberalization has led to considerable growth in the banking sector, which offers an opportunity to examine the effect of liberalization on the cash flow sensitivity of investment. Comparing the impulse response of investment to cash flow shocks between the early and later years of liberalization, I find that the effect of cash flow has been reduced in recent years. The reductions in the cash flow sensitivity of investment are especially larger among financially constrained small and privately owned establishments.

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