Family Financing and Aggregate Manufacturing Productivity in Ghana*

Preliminary and incomplete. Please do not cite.

Andrea Szabó and Gergely Ujhelyi

Economics Department, University of Houston

E-mail: aszabo2@uh.edu, gujhelyi@uh.edu

October 12, 2015

Abstract

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. To quantify this effect, we estimate a dynamic model of firm behavior using data from the Ghanaian Manufacturing Survey 1991-2002. A counterfactual analysis with no family financing indicates an average productivity gain of about 10% over 20 years relative to a situation where all firms have access to family loans. This increase in productivity is accompanied by large gains in average output produced. To the extent that improving formal lending reduces the availability of family loans, this suggests an additional channel through which improving credit market conditions may increase productivity in developing economies.

*We would like to thank Patrick Bajari, Amil Petrin, Simon Quinn, Chris Timmins, and seminar participants at Chicago, Minnesota, Rice and NEUDC 2012 for comments and suggestions.

1 Introduction

In developing countries, extended families provide a variety of important resources to businesses, including financing, labor, physical capital, information, etc. Many of these roles are as of yet little understood.

Family financing in the form of loans from relatives for startup capital, investment or intermediate input purchase, is generally available at lower interest rates than formal financing.[1] Studies typically report zero or even negative interest rates on loans provided by relatives, therefore family financing is a substitute to formal bank loans. 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. These 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 assess the empirical relevance of this hypothesis using micro data from the Ghanaian Manufacturing Survey 1991-2002. In Ghana, the examined period corresponds to an improvement of the general credit market conditions, and we observe large variation in the availability of family loans in the sample. We present evidence using both aggregate data and newly collected data on the number of bank branches in a city that better access to credit markets is associated with a lower prevalence of family financing. In turn, we show that fewer family loans are associated with increased exit among manufacturing firms in the sample. To calculate productivity, we estimate production functions using a modification

[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) show that after the owner's own savings, the main source of start-up capital is relatives and friends because only a small fraction of firms could gain access to bank loans. Fafchamps and Minten (1999) find that among agricultural traders in Madagascar, 53.2% were helped by family and friends at start-up and close to half learned the business with a relative or friend.

of the Levinsohn and Petrin (2003) method proposed by Wooldridge (2009). The estimates show that mean productivity is lower for firms who receive family money in various ways. First, we show that receiving financial help from the family for business startup is associated with lower mean productivity throughout the sample period. Second, 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. We show that firms solving such liquidity problems using family financing have a lower average productivity as well.

To quantify the link between credit market conditions, availability of family loans, formal lending and the production process, we estimate a dynamic model of firm behavior. 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, we apply the simulation-based 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, as well as the maximum amount of loan provided by the family. In counterfactual experiments we use the estimated model to simulate the Ghanaian manufacturing sector over a 20 year period. We find that changing the fraction of firms that have access to family financing from 1 to 0 leads to a productivity increase of 10% by the end of the period. The average firm in the market is also larger in terms of labor, capital and output. In this sense, the presence of family financing is a potentially important 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

Schündeln (2007), who estimates a dynamic model of firm-level investment in the presence of financing constraints. He uses earlier years of the Ghanaian Manufacturing Survey and focuses on formal loans and the constraints arising from banks' collateral requirements. By contrast, this paper focuses on the role of family financing. We identify one of the causes of low aggregate productivity in the economy, and we evaluate the effect of changes in the availability of family loans. We also relate the availability of family loans to credit market conditions such as properly working financial institutions and the availability of formal credit.

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, 1991-2002, conducted by the World Bank, the Centre for the Study of African Economies at Oxford, the Ghana Statistical Service, and the University of Ghana.[2] This provides a long panel of 12 years, and contains detailed information about general firm characteristics as well as the labor market and financial market activities of the firms. Information collected includes detailed questions on family financing and what family loans were used for. The dataset also contains *firm-specific* price indices (these are computed by the survey team using information collected on quantities and prices of each product produced by a firm), which is important for the consistent estimation of production function coefficients (see more on this in Section 3.3.1).

Initially, a sample of 200 firms was selected to participate in the survey, designed to be representative based on size and industry structure according to the 1987 National Industrial Census.[3] About half of these firms remain in the sample for all survey waves. In each wave, exiting firms were replaced by similar firms to keep the sample representative and the number of firms constant across waves. Over the 12 waves, a total of 312 firms were interviewed. In the analysis below, we include only domestic private firms (exclude state-owned and foreign firms). Family loans are likely to play a more important role for private Ghanaian firms than for state and foreign owned firms that have different opportunities to get financing. The data used in our analysis is further restricted by the availability of information necessary to estimate the production function. The final sample consists of 1484 firm-period observations. Summary statistics appear in Table 1 and Table 13 in the Appendix presents the sectoral distribution of the sample.

Real output is obtained as firm revenue deflated with firm-specific price deflators provided by the survey team (these price deflators were constructed using information collected on each firm's products and their prices). Capital is measured as the replacement value of the

[2] Teal (2011) describes the construction of the dataset. The questionnaire and the data is available from http://www.csae.ox.ac.uk/datasets/Ghana-rped/Ghmain.html. The newest rounds of the data were published only recently. Studies using earlier rounds include Jones (2001), Schündeln (2005), and Frazer (2005, 2006).

[3] The National Industrial Census was collected only three times by the Ghana Statistical Service in 1962, 1987 and 2003. It contains basic information, such as firm location and the number of employees. It does not contain the information necessary to estimate production functions.

stock of plants and equipment.[4] To measure intermediate inputs, we use the total cost of raw material inputs per year. Real values are constructed using firm-specific material price indices provided in the survey (these were constructed using information collected on the materials used by each firm and their prices). Employment at the firm includes all salaried employees. The values of all monetary variables in the paper are deflated to 1991 Ghanaian Cedis.

In developing countries such as Ghana, borrowing can come from many sources, including informal sources such as family and friends, or from overdraft facilities. Different lending sources operate with a wide variety of interest rates. An advantage of the survey used here is that it provides information on the various financing sources used by the firm. In the data, we can observe the loan amount with the interest rate provided by a formal financial institution in a given year. We also have data on the loan amount 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 we focus on here. We calculate the interest rate for loans coming from family using the loan amount and the expected repayment. Table 12 in the Appendix presents the average of the highest observed interest rates in a given year, as well as the risk-free interest rate on deposits from the World Bank for comparison. As expected, interest rates on formal loans generally follow the trend observed in the deposit interest rate. The wedge between these two measures is 8 percentage points on average. Yearly averages computed including the informal interest rates are lower, reflecting the fact that interest rates on loans from family and friends have a median of zero.[5] Overall, end-of-year net financial assets (savings minus loans) are positive for 11% of the observations in the data and negative for 26% of them.

[4] The capital variable is calculated as described in Teal (2011) assuming a 2 percent depreciation rate.

[5] These low interest rates are one of the main reasons firms use informal sources in the first place. When asked why they chose to borrow from informal sources, 29% of respondents in the survey cited the low interest rates (49% cited easier formalities, and 11% that no collateral was required). We discuss why it makes sense for households to lend to the family firm at low interest rates below.

Table 1: Summary statistics

	Mean	Std. dev	10 %	90 %	N
Employment	33.31	47.66	4	90	1484
Capital	74.69	211.65	0.15	160.15	1484
Output	94.89	262.07	1.70	218.22	1484
Value added	34.92	99.30	0.32	83.10	1483
Material inputs	46	147.90	0.78	93.15	1484
Wage	0.19	0.23	0.02	0.46	1274
Earnings	0.26	0.23	0.05	0.53	1359
Loans					
Formal loan amount	152.81	368.13	0.50	407.07	301
Formal interest rate (%)	32.52	12.87	15	46	301
Informal (family) loan amount	3.79	19.93	0.02	4.31	227
Informal interest rate (%)	5.10	27.68	0	32	227
Average portfolio interest rate (%)	7.64	16.22	0	37	1484
Input price	1.01	0.06	1	1	1484
Loan for investment	8.80	38.17	0.04	288.06	502
Loan for intermediate input purchase	98.93	306.12	0	18.54	429
Investment					
Investment in pland and equipment	4.70	28.20	0	3.60	1484
Investment in land and buildings	0.56	14.85	0	0	1484
Total investment	5.26	34.10	0	4.30	1484

Notes: All monetary values are in Million 1991 Ghanaian Cedis or about 2500 USD.

Firms report their yearly wage bill, which we divide by the number of employees to get the price of labor. We have non-zero wage data for 1423 observations. In some cases, workers receive (in-kind or cash) allowances or bonuses in addition to wages. As a robustness check, we compute some of the results below with the available earnings data which includes these allowances. Note that there is very little difference in the averages of these two variables. The summary statistics are in Table 1.

We supplemented the manufacturing survey with two additional data sources to capture aggregate credit market conditions. First, we took various measures of financial market conditions from the WDI. These include the deposit interest rate, net domestic credit, and claims on the private sector. Second, to obtain a more disaggregated measure, we collected original data on the number of bank branches operating in Ghana in various years. For years prior to 2000 this information is not available in any government database (such as databases maintained by the central bank, the chief regulator of banks in Ghana) or record archive (such as the National Archives of Ghana). To gather the data, we collected old phonebooks and manually counted the number of bank branches operating in the country. We focused on commercial bank branches, excluding headquarters with no commercial services provided and special banking institutions such as office of the World Bank or the Bank of Ghana. For years after 2000, we use phonebooks as well as data provided by the Banking Supervision Department of the Bank of Ghana. See the Online Appendix for more details of the data sources and construction of the bank branch measures.

3 Patterns in the data

This section looks at the correlations in the data. First, we document a negative correlation between the probability that firms in a given year receive family financing and various credit market conditions. When credit markets function better, there is less family financing available. Second, we show that family loans are associated with a lower exit rate at the firm level. Firms that have access to family financing at low interest rates are more likely to stay in the market. Third, we document a negative correlation between access to family loans and firm productivity. To do this, we use measures of productivity derived from explicitly estimating firms' production function.

3.1 Family financing and credit market conditions

What determines the likelihood that family financing is available to a firm? Aryeetey (1998) explains that family members often provide financial help as a favor because they do not have access to investment opportunities with a positive interest rate. During our period of study, households faced very limited savings options. A typical household would not have convenient access to a bank branch: traveling to one to make a deposit might take several hours, which would need to be repeated for each withdrawal. As late as 2006, 84% of households interviewed in the Ghana Statistical Service's Financial Service Survey did not have a bank account. Average traveling time to the nearest bank branch indicated by those without an account was 52 minutes, compared to 36 among those with an account. In the latter group, 42% indicated that the location of the nearest bank was very convenient, compared to only 19% among those without a bank account. Among the respondents without an account, 10% said that they did not know where the neareast bank was. Minimum balance requirements and fees for opening and keeping a bank account are also a constraint. In the same survey, respondents without an account were asked to indicate why they did not open one. The main reasons given were not meeting the minimum requirements, not meeting the balance requirement, and never having thought about it (see Table 2). Limited access to banks affects both the saving and the borrowing behavior of households. In the Financial Service Survey cited above, 5% of households reported ever borrowing from a bank, while over 50 percent reported ever borrowing from family and friends (see Table 3).

Households that use banks for their savings often use them for different reasons from what is typical in developed countries. Most households live in neighborhoods affected by crime in dwellings that are difficult to keep secure. Keeping savings at home is risky and people value the safety of a bank. Some people may also value bank accounts as a form of commitment savings. In the Financial Service Survey, the two top reasons indicated for having a bank account were to save (34%) and to keep money safe (23%), and 9.4% listed "to manage money better" (Table 2).

Under these circumstances, keeping savings in the family firm is a good substitute for banks even at zero interest rates. This in turn suggests that the availability of family financing to firms will be affected by general credit market conditions, including the public's access to financial institutions, the process of credit approval, and available domestic credit to the private sector. For example, when a bank branch opens in a village, local residents may choose this convenient saving opportunity over investing their money in the family

Table 2: Households' reasons for (not) having a bank account

A. Main reason for not opening bank account (N = 2794)		
	N	Percent
Charges and fees are too high	153	5.5
No banks or institutions closeby	101	3.6
Does not meet minimum requirements	652	23.3
Too much corruption	21	0.8
Hours of operation not convenient	13	0.5
Does not have an identity document	29	1.0
Cannot afford to keep a minimum balance	506	18.1
Does not trust banks	16	0.6
Prefers to deal in cash	175	6.3
Too young to qualify for an account	166	5.9
Never thought about it	349	12.5
Other	613	21.9
B. Main reason for having a bank account (N = 524)		
	N	Percent
Access a home loan	16	3.1
Access a personal laon	71	13.6
Save	177	33.8
Keep money safe	121	23.1
Managing money better	49	9.4
Access a business loan	16	3.1
Deposit money from employer	8	1.5
Deposit money from own business	4	0.8
Pay insurance	3	0.6
Pay debt	2	0.4
Withdraw money when needed	40	7.6
Transfer money safely/cheaply	3	0.6
Other	14	2.7

Notes: Source: Financial Service Survey 2006, Ghana Statistical Service.

Table 3: Households' sources of borrowing (N = 3318)

Source	N	Percent
Bank	168	5.1
Government	38	1.2
Credit union	32	1.0
Micro-finance lender	66	2.0
Employer	106	3.2
Money lender	226	6.8
Welfare scheme	70	2.1
Family or friends	1670	50.3
Never borrowed	1481	44.6

Notes: Source: Financial Service Survey 2006, Ghana Statistical Service.

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 banking reforms of Ghana were considered to be one of the most successful ones in Africa. Macroeconomic and credit market indicators show considerable improvement during our study period (1991-2002). 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 by 2002, with values as high as 24 percent in the late 1990s. Domestic credit as a percent of GDP increased from 4 percent to 12 percent (second panel of Figure 1).[6]

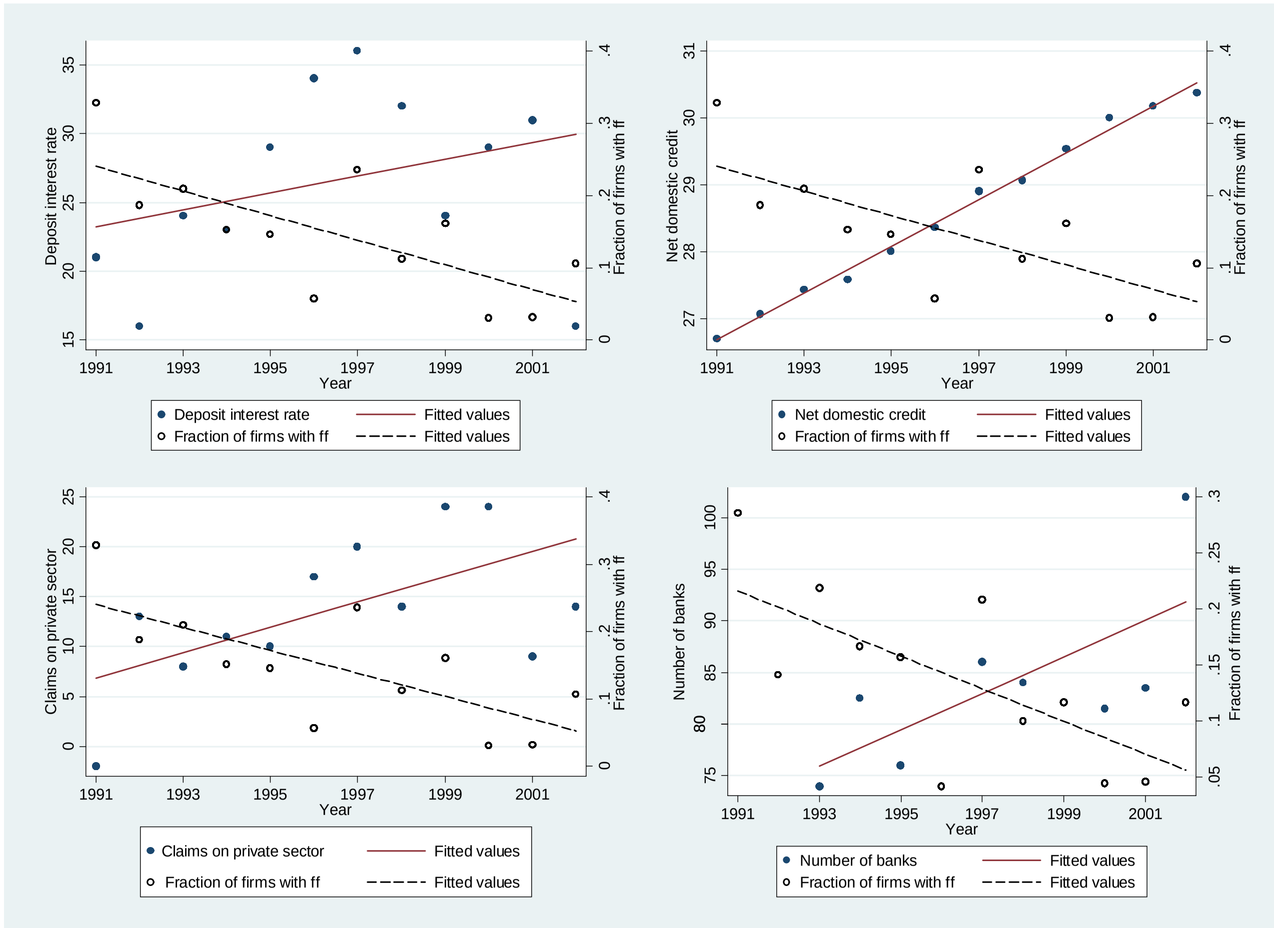
Over this period of improving formal credit markets, we observe a decline in the probability that family loans are available (Figure 1). For example, the 16 percentage point increase in the private sector's share of claims on the banking system was accompanied by

[6] Source: World Development Indicators.

a 22 percentage point decrease in the likelihood that firms in the data use family financing.

Using the bank branches data allows for studying the correlations at a more disaggregated level. The last panel of Figure 1 shows the number of bank branches operating in Accra (the most developed city in the country) and restricts attention to surveyed firms located in Accra. This yields a very similar picture. The number of bank branches operating in Accra increased by 38% between 1993 and 2002. This was accompanied by a reduction in the fraction of firms using family financing from above 20 percent in the early 90's to below 10 percent in the early 2000's.

Figure 1: Credit market conditions and family financing over time



Notes: Deposit interest rate, Net domestic credit (in logs), and Claims on private sector (annual growth in percentage of M2) are from the WDI. Fraction of firms with family financing is from the Ghanaian Manufacturing Survey. The last panel is for the city of Accra: number of banks in Accra was computed from phone directories as described in the text, the fraction of firms with family financing is from the Ghanaian Manufacturing Survey.

3.2 Family financing and firm dynamics

Two factors suggest that the presence or absence of family loans can make a difference in firms' exit decisions. First, as can be seen from Table 1, interest rates on formal and informal loans tend to be very different. Consistent with the patterns documented in earlier studies, 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 our dataset, the median interest rate is zero with an average of 5.1%. This is significantly lower than the interest rate on loans from formal sources (mean: 32.5%). As a result, family financing, if available, can substantially lower the interest rate on firms' portfolio.

Second, unlike a typical Western company, firms in Ghana often rely on loans to finance their daily operations. A typical Western firm would use loans mainly for purchasing investment goods and it would deal with liquidity problems using trade credit or other short term business credits, such as overdrafts. By contrast, among firms in Ghana, investment is not common. In the data, every year between 47 and 72 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.[7] This is what the data shows: on average, firms spend 11 times more from loans on intermediate inputs than on investment goods (see the Appendix for the distribution of how loans are spent). Since firms that can get lower interest rates are effectively facing lower input prices, they may gain considerable cost advantage on the market.

Tables 4 and 5 document a negative correlation between access to family loans and firms' propensity to exit the market. Table 4 looks at firms observed in the first year of the sample and tabulates them based on whether they have family loans and their propensity to exit the market either in the following year or during the study period. Firms without access to family financing are more likely to exit. Table 5 presents corresponding regressions that

[7] The mean value of intermediate input purchases is on average 9 times higher than the mean value of investment (see the Appendix).

Table 4: Correlation between exit and family financing

	Family loans		
	No	Yes	Total
Number of firms	86	42	128
Exit in next period	7.0%	2.3%	5.5%
Exit ever	60.5%	50.0%	57.0%

Notes: Tabulation of the 128 firms observed in the first year of the study period. Exit in next period is 1 if the firm exits by year two. Exit ever is 1 if the firm exits in any year during the study period. Family loan is 1 if the firm holds positive family loans in the first year.

control for various firm level variables. Again, we see a negative correlation between family loans and exit.

3.3 Family financing and aggregate productivity

The goal of this section is to assess the correlation between firm productivity and family financing. Measuring firm productivity requires production function estimates, which are presented below.

3.3.1 Production function estimation

The basic framework of the estimation used here follows the Wooldridge (2009) modification of the Levinsohn-Petrin method. Szabó (2014) uses this method to estimate production functions based on the Manufacturing Survey for the entire sample of manufacturing firms operating in Ghana (including state and foreign-owned firms) and we follow the same method for the sample used here. The standard framework is extended to allow for endogenous exit, labor market frictions, and different input prices. An overview is provided below, see Szabó (2014) for further details.

Let the firm's technology be described by a Cobb-Douglas production function of the

Table 5: Correlation between exit and family financing: Probit regressions

Dep. variable	Exit next period	Exit ever
	(1)	(2)
Family loan (yes/no)	-0.867*	-0.401
	(0.461)	(0.262)
Output	-0.073	-0.191*
	(0.143)	(0.105)
Labor	0.001	0.005
	(0.004)	(0.004)
Productivity	0.890	-0.268
	(0.709)	(0.448)

Notes: The table presents Probit regressions of an indicator for whether a firm exits in the second year of the study period (column (1)) or at any point during the study period (2). The sample is the 128 active firms observed in the first year of the study period. Dependent variables are an indicator for whether the firm is holding family loans, whether it has formal loans, output, the number of workers, and productivity. The latter is derived from production function estimates as described in Section 3.3 below. Robust standard errors in parentheses. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

form

$$q_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_M m_{it} + \beta_a a_{it} + \varepsilon_{it}, \tag{1}$$

where q_{it} is output in period t, l_{it} is the number of employees, k_{it} is the real capital stock, m_{it} is the quantity of intermediate inputs (materials), and a_{it} is the age of the firm (to proxy for learned productivity), all in logs. The productivity shock ε_{it} satisfies

$$\varepsilon_{it} = \omega_{it} + \eta_{it}. \tag{2}$$

Here ω_{it} is the "transmitted component," which is known by the firm but not by the econometrician and assumed to follow and exogenous first order Markov process. The term η_{it} is an unpredictable (both to the firm and to the econometrician) i.i.d. productivity shock assumed to be uncorrelated with input choices. Following Levinsohn and Petrin (2003), one can proxy the transmitted component with

$$\omega_{it} = g(k_{it}, m_{it}, a_{it}). \tag{3}$$

Using intermediate inputs as a proxy variable is particularly relevant since every year between 46 and 80 percent of the firms in the data do not report investments above the startup capital. Therefore much information would be lost in dropping these cases, as would be required by the Olley and Pakes (1996) method which uses investment as a proxy.

Firms are assumed to solve a standard dynamic programming problem with the state variables k, a, and ω, choosing their level of investment. Investment I_{it} determines the evolution of the capital stock according to $k_{it+1} = (1-\delta)k_{it} + I_{it}$, where δ is the depreciation rate.

Traditionally, equation (1) is estimated in two steps. The first stage involves estimating the inverse intermediate input demand function as well as the coefficient on labor. The second stage identifies the capital and age coefficients. The method proposed by Wooldridge (2009) combines these two stages into a single set of moment conditions and estimates the parameters in one step using GMM. This method yields more efficient parameter estimates than the two-step procedures. Another advantage of the Wooldridge (2009) method that is particularly important in the present context is that it allows separating the predictable (transmitted) component ω of the error term from the i.i.d. shock η in equation (2). This allows us to use estimated productivity ω as a state variable in the model in section 4 below.

Following Wooldridge (2009), the production function parameters are estimated from the system

$$q_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_M m_{it} + \beta_a a_{it} + g(k_{it}, m_{it}, a_{it}) + \eta_{it} \text{ for } t = 1, ..., T$$

$$q_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_M m_{it} + \beta_a a_{it} + f[g(k_{it-1}, m_{it-1}, a_{it-1})] + u_{it} \text{ for } t = 2, ..., T$$

where $u_{it} = \omega_{it} - E(\omega_{it}|\omega_{it-1}) + \eta_{it}$. We implement this specifying f as a second degree polynomial and g 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:

$$\begin{pmatrix} r_{it1}(\theta) \\ r_{it2}(\theta) \end{pmatrix} = \begin{pmatrix} q_{it} - \alpha_0 - \beta_L l_{it} - \beta_K k_{it} - \beta_M m_{it} - \beta_a a_{it} - \mathbf{c}_{it}\boldsymbol{\lambda} \\ q_{it} - \varphi_0 - \beta_L l_{it} - \beta_K k_{it} - \beta_M m_{it} - \beta_a a_{it} - \rho_1 \mathbf{c}_{it-1}\boldsymbol{\lambda} - \rho_2 (\mathbf{c}_{it-1}\boldsymbol{\lambda})^2 \end{pmatrix}$$

where $\mathbf{c}_{it}$ is a vector of the terms in the polynomial function g, and all Greek letters denote parameters. This yields the moment conditions $E[\mathbf{Z}'_{it}\mathbf{r}_{it}(\theta)] = 0$ for $t = 2, ..., T$, for identification, where $\mathbf{Z}_{it}$ is a matrix of instruments given by

$$\mathbf{Z}_{it} = \begin{pmatrix} (1, l_{it}, c_{it}, k_{it-1}, l_{it-1}, a_{it-1,}\mathbf{c}_{it-1}, \mathbf{h}_{it-1}) & 0 \\ 0 & (1, k_{it-1}, a_{it-1,} l_{it-1}, \mathbf{c}_{it-1}, \mathbf{h}_{it-1} \end{pmatrix}$$

and $\mathbf{h}_{it-1}$ is a second degree polynomial of $\mathbf{c}_{it-1}$. In the estimation, we include industry fixed effects (Furniture/Wood, Textile/Garment, Metal/Machinery, and Bakery/Food/Alcohol) in equation (1) to account for technology differences between industries.

In the production function literature, due to the available data, the production function in (1) typically has to be estimated using data on revenues rather than the physical quantity of output (Olley and Pakes (1996) refer to this as a "sales generating function"). This has the potential to result in inconsistent coefficient estimates if firm-specific output prices are correlated with technology or input use. This can be alleviated if industry-specific price indices are available to deflate the revenue data (Petrin and Sivadasan (2013) refer to this as a "gross output production function"). In this case, the estimates are valid as long as the deviation of firms' prices from the industry average is uncorrelated with technology or input use. The data used here allows the identification of production function parameters under weaker assumptions because it contains *firm-specific* price indices. Using these to deflate firm revenue yields consistent production function coefficients as long as technology and input use is uncorrelated with changes in a firm's output price within an industry. Following Petrin and Sivadasan (2013), we will refer to the estimates below as the parameters of a gross output production function.

The estimation includes three extensions to the framework described above.

Endogenous exit. Firm exit may create a selection bias if firms exit based on unobserved productivity. To correct for this, we follow Olley and Pakes (1996) who specify an exit rule for firms that depends on a productivity cutoff $\overline{\omega}_t(k_{it}, a_{it})$.We can control for this cutoff using data on observed exit conditional on the information available at $t - 1$:

$$P_{it} \equiv \Pr(no\ exit|k_{it-1}, a_{it-1}) = \Pr(\omega_{it} \geq \overline{\omega}_t(k_{it}, a_{it})|k_{it-1}, a_{it-1}) \tag{4}$$

We estimate equation (4) non-parametrically, modelling the probability of surviving in t as a function of k_{it-1}, a_{it-1} using a probit model with a 4th order polynomial. Equation (4) can be inverted to obtain $\overline{\omega}_t$ as a function of ω_{it-1} and $\widehat{P}_{it}$, i.e., use $\overline{\omega}_t(k_{it}, a_{it}) = g(\omega_{it-1}, \widehat{P}_{it})$.

Labor market frictions. In the standard formulation, labor l is taken to be a non-dynamic input chosen freely in every period. If hiring and firing is associated with high fixed costs, labor becomes a dynamic variable chosen by the firm conditional on expected productivity next period. To control for this, we compute estimates that allow labor to be a dynamic variable.

Accounting for different input prices. The above estimation procedure assumes that firms face the same intermediate input (material) prices. As described in Section 3.2, firms in Ghana use a variety of financing sources to purchase materials, including loans from banks, loans from family, and their own financial assets. Firms using different financing sources effectively face different input prices: for example, if they finance the purchase from bank loans, the corresponding interest rate will increase the price of materials. Since firms that face lower material prices can purchase more materials for given productivity, this may violate the assumption that input demand is monotonic in productivity, which is needed to write down equation (3). In this case, monotonicity may only hold conditional on the material price, and we therefore include a measure of material prices based on the source of financing in the estimation.[8]

To calculate the interest rate on firms' portfolio, we take a weighted average of the formal and informal interest rates, using the relative loan amounts as weights. Denote D_{it} a firm's total loans (from formal or informal sources) and r_{it}^{p} the average interest rate on its portfolio. After normalizing the market price of materials (on which we have no data) to 1, we write the material price as

$$p_{it}^{m} = \begin{cases} 1 \; if \; D_{it} \leq 0 \; or \; (D_{it} > 0 \; and \; I_{it} \geq D_{it}) \\ 1 + \frac{r_{it}^{p}}{100} \frac{D_{it} - I_{it}}{M_{it}} \; if \; D_{it} > 0 \; and \; I_{it} < D_{it} \\ 1 + \frac{r_{it}^{p}}{100} \; if \; D_{it} > 0 \; and \; I_{it} = 0 \end{cases} \tag{5}$$

where I_{it} is the firm's investment in capital. If the firm does not borrow, or if investment is greater than the loan amount, then the firm is assumed to pay the market price for the materials. This assumes that the firm uses the loan first to purchase investment goods and only the remaining part of the loan is used for purchasing materials. Similarly, if the firm makes an investment, then only the remaining part of the loan will count toward an increase in the material price. If the firm does not invest, then the firm spends the entire loan on purchasing materials. Table 6 shows the summary statistics of the input price variable.

With these extensions, the proxy function for the transmitted component of productivity (equation (3)) becomes

$$\omega_{it} = g(k_{it}, m_{it}, a_{it}, l_{it}, \widehat{P}_{it}, p_{it}^{m}). \tag{6}$$

The estimation results are in the last column of Table 7 (the first three columns present alternative specifications for comparison). As expected, materials have the highest and

[8] We know of only one other attempt to deal with the heterogeneity of input prices across firms in the estimation of production functions. De Loecker et al. (2014) deal with unobserved input prices by proxying for them with an index of output quality. In the Ghanaian context, the variation in firms' sources of financing is likely to be a more important determinant of input price differences.

Table 6: Intermediate input price

	Mean	Std. dev	10%	90%	N
Input price	1.013	0.057	1.000	1.000	1484
Input price conditional on Debt > 0	1.037	0.093	1.000	1.130	502
Price conditional on Debt > 0 and Investment $= 0$	1.083	0.125	1.000	1.256	225

Notes: Intermediate input prices are computed based on (5). Prices are increased with the interest rate if the input is purchased using a loan. Prices are deflated to 1991 Ghanaian Cedis.

Table 7: Production function parameter estimates

	Pooled OLS	Fixed effects	Levinshon/Petrin	Wooldridge (2009)
Capital	0.184***	0.063	0.090	0.074***
	(0.029)	(0.042)	(0.217)	(0.014)
Material	0.478***	0.368***	0.790**	0.820***
	(0.068)	(0.011)	(0.365)	(0.045)
Labor	0.337***	0.282***	0.210***	0.131**
	(0.037)	(0.037)	(0.037)	(0.053)
N	1280	1280	1280	1280

*Notes:*The estimation controls for three ownership dummies, the firm's age and four sector dummies. Robust standard errors clustered by firm in parentheses. For column (4), Hansen's J statistic is 49.11 with a p-value of 0.11. * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

capital the lowest share among these firms. Column (4) is the preferred specification in Szabó (2014), who presents a detailed comparison to alternative specifications, including ones that do not take into account dynamic labor choice, endogenous exit, or firm-specific input prices.[9]

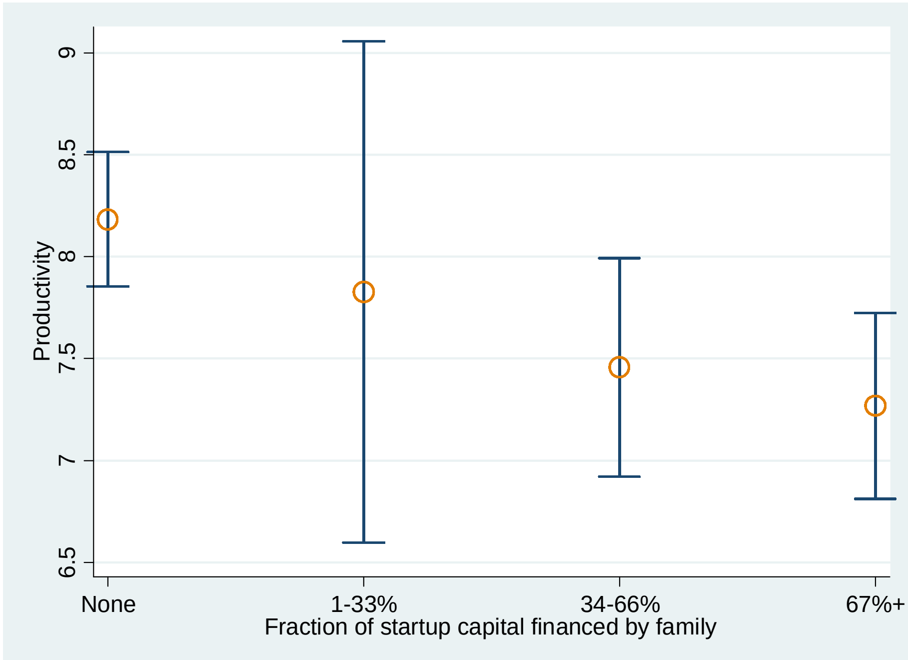
3.3.2 Productivity by type of family financing

To document the relationship between family financing and productivity, we look at family loans based on their use.

Financing the startup capital. The survey asked firms how they financed their business startup. We have data for 127 sample firms regarding the financing of the business startup.

[9]The coefficient estimates in the preferred specification are also in line with those reported by Soderbom and Teal (2004) using a different estimation method on a different subset of the same dataset.

Figure 2: Firm productivity and family financing of the startup capital



Notes: The figure shows the average productivity of firms grouped by the fraction of startup capital financed from family sources. Bands represent 95 percent confidence intervals.

Of these firms, 28.3% used some financial help from family to start their business, and 20.5% financed more than half of the startup cost from these sources. Among those who used family financing, family contributed on average 71.3% of the startup cost, and more than half of the firms financed the startup cost entirely from family sources.

Figure 2 presents the estimated mean firm productivity levels by groups. Firms receiving more than two thirds of the startup capital from the family have 11.2% lower productivity than firms who did not use family loans.

Liquidity problems. During the 12 years of the survey, firms were asked about liquidity problems five times. Summary statistics for these questions are in Table 8. Each year, between 67-82% of the firms reported liquidity problems in the current year. Of these firms, 17-27% borrowed money from family and friends to continue their businesses.

As expected, firms that never experienced liquidity problems (16 % of the sample) have higher estimated productivity (by 20 percent) than those who experienced some liquidity problems. Figure 3 shows the breakdown of the average productivity estimates depending on whether firms borrowed from the family. Firms that rely more heavily on family loans to solve liquidity problems have lower productivity on average.

Table 8: Liquidity problems and solutions reported by firms

	Wave 3	Wave 4*	Wave 5*	Wave 6*	Wave 7*
Reported liquidity problem	78.3	78.1	82.1	72.8	66.7
Solution of liquidity problem					
Sold off raw materials	-	0.93	-	-	-
Sold some equipment	-	-	2.97	1.20	2.41
Borrowed from bank (overdraft)	16.33	14.02	17.82	19.28	8.43
Borrowed from bank (loans)	3.06	8.41	15.84	10.84	13.25
Used personal cash reserves	11.22	10.28	9.90	22.89	7.23
Borrowed informally	22.45	27.10	16.83	19.28	21.69
Took cash advances from clients	11.22	24.30	14.85	19.28	12.05
Obtained supplier credit	19.39	25.23	41.58	25.30	14.46
Other	16.33	12.15	18.81	12.05	7.23
N	129	137	123	114	90

Notes: *Multiple answers were allowed

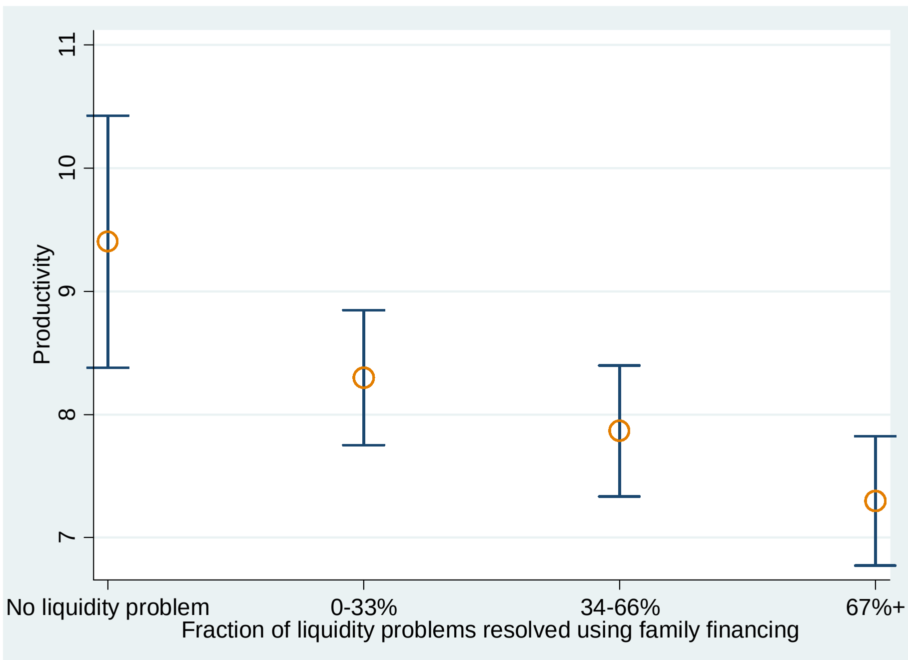
The results above establish that, on average, reliance on family loans is associated with lower aggregate productivity among manufacturing firms in Ghana. Below, we present a dynamic model where the availability of family loans depends on general credit market conditions, and firms with family financing have a cost advantage that allows them to stay in the market even if they are less productive. We show that the model is consistent with the data, and use it to quantify the effect of family loans on aggregate productivity in a counterfactual exercise.

4 Model setup

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

$$Y_{it} = L_{it}^{\alpha_L} Mi_t^{\alpha_M} K_{it}^{\alpha_K} e^{\omega_{it}},$$

Figure 3: Firm productivity and family financing of liquidity problems



Notes: The figure shows the average productivity of firms grouped by the fraction of liquidity problems resolved using family financing. The first category represents firms that did not report any liquidity problems. Bands represent 95 percent confidence intervals.

where Y_{it} is the firm's output in period t, L_{it} is labor, M_{it} is the intermediate input, and K_{it} is capital. ω_{it} is a productivity shock that is not observed by the econometrician but is observed by the firm and affects its input decisions. We assume that ω_t follows an exogenous first order Markov process.[10] The i subscript is omitted from now on for simplicity.

The firm uses its profit to pay for inputs, buy capital, buy financial assets, and pay a dividend. Investment in next period capital is denoted I_t and the capital stock evolves according to

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

where δ is the depreciation rate given exogenously. Assets are denoted A_t, with $A_t < 0$ if the firm took out loans in the previous period. The dividend paid in period t, d_t, satisfies

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

where w_t is the wage and r_t is the interest rate on the firm's portfolio (see below). This formulation assumes that any loans from the previous period ($A_t < 0$) are repaid in full before any dividend is paid.

While on the market, the firm chooses L_t, M_t, A_{t+1} and I_t to maximize the expected present value of its dividend stream,

$$E_0 \sum_{t=0}^{\infty} \beta^t (d_t + \epsilon_t),$$

where $\beta \in (0,1)$ denotes the one-period discount factor, and ϵ_t is a choice-specific stochastic payoff component.

At the end of each period, after production, the firm decides whether to stay in the market for the next period ($E_{t+1} = 0$) or exit ($E_{t+1} = 1$). We assume that a firm who would

[10] One can also introduce a shock η_{it} that is unobservable both to the firm and to the econometrician, as in Section 3.3.1 Because the firm can only base its decision on ω_{it}, this would make no difference in the model below.

generate a negative dividend for next period automatically exits the market. If the firm exits, its payoff is zero forever.

The firm can borrow from two sources: informal sources (family and close friends) and formal institutions (banks). There is a firm-specific interest rate on loans from banks. We will use the following specification of the cost-of-credit function from formal sources:

$$r_t^{bank} = \bar{r}_t(C_t) + g(K_t, A_t),$$

where C_t is some measure of general credit market conditions, $\bar{r}_t$ is the risk-free interest rate, and $g(K_t, A_t) > 0$ is a "wedge" that depends on the firm's current capital (a proxy for the available collateral) and assets (indicating the firm's current indebtedness). This specification guarantees that the interest rate is positive for all parameter vectors and also higher than the risk-free interest rate.

In each period a firm may have financing available from family sources. We model the family's willingness to give a loan as a state variable for the firm, denoted F_t: $F_t = 1$ if family loan is available, and $F_t = 0$ otherwise. We let $\Pr(F_t = 1) = \phi(C_t)$ so that families' willingness to give loans to firms may depend on credit market conditions. For example, if there are no formal bank branches, family members may be more willing to invest their money in the family firm. We assume that family loans have a fixed interest rate $r^{family} = 0$. This is consistent with the data, where the interest rate on family loans is zero for 75 percent of observed loans. For simplicity, we also assume that, if available, all family loans have a maximum amount Z_F. This will be treated as a parameter and estimated below. Since family loans have an interest rate of 0, it follows that the firm will always exhaust any available financing from the family before borrowing from the formal sector.

The interest rate on the firm's portfolio depends on whether the firm has positive assets or loans as well as the source of its loans (family or banks). It is given by

$$r_t = \begin{cases} \bar{r}_t \text{ if } A_{t+1} \geq 0 \\ r_t^{bank} \text{ if } A_{t+1} < 0 \text{ and } F_t = 0 \\ r^{family} \text{ if } A_{t+1} < 0 \text{ and } F_t = 1 \text{ and } Z_F > -A_{t+1} \\ r_t^{Portfolio} = \frac{Z_F}{-A_{t+1}} r^{family} + \frac{A_{t+1}+Z_F}{A_{t+1}} r_t^{bank} \text{ if } A_{t+1} < 0 \text{ and } F_t = 1 \text{ and } Z_F < -A_{t+1} \end{cases} \tag{7}$$

The solution of the firm's intertemporal problem is described by the value function

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

where $S \ni s$ is the state space and $\Sigma(s) \ni \sigma$ 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, the interest rates $\bar{r}_t$ and r_t^{bank}, the indicator F_t denoting the availability of family loans, and the general credit market conditions C_t. The choice variables are K_{t+1}, A_{t+1}, L_t, M_t, and E_{t+1}.

5 Estimation

The parameters to be estimated include the production function parameters and the maximum amount of family loan. One possible approach to estimation would be simulated maximum likelihood. However, since the value function has no closed form solution it would have to be solved numerically or simulated for each state, making this approach computationally very costly. Bajari, Benkard and Levin (2007) propose a computationally faster estimation method that avoids explicit numeric dynamic programming. Unfortunately this is not applicable to the present model due to the presence of the firm-specific interest rates (7) appearing in the firm's budget constraint, determined not only by the parameters but also by the endogenous state variables. This budget constraint implies choice-specific value functions which are not linear in the parameters as would be required for the Bajari, Benkard and Levin (2007) approach. A further complication arises from the fact that the distribution of some choice variables in the data is “lumpy.” This is especially true of investment, which is rare among small firms in developing countries (see above). Treating choices as continuous would only allow estimating the policy function under strong parametric assumptions. To overcome these difficulties, we use an estimation method from the discrete choice literature (which also avoids numeric dynamic programming to compute the value function). The estimation method is described in Hotz and Miller (1993) and Hotz, Miller, Sanders, and Smith (1994). Below we provide details about the key elements of the estimation procedure.

5.1 Estimation procedure

The value function has four parameters to be estimated: three production function parameters, $\{\alpha_L, \alpha_M, \alpha_K\}$, and Z_F, the maximum available loan from the family. 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. The deterministic part of the maximized period profit (dividend) has the following form:

$$
d(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) =
\begin{cases}
\pi(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) - \frac{A^*}{1+\bar{r}} \text{ if } A^* > 0 \\
\pi(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) - \frac{A^*}{1+r^{bank}} \text{if } A^* < 0 \text{ and } F = 0 \\
\pi(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) - \frac{A^*}{1+r^{family}} \text{if } A^* < 0 \text{ and } F = 1 \text{ and } Z_F > -A^* \\
\pi(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) - \frac{(A^*)^2}{A^* - Z_F r^{family} + (A^* + Z_F) r^{bank}} \text{ if } A^* < 0, F = 1 \text{ and } Z_F < -A^*,
\end{cases}
$$

where $\pi(s;\sigma,\alpha_L,\alpha_M,\alpha_K,Z_F) \equiv K^{\alpha_K} L^{\alpha_L} M^{\alpha_M} e^{\omega} - wL - M + A - K^* + (1-\delta)K$.

With estimates of the choice probabilities conditional on the state variables and the state transition matrix, we can construct the choice-specific value functions for a given value of the parameter vector $\theta = (\alpha_L, \alpha_K, \alpha_M, Z_F)$. This is the present value of per-period profits from taking choice σ at state s. Let $\widetilde{V}(s,\sigma,\theta)$ denote the choice specific value function minus the choice-specific error ϵ:

$$\begin{aligned}\widetilde{V}(s,\sigma,\theta) &= d(s,\sigma,\theta)+\beta E_{s'|s,\sigma}E_{\sigma'|s'}E_{\epsilon'|\sigma',s'}[d(s',\sigma',\theta) \\ &\quad +\epsilon'+\beta E_{s''|s',\sigma'}E_{\sigma''|s''}E_{\epsilon''|\sigma'',s''}[d(s'',\sigma'',\theta)+\epsilon''+\beta...]]\end{aligned} \tag{8}$$

Assume that the choice-specific errors ϵ follow a Type we Extreme Value distribution, i.i.d. across choices and time periods. Then $E(\epsilon|\sigma,s)=\gamma-\log(\Pr(\sigma|s))$, where γ is Euler's constant. Using this, the simulation estimate of $\widetilde{V}(s;\sigma;\theta)$ in (8) can be obtained as the average

$$\begin{aligned}\widetilde{V}(s;\sigma;\theta) &\approx \frac{1}{100}\sum_{n=1}^{100}[d(s,\sigma,\theta)+\beta[d(s'^n,\sigma'^n,\theta)+\gamma-\log(\hat{P}(\sigma'^n|s'^n)) \\ &\quad +[\beta d(s''^n,\sigma''^n,\theta)+\gamma-\log(\hat{P}(\sigma''^n|s''^n))+\beta...]]].\end{aligned}$$

This is computed starting from each possible state and action combination by forward-simulating the model. All 2520×31 choice specific value functions are simulated by drawing 100 sequences of (s_t,σ_t) for a given initial value, and computing the present discounted profit corresponding to each sequence.

Given the estimates of $\widetilde{V}(s;\sigma;\theta)$, we compute the predicted choice probabilities using

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

To estimate θ, we 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:[11]

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

[11] Note that the predicted choice probabilities $\widetilde{P}(\sigma|s,\theta)$ are different from $\widehat{P}(\sigma|s)$ which are the actual choice probabilities computed from actual data. The predicted choice probabilities depend on the parameters θ, whereas $\widehat{P}(\sigma|s)$ depend solely on the data.

5.2 Implementation

State space. The state space contains eight variables: K_t, A_t, E_t, F_t, ω_t, $\bar{r}, r^{bank}$ and credit market conditions represented by a stochastic process C_t. [Currently, labor is treated as a static but stochastic choice variable. See below.] For estimation, the data on capital K_t is discretized into 14 grid points, assets A_t are discretized into 9 grid points, and ω_t is discretized into 10 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) and the indicator for whether the family provides a loan to the firm (F_t) each can have two values, 0 or 1. In the dataset we have 1484 firm-time observations, as described in Section 2.

State transition. The optimal policy will determine the next state for K_t, A_t and E_t. The measure for credit market conditions C_t is discretized into four states and assumed to follow a Markov process. We estimate the transition matrix nonparametrically. The availability of a family loan F_t and the risk-free interest rate $\bar{r}_t$ are treated as exogenous state variables for the firm. Both of these are assumed to be determined by credit market conditions, and we estimate their distribution nonparametrically from the data for each of the four credit market categories. Based on the 1484 observations, the average probability that a firm will have a family loan available is 15 percent. During the survey period, this probability changes from a maximum of 33 percent to 3 percent. The firm-specific interest rate r_t^{bank} is given by the sum of the risk-free interest rate plus a firm-specific "wedge" that depends on credit market conditions and the firm's capital and loans. We nonparametrically estimate the wedge from the data as a function of the observed state variables (Asset and Capital). In Section 6.3, we present an alternative specification, using a widely used parametric expression for the wedge.

The state variable ω_t, the firm's observed productivity term, is estimated from the data as described in Section 3.3.1. Once the productivity term is recovered, we estimate the transition matrix for ω_t from the data. Specifically, we run an ordered logit regression where the categorized ω_t is explained by the categorized ω_{t-1}. Next period's state is generated using the resulting probability distribution and the current state.

Choice probabilities for K, A, and E. 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. Although firms do not change capital by more than two categories from one year to the next, their asset holdings show more variation in the data. Consequently, we allow firms to choose any of the possible 9 asset categories for the next period. In total, there are 37 possible actions based on these categories. In the sample, we observe 31 of these being actually chosen and we calculate the choice probabilities of these observed actions.

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 data might be biased (Rust, 1987). To smooth the outlier choice probabilities for the cases with few observations, we estimate a multinomial logit regression of the actions on the categorical variables of states as the independent variables.

Material and labor choices. The action of the firm also includes the static decision regarding labor and the intermediate input. These depend on the firm's current state. We estimate the transition matrix for L_t and M_t separately from the data by running ordered logit regressions of L_t or M_t on the categorized values of the relevant states. The current period's labor and material choice is generated using the resulting probability distribution and the current states. The fact that labor and material use is modeled as a static decision makes the dynamic programming problem feasible given the data by reducing the number of actions.

Other parameter choices. The following additional parameters are computed from the data as opposed to from the dynamic model. The interest rate on loans from family appears in equation (7). In the main version of the estimation, we use 0 percent for this interest rate based on the fact that 75 percent of informal loans observed in the data have an interest rate of zero (Table 1). The data does not show any important variation in this interest rate over time.

To compute the profit of the firm, it is necessary to know the firm's wage rate. We use 0.19 million Cedis, which is the mean wage observed in the data over the sample period. We also reestimate the structural parameters of the model using different wage measures.

A depreciation rate for capital of 6 percent is provided in the dataset (computed by the survey team). Finally, we compute the discount factor based on the average risk-free interest rate observed over the study period (26.25%).

5.3 Identification

Identification of the production function proceeds in two steps. First, we estimate productivity as described above, using the Wooldridge (2009) modification of the Levinsohn-Petrin method. In the second step, these estimates are treated as data in the dynamic model, so that variation in labor, capital, and materials is sufficient to identify the respective production coefficients.

The identification of the family loan parameter is as follows. Once the production function parameters are identified, we can compute the optimal investment of the firm in period t. We also know the asset holdings of the firms, so we know how much loan the firm would need to optimally invest conditional on the interest rate in t. Assuming that family financing has a lower interest rate, rational firms will take family loans whenever available and use formal loans only when family financing is not available in sufficient quantity. Thus, identification relies on firms that hold both family and formal loans. In the data about 15.2% of firm-year observations have positive family loans. In most cases (88.5% of these cases) the firm has no formal loan and the remaining 11.5 percent has both formal and family loans. Firms with both types of financing have on average three times as much family loan than firms with only family family financing.

In principle it would be possible to allow for the maximum amount of family loan to change over time, but identification would require enough firms with both formal and informal loans in every time period. The current dataset does not have enough variation of this type.

6 Results

6.1 Parameter estimates

Table 9 contains the parameter estimates from the dynamic model. For comparison, we report the parameter estimates from the production function estimation described in Section 3.3.1. The production function parameter estimates from the full model are close to the coefficients calculated with the Wooldridge-LP method.

The maximum available family loan parameter is estimated at 6.5 million Cedis (about 2600 USD). By comparison, the average family loan held by all firms with positive family loans is 3.8 million Cedis. The average among the subset of firms that hold / do not hold formal loans is, respectively, 9.6 / 3.0 million Cedis. This estimate is interesting in its own right as it provides information about the financing capacity of the family. It also provides an estimate of the deposits that may be expected from households into the banking system once this investment channel becomes available.

Table 9: Parameter estimates

	Full model		Wooldridge-LP	
	Estimate	SE	Estimate	SE
Labor coefficient	0.132	(0.063)	0.128	(0.049)
Material coefficient	0.816	(0.078)	0.820	(0.045)
Capital coefficient	0.089	(0.039)	0.074	(0.014)
Maximum available family loan	6.520	(3.178)		

Notes: The table shows the parameter estimates from the full dynamic model, as well as the production function coefficients from the Wooldridge-LP estimation (fourth column of Table 5) for comparison.

Table 10: Means of observed and simulated values

	Data	Data winsorized 5 percent	Data winsorized 2 percent	Simulation
Output	94.89	68.79	80.70	94.56
Labor	33.31	30.87	32.17	32.08
Material	46.00	30.80	36.71	36.58
Capital	74.69	47.28	69.62	68.89
Productivity	7.98	7.63	7.79	7.73
Asset (= -Debt)	18.19	4.89	11.50	11.08

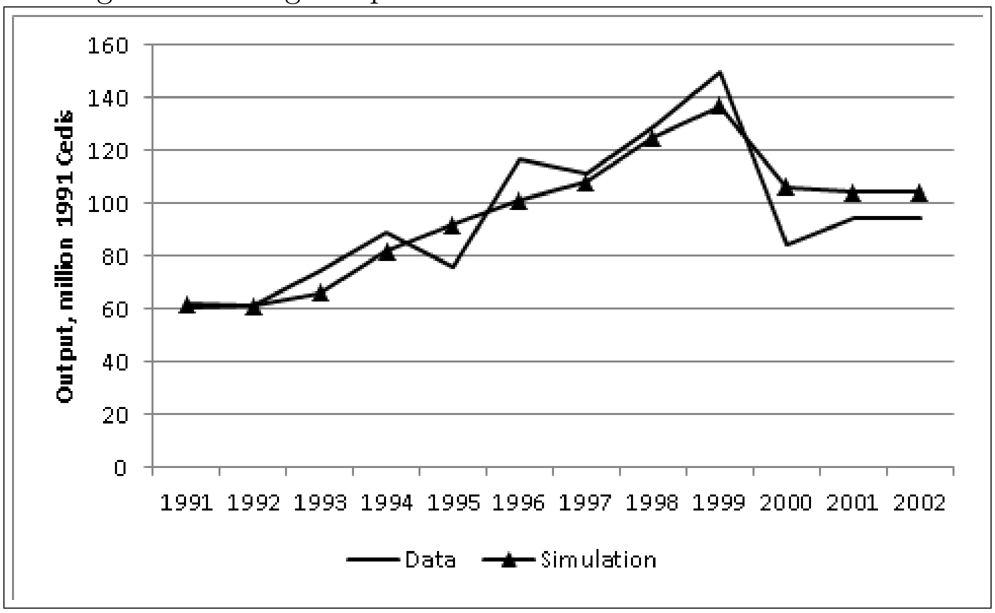
Notes: The table shows means from the data (full sample as well as two winsorized samples) and from simulating the estimated model. Number of simulations=100.

6.2 Model performance

To evaluate the model's performance, we replicate our dataset by simulating 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 variables, including the availability of family loans, are drawn separately using the distributions estimated from the data. We allow wages to change by year, using the yearly averages from the data (the real wage bill for the average firm increases from 0.15 million Cedis in 1991 to 0.23 million Cedis in 2002, with a mean of 0.19 million). The model endogenously generates exit based on the policy function. In the simulated model, entry is based on observed entry in the dataset. Specifically, in any year when we observe entry in the data, we randomly choose similar firms to enter in the simulation. All firms entering the simulation have the same initial state variables as firms entering the observed data.

We 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 10. Means from the simulated datasets match the data reasonably well. Figure 4 shows the evolution of average output over the sample period in the data and the simulation.

Figure 4: Average output in the estimated model and the data



Notes: The figure shows mean output from simulating the panel data 100 times using the estimated parameters.

6.3 Robustness

In this section, we present a number of robustness checks.

1. Explore the importance of the assumption that labor choice is a dynamic variable.

2. We estimate the model using a parametric formal interest rate function. As in the main estimation, there is a firm-specific interest rate on loans from banks. We use the following specification of the cost-of-credit function from formal sources:

$$r_{t,I} = \overline{r}_t + \exp(\gamma_0 + \gamma_1 \frac{I_{t,i}}{K_{t,i}} + \gamma_2 A_{t+1,i} + \varepsilon_{t,i}).$$

This functional form guarantees that the interest rate is positive for all parameter vectors and higher than the risk-free interest rate $\overline{r}$. The wedge between the risk-free and the firm-specific interest rate depends on the current assets (loans) of the firm and the ratio of current investment to the capital stock, which is a proxy for the firm's available collateral. Both the coefficient γ_1 on the investment to capital ratio and the coefficient γ_2 on assets is expected to be negative. The higher the firm's accumulated debt or the lower its available collateral, the higher is the interest rate for additional loans form a bank.

3. Reestimate the model with $\beta = 0.90$ and 0.97 instead of using the observed average interest rate in the data (which implies $\beta = 0.79$.)

4. We use information on the number of banks to estimate the likelihood of family financing. Specifically, we use the number of banks in Accra as a proxy for the family's willingness to provide loans to firms instead of depositing their savings in a bank.

5. Change the productivity measure for the firms, including both the observed component (ω) and the unobserved component (ε) in the productivity term. The state transition is calculated based on this modified productivity variable.

6. Use an alternative measure of wages in the construction of the per period profit function. We use earnings, which includes bonuses and in-kind payments additional to wages.

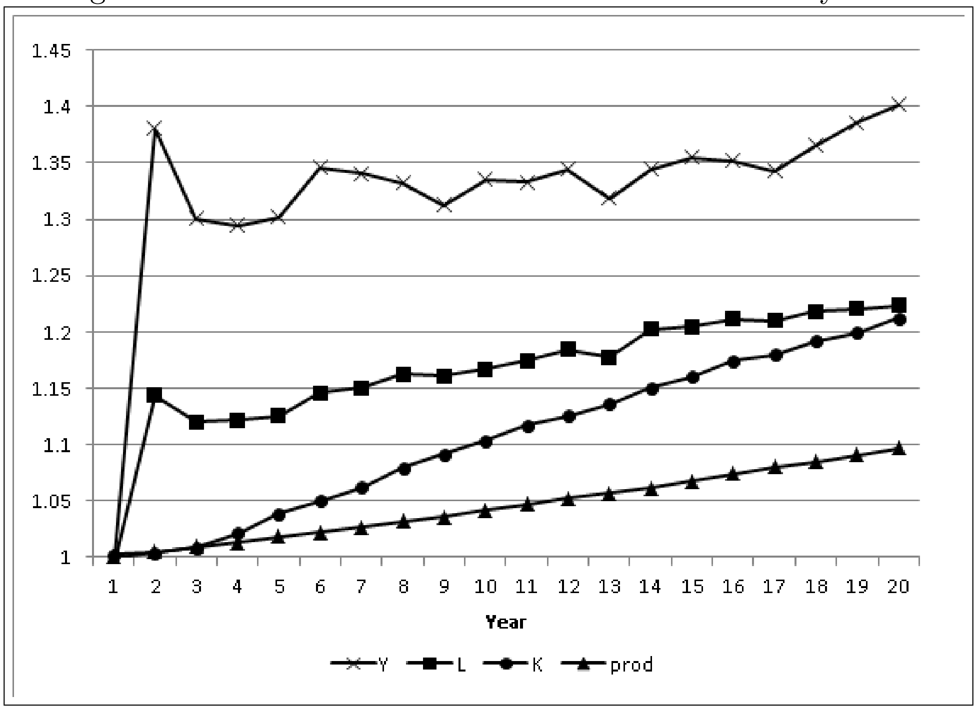
7. Treat the interest rate on family loans as stochastic and allow it to vary by firm. Specifically, we assume that the interest rate available to a firm is drawn from a lognormal distribution and we estimate the parameters of this distribution.

8. Treat the maximum amount of family loan (Z_F) as a stochastic variable and allow it to vary by firm. Specifically, we assume that the amount of financing available to a firm is drawn from a lognormal distribution and we estimate the parameters of this distribution.

6.4 Policy Experiment

Using the estimated model, we conduct counterfactual policy experiments where the likelihood that family financing is available changes. The goal of the experiment is to estimate the resulting changes in production, productivity and input use among manufacturing firms. For each simulation described below, we draw 1000 random firms from the initial conditions observed in the data in the first year. We forward simulate the industry for 20 years, keeping the exogenous state variables and parameters fixed. Specifically, the wage rate is fixed at 0.15 million Cedis, and the risk free deposit interest rate is set at the sample average in the

Figure 5: Simulation results: No vs. full access to family loans



Notes: Relative average output, input use, and productivity: no family loans vs. full access to family loans.

observed period (24 percent). All parameters, including the maximum available family loan, are set at their values estimated above.

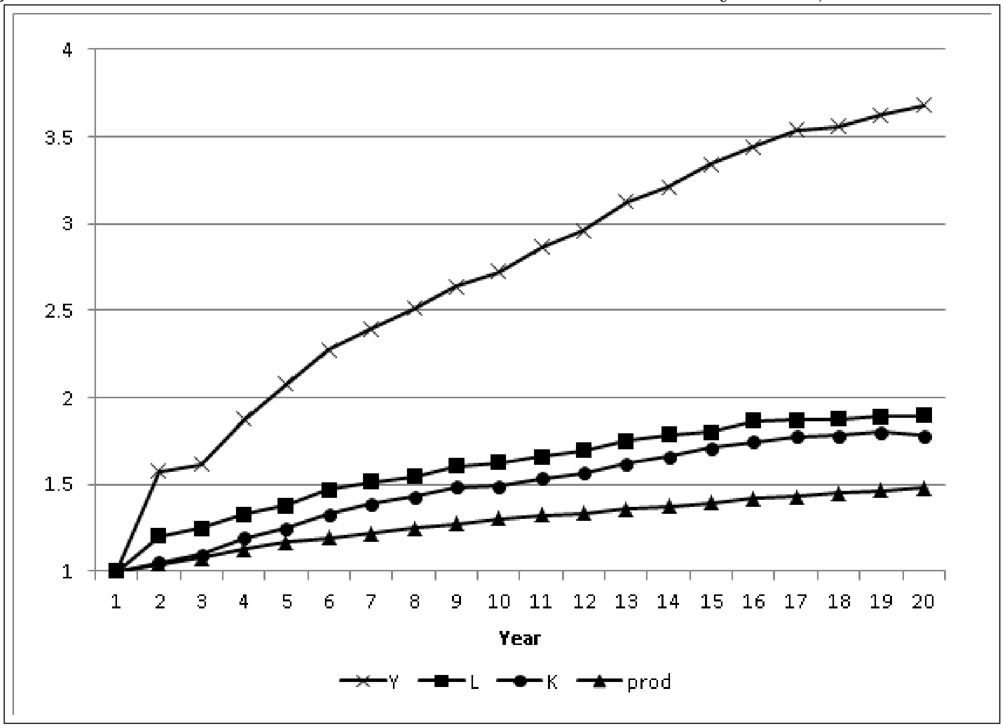
We consider several counterfactual scenarios with different probabilities of family financing. First, we compare the two extreme scenarios: all firms are offered a family loan ($F = 1$) or no firms have access to such loans ($F = 0$). Figure 5 shows relative average output, input use, and productivity between these two cases (values in the no-family-loan case divided by values in the with-family-loan case). Starting from the same states, the no-family-loan scenario results in higher average productivity, and the gap increases over time. After 20 years, this case yields 10 percent higher average productivity in the economy. This larger productivity is accompanied by higher input use and higher average output. Between the two extreme cases, the scenario with no family loans yields 30-40 percent higher average output than the scenario where all firms have access to family financing.

The mechanism behind these results is as follows. The rate of exit from the industry is higher without the presence of family financing, since the inexpensive family loans no longer provide a cost advantage to the firms. In the simulation, full family financing results in an exit rate around 6.3-6.8 percent every year, and taking away family loans increases this by about 20 percent. Firms with lower productivity are more sensitive to the availability of family financing. Consequently, we see more low productivity firms exit from the industry. In the simulation, exiting firms have 5-10 percent lower productivity than firms that decide to stay in the market in a given year. This has several implications. First, aggregate productivity increases over time compared to a situation where family financing is available. Firms that remain in the market are larger in terms of labor. They also have more loans from the formal sector on average, since on average they have access to lower formal interest rates. Between the extreme cases of full vs. no family financing, the average firm on the market has 30-40 percent more formal loans in the latter case compared to the former. Note that the interest rate on bank loans depends on the risk free deposit interest rate (which is held constant throughout this simulation) and on capital (as a proxy for collateral). Since active firms are larger on average, they have more capital and thus lower interest rates, which in turn leads to higher investments. With more labor, intermediate input purchases are also higher, and total output produced is higher.

In the above simulation, firms may exit but we ignore entry. Figure 6 shows the results of the same simulation if we allow for entry. In these simulations, we draw 100 new firms every year. Since in the data we do not observe firms entering under the extreme cases of full or no family financing, we need to simulate the initial conditions of the entering firms under these counterfactual scenarios. To do this, we first use our data to estimate the correlation between the fraction of firms with family loans and the initial state variables of entering firms by estimating a system of seemingly unrelated regressions.[12] We also compute the within-sample prediction errors of this system. Second, we use these estimates to form out-of-sample predictions for the initial state variables (assets, capital and productivity) of entering firms

[12] Our regressors are an indicator for whether the entering firm has family loans, the fraction of all firms with family loans in the given year, and the interaction of the two.

Figure 6: Simulation results: No vs. full access to family loans, with firm entry



Notes: Relative average output, input use, and productivity: no family loans vs. full access to family loans. In each year, 100 new firms are added with initial conditions simulated as described in the text.

under the no-family-loans and full-family-loans scenario. We take the predicted values and then draw 100 vectors of prediction errors randomly from the distribution corresponding to the given counterfactual.

As can be seen, allowing for entry results in much larger gaps between the no-family-loans and full-family-loans scenarios. This is not surprising, since in the data firms with no family loans tend to have higher productivity and be larger than firms with family loans (see section 3.3.2). This carries over to our simulated entrants, increasing the gaps in productivity, input use and output between the two counterfactual scenarios.

Next, as an approximation of the effect of the banking reforms in Ghana throughout the 90's, we simulate the industry assuming that exogenous state variables remain equal to the initial values in the first year of our dataset. Specifically, we set the probability of receiving a family loan equal to its value at the beginning of the study period. The simulation results from this exercise are summarized in the third column of Table 11.

Lastly, we attempt to measure the effect of improving credit markets. In 1991, there were 74 banks in Accra and 28.4 percent of the firms there received a family loan. By 2002, the number of banks increased to 120 and the fraction of firms receiving family loans declined to 10.6 percent. Based on these numbers, in an average year 5 new banks opened and the likelihood of family financing fell by 1.8 percentage points. To simulate these developments, we set the probability of family financing to 1 in the first year and decrease it by 1.8 percentage points in every subsequent year. The fourth column of Table 11 shows the results of this simulation.

7 Conclusion

This paper analyzes the role of family loans in aggregate productivity among manufacturing firms in Ghana. Families provide low-cost financing that can allow less productive firms to stay in the market. To quantify this effect, we estimate a dynamic model of firm behavior using data from the Ghanaian Manufacturing Survey. We find that compared to a scenario where every firm has access to family loans, a situation without family financing yields large gains in average productivity and output. 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 provides an additional channel through which improving credit market conditions may increase measured productivity in developing economies. Family loans raise 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). To the extent that financial support for small business startup is provided without selecting among the applicants based on strict criteria, this exhibits similarities to the transactions between a firm and the owner's relatives. Understanding the

Table 11: Counterfactual experiments

	Likelihood of family financing available				Ratio of Zero
			First year	Declining	
	Zero	One	observed	over time	to One
Panel A: 5 year average					
output	51.71	41.36	48.62	41.49	1.25
labor	29.27	26.60	28.49	26.62	1.10
capital	17.97	17.70	17.93	17.71	1.02
debt	7.92	6.46	7.60	6.44	1.23
productivity	7.39	7.33	7.37	7.31	1.01
exit rate	0.08	0.07	0.07	0.07	1.16
Panel B: 10 year average					
output	56.69	43.81	53.38	44.85	1.29
labor	30.71	27.19	29.78	27.43	1.13
capital	18.80	17.96	18.68	17.98	1.05
debt	9.34	7.22	9.12	7.34	1.29
productivity	7.45	7.30	7.40	7.29	1.02
exit rate	0.08	0.07	0.07	0.07	1.18
Panel C: 20 year average					
output	64.24	48.40	60.77	51.48	1.33
labor	33.12	28.36	32.24	29.27	1.17
capital	20.41	18.43	20.23	18.75	1.11
debt	11.29	8.47	11.21	9.26	1.33
productivity	7.59	7.26	7.47	7.28	1.05
exit rate	0.08	0.06	0.07	0.07	1.18

Notes: The table shows the results of 4 counterfactual experiments as described in the text. Simulations are conducted by drawing 1000 firms from the observed initial states, and forward simulating the model 100 times for 20 years. Displayed values are the means of the resulting annual values computed separately for 5, 10, and 20 years. The last column is the ratio of the first two..

role of such low-cost credit in firm dynamics is an interesting question for future research.

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] Soderbom, M., and F. Teal (2004): "Size and efficiency in African manufacturing firms: evidence from firm-level panel data," *Journal of Development Economics* 73, 369-394.

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

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

[26] Wooldridge, J. M. (2009): "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," *Economics Letters* 104(3), 112-114.

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

8 Appendix

8.1 Data

Table 12: Interest rate by year

	Formal loans	Formal and family loans	WDI deposit interest rate
1992	0.30	0.21	0.16
1993	0.31	0.21	0.24
1994	0.37	0.29	0.23
1995	0.37	0.30	0.29
1996	0.39	0.32	0.34
1997	0.38	0.27	0.36
1998	0.29	0.25	0.32
1999	0.36	0.32	0.24
2000	0.36	0.33	0.29
2001	0.35	0.32	0.31
2002	0.31	0.25	0.16

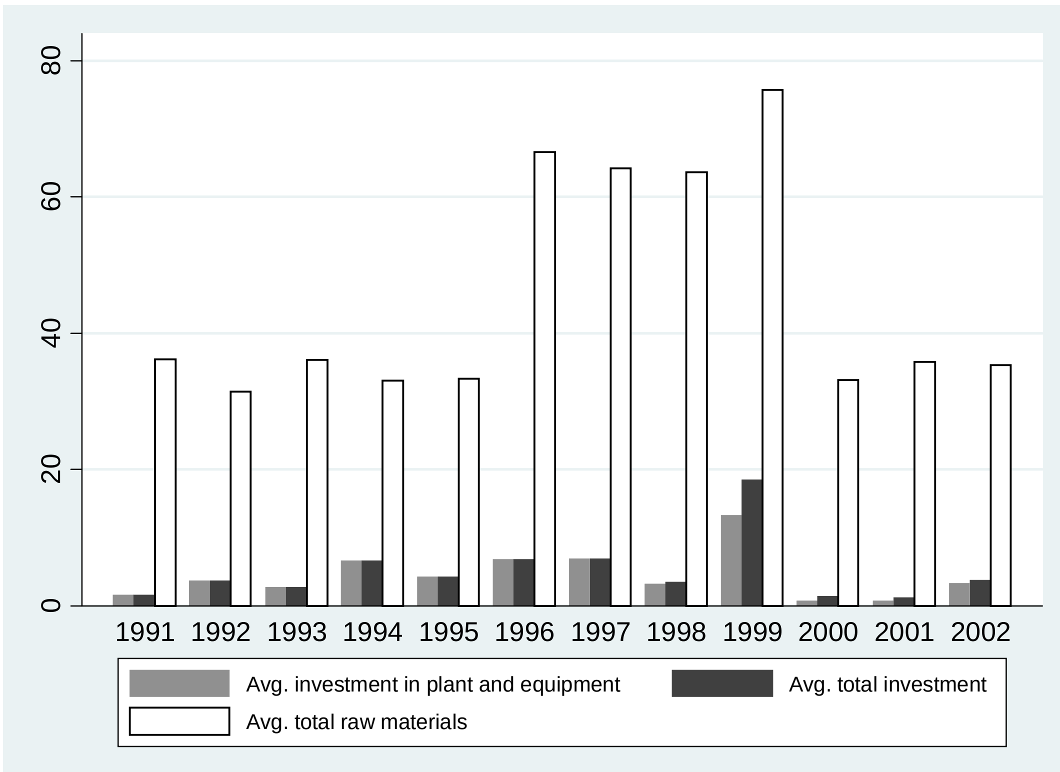
Notes: The first two columns contain the average annual interest rates from the dataset. The third column shows the Ghanaian deposit interest rate reported in the World Bank's World Development Indicators http://data.worldbank.org/data-catalog/world-development-indicators

Table 13: Firms by sector

Sector name	N	Percent
Alcohol	11	0.74
Bakery	181	12.2
Chemical	25	1.68
Food (exc drink)	139	9.37
Furniture	313	21.09
Garment	368	24.8
Machines	48	3.23
Metal	277	18.67
SSRII	12	0.81
Textile	16	1.08
Wood	94	6.33
Total	1484	100

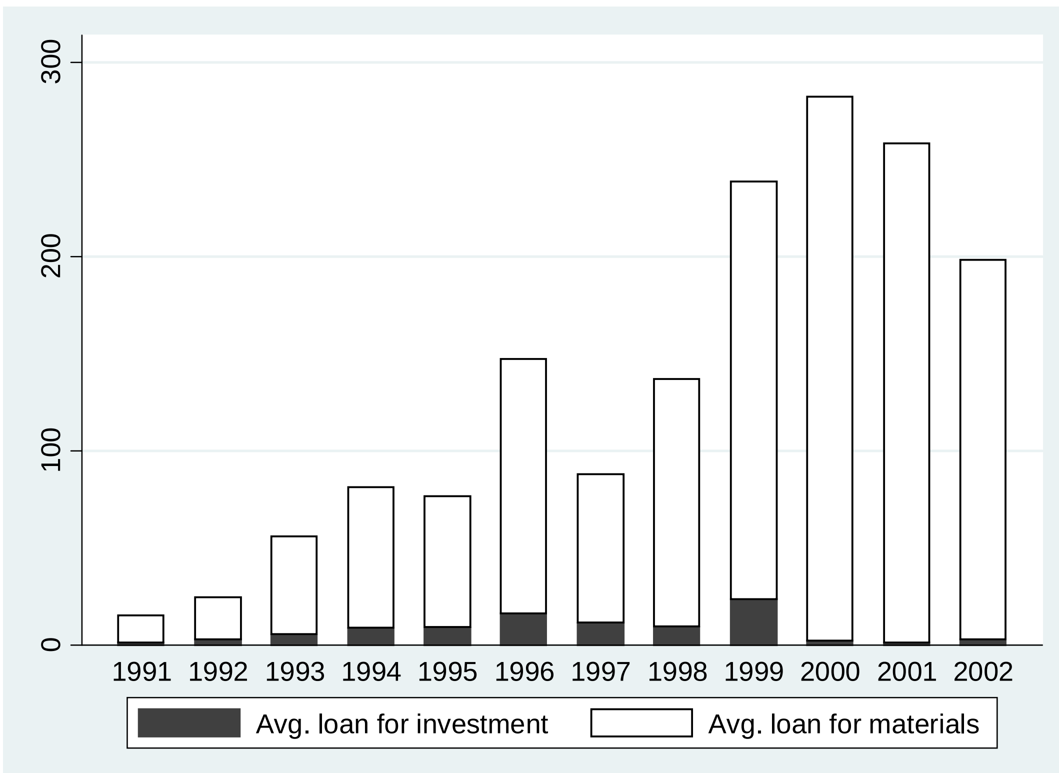
Notes: All monetary values are in Million 1991 Ghanaian Cedis.

Figure 7: Investment and intermediate input purchase, 1991-2002



Notes: Investment and input purchase in million 1991 Cedis.

Figure 8: Loan for investment and intermediate input purchase, 1991-2002



Notes: Loan amounts in million 1991 Cedis.

Table 14: Source of the bank data

Year	Source	Notes
1993	Ghana National Chamber of Commerce, 27th Annual Report and Membership Directory	
1993	L'indicateur FIT Business Directory, Edition of Ghana, 1993-94	
1994	A-Z Yellow and brown pages Ghana and International	
1994	Ghana Telephone Directory, Posts and Telecommunications Corporation Telephone Directory	
1995	L'indicateur FIT Business Directory, Edition of Ghana	
1997	L'indicateur FIT Business Directory, Edition of Ghana	
1998	Kumasi Business Directory	For Kumasi only
1998	L'indicateur FIT Business Directory, Edition of Ghana	
1998	Ghana Telecom Telephone Directory	
1999	Kumasi Business Directory	For Kumasi only
2000	L'indicateur FIT Business Directory, Edition of Ghana	For Kumasi and Takorodi only
2000	Ghana Telecom Telephone Directory	
2000	Provided by Bank of Ghana, Banking Supervision Department	
2001	Yellow Pages of Ghana, Surf Publication	Not for Cape Coast
2001	Provided by Bank of Ghana, Banking Supervision Department	
2002	Yellow Pages of Ghana, Surf Publication	Not for Cape Coast
2002	Provided by Bank of Ghana, Banking Supervision Department	