Family Financing and Productivity Among Small Manufacturing Firms in Ghana*

Preliminary draft

Andrea Szabo
Economics Department, University of Houston
E-mail: aszabo2@uh.edu

October 18, 2012

Abstract

This paper argues that family financing through loans for investment or intermediate input purchases may allow relatively unproductive firms to stay in the market, reducing average productivity in the economy. Evidence from the Ghanaian Manufacturing Survey 1991-1998 is consistent with this hypothesis. I present reduced form estimates as well as a dynamic model which I estimate structurally using simulation methods. The counterfactual analysis with no family financing indicates an average productivity gain of 15% relative to a situation where all firms have access to family loans. The data shows that improving formal lending reduces the availability of family loans, suggesting an additional channel through which improving credit market conditions may increase productivity in developing economies.

*I would like to thank Patrick Bajari, Amil Petrin, Chris Timmins, Gergely Ujhelyi, and seminar participants at the University of Minnesota and Rice University / University of Houston for comments and suggestions.

1 Introduction

In developing countries, small firms' organizational structure is often different from that of their Western counterparts. One aspect of this difference is that firms employ social networks in their business practices at several different levels. Family connections in particular are an important but little understood resource for small businesses.

Family financing, such as loans from relatives and close friends for startup capital, investment or intermediate input purchase, is generally available at lower interest rates than formal financing. Many studies report zero, or even negative interest rates on loans provided by relatives, therefore family financing is a substitute to formal bank loans.[1] Firms who were rejected by a formal lending institution or to whom banks only offered loans with a very high interest rate often use family loans if available. Family loans are typically not subject to the type of scrutiny (credit checks, feasibility of the business plan, etc.) used by formal institutions. Since lower interest rates and available financing from family give some firms a competitive advantage, they may allow less productive firms to stay in the market. Thus, the availability of family financing may keep less productive firms in the market, resulting in lower mean productivity in the economy.

The goal of this paper is to asses the empirical relevance of this hypothesis using micro data from the Ghanaian Manufacturing Survey 1991-1998.[2] In Ghana, the examined period corresponds to the improvement of the general credit market conditions, and we observe large variation in the availability of family loans in the sample. I begin by assessing any correlation between family financing and mean firm level total factor productivity (TFP). To calculate TFP, I estimate the production function using an estimation method described in Wooldridge (2009), with a proxy variable suggested by Levinsohn and Petrin (2003). The estimates show that mean productivity is lower for firms who receive family money in various ways. First, I show that firms receiving financial help from the family for business startup encounter lower mean productivity throughout

[1] Surveys from six African countries show that about half of small firms used loans from relatives and friends to start their businesses (World Bank, 2007). Banerjee and Munshi (2000) show that the network capital for business start-up is so important that it can influence migration patterns and location choice of businesses in India. Aryeetey et al., 1994 shows that after the owner's own savings, the main source of start-up capital is relatives and friends, since only a small fraction of these firms could gain access to bank loans. Fafchamps and Minten (1999) find that among agricultural traders in Madagascar, 53.2% of the traders were helped by family and friends at start-up and close to half learned the business with a relative or friend.

[2] A priori, the effect of the availability of family loans on firms' performance is not obvious. Start-up capital from the family might help firms achieve higher productivity through the smaller cost of credit. Such firms may also have more resources to spend on investment, introduce new technologies etc., which might result in higher productivity.

their operation. Second, small manufacturing firms in Ghana often take loans from banks and family not only to finance investment or start-up capital, but to purchase the intermediate inputs necessary for operation. I show that firms solving such liquidity problems using family financing have a lower average productivity in the economy as well.

To establish the link between credit market conditions, availability of family loans, formal lending and the production process, I develop a dynamic model. In this model, firms maximize their expected profits by choosing inputs as well as the amount of investment and loans. The model includes a firm specific interest rate function on loans and also incorporates families' willingness to give a loan. To estimate this dynamic model, I apply the method proposed by Hotz and Miller (1993) which avoids explicit dynamic programming to compute the value function for every parameter vector. The estimated parameters are the parameters of the profit function, including a set of production function parameters and a set of interest rate function parameters. I also estimate the maximum amount of loan provided by the family. In a counterfactual experiment, I find that in a situation without family loans, productivity increases by 15.6% and output by 13.9% relative to a situation where all firms have access to family financing. In this sense, family financing is an additional channel through which the lack of properly working credit markets contributes to a lower average productivity in the economy.

The paper is related to several strands of existing literature. Several studies attempt to quantify the effect of credit constraints on firms in developing countries (e.g., Banerjee and Munshi (2004), Banerjee and Duflo (2004)). This paper is most closely related to Schundeln (2007), who estimates a dynamic model of firm-level investment in the presence of financing constraints. He uses the same dataset and finds that removing the constraints would imply an economically significant increase in investment. However, he includes only formal loans and his main constraint is that banks require high collateral. In contrast, this paper focuses on the role of family financing. I identify one of the causes of low aggregate productivity in the economy, and I evaluate the effect of changes in the maximum amount of available family loan. I also relate the availability of family loans to credit market conditions such as properly working financial institutions and the availability of formal credit. To my knowledge, this is the first paper to measure the contributions of family financing to aggregate productivity in developing countries.

In the development literature, several papers argue that informal markets are beneficial, since they are a substitute to formal markets when these do not work properly (see Bertrand and Schoar, 2006 for a survey). Without disputing this argument, this paper shows that under improving credit markets, removing informal lending sources may increase overall productivity.

Finally, this paper also relates to a group of papers analyzing the effects of microfinance programs on small firms' performance and profitability (e.g., Banerjee et al., 2010). Considering several similarities between microfinance programs and the transactions between the firm and family members, understanding the impact of relatives' involvement might lead to new insights about the impacts of microfinance programs on firms' performance.

The remainder of the paper is organized as follows: Section 2 describes the data used in the empirical analysis. Section 3 presents the reduced form analysis, and Section 4 contains the dynamic model used for the structural estimation. Section 5 describes the steps of the estimation method and Section 6 presents the estimation results. Section 7 describes the policy experiment, and Section 8 concludes.

2 Data

The main data source for this study is the Ghanaian Manufacturing Survey, 1991-1997.[3] The survey was conducted by the World Bank and the Centre for Study of African Economies at Oxford University.[4] The survey includes an extensive list of questions about general firm characteristics, as well as the labor market and financial market interactions of the firms. The survey was designed as a panel study of 200 firms. After the first round, new firms were included in the sample to replace any exiting firms. In five waves, a total of 278 firms were interviewed. In my analysis, I include only domestic private firms (exclude state-owned and foreign firms). The reason for this is twofold. First, the role of the family is more important in private Ghanaian firms. Second, state and foreign owned firms might have different opportunities to get financing. The final sample consists of 803 firm-period observations. Appendix 1 contains the survey questions used in the analysis and the definitions of the variables that were created. Summary statistics appear in Table 1.

Capital is measured as the replacement value of the stock of plant and equipment. It is calculated

[3] Other studies using this dataset include Teal (2002), Frazer (2001, 2006, 2007), Schundeln (2002, 2007).

[4] Teal (2002) describes the construction of the dataset. The questionnaire and the data are available from http://www.csae.ox.ac.uk/datasets/Ghana-rped/Ghmain.html. The definitions of the variables used in this study are in Appendix 1.

Table 1: Summary statistics

	Mean	Std. dev	Min	Max	N
Employment	28.87	39.25	1	328	803
Capital	78.33	329.08	0.006	4049.49	803
Output	69.94	190.67	0.098	1933.08	803
Value added	27.77	77.12	0.003	798.43	803
Material inputs	35.24	100.06	0.006	1082.49	803

Table 2: Firms by sector

Sector	N
Foods/Bakery	167 (21%)
Furniture/ Wood	218 (27%)
Garment/Textile	220 (27%)
Machines/Metal	191 (24%)
Other	7 (1%)
Total	803

as described in Teal (2002), assuming a 2 percent depreciation rate. To measure intermediate inputs, I use the total cost of raw material inputs. This data is available for 803 time-firm observations. All values are deflated to 1991 Ghanaian Cedis (indexes are provided by the survey team). My analysis focuses on changes in various measures over the survey period. Because focusing on particular sectors would result in a small number of observations, I pool all sectors together. As Table 2 shows, the four main sectors have similar proportions in the data.

3 Productivity and family financing

I begin by documenting that, in the data, interest rates on family loans are substantially lower than market rates, providing an advantage for firms that have such financing available. Second, I show that loans are often used to purchase intermediate inputs rather than just for capital investment. This suggests that firms having access to family financing face lower effective input prices, and therefore face a competitive advantage on the market. Under this interpretation, we might expect family financing to keep some less productive firms in the market, who would have exited had such financing not been available. As an initial test of this hypothesis, I calculate a productivity measure and compare the productivity of firms with and without family financing. In order to calculate

Table 3: Summary statistics - Variables used in interest rate function estimation, Million 1991 Cedis

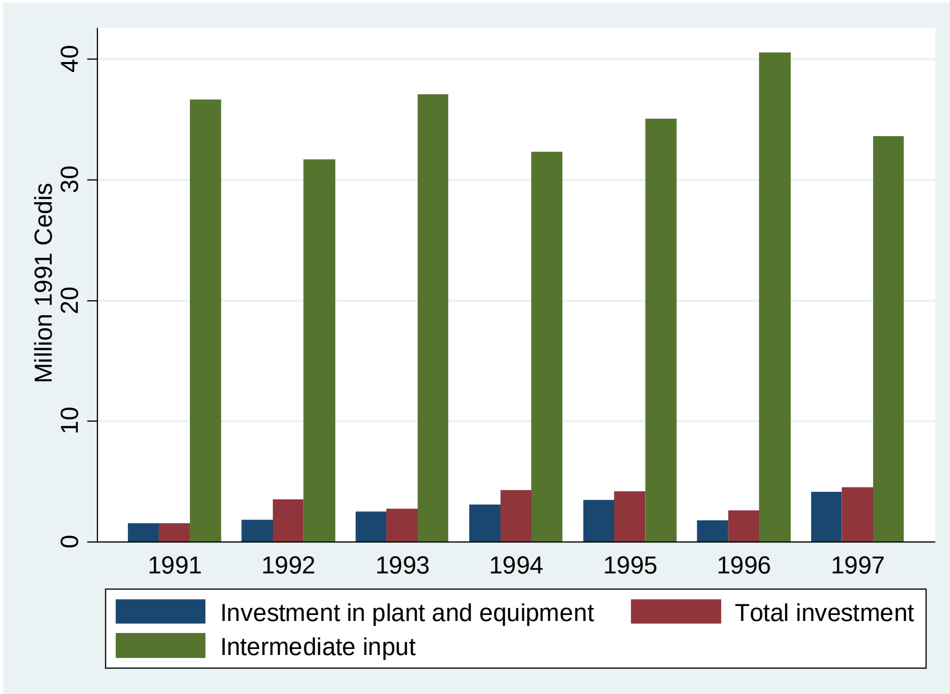
	Mean	Std. Dev.	Min	Max	N
All firms (N=803)					
Formal loan amount	86.08	160.57	0.02	1064.05	158
Formal interest rate (%)	33.98	14.37	1.40	125.00	158
Informal (family) loan amount	3.75	21.16	0.001	239.81	159
Informal interest rate (%)	3.77	29.25	-100	120	159
Average portfolio interest rate (%)	8.06	17.47	0	125	803
Firms with less than 30 employees at startup (N=613)					
Formal loan amount	24.14	58.93	0.02	296.56	67
Formal interest rate (%)	34.57	19.35	1.40	125.00	67
Informal (family) loan amount	0.95	2.66	0.00	20.98	146
Informal interest rate (%)	3.76	29.77	-100	120	146
Average portfolio interest rate (%)	5.44	16.40	0	125	613

productivity, I employ the Wooldridge (2009) production function estimation method.

Firms use financing from a variety of sources, and some interest rates are not directly observable. In the data, I can observe the loan amounts provided to each firm by formal financial institutions in a given year with the corresponding interest rate. I also have data on the loan amounts from various informal sources and the expected repayment (either in 1991 Cedis, or in-kind where the monetary value is given in the survey). Among informal sources, "relatives and close friends" are by far the most common category (over 90% of cases), and this is what I focus on here. I calculate the interest rate for loans coming from family using the loan amount and the expected repayment, and to get the interest rate on the firm's portfolio, I take a weighted average of the formal and informal interest rates, using the relative loan amounts as weights. The summary statistics of these variables are in Table 3.

As can be seen from the Table 3, interest rates on formal and informal loans tend to be very different. As documented in the literature, interest rates from the family are very low, often negative, which means that the loan is not expected to be paid back in full (see, e.g., Banerjee and Munshi, 2004). In my dataset, the median interest rate is zero. This is consistent with the findings in Aryeetey (1998) which show that family members, not having other investment opportunities with a positive interest rate, often provide financial help as a favor. In some cases, even though an investor could get a low positive interest rate on a bank deposit, banks may not be easily accessible, and the monetary and time cost of travel makes a trip to the nearest bank not worthwhile, especially

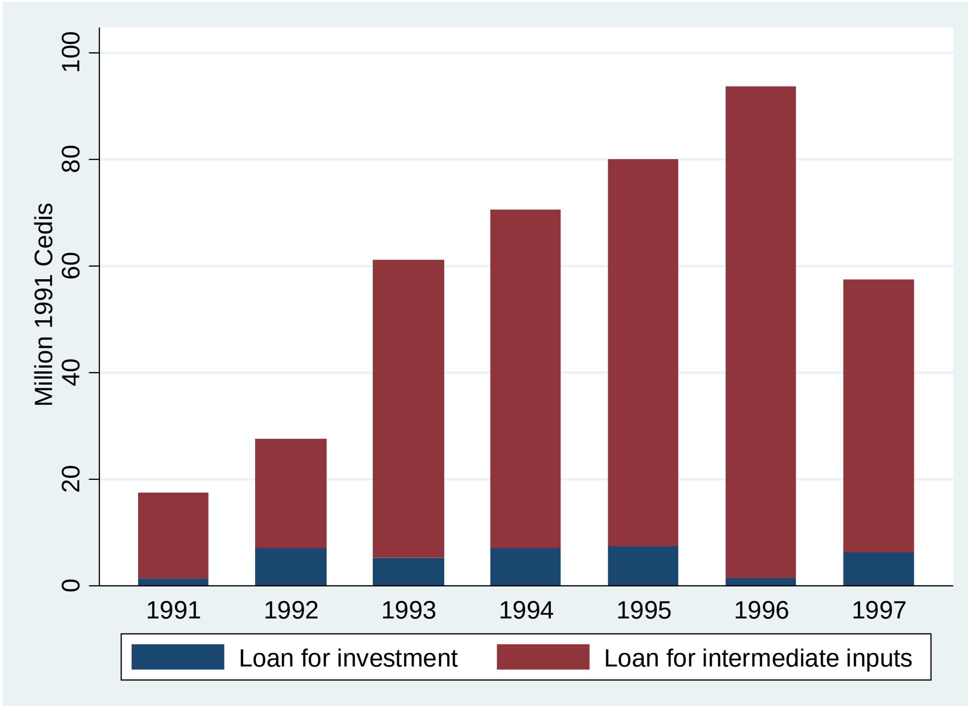
Figure 1: Investment and intermediate input purchase, 1991-1997, Million 1991 Cedis



when considering that a future withdrawal would be as difficult as the deposit. As a result, family financing, if available, can substantially lower the interest rate on firms' portfolio.

The notion that loans are used to purchase inputs may be unfamiliar, as a typical Western firm would use loans mainly for purchasing investment goods. It would deal with liquidity problems using trade credit or other short term business credits, such as overdrafts. By contrast, among small firms in Ghana, investment is not common. In the data, every year between 52 and 80 percent of the firms do not invest above their startup capital. At the same time, they accumulate substantial debt, which suggests that loans are used to deal with liquidity problems, including the purchase of intermediate inputs. As shown in Figure 1, the mean value of intermediate input purchases is on average 22 times higher than the mean value of investment. The majority of the loans are used to purchase intermediate inputs as shown in Figure 2. Since firms that can get lower interest rates are effectively facing lower input prices, they gain a competitive advantage on the market.

Figure 2: Loan for investment and intermediate input purchase, 1991-1997, Million 1991 Cedis



3.1 Production function estimation

I assume that firms face a Cobb-Douglas production function given by

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \varepsilon_{it}, \tag{1}$$

where q_{it} is the log of the real output, l_{it} is the log of the number of employees, k_{it} is the log of the real capital stock, and m_{it} is the log of the real value of intermediate materials.[5] The term ε_{it} is a productivity shock that satisfies

$$\varepsilon_{it} = \omega_{it} + \eta_{it},$$

where ω_{it} is the transmitted component and η_{it} is an unpredictable iid productivity shock. To estimate (1) I apply the estimation method proposed by Wooldridge (2009). This takes into account the simultaneity problem as described in Levinsohn and Petrin (2003) and Olley and Pakes (1996), and deals with the identification problem described by Ackerberg, Caves and Fraser (2006). To

[5] The choice of the dependent variable (real output rather than value added) addresses the identification problem and bias of the productivity measure as described in Gandhi, Navarro and Rivers (2011).

proxy to transmitted component of the productivity shock I use

$$\omega_{it} = g(k_{it}, m_{it}),$$

where ω_{it} depends on the firm's state variable k_{it} and the proxy variable m_{it}, intermediate inputs. The choice intermediate inputs as the proxy variable (rather than investment, as in Olley and Pakes, 1996) is particularly important since many small firms in the dataset report zero investments, as it is typical for developing country datasets. Therefore much information would be lost in dropping these cases, as would be required by Olley and Pakes (1996).[6]

The choice of the functional form for g and the details of the estimation are in the Appendix. See Szabo (2012) for various robustness checks. I also report the parameter estimates using several other production function estimation methods for comparison. The Wooldrige-L-P method produces production function coefficients which are significant at the 1 percent level. All results presented below are based on these estimates.[7] The Appendix also contains the overidentification test and the estimated returns to scale. In the next section I use the firm-level productivity estimates to calculate an average productivity index for groups of firms with various forms of family involvement.

3.2 Productivity by type of family financing

The goal of this section is to test the hypothesis that firms which use family financing for startup capital or to overcome liquidity problems have a different mean productivity level than non-family firms.

Financing the startup capital

The survey asked firms how they financed their business startup. Out of 278, 262 firms answered this question, and 39 of them (14.8%) borrowed from friends or relatives. Among these firms, the average percentage borrowed from relatives from the overall startup cost is 67.8%. Since I consider

[6]The zero firm level investment does not mean that we do not have information on the firm's investment activity. A zero reported investment means that the firm did not invest in a particular year. This investment data can be used in the construction of the capital stock, but not as a proxy for the transmitted productivity.

[7]Applying Woodridge (2009) also has the advantage that we are able to separate the predictable (transmitted) component of the error term. This is important, since the firms base their variable input decisions only on the transmitted component of the productivity shock. This recovered productivity part is used in the structural estimation as a state variable for the firm.

Table 4: Startup capital, percentage financed by family members

Percentages	Mean firm level TFPs	N
0	1.123	376
>0	1.047	153
<=50, but positive	1.051	56
>50	1.046	97
Total	1.101	529

only domestic private firms in my analysis, these numbers are higher in my subsample. In this sample there are 120 firms, and I have data for 78 firms regarding the financing of the business startup. Of these firms, 34.6% used some financial help from family to start their business, and 21.8% financed more than half of the startup cost from these sources. Among those who used family financing, family contributed on average 72.5% of the startup cost, and half of the firms financed the startup cost entirely from family sources.

Table 4 presents the estimated mean firm TFP levels by groups. Firms which used family money to finance the startup of the business have 6.8% lower productivity than firms who did not use it.

Liquidity problems

During the seven years of the survey, there were three questions about liquidity problems. Summary statistics for these questions are in Table 5. Each year, between 75-81% of the firms reported liquidity problems during that year. Of these firms, 15.6-18.3% borrowed money informally to continue their businesses.

As can be expected, firms that never experienced liquidity problems (5 % of the sample) have productivity estimates which are more than 3 times higher than those who experienced some liquidity problems. Table 6 shows the breakdown of productivity estimates depending on whether firms borrowed from the family. Firms which reported liquidity problems but did not use informal borrowing have higher productivity. Firms which borrowed money two or more times informally have 10.2% lower productivity.

The results above establish that, on average, reliance on family loans is associated with lower aggregate productivity among small manufacturing firms in Ghana. Below, I present a dynamic model where the availability of family loans depends on general credit market conditions, and firms with family financing have a cost advantage over their competitors that allows them to stay in the

Table 5: Share of firms reporting liquidity problems, *Multiple answers were allowed
Q: Have you had any liquidity problems in the last year?
What did you do about it?

	Wave 3	Wave 4*	Wave 5*
Reported liquidity problem	0.77	0.77	0.84
N	113	114	105
Solution at liquidity problem			
Sold off raw materials %	-	0.01	-
Sold some equipment	-	-	0.03
Borrowed from bank (overdraft)	0.13	0.07	0.11
Borrowed from bank (loans)	0.03	0.06	0.11
Used personal cash reserves	0.1	0.08	0.1
Borrowed informally	0.14	0.25	0.14
Took cash advances from clients	0.1	0.21	0.13
Obtained supplier credit	0.12	0.17	0.33
Other	0.13	0.1	0.18

Table 6: Productivity measures by groups, informal borrowing at liquidity problems

	Mean	Std. Dev.	N
At least one liquidity problem, but borrowed formally or less than 1/3 of the time informally	1.125	0.585	137
Informal borrowing 1/2 of the time at liqudity problem	1.086	0.362	60
Informal borrowing 2/3 of the time at liqudity problem	1.056	0.36	22
Always informal borrowing at liquidity problem	1.011	0.308	61

market even if they are less productive. I show that the model is consistent with the data, and study the effects of improving credit markets through family loans in a counterfactual exercise.

4 Model setup

The production process is assumed to be Cobb-Douglas, with the production function

$$Y_t = L_t^{\alpha_L} M_t^{\alpha_M} K_t^{\alpha_K} e^{\omega_t},$$

where Y_t is the firm's real output, L_t is labor, M_t is the intermediate input, and K_t is capital. ω_t is a productivity shock, which is not observed by the econometrician, but is observed by the firm and affects its input decisions. I assume that ω_t follows a Markov process with

$$\omega_{t+1} = \rho\omega_t + \varepsilon_{t+1}.$$

At the end of each period, after production, the firm decides whether it exits the market ($E = 1$) or stays in the market for the next period ($E = 0$). For next period production, the firm needs to buy intermediate inputs and pay wages, which requires financial assets. Next period production can be financed from current profits, accumulated financial assets (A_t), or loans. The firm will exit if $A_t < 0$ and there is no more available credit. I assume that a firm which produces zero in a given year exited the market. If the firm exits, its payoff is zero forever.[8]

The current profit of the firm can be used to purchase capital goods (K_t) or intermediate inputs (M_t), pay out dividends (d_t), or it can be kept in the firm as financial assets (A_t). Financial assets can also be accumulated from loans.

In many applications, firms face credit constraints that prevent them from buying the sufficient amount of capital goods. In the case of small manufacturing firms, liquidity constraints are a more relevant problem. The capital necessary for production is usually purchased at the business start-up. The lack of sufficient inputs restricts production. As discussed earlier, firms need to accumulate financial assets not only for investment but also to purchase intermediate inputs.

The firm can use its profit, financial assets and loans to finance investment (I_t). The capital stock evolves according to

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

where δ is the depreciation rate, which is given exogenously.

The intermediate input demand is defined as:

$$M_t = m_t(K_t, \omega_t)$$

[8] In some studies it is assumed that the firm (the owner) maximizes his utility instead of the firm's profit. In this case, if the firm exits, the firm's owner earns his outside option, e.g., the average wage. The assumption of profit maximizing behavior is better suited for our setting, since the firms are not managed by a single person, but rather a group of people, in many cases from the same family.

After inversion, we have

$$\omega_t = \omega_t(K_t, M_t)$$

which will simplify the production function.

The firm can borrow from informal sources (family and close friends) and formal institutions (banks) for purchasing capital goods and intermediate inputs, and thus ensure that the required financial assets are available for a given period. There is a firm-specific interest rate on loans from banks. I will use the following specification of the cost-of-credit function from formal sources:

$$r_{t,i} = \overline{r} + \exp(\alpha + \beta_1 \frac{I_{t,i}}{K_{t,i}} + \beta_2 A_{t+1,i} + \varepsilon_{t,i}),$$

where $\overline{r}$ is the risk-free interest rate.

I assume that the interest rate on loans offered by the family is a constant (r^{Family}), and this is calculated from the data as the mean interest rate.[9] The maximum loan amount offered by the family (Z_F) is a parameter which is estimated in the structural estimation.[10] I model the family's willingness to give a loan as a state variable for the firm. Let F denote this element of the state space for the firm, with $F = 1$ if family loan is available, and $F = 0$ otherwise.

Let us denote the one-period discount factor by β, with $0 < \beta < 1$, and the dividend paid in period t by d_t. The firm maximizes the present value of its expected dividends:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t d_t,$$

subject to

$$A_{t+1} = (1 + r_t)(Y_t - w_t L_t - M_t + A_t - K_{t+1} + (1 - \delta)K_t - d_t).$$

[9] The average interest rate on loans from family is 2.7 percent. This low number is explained by the fact that over 85 percent of the recorded interest rates are zero.

[10] The maximum loan amount offered by the family is assumed to be constant across periods. This assumption is consistent with the data.

The interest rate faced by the firm is given by

$$r_t = \begin{cases} \overline{r} \text{ if } A_{t+1} \geq 0 \\ r^{Bank}(= \overline{r} + \exp(\alpha + \beta_1 \frac{I_t}{K_t} + \beta_2 A_{t+1} + \varepsilon_t)) \text{ if } A_{t+1} < 0 \text{ and } F = 0 \\ r^{Family} \text{ if } A_{t+1} < 0 \text{ and } F = 1 \text{ and } Z_F > -A_{t+1} \\ r^{Portfolio}(= \frac{Z_F}{-A_{t+1}} r^{Family} + \frac{A_{t+1}+Z_F}{A_{t+1}} r^{Bank}) \text{ if } A_{t+1} < 0 \text{ and } F = 1 \text{ and } Z_F < -A_{t+1} \end{cases} \tag{2}$$

The value function of the firm is

$$V(s) = \max_{exit,stay} \left[0, \sup_{\sigma \in \Sigma(s)} E\left\{ d(s,\sigma) + \beta V(s'|s,\sigma) \right\} \right],$$

where $S \ni s$ is the state space and $\Sigma(s)$ are the possible choices in state s. Each state s is described by K_t, A_t, the productivity shock ω_t, the exit indicator E_t, and the indicator function F_t denoting the availability of family loans. The choice variables are K_{t+1}, A_{t+1}, L_t, M_t, d_t and E_{t+1}.[11] The dividend d_t is computed as a residual.

5 Estimation

The parameters to be estimated include a set of production function parameters, a set of interest rate function parameters and a parameter for the maximum amount of family loan (which cannot be inferred from the data). Estimation of this model is complicated by the firm-specific interest rate (2) appearing in the firm's budget constraint, which is determined not only by the parameters but also by the endogenous state variables. First, the policy function cannot be written down as a function of parameters and state variables directly from the model. Second, the budget constraint implies choice-specific value functions which are not linear in the parameters, therefore I cannot use a computationally faster estimation method such as the Bajari, Benkard and Levin (2007) approach.

I use an estimation method which avoids explicit numeric dynamic programming to compute the value function for every parameter vector. The estimation method is described in Hotz and

[11] It is assumed that L_t and m_t are chosen optimally by the firm in a static sense, and they do not enter the dynamic problem of the firm. Schundeln (2007) provides evidence for the validity of this assumption using a different sub-sample of the same dataset.

Miller (1993) and Hotz, Miller, Sanders, and Smith (1994).

State space

The state space contains four variables: K_t, A_t, E_t, F_t, ω_t. First, I discretize the data for capital and the loan amount: K_t is discretized into 31 grid points, A_t is discretized into 9 grid points, and ω_t is discretized into 14 grid points. The length of the grid intervals are not equal, since both K_t and A_t have a highly skewed distribution. Exit (E_t) is directly observable from the data. I also observe whether the family provides a loan to the firm (F_t). Thus, the state space has $31 \times 9 \times 14 \times 2 = 7812$ elements if the firm is still in the market. In the dataset I have 803 firm-time observations, as described in Section 3.

State transition

The optimal policy will determine the next state for K_t and A_t. I assume that the availability of a family loan is an exogenous state variable for the firm. I estimate the probability that such a loan is available nonparametrically from the data and use this probability distribution to generate new states. Based on the 803 observations, the average probability that a firm will have a family loan available is 24%. During the survey period, this probability decreased from 38.2% to 9.5%. The transition matrix for ω_t is estimated from the data.

Choice probabilities

An action σ_t of a firm contains three variables: K_{t+1}, A_{t+1}, E_{t+1}.[12] Calculating the transition matrix for K_t from the data, exactly four different patterns can be observed. The capital stock of the firm either stays in the same category, increases by one or by two categories, or decreases by one category. These will be the actions of the firm regarding the capital choice. There are 37 possible actions based on the discretization of the data.[13] In the sample, I can observe 25 different actions. I calculate the choice probabilities of these observed actions as follows.

An action is conditional on the state variables. However, the dataset lacks a sufficient number of observations for each state. In these cases, the choice probabilities calculated directly from the

[12] Strictly speaking, it also includes the static decision rule of the firm regarding the labor and intermediate input choice.

[13] Capital choice and loan amount are both categorized into four categories. This yields $4 \times \ 4 = 16$ actions. The 17th action is exit from the market.

data might be biased (Rust, 1987). To smooth the outlier choice probabilities for the cases with few observations, I estimate a multinomial logit regression of the actions on the categorical variables of states as the independent variables. The most probable action across states is for the firm to stay in the same capital category, which means that the firm either does not invest or the investment is so low that it does not enter into the next capital stock category. This also means that the firm does not take any loans.

Other parameter choices

As described above, the literature has documented the fact that interest rates from the family are very low, often negative, which means that the loan is not expected to be paid back in full. In my dataset, the median interest rate is zero, and this is the value I assume in the estimation. I take the wage rate to be 0.15 million Cedis, following Shundeln (2007) who calculates this value from the Ghanaian Living Standards survey.

Choice Specific Value function

The value function has seven parameters to be estimated: three interest rate function parameters, $\{\alpha, \beta_1, \beta_2\}$, three production function parameters, $\{\alpha_L, \alpha_M, \alpha_K\}$, and Z_F, the maximum available loan from the family. To construct the value function, note first that from the intertemporal budget constraint, the period-t dividend is

$$d_t = Y_t - w_t L_t - M_t + A_t - K_{t+1} + (1-\delta)K_t - \frac{A_{t+1}}{1+r_t}.$$

Let $K^*(s)$ and $A^*(s)$ denote the value of K_{t+1} and A_{t+1} based on the estimated policy function for the state $s = (K, A, F, E, \omega)$. The maximized period profit (dividend) has the following form:

$$d(s;\sigma;\alpha,\beta_1,\beta_2,\alpha_L,\alpha_M,\alpha_K,Z_F) =$$

$$\begin{cases} K^{\alpha_K}L^{\alpha_L}M^{\alpha_M}e^{\omega} - wL - M + A - K^* + (1-\delta)K - \frac{A^*}{1+\bar{r}} \text{ if } A^* > 0 \\ K^{\alpha_K}L^{\alpha_L}M^{\alpha_M}e^{\omega} - wL - M + A - K^* + (1-\delta)K - \frac{A^*}{1+(\bar{r}+\exp(\alpha+\beta_1\frac{K^*-(1-\delta)K}{K^*}+\beta_2 A^*))} \text{if } A^* < 0 \text{ and } F = 0 \\ K^{\alpha_K}L^{\alpha_L}M^{\alpha_M}e^{\omega} - wL - M + A - K^* + (1-\delta)K - \frac{A^*}{1+r^{Family}} \text{if } A^* < 0 \text{ and } F = 1 \text{ and } Z_F > -A^* \\ K^{\alpha_K}L^{\alpha_L}M^{\alpha_M}e^{\omega} - wL - M + A - K^* + (1-\delta)K \\ -\frac{(A^*)^2}{A^*-Z_F r^{Family}+(A^*+Z_F)(\bar{r}+\exp(\alpha+\beta_1\frac{K^*-(1-\delta)K}{K^*}+\beta_2 A^*))} \text{ if } A^* < 0, F = 1 \text{ and } Z_F < -A^*. \end{cases}$$

With estimates of the choice probabilities conditional on the state variables and the state transition matrix, I can construct the choice-specific value functions for a given value of the parameter vector $\theta = (\alpha, \beta_1, \beta_2, \alpha_L, \alpha_K, \alpha_M, Z_F)$. This is the present value of per-period profits from taking choice σ at state s:

$$\widetilde{V}(s;\sigma;\theta) = d(s;\sigma;\theta)+\beta E_{s'|s,\sigma}E_{\sigma'|s'}E_{\epsilon'|\sigma',s'}[d(s';\sigma';\theta)+\epsilon'+\beta E_{s''|s',\sigma'}E_{\sigma''|s''}E_{\epsilon'|\sigma'',s''}[d(s'';\sigma'';\theta)+\epsilon'+\beta...]]$$

This is computed for each possible state and action combination by forward-simulating the model. All 7812×25 choice specific value functions are simulated 100 times by drawing 100 sequences of $(s_t;\sigma_t)$ for a given initial value, and computing the present discounted profit corresponding to each sequence. Then the simulation estimate of $\widetilde{\widetilde{V}}(s;\sigma;\theta)$ is obtained as the average

$$\widetilde{V}(s;\sigma;\theta) \approx \frac{1}{100}\sum_{n=1}^{100}\left[d(s;\sigma;\theta) + \beta\left[d(s'^n;\sigma'^n;\theta) + \beta\left[d(s''^n;\sigma''^n;\theta) + \beta...\right]\right]\right].$$

Parameter estimation

Given the estimates of $\widetilde{V}(s;\sigma;\theta)$, I compute the predicted choice probabilities using the multinomial logit formula.

$$\widetilde{P}(\sigma|s,\theta) = \frac{\exp\{\widetilde{V}(s;\sigma;\theta)\}}{\sum_{\sigma'\in\Sigma(s)}\exp\{\widetilde{V}(s;\sigma';\theta)\}}$$

To estimate θ, I minimize the distance between $\widetilde{P}(\sigma|s,\theta)$ and the actual choice probabilities observed in the data ($\widehat{P}(\sigma|s)$) with respect to the parameters:

$$\widehat{\theta} := \arg\min_{\theta} \parallel \widehat{P}(\sigma|s) - \widetilde{P}(\sigma|s,\theta) \parallel .$$

6 Results

6.1 Parameter estimates and model performance

Table 7 contains the parameter estimates from the dynamic model. For comparison, I report the parameter estimates from a reduced from analysis whenever available. Reduced form estimates of the cost of credit function are in the Appendix. The signs of the parameters are as expected. In the interest rate function the coefficient on assets A_t is expected to be negative: the higher the accumulated debt of a firm, the higher is the interest rate for additional loans form a bank. I use the ratio of investment to capital stock to proxy for (the lack of) available collateral from the firm in the year when the loan is provided. As expected, the coefficient of this variable in the interest rate function is negative. The production function estimates from the dynamic model are close to the coefficients calculated with the Wooldridge method.

The observed average loan from family is about 422 USD in the dataset. One of the model's structural parameters is the maximum amount of available family loan, which is estimated at 0.3 Million Cedis = 750 USD. This estimate gives valuable information about the financing capacity of the family. This information can also be used to gauge the possible future amount of deposits from households into the banking system once this investment channel becomes available.

To evaluate the model's performance, I simulate the estimated model for the initial states observed in the data. The endogenous state variables are obtained using the estimated policy function, while the exogenous state variable (the availability of family loans) is drawn separately using the distribution estimated from the data. I simulate the panel dataset 100 times, and compare the mean of each variable to those in the data. The mean values from the dataset and from the simulations are in Table 8. All monetary values are deflated to 1991 values and in million Ghanaian Cedis. Means from the simulated datasets match the data reasonably well.

Table 7: Parameter estimates, Number of simulations=100

	Dynamic model	Reduced form
Production function estimates		
alfa L	0.170	0.172 (0.000)
alfa M	0.785	0.810 (0.000)
alfa K	0.060	0.057 (0.004)
Cost-of-credit function parameters		
beta 1	0.548	0.600 (0.068)
beta 2	-0.354	-0.367 (0.098)
alfa (const)	-1.249	-1.319 (0.000)
Zf Maximum amount of available family loan	0.3	
Family loan taken by the firm (mean from the data)		0.169

Table 8: Means of observable and simulated values, Number of simulations=100

Means	Data	Simulation
Output	69.94	67.68
Labor	28.87	27.65
Material	35.24	37.07
Capital	78.33	73.54
Productivity	1.10	1.02
Asset (= -Debt)	-17.40	-18.97

Table 9: Value added and productivity levels, Number of simulation=100

	Probability of getting a family loan					
	1	0.8	0.5	0.24	0.1	0
Output	61.11	61.35	65.45	67.78	69.54	69.62
Labor	27.18	27.44	27.60	27.65	28.06	28.17
Capital	72.44	72.95	73.02	73.54	75.08	75.25
Productivity	0.91	0.93	0.99	1.02	1.04	1.05
Asset	-11.20	-13.30	-15.06	-18.97	-19.03	-19.50

6.2 Policy Experiment

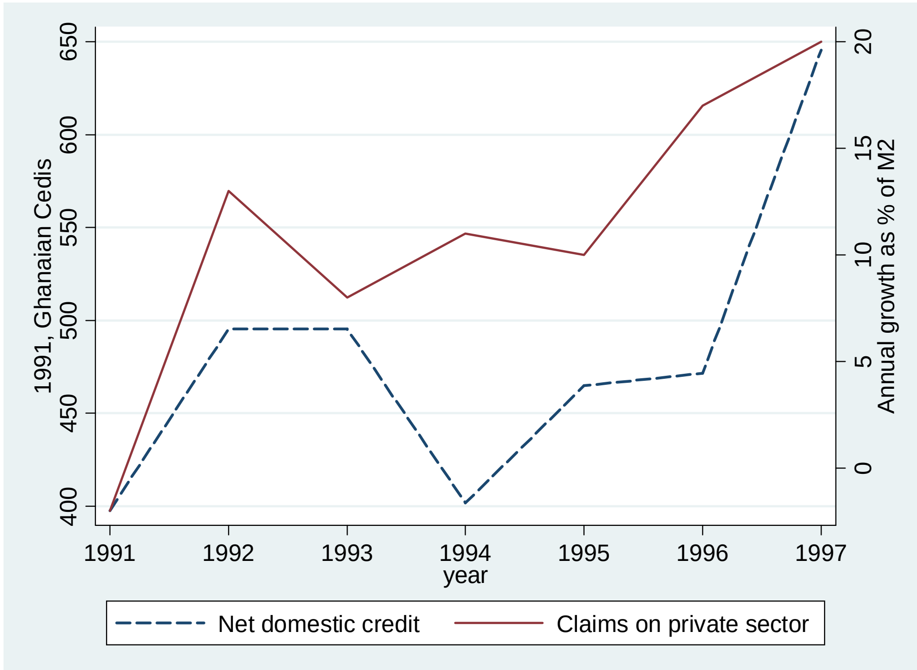
Using the estimated model, I conduct a counterfactual policy experiment where the likelihood that family financing is available changes. The goal of the experiment is to identify the resulting changes in production and productivity among small manufacturing firms. Table 9 contains the main firm level variables at different probabilities $\Pr(F = 1)$ (the average probability in the data is 0.24). As the availability of a family loan becomes more likely, average output, employment, capital and productivity all decline. Going from a situation where family financing is available with probability 1 to one where there is no financing for sure leads to a productivity gain of 15.6% and increases output by 13.9%.

6.3 Connection between family financing and formal credit markets

What determines the likelihood that family financing is available? One possible story relates this to the general credit market conditions in the country, including the process of credit approval, available domestic credit to the private sector, or the general accessibility of financial institutions. For example, when a bank branch becomes accessible in a village, the locals may choose this convenient investment opportunity over investing their money in the family business.

Beginning in 1989, Ghana implemented a financial sector reform program. In the first wave of the program (1990-1991), most nonperforming loans were swapped with government-guaranteed interest-bearing bonds issued by the Bank of Ghana. A total of 62 billion Cedis worth of nonperforming loans were removed from banks' portfolios. The second wave of the program started in 1992, and focused on increasing competition and efficiency in the system. The World Bank and the IMF provided continuous help with Ghana's macroeconomic transformation. The early bank-

Figure 3: Change in credit market measures, 1991-1998, Ghana



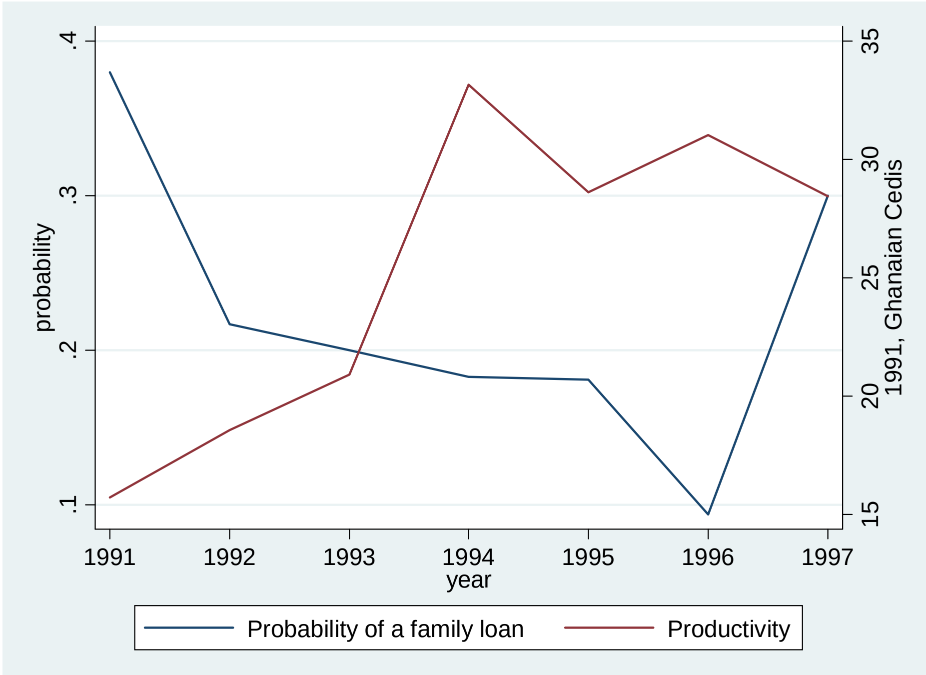
ing reforms of Ghana were considered one of the most successful ones in Africa. Macroeconomic and credit market indicators show considerable improvement during the survey period, 1991-1998. Claims on the private sector, which include gross credit from the financial system to individuals and enterprises (annual growth as percent of M2) increased from -2 to 14 percent (Figure 3). Domestic credit as a percent of GDP increased from 4 percent to 9 percent.[14]

Over this period of improving formal credit markets, I observe a decline in the probability that family loans are available (Figure 4). A 10 percentage point decrease in the likelihood of family financing is associated with a 14 percentage point increase in the private sector's share of claims on the banking system. The average aggregate productivity in the economy moves in the opposite direction, increasing as family financing declines.[15]

[14] Source: World Development Indicators.

[15] The graph shows a sharp increase in family financing in 1997. This coincides with an episode of major check fraud, the "A-Life affair," in which collusion by 3 large banks and a chain of supermarkets led to a 1% drop in Ghana's GDP. Following this, the Bank of Ghana banned the use of checks in the country and froze the assests of the banks involved. This could explain firms' increasing reliance of family financing.

Figure 4: Probability of the family loan and mean productivity, 1991-1998



7 Conclusion

This paper analyzes the effect of family loans on productivity among small manufacturing firms in Ghana. Using the Ghanaian Manufacturing Survey, I find that firms receiving more family loans for investment or intermediate input purchase have lower average productivity than firms operating without any form of family financing. My explanation is that family money allows less productive firms to stay in the market. I provide a dynamic model which is able to measure the effect of family loans on aggregate productivity in the economy. I find that in a situation without family loans, there is a productivity gain of 15.6% and an increase in output of 13.9% relative to a situation where all firms have access to family financing.

Since the availability of family loans is likely to be tied to general credit market conditions, this suggests that improving formal lending will reduce the amount invested in family firms and provide an additional channel through which improving credit market conditions may increase productivity in developing economies. In this respect, the reliance of family ties raises similar questions as the microfinance programs widely used in developing countries. One aspect of the debate on whether microfinance programs are the most cost-effective way of reducing poverty is that the money might support potentially less productive firms (Morduch, 1999, Pitt and Khandker, 1998, McKernan, 2002, Khandker, Samad and Khan, 1998). For example, the IMF and other international organizations' policy is to provide financial support for small business startup without selecting among the applicants based on strict criteria. This shows similarities with the transactions between a firm and the owner's relatives. Understanding the impact of relatives' involvement might lead to new insights about the effects of microfinance programs on firms.

References

[1] Aryeetey, E. (1998): "Informal Finance for Private Sector Development in Africa," *African Development Report Working Paper*, University of Ghana.

[2] Aryeetey, E., A. Baah-Nuakoh, H. Duggleby, H. Hettige, and W. F. Steel (1994): "The Supply and Demand for Finance among SMEs in Ghana," Discussion Paper 251, Africa Technical Department, World Bank.

[3] Bajari P., L. Benkard and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica* 75(5), 1331–1370.

[4] Banerjee, A., and K. Munshi (2000): "Networks, Migration and Investment: Insiders and Outsiders in Tirupur's Production Cluster," MIT Working Paper Series No. 00-08.

[5] Banerjee A. and K. Munshi (2004): "How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur," *Review of Economic Studies* 71(1), 19-42.

[6] Bertrand M., and A. Schoar (2006): "The Role of Family in Family Firms," *Journal of Economic Perspectives* 20(2), 73-96.

[7] Fafchamps, M., and B. Minten (1999): "Relationships and Traders in Madagascar," *The Journal of Development Studies* 35(6), 1-35.

[8] Frazer, G. (2001): "The Firm and the Family Network: Measuring the Relative Productivity of Relatives," Working Paper, Yale University.

[9] Frazer, G. (2005): "Which Firms Die? A look at Manufacturing Firm Exit in Ghana," *Economic Development and Cultural Change* 53, 586-617.

[10] Frazer G. (2007): "Learning the Master's Trade: Apprenticeship and Human Capital in Ghana," Working Paper, University of Toronto.

[11] Hotz V. J., and R. A. Miller (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models of Discrete Choice," *Review of Economic Studies* 61(2), 265-289.

[12] Khandker S.R., H. A. Samad, and Z. H. Khan (1998): "Income and Employment Effects of Micro-Credit Programs: Village level Evidence from Bangladesh," *Journal of Development Studies* 35, 96-124.

[13] Levinsohn, J., A. Petrin and P. B. Poi (2004): "Production Function Estimation in Stata Using Inputs to Control for Unobservables," Stata Corporation.

[14] Levinsohn J., A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies* 70(2), 317-342.

[15] McKernan, S.M. (2002): "The Impact of Microcredit Programs on Self-Employment Profits: Do Noncredit Program Aspects Matter?" *Review of Economics and Statistics* 84, 93-115.

[16] Morduch J. (1999): "The Microfinance Promise," *Journal of Economic Literature* 37, 1569-1614.

[17] Olley, S. G. and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64(6), 1263-1297.

[18] Pakes, A. (1991): "Dynamic Structural Models: Problems and Prospects. Mixed continuous discrete controls and market interactions," Cowles Foundation for Research in Economics at Yale University, Discussion Paper No. 984.

[19] Pitt, M. M., and S. R. Khandker (1998): "The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?" *Journal of Political Economy* 106, 958-996.

[20] Rust, J. (1987): "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica* 55(5), 999-1033.

[21] Schundeln M. (2007): "Financing Constraints: A New Test and an Application to Developing Countries," Working Paper, Harvard University.

[22] Schundeln, M. (2007): "Modeling Firm Dynamics to Identify the Cost of Financing Constraints in Ghanaian Manufacturing," Working Paper, Harvard University.

[23] Szabo, A. (2012): "Input misallocation in developing countries: Structural estimates from Ghana," Working Paper, University of Houston.

[24] Teal, F. (2002): "A Note on Data for Ghanaian Manufacturing Firms: 1991-1997," University of Oxford, Centre for the Study of African Economies.

[25] Word Bank (2007): "Finance for All? Polices and Pitfalls in Expanding Access, World Bank," Policy Research Report.

8 Appendix

8.1 Data

Table 10: Definition of the variables

All monetary values are included in 1991 Cedis	
FAMILY LOAN	Total borrowing from family and close friends.
FORMAL LOAN	Total borrowing from formal and semi-formal financial institutions.
INVESTMENT	Investment in plant and equipment. It does not include investment in land and buildings.
CAPTIAL STOCK	Imputed replacement value of capital stock of plant and equipment.
INTEREST	Interest rate on the firm's portfolio, which includes loans from formal and informal sources. Created variable, described in part 4. Used for the L-P production function estimation.
r_{Family}	Interest rate on loans from the family. Used in the dynamic estimation. Currently r_{Family}=2.07 which is the sample mean.
r_{Bank}	Interest rate on loans from formal financial institutions. Used in the dynamic estimation. Described in part 5.
$r_{Portfolio}$	Interest rate on the firm's portfolio. Used in the dynamic estimation. Described in part 5.
DEBT	Firm's aggregate debt level. This is measured as amounts of borrowing from both formal sources and informal sources over the previous 12 months les the amount of informal lending made by firm to various types of recipients.
ASSET	Available financial asset for the firm. ASSET = -DEBT
LABOR	It contains all occupational groups: management, production and support workers and apprentices.
INTERMEDIATE INPUT	Firm's raw material costs plus indirect costs, including rent, utilities and other overheads.
INPUT PRICE	The price of the intermediate inputs. Created variable, described in part 4.
OUTPUT	Value of firm's total production during previous year. Note that where there is a missing observation, output is set as the value of firm's total sales in the previous year. (Following the survey team's suggestion.)
VAD	Value added. Calculated by taking firm output less intermediate inputs and indirect costs.
δ	Depreciation rate. δ=0.02 (The value is suggested by the survey team, this value is used for the construction of the capital stock).
β	Set β=0.97.

8.2 Production function estimation

This section contains the details of the Wooldridge (2009) production function estimation. This estimation procedure allows me to recover the transmitted part of the productivity shock of the firms which is used in two ways in this paper. First, I compute average productivity levels for different subgroups of firms (e.g., firms with and without family loans) and provide evidence that firms with access to informal financial markets have a lower average productivity in the economy. Second, I use the recovered transmitted productivity as a state variable for the firm in the structural analysis.

The estimated equations correspond to equation (2.10) and (2.11) in Wooldridge (2009). Specifically, the production function parameters are identified from

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + g(k_{it}, m_{it}) + \eta_{it} \text{ for } t = 1, ..., T$$

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f[g(k_{it-1}, m_{it-1})] + \varepsilon_{it} \text{ for } t = 2, ..., T$$

In my implementation, f is a second order polynomial and g is a general third degree polynomial. The GMM estimation and the choice of instruments follows Wooldridge (2009). After parametrization of g and f, the residual function is defined for each $t > 1$ and can be written as:

$$\begin{pmatrix} r_{it1}(\theta) \\ r_{it2}(\theta) \end{pmatrix} = \begin{pmatrix} q_{it} - \alpha_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - c_{it}\lambda \\ q_{it} - \varphi_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - \rho_1 c_{it-1}\lambda - \rho_2 (c_{it-1}\lambda)^2 \end{pmatrix}$$

where c_{it} is a vector of the terms in the polynomial function g. This yields the following moment conditions for identification:

$$E[Z_{it}' r_{it}(\theta)] = 0 \text{ for } t = 2, ..., T,$$

where Z_{it} is matrix of instruments given by

$$Z_{it} = \begin{pmatrix} (1, l_{it}, c_{it}, k_{it-1}, l_{it-1}, c_{it-1}, h_{it-1}) & 0 \\ 0 & (1, k_{it-1}, l_{it-1}, c_{it-1}, h_{it-1} \end{pmatrix}$$

where h_{it-1} is a set of nonlinear functions of c_{it-1}. The estimation results are in Table 11.

Table 11: Production function estimates, N=635

	Coefficient	p
Pooled OLS		
β_l	0.199	0.000
β_k	0.093	0.000
β_m	0.744	0.000
Random Effects (GLS)		
β_l	0.194	0.000
β_k	0.124	0.000
β_m	0.670	0.000
Fixed Effects		
β_l	0.176	0.000
β_k	0.015	0.849
β_m	0.673	0.000
Levinsohn/Petrin[a]		
β_l	0.178	0.000
β_k	0.250	0.000
β_m	0.420	0.000
Wooldridge (2009)[b]		
β_l	0.172	0.000
β_k	0.057	0.004
β_m	0.810	0.000

[a] L/P estimates are bootstrapped (50 repetitions)

Wald test of CRS chi^2 = 4.21, p=0.0402

[b] Standard errors are clustered at the firm level

Hansen J statistic for test of overidentifying restrictions: J=23.27 (p=0.1405)

Table 12: Summary statistics - Variables used in interest rate function estimation, Million 1991 Cedis

	Mean	Std. dev	Min	Max	N
Formal loan amount	86.08	160.56	0.017	1064.05	158
Formal interest rate (%)	33.98	14.37	1.4	125	158

8.3 Reduced form estimates of the credit cost function

This section examines the empirical relationship between the formal interest rate of the firm and other firm specific variables. Specifically, I would like to know how the interest rate is affected by accumulated debt, the investment-capital ratio. The dependent variable is the interest rate. In the data, I can observe the loan amount with the interest rate provided by a formal financial institution for the firms in a given year. The interest rate is expected to depend on the accumulated debt of the firm. I therefore include $DEBT$ in the interest rate regression. Its coefficient is expected to be positive: the higher the accumulated debt of a firm, the higher is the interest rate for additional loans form a bank.

Banks in Ghana often ask for a collateral before providing funds. One option would be to measure the firm's ability to provide collateral with its capital stock. However, as discussed earlier, in many developing countries such as Ghana, small manufacturing firms do not make substantial investments in capital after startup. In a given year, the capital stock of a firm is likely to be very close to its startup capital, which may have already been used as collateral in previous periods.[16] The older the firm is, the less likely that the initial capital stock is currently available for collateral. Instead, I use the ratio of investment to capital stock to proxy for (the lack of) available collateral in the firm in the year when the loan is provided. I expect its coefficient in the interest rate function to be negative. The summary statistics of the variables used in the estimation are in Table 12.

Based on the above, I write down the following equations.

$$r_{t,i} = \overline{r} + \exp(\alpha + \beta_1 \frac{I_{t,i}}{K_{t,i}} + \beta_2 DEBT_{t+1,i} + \varepsilon_{t,i})$$

[16] Based on the survey data, 52-80% of the firms do not invest per year. The average capital stock is 15 million Cedis in 1991 and slowly grows to 24 million Cedis by 1998. However, an average firm spends 8-17 Million Cedis on intermediate input purchase and the mean loan amount from formal sources is 24 Million Cedis per year. Compared to these numbers, an average 7 million Cedis increase in capital stock during the 7 year period is not substantial.

Table 13: Instrumental variables (2SLS) regression estimates, N=72

Dependent var: INTEREST	Coef	Std. Error	P>|z|
DEBT	0.600	0.329	0.068
INVEST/CAP	-0.367	0.222	0.098
cons	-1.319	0.058	0.000
Instrumented: DEBTt+1,i			
Instrument: DEBTt,i			
Robust standard errors are reported			
Debt variable is in 1991 Cedis, Billion			

where $\overline{r}$ is the risk free interest rate.

$$DEBT_{t+1,i} = \gamma + \delta_{1r_{t,i}} + \varphi_{t,i}$$

This is a simultaneous equation problem very similar to a traditional demand and supply system. To estimate it, I use an instrumental variable regression where $DEBT_{t+1,i}$ is instrumented with $DEBT_{t,i}$. The results are in Table 13. The parameter estimates are significant at the 10 percent level. The signs of the estimated coefficients are as expected. Higher investment-capital ratio reduces the interest rate and higher accumulated debt increases the interest rate of the firm.