An Estimated Structural Model of Entrepreneurial Behavior

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Abstract

Using a rich panel dataset of New York dairy farms, we provide detailed new evidence on entrepreneurial behavior. We estimate a dynamic structural model of farms facing uninsured risks, borrowing limits and liquidation costs. The model also allows for occupational choice, renegotiation and retirement. We estimate the model via simulated minimum distance, matching both production and financial data. The model fits the data well in the aggregate and in the cross section. Policy experiments indicate that financial factors play an important role. Farms with high productivity appear to be more constrained than those whose productivity is low. Collateral constraints and short-term liquidity restrictions inhibit the accumulation

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of capital and assets. Debt renegotiation allows productive farms to continue operations despite temporary setbacks. Large non-pecuniary benefits to farming have significant effects on farm behavior.

1 Introduction

Entrepreneurs have long been recognized as a crucial force in the economy. As exemplified in Schumpeter's theory of creative destruction, entrepreneurs are considered to be engines of innovation and economic growth.[1] Another strand of the literature on entrepreneurs focuses on their position in the wealth distribution and their role in wealth creation (Quadrini 2000, 2009, Cagetti and De Nardi 2006). In these studies, entrepreneurs amass wealth because they utilize unique production technologies, and because they reinvest their income in their own businesses.

Identifying the influence of financial constraints is often considered key to understanding entrepreneurial decisions and their implications for investment and growth.[2] In this paper, we formulate and estimate a dynamic structural model of entrepreneurial behavior, using detailed production and financial data from a panel of owner-operated New York State dairy farms. We use the model to identify the financial constraints facing entrepreneurs, and to quantify their importance for asset accumulation, borrowing, and exit.

Many analyses of entrepreneurial behavior also emphasize non-pecuniary considerations. Moskowitz and Vissing-Jørgensen (2002) find that the returns entrepreneurs earn on their undiversified and risky investments are no greater than the returns on public equities. Hamilton (2000) finds that self-employment typically results in lower earnings. Both findings suggest that entrepreneurs receive non-pecuniary benefits from their chosen occupations. On the other hand, Vereshchagina and Hopenhayn (2009) note that entrepreneurs operate in a financial environment that can encourage risky investment even in the absence of a return premium.[3] Our model contains features that allow for both mechanisms, which are by no means mutually exclusive. Occupational choice and limited liability encourage risk-taking, while non-pecuniary benefits and liquidation costs discourage it. We use the model to assess the strength of each mechanism.

Our data are unusually well-suited for these tasks. They contain information on both real and financial activities, including input use, output and revenue, investment, borrowing and equity.[4] The farms in our data face substantial uninsured risk. Since they

[1] Caree and Thurik (2003) provide an extended literature review, while Wong, Ho and Autio (2005) include a review of recent empirical work. Also see Quadrini (2009) and Decker et al. (2014).

[2] Surveys of this literature appear in Parker (2005), Quadrini (2009) and Carreira and Silva (2010).

[3] This builds on earlier work on occupational choice by Kihlstrom and Laffont (1979), where risk loving individuals become entrepreneurs and risk averse ones prefer to be workers.

[4] Most plant-level datasets contain detailed information on real activity such as input use and investment at a nationally representative level, but do not cover financial variables. On the other hand, datasets with detailed financial information, such as COMPUSTAT, focus on publicly traded companies, and do

are drawn from a single region and industry, they are less vulnerable to issues of unobserved heterogeneity. Our panel spans a decade, which allows us to measure farm-level fixed effects, and sharpens the identification of the model's dynamic mechanisms. We are therefore able to disentangle the effects of real and financial factors on the operating decisions of firms, a classic problem in economics.[5] By allowing us to measure the risk and returns to dairy farming, our data also allows us to estimate the non-pecuniary value of being a dairy farmer.

Our analysis fills a niche in the literature on entrepreneurship. While structural models of entrepreneurship have been estimated with firm-level data for developing countries, many using Townsend's Thai data,[6] a lack of data has hindered the estimation of similar models for developed countries. The structural models of Buera (2009) and Evans and Jovanovic (1989) focus on the decision to become an entrepreneur, rather than the behavior of established businesses. Although the farms in our data are substantial enterprises, with an average of almost 3 million dollars in assets, and use increasingly sophisticated technology (McKinley 2014), they are almost all run by one or two operators. Our analysis thus provides a useful complement to recent work in structural corporate finance, where dynamic models with financial constraints are fit to data for corporations (Pratap and Rendon 2003, Henessey and Whited 2007, Strebulaev and Whited 2012). The paper arguably most similar to ours is Herranz et al. (2008), who match the unconditional cross-sectional distribution of owner equity and assets in the Survey of Small Business Finance. Our detailed panel dataset allows us to develop a much richer model, and to estimate it by matching disaggregated trajectories through time.

We begin our analysis with a description of our data. Using production parameters estimated from our structural model, we construct a measure of total factor productivity, which we decompose into a permanent farm-specific component, transitory idiosyncratic shocks, and transitory aggregate shocks. We find that high-productivity farms (as measured by the permanent farm-specific component) operate at much larger scales, invest

not provide information on family- or single entrepreneur-operated firms.

[5] This question lies at the heart of the volumnious, and often contentious literature on investment-cash flow regressions. Fazzari, Hubbard and Peterson (1988), who kick off this literature, find that financial constraints are important in determining investment. Kaplan and Zingales (1997) is the most prominent study to argue that the investment-cash flow relationship reflects expected future returns. Bushman et al. (2011) contains a review. Of note for our purposes are Bierlen and Featherstone (1998), who perform cash flow regressions on a dataset of Kansas farms. Studies using simulated data from structural models to analyse the performance of these regressions include Gomes (2001), Pratap (2003) and Moyen (2004).

[6] These data are described in Townsend et al. (1997) and Samphantharak and Townsend (2010). A recent study especially relevant to the project at hand is Karaivanov and Townsend (2014), which also contains a literature review.

more and pay down their debt at faster rates than low productivity farms. We also calculate the static optimal capital stock in a frictionless environment, and find that high productivity farms operate at a level further below below their optimal compared to low productivity farms. This justifies their higher investment rates and suggests that financial constraints may be important in explaining their distance from the optimum. In this respect, our work is similar in spirit to studies assessing the allocation of resources across firms, such as Hsieh and Klenow (2009), Jeong and Townsend (2007), Buera, Kaboski and Shin (2011), Midrigan and Xu (2014).

Our measure of aggregate productivity correlates closely with changes in the price of milk. We find that periods of higher aggregate productivity are also periods of higher investment. Because aggregate productivity appears to be serially uncorrelated, this suggests that cash flow directly affects investment. We find that cash flow and investment are indeed positively correlated with each other, controlling for productivity.

We then move to the model. Risk-averse farmers face uninsured risks, collateral constraints, and working capital/liquidity constraints which require them to hold cash. Older farmers retire, and farmers of any age can exit the industry, albeit with liquidation costs. A key feature of our financial environment is that it allows for renegotiation of debt. This is consistent with actual practice, which shows that many farms declaring bankruptcy reorganize rather than liquidate (Stam and Dixon, 2004). Another key feature is that farms must purchase intermediate goods before their productivity shocks are fully realized, exposing them to significant financial risk. We estimate the model using a form of simulated minimum distance, matching both the production and the financial sides of the data. Regressions on model-simulated data show that farms with high cash flow have larger investment rates, as observed in the data.

Uncovering the parameters of the model allows us to perform policy experiments to assess the importance of each constraint. We find that the collateral constraints significantly constrict capital holdings. Similarly, requiring farms to hold more cash leads to lower levels of capital, assets and output. The ability to renegotiate their debt allows productive farms to continue operating despite temporary setbacks.

Our estimates imply that non-pecuniary benefits play a significant role in discouraging exit from farming. More generally, financial constraints and occupational choice interact in important ways. Liquidation costs discourage farms from shutting down. Collateral constraints, on the other hand, encourage exit, by lowering farm profitability. High non-pecuniary benefits encourage cautious financial behavior.

The rest of the paper is organized as follows. In section 2 we introduce our data and

perform some diagnostic exercises. In section 3 we construct the model. In section 4 we describe our estimation procedure. In section 5 we present parameter estimates and assess the model's fit. In section 6 we perform a number of numerical exercises, designed to quantify the effects of financial constraints. We conclude in section 7.

2 Data and Descriptive Analysis

2.1 The DFBS

The Dairy Farm Business Survey (DFBS) is an annual survey of New York dairy farms conducted by Cornell University. The data include detailed financial records of revenues, expenses, assets and liabilities. Physical measures such as acreage and herd sizes are also collected. Assets are recorded at market as well as book value. The data allow for the construction of income statements, balance sheets, cash flow statements, and a variety of productivity and financial measures (Cornell Cooperative Extension, 2006; Karzes et al., 2013). Participants can then compare their management practices to those of their peers. These diagnoses are an important benefit of participation, which is voluntary (Cornell Cooperative Extension, 2015). Given such considerations, the DFBS data are not representative,[7] but they are quite likely to be of high quality.

Our dataset is an extract of the DFBS covering calendar years 2001-2011. This is an unbalanced panel containing 541 distinct farms, with approximately 200 farms surveyed each year. We trim the top and bottom 2.5% of the size distribution; the remaining farms have time-averaged herd sizes ranging between 34 and 1,268 cows. Since our model is explicitly dynamic, we also eliminate farms with observations for only one year. Finally we eliminate farms for which there is no information on the age of the operators. Since these are family-operated farms, we would expect retirement considerations to influence both production and finance decisions. These filters leave us with a final sample of 338 farms and 2,037 observations. During the same period, the number of dairy farms in New York State fell from 7,180 to 5,240 (New York State Department of Agriculture and Markets, 2012), so that our sample contains roughly 5 percent of all New York dairy

[7] Farms in our sample have larger revenues and herd sizes than the average New York State diary farm. In 2011, average revenue in our sample was $2,285,000, compared to the state average of $520,000. In the same year, the average herd size of New York State dairy farms was 209 cows, while our sample had an average herd size of 403. In demographic terms the sample is very similar to state averages: the principal operator statewide has an average age of 51, as in our sample. All the farms in our sample are family-owned, as are virtually all (97 percent) of the dairy farms in New York state. (New York State Department of Agriculture and Markets 2012).

Variable	Mean	Median	Standard Deviation	Maximum	Minimum
No. of Operators	1.82	2	0.93	6	1
Operator 1 Age	51.04	51	10.68	87	16
Youngest Operator Age	43.04	43	10.60	74	12
Herd Size (Cows)	302	169	286	1,268	34
Total Capital	2,793	1,802	2,658	15,849	212
Machinery	654	446	606	4,164	13
Real Estate	1,443	924	1,451	10,056	0
Livestock	696	394	700	5,215	39
Owned Capital	2,267	1,496	2,132	14,286	83
Machinery	490	331	461	2,895	3
Real Estate	1,097	710	1,103	9,100	0
Livestock	680	390	674	3,467	39
Owned/Total capital	0.84	0.86	0.12	1.00	0.26
Revenues	1,417	726	1,490	8,043	68
Total Expenses	1,199	608	1,278	6,296	57
Variable Inputs	1,098	553	1,177	5,846	55
Leasing and Interest	101	52	120	1,026	0
Total Assets	2,707	1,738	2,565	16,134	103
Total Liabilities	1,302	710	1,346	7,560	0
Net Worth	1,404	824	1,597	12,951	-734

Notes: Financial variables are expressed in thousands of 2011 dollars.

Table 1: Summary Statistics from the DFBS

farms.

Table 1 shows summary statistics. A detailed data description is provided in Appendix A. The median farm is operated by two operators and more than 80 percent of farms have two or fewer operators. The average age of the main operator is 51 years. For multi-operator farms, however, the relevant time horizon for investment decisions is the age of the youngest operator, who will likely become the primary operator in the future. On average, the youngest operator tends to be about 8 years younger than the main operator. In our analysis we will consider the age of the youngest operator as the relevant one for age-sensitive decisions.

Table 1 also illustrates that these are substantial enterprises: the yearly revenues of the average farm are in the neighborhood of 1.5 million dollars in 2011 terms. The distribution of revenues is heavily skewed to the left, with median farm revenues equal to about half the mean. For more than 80 percent of farm-year observations, farm revenues are under 2

million dollars. A large part of farm expenses are accounted for by what we term variable inputs: intermediate goods and hired labor. Of these labor expenses are relatively small, on average about 14 percent of all expenditures on variable inputs. The remainder is accounted for by intermediate goods such as feed, fertilizer, seed, pest control, repairs, utilities, insurance, etc. We also report the amounts spent on capital leases and interest, which are less than 10 percent of total expenditures on average.

Capital stock consists of machinery, real estate (including land and buildings) and livestock, of which real estate is the most valuable. Most of the capital stock is owned, but the median farm leases about 14 percent of its capital. (See Appendix A.) Real estate is the most intensively leased form of capital. The majority of farms lease less than 20 percent of their machinery and equipment. Livestock is almost always owned. Capital is by far the predominant asset, accounting for more than 80 percent of farm assets.

Farm liabilities include accounts payable, debt, and financial leases on equipment and structures. For the median farm, this accounts for about 70 percent of total liabilities. Deferred taxes constitute the remainder. Combining total asssets and liabilities reveals that the average farm has a net worth of 1.4 million dollars. Only 28 (or 1.4 percent) of all farm-years report negative net worth.

The DFBS reports net investment for each type of capital. It also reports depreciation, allowing us to construct a measure of gross investment. Following the literature, we will focus on investment rates, scaling investment by the market value of owned capital at the beginning of each period. Table 2 describes the distribution of investment rates. Cooper and Haltiwanger (2006) show, using data from the Longitudinal Research Database (LRD), that plant-level investment often occurs in large increments, suggesting a prominent role for fixed investment costs. Table 2 shows statistics comparable to theirs, and for reference reproduces the statistics for gross investment rates shown in their Table 1. Relative to the LRD, investment spikes are much less frequent in the DFBS. The average investment rate is also a bit lower, and the inaction rate is slightly higher. These suggest that fixed investment costs are less important in the DFBS, and in the interest of tractibility we omit them from our structural model.

Farm technologies can be divided into two categories: stanchion barns and and milking parlors, the latter considered the newer and larger-scale technology. About two-thirds of the farms in our sample are parlor operations. Table 3 displays summary statistics by size and technology splits. Large farms are defined as those whose time-averaged per-operator herd sizes are larger than the median. As the table shows, large farms have higher investment and debt to asset ratios, hold more cash, and pay higher dividends

Variable	Gross Investment / Owned Capital	Cooper-Haltiwanger LRD
Average investment rate	0.086	0.122
Inaction rate (< abs(0.01))	0.097	0.081
Fraction of observations < 0	0.087	0.104
Positive spike rate (>0.2)	0.074	0.186
Negative spike rate (<-0.2)	0.002	0.018
Serial correlation	0.097	0.058

Table 2: Investment Rates

	All Farms		Stanchion Barns		Milking Parlors	
	Small	Large	Small	Large	Small	Large
Total Capital	544	1,915	476	779	707	2,461
Intermed. Goods/Capital	0.28	0.39	0.26	0.27	0.33	0.41
Output/Capital	0.39	0.51	0.36	0.37	0.44	0.53
Investment/Capital	0.04	0.07	0.03	0.03	0.05	0.08
Debt/Asset	0.43	0.50	0.39	0.46	0.46	0.51
Cash/Asset	0.11	0.16	0.09	0.12	0.14	0.17
Dividends	18.03	40.54	14.71	23.79	23.60	44.24
Cows	51	203	41	76	78	277

Notes: Financial variables normalized by family size and expressed in thousands of 2011 dollars. Large farms have a larger than median herd size per operator within each category.

Table 3: Medians by Technology and Size

than small farms. Interestingly, large operations also use more variable inputs per unit of capital, which suggests that their technology may differ from that of small operations.

The small-large distinction does not neatly coincude with the stanchion-parlor distinction. Although parlor operations are typically larger, about 30 percent of parlors can be classified as small farms, and 10 percent of the stanchion operations can be classified as large. Moreover, as Table 3 shows, differences between small and large operations within each technology group are quite substantial. Along many dimensions small parlor operations are closer to large stanchion operations than to large parlor operations. Alvarez et al. (2012), who sort farms using a latent class model, also find the stanchion-parlor distinction to be inadequate. Accordingly, in our estimation we will allow the production function to vary by farm size, rather than by milking technology.

2.2 Productivity

2.2.1 Our Productivity Measure

We assume that farms share the following Cobb-Douglas production function

$$Y_{it} = z_{it} M_{it}^{\alpha} K_{it}^{\gamma} {N_{it}}^{1-\alpha-\gamma},$$

where we denote farm i's gross revenues at time t by Y_{it} and its entrepreneurial input, measured as the time-averaged number of operators, by M_{it}.[8] K_{it} denotes the capital stock; N_{it} represents expenditure on all variable inputs, including hired labor and intermediate goods; and z_{it} is a stochastic revenue shifter reflecting both idiosyncratic and systemic factors.[9] With the exception of operator labor, all inputs are measured in dollars. Although this implies that we are treating input prices as fixed, variations in these prices can enter our model through changes in the profit shifter z_{it}.

In per capita terms, we have

$$y_{it} = \frac{Y_{it}}{M_{it}} = z_{it} k_{it}^{\gamma} {n_{it}}^{1-\alpha-\gamma}.$$

In this formulation, returns to scale are $1-\alpha$, with α measuring an operator's "span of control" (Lucas, 1978).

Following Alvarez et al. (2012) and based on the descriptive statistics in the previous section, we allow for two production technologies. Using the structural estimation procedure described below, we find that for small-herd operations $\widehat{\alpha} = 0.155$ and $\widehat{\gamma} = 0.158$, and for large-herd operations $\widehat{\alpha} = 0.162$ and $\widehat{\gamma} = 0.117$. In other words, large farms have more decreasing returns to scale and lower returns to capital than small farms. This allows us to calculate total factor productivity as

$$z_{it} = \frac{y_{it}}{k_{it}^{\widehat{\gamma}} {n_{it}}^{1-\widehat{\alpha}-\widehat{\gamma}}}. \tag{1}$$

We assume that the resulting TFP measure can be decomposed into an individual fixed effect μ_i, a time-specific component, common to all farms, Δ_t, and an idiosyncratic i.i.d

[8] More than two thirds of all farms and 90 percent of farm-years display no change in family size.

[9] The assumption of decreasing returns to scale in non-management inputs is not inconsistent with the literature. Tauer and Mishra (2006) find slightly decreasing returns in the DFBS. They argue that while many studies find that costs decrease with farm size: "Increased size per se does not decrease costs—it is the factors associated with size that decrease costs. Two factors found to be statistically significant are efficiency and utilization of the milking facility."

component ε_{it}:

$$\ln z_{it} = \mu_i + \Delta_t + \varepsilon_{it}. \tag{2}$$

A Hausman test rejects a random effects specification. Regressing z_{it} on farm and time dummies yields estimates of all three components. The fixed effect is dispersed between 0.40 and 1.58, with a mean of 1.022 and a standard deviation of 0.21. There are significant time-invariant differences in productivity across farms. The time effect Δ_t is constructed to be zero mean. This series is effectively uncorrelated,[10] and has a standard deviation of 0.061. The idiosyncratic residual ε_{it} can also be treated as uncorrelated (the serial correlation is 0.009), with a standard deviation of 0.069.

To provide some insight into this productivity measure, Figure 1 plots the aggregate component Δ_t against real milk prices in New York State (New York State Department of Agriculture and Markets, 2012).[11] The aggregate component of TFP follows milk prices very closely – the correlation is well over 90% – which gives us confidence in our measure. On the same graph we plot the average value of the cash flow (net operating income less estimated taxes) to capital ratio. Aggregate cash flow is also closely related to our aggregate TFP measure. Cash flow varies quite significantly, indicating that farms face significant financial risk.

2.2.2 Productivity and Farm Characteristics: Descriptive Evidence

How are productivity and farm performance related? Figures 2 and 3 illustrate how farm characteristics vary as a function of the time-invariant component of productivity, μ_i. We divide the sample into high- and low-productivity farms, splitting around the median value of μ_i, and plot the evolution of several variables. To remove scale effects, we either express these variables as ratios, or divide them by the number of operators. More than 90 percent of the low productivity farms are small, and about 60 percent of them are stanchion barn operations. A very small fraction (10 percent) of the high productivity farms are stanchion barns. About 90 percent of high productivity farms are large.

Our convention will be to use thick solid lines to represent high-productivity farms

[10] It is often argued that milk prices follow a three-year cycle. Nicholson and Stephenson (2014) find a stochastic cycle lasting about 3.3 years. While Nicholson and Stepheson report that in recent years a "small number" of farmers appear to be planning for cycles, they also report (page 3) that: "the existence of a three-year cycle may be less well accepted among agricultural economists and many ... forecasts ... do not appear to account for cyclical price behavior. Often policy analyses ... assume that annual milk prices are identically and independently distributed[.]"

[11] Although the government intervenes extensively in the market for raw milk, much of the current regulation only imposes price floors, with actual prices varying according to market conditions. Manchester and Blaney (2001) provide a review.

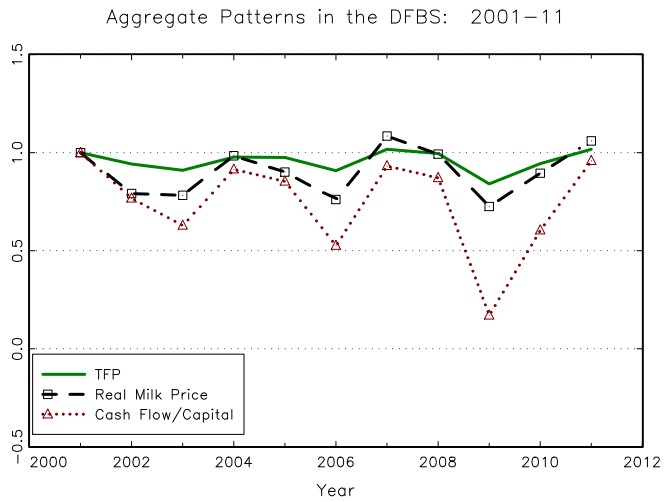

Figure 1: Aggregate TFP, real Milk Prices, and Cash Flow

and the thinner dashed lines to represent low-productivity farms. Figure 2 shows output/revenues and input choices. The top two panels of this figure show that high-productivity farms operate at a scale 4-5 times larger than that of low-productivity farms.[12] This size advantage is increasing over time: high productivity-firms are growing while low-productivity firms are static. The bottom left panel shows that high-productivity farms lease a larger fraction of their capital stock (18 percent vs. 8 percent). The leasing fractions are all small and stable, however, implying that farms expand primarily through investment.

The bottom right panel of Figure 2 shows that the ratio of variable inputs – feed, fertilizer, and hired labor – to capital is also higher for high productivity farms (40% vs. 30%). This could be due to differing production functions between small and large farms, as described earlier, since larger farms also tend to be higher productivity farms. Another explanation for this difference in input use could be financial constraints on the purchase of variable inputs. We will account for this possibility in our model as well.

Figure 3 shows financial variables. The top two panels contain median cash flow and gross investment. These variables are positively correlated in the aggregate; for example, the recession of 2009 caused both of them to decline. Given that the aggregate shocks are not persistent, the correlation of cash flow and investment suggests financial constraints, which are relaxed in periods of high output prices. The middle left panel shows investment as a fraction of owned capital, and confirms that high-productivity

[12] Using the 2007 U.S. Census of Agriculture, Adamopoulos and Restuccia (2014) document that farms with higher labor productivity are indeed substantially larger.

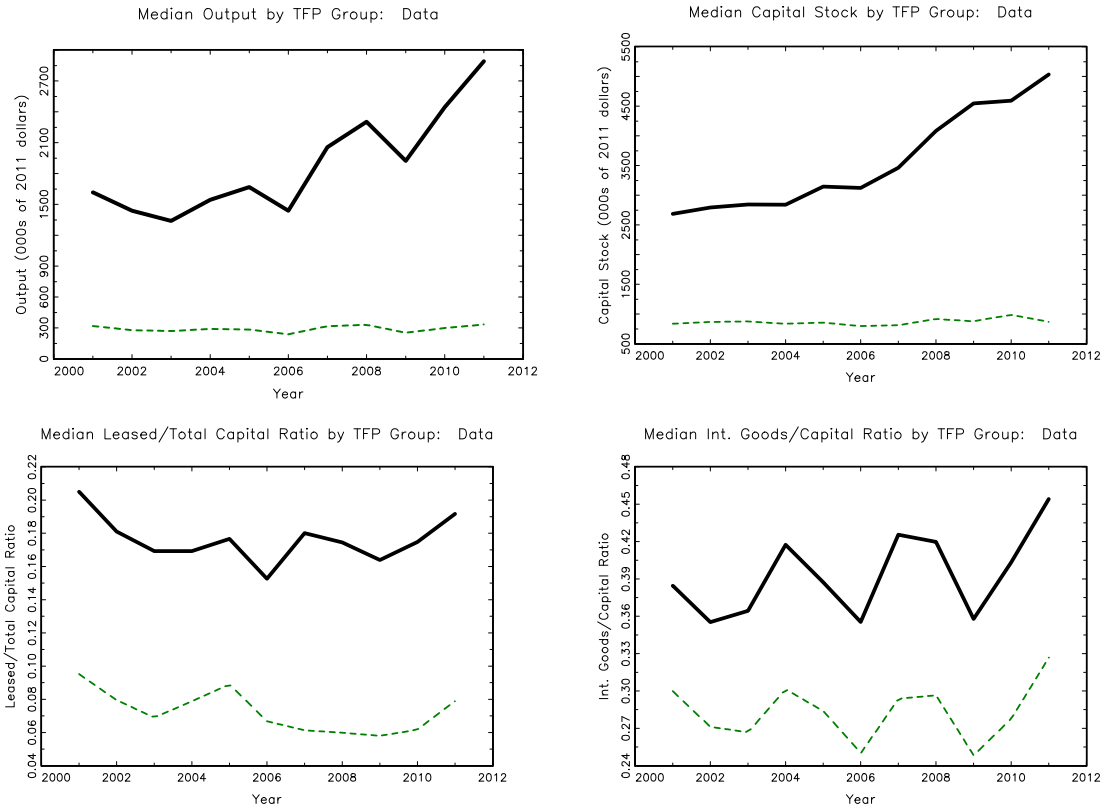

Figure 2: Production and Inputs by TFP and Calendar Year

farms generally invest at higher rates. The middle right panel shows dividends, which are also correlated with cash flow. Dividend flows are in general quite modest, especially for low-productivity farms.

The bottom row of Figure 3 shows two sets of financial ratios. The left panel shows debt/asset ratios.[13] Although high-productivity farms begin the sample period with more debt, over the sample period they rapidly decrease their leverage. By 2011, the debt/asset ratios of high and low-productivity farms are much closer. This suggests that the high-TFP firms are using their profits to de-lever as well as to invest.

In a static frictionless model, the optimal capital stock for a farm with productivity level μ_i is given by $k_i^* = [\kappa \exp(\mu_i)]^\alpha$, where κ is a positive constant.[14] The bottom right panel of Figure 3 plots median values of the ratio k_{it}/k_i^*, showing the extent to which farms operate at their efficient scales. The median low-productivity farm is close to the optimal capital stock over the entire sample period. In contrast, the capital stocks of high-productivity farms are well below their optimal size, even as they grow rapidly. This suggests that financial constraints hinder the efficient allocation of capital. Midrigan and Xu (2014) find that financial constraints impose their greatest distortions by limiting entry and technology adoption. To the extent that high-productivity farms are more likely to utilize new technologies, such as robotic milkers (McKinley, 2014), our results are consistent with their findings. Our results also comport with Buera, Kaboski and Shin's (2011) argument that financial constraints are most important for large-scale technologies.

2.2.3 Productivity and Farm Characteristics: Regression Evidence

To further explore what lies behind the variations in the n/k ratio, we construct a measure of distortions following Hsieh and Klenow (2009). The first order conditions of a static optimization problem imply that

$$\begin{aligned} \frac{n_{it}}{uc \cdot k_{it}} &= \frac{1-\alpha-\gamma}{\gamma}, \\ \Rightarrow \omega_{it} &= \left(\frac{n_{it}}{uc \cdot k_{it}}\right) \frac{\gamma}{1-\alpha-\gamma} = 1, \end{aligned}$$

[13] To ensure consistency with the model, and in contrast to Table 1, we add capitalized values of leased capital to both assets and liabilities.

[14] This expression can be found by maximizing $E(z_{it})k_{it}^{\gamma} n_{it}^{1-\alpha-\gamma} - n_{it} - (r+\delta-\varpi)k_{it}$. In contrast to the construction of capital stock described in Appendix A, here we use a single user cost for all capital. Standard calculations show that $\kappa = \left(\frac{\gamma}{r+\delta-\varpi}\right)^{\alpha+\gamma} (1-\alpha-\gamma)^{1-\alpha-\gamma} E(\exp(\Delta_t \varepsilon_{it}))$.

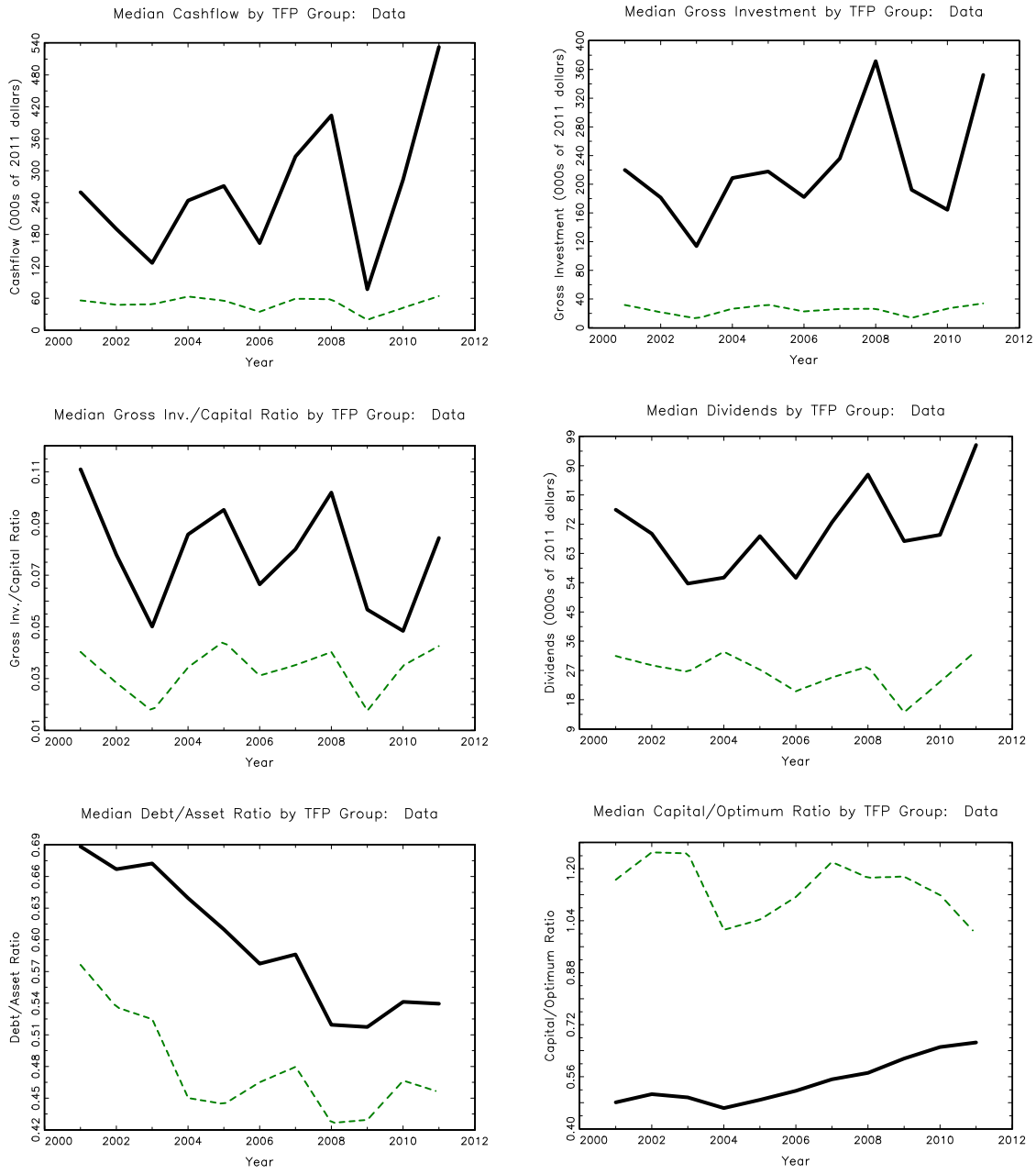

Figure 3: Investment and Finances by TFP and Calendar Year

	Median	Std. Dev	Maximum	Minimum
ω_{it}: Small Farms	1.11	0.39	3.01	0.27
ω_{it}: Large Farms	1.10	0.34	2.60	0.27
Regression Coefficients: Dependent Variable = $(\omega_{it} - 1)^2$				
	Coefficient	Std. Error	Coefficient	Std. Error
z_{it}	0.071	0.070	0.011	0.071
Total Assets×Small	-0.821*	0.108		
Total Assets×Large	-0.077*	0.012		
Net Worth×Small			-0.167*	0.080
Net Worth×Large			-0.050*	0.015
Individual Effects	Yes		Yes	
Time Dummies	Yes		Yes	

Table 4: Input Distortions

where: uc denotes the frictionless user cost of capital, based on a real interest rate of 4% and a depreciation rate (net of capital gains) calibrated from the data. The price of variable inputs is normalized to 1. Any suboptimal input use will result in a value of ω different from 1. ω_{it} is therefore a measure of the degree of distortion of input use, which will take values above (below) 1 if the farm uses a higher (lower) n/k ratio than that implied by the first order conditions of its optimization problem.

The top of Table 4 summarizes this measure for small and large farms. Since the production parameters are identified from median expenditure shares, the median distortion is unsurprisingly close to 1 for both small and large operations. However, as Restuccia and Rogerson (2008) emphasize,the dispersion of distortions is the indicator of the extent of resource misallocation. We find that small farms have a larger dispersion than large ones. The regression coefficients also suggest that financial variables play an important role in determining the degree to which the input mix is distorted. Asset-rich farms, both large and small, are more likely to use inputs optimally. Similar results obtain for net worth. Distortions are more sensitive to financial variables when farms are small, implying that a marginal increase in funds is more likely to improve the input mix in a small operation. TFP does not have a significant effect, suggesting that the effect of TFP may be to create better financial health, which in turn facilitates a closer-to-optimal input mix.

Next, we reconsider the empirical correlates of investment. In the standard investment regression, investment-capital ratios are regressed against a measure of Tobin's q and a measure of cash flow. While our farms are not publicly traded firms, and we cannot construct Tobin's q, we can use z_{it} or one of its components as a substitute. Table 5 reports the coefficient estimates.

Dependent Variable: Gross Investment/Capital				
	Coefficient	Std. Error	Coefficient	Std. Error
Operator Age	-0.002*	0.000	-0.007*	0.002
Cash Flow/Capital×Small	-0.162	0.144	1.042*	0.326
Cash Flow/Capital×Large	0.443*	0.107	0.718*	0.237
z_{it}×Small			0.526*	0.139
z_{it}×Large			-0.160	0.142
μ_i×Small	0.184*	0.056		
μ_i×Large	0.104*	0.037		
Fixed Effects	No		Yes	
Time Effects	Yes		Yes	

Table 5: Investment-Cash Flow Regressions

The first column of Table 5 shows that farms with higher values of the TFP fixed effect μ_i have higher investment rates. Decreasing returns to per-operator inputs are manifested in the larger responsiveness of small farms to μ_i. Investment rates also decline with age, although the coefficient is small. This shows (weak) evidence of life cycle behavior on the part of the farmers. Investment is positively related to cash flow for large operations, but does not seem to be so for small ones.

The results change once we introduce fixed effects in the third column. Cash flow is now strongly sensitive to investment for both small and large firms.[15] The transitory component of TFP is significant for small operations, but not for large ones. Our results contrast to those of Weersink and Tauer (1989), who estimate investment models using DFBS data from 1973-1984. Weersink and Tauer find that investment levels are decreasing in cash flow and increasing in asset values (which proxy for profitability).

3 Model

Consider a farm family seeking to maximize expected lifetime utility at "age" q:

$$E_q\left(\sum_{h=q}^{Q}\beta^{h-q}\left[u\left(d_h\right)+\chi\cdot 1\{\text{farm operating}\}\right]+\beta^{Q-q+1}V_{Q+1}\left(a_{Q+1}\right)\right),$$

[15] A larger coefficient on cash flow for small firms need not indicate tighter financial constraints, as documented by Kaplan and Zingales (1997). Pratap (2003) shows that in the presence of adjustment costs the investment of constrained firms may be *less* responsive to cash flow.

where: q denotes the age of the principal (youngest) operator; d_q denotes farm "dividends" per operator; the indicator $1\{\text{farm operating}\}$ equals 1 if the family is operating a farm and 0 otherwise, and χ measures the psychic/non-pecuniary gains from farming; Q denotes the retirement age of the principal operator; a denotes assets; and $E_q(\cdot)$ denotes expectations conditioned on age-q information. The family discounts future utility with the factor $0 < \beta < 1$. Time is measured in years. Consistent with the DFBS data, we assume that the number of family members/operators is constant. We further assume a unitary model, so that we can express the problem on a per-operator basis. To simplify notation, throughout this section we omit "i" subscripts.

The flow utility function $u(\cdot)$ and the retirement utility function $V_{Q+1}(\cdot)$ are specialized as

$$\begin{aligned} u(d) &= \frac{1}{1-\nu}\left(c_0 + d\right)^{1-\nu}, \\ V_{Q+1}(a) &= \frac{1}{1-\nu}\theta\left(c_1 + \frac{a}{\theta}\right)^{1-\nu}, \end{aligned}$$

with $\nu \geq 0$, $c_0 \geq 0$, $c_1 \geq c_0$ and $\theta \geq 1$. Given our focus on farmers' business decisions, we do not explicitly model the farmers' personal finances and saving decisions. We instead use the shift parameter c_0 to capture a family's ability to smooth variations in farm earnings through outside income, personal assets, and other mechanisms. The scaling parameter θ reflects the notion that upon retirement, the family lives for θ years and consumes the same amount each year.

Before retirement, farmers can either work for wages or operate a farm. While working for wages, the family's budget constraint is

$$a_{q+1} = (1+r)a_q + w - d_q, \tag{3}$$

where: a_q denotes beginning-of-period financial assets; w denotes the age-invariant outside wage; and r denotes the real risk-free interest rate. Workers also face a standard borrowing constraint:

$$a_{q+1} \geq 0.$$

Turning to operating farms, recall that gross revenues per operator follow

$$y_q = z_{qt} k_q^{\gamma} {n_q}^{1-\alpha-\gamma}, \tag{4}$$

where k_q denotes capital, n_q denotes variable inputs, and z_{qt} is a stochastic income shifter

reflecting both idiosyncratic and systemic factors. These factors include weather and market prices, and are not fully known until after the farmer has committed to a production plan for the upcoming year. In particular, while the farm knows its permanent TFP component μ, it makes its production decisions before observing the transitory effects Δ_t and ε_q.

A farm that operated in period $q-1$ begins period q with debt b_q and assets $\tilde{a}_q$. As a matter of notation, we use b_q to denote the total amount owed at the beginning of age q: r_q is the contractual interest rate used to deflate this quantity when it is chosen at age $q-1$. Expressing debt in this way simplifies the dynamic programming problem when interest rates are endogenous. At the beginning of period q, assets are the sum of undepreciated capital, cash, and operating profits:

$$\tilde{a}_q \equiv (1-\delta+\varpi)k_{q-1} + \ell_{q-1} + y_{q-1} - n_{q-1}, \tag{5}$$

where: $0 \leq \delta \leq 1$ is the depreciation rate; ϖ is the capital gains rate, assumed to be constant; and ℓ_{q-1} denotes liquid (cash) assets, chosen in the previous period.

A family operating its own farm must decide each period whether to continue the business. The family has three options: continued operation, reorganization, or liquidation. If the family decides to continue operating, it will have two sources of funding: net worth, $e_q \equiv \tilde{a}_q - b_q$, and the time-$q$ value of new debt, $b_{q+1}/(1+r_{q+1})$. (We assume that all debt is one-period.) It can spend these funds in three ways: purchasing capital; issuing dividends, d_q; or maintaining its cash reserves:

$$e_q + \frac{b_{q+1}}{1+r_{q+1}} = \tilde{a}_q - b_q + \frac{b_{q+1}}{1+r_{q+1}} = k_q + d_q + \ell_q. \tag{6}$$

Combining the previous two equations yields

$$\begin{aligned} i_{q-1} &= k_q - (1-\delta+\varpi)k_{q-1} \\ &= [y_{q-1} - n_{q-1} - d_q] + [\ell_{q-1} - \ell_q] + \left[\frac{b_{q+1}}{1+r_{q+1}} - b_q\right]. \end{aligned} \tag{7}$$

Equation (7) shows that investment can be funded through three channels: retained earnings (d_q is the dividend paid after y_{q-1} is realized), contained in the first set of brackets; cash reserves, contained in the second set of brackets; and new borrowing, contained in the third set of brackets.

Operating farms face two financial constraints:

$$\psi b_{q+1} \leq k_q \tag{8}$$

$$n_q \leq \zeta \ell_q, \tag{9}$$

with $\psi \geq 0$ and $\zeta \geq 1$. The first of these constraints, given by equation (8), is a collateral constraint of the sort introduced by Kyotaki and Moore (1997). Larger values of ψ imply a tighter constraint, with farmers more dependent on equity funding. The second constraint, given by equation (9), is a cash-in-advance or working capital constraint (Jermann and Quadrini, 2012). Larger values of ζ imply a more relaxed constraint, with farmers more able to fund operating expenses out of contemporaneous revenues. Because dairy farms provide a steady flow of income throughout the year, in an annual model ζ is likely to exceed 1.

As an alternative to continued operation, a farm can reorganize or liquidate. If it chooses the second option, reorganization, some of its debt is written down.[16] The debt liability b_q is replaced by $\hat{b}_q \leq b_q$ and the restructured farm continues to operate. Finally, if the family decides to exit – the third option – the farm is liquidated and assets net of liquidation costs are handed over to the bank:

$$\begin{aligned} k_q &= 0, \\ a_q &= \max\left\{(1-\lambda)\tilde{a}_q - b_q, 0\right\}. \end{aligned}$$

We assume that the information/liquidation costs of default are proportional to assets, with $0 \leq \lambda \leq 1$. Liquidation costs are not incurred when the family (head) retires at age Q.

The interest rate realized on debt issued at age q, $\widehat{r}_{q+1} = \widehat{r}_{q+1}(s_{q+1}, r_{q+1})$, depends on the state vector s_{q+1} (specified below) and the contractual interest rate r_{q+1}. The function $\widehat{r}(\cdot)$ emerges from enforceability problems of the sort described in Kehoe and Levine (1993). If the farmer to chooses to honor the contract, $\widehat{r}_{q+1} = r_{q+1}$. If the farmer chooses to default,

$$\widehat{r}_{q+1} = \frac{\min\left\{(1-\lambda)\tilde{a}_{q+1}, b_{q+1}\right\}}{b_{q+1}/(1+r_{q+1})} - 1 = (1+r_{q+1})\frac{\min\left\{(1-\lambda)\tilde{a}_{q+1}, b_{q+1}\right\}}{b_{q+1}} - 1.$$

[16] Most farms have the option of reorganizing under Chapter 12 of the bankruptcy code, a special provision designed for family farmers. Stam and Dixon (2004) review the bankruptcy options available to farmers.

The return on restructured debt is $\widehat{r}_{q+1} = \left[(1+r_{q+1})\min\left\{\hat{b}_{q+1}, b_{q+1}\right\}/b_{q+1}\right] - 1$. We assume that loans are supplied by a risk-neutral competitive banking sector, so that

$$E_q(\widehat{r}_{q+1}(s_{q+1}, r_{q+1})) = r, \tag{10}$$

where r is the risk free rate. While we allow the family to roll over debt (b_{q+1} can be bigger than $\tilde{a}_{q+1}$), Ponzi games are ruled out by requiring all debts to be resolved at retirement:

$$b_{Q+1} = k_{Q+1} = 0; \quad a_{Q+1} \geq 0.$$

To understand the decision to default or renegotiate, the family's problem needs to be expressed recursively. To simplify matters, we assume that the decision to work for wages is permanent, so that the Bellman equation for a worker is:

$$\begin{aligned} V_q^W(a_q) = & \max_{0 \leq d_q \leq (1+r)a_q + w} u(d_q) + \beta V_{q+1}^W(a_{q+1}), \\ & s.t. \text{ equation (3).} \end{aligned}$$

The Bellman equation for a family who has decided to fully repay its debt and continue farming is

$$\begin{aligned} V_q^F(e_q, \mu) = & \max_{\{d_q \geq -c_0, b_{q+1} \geq 0, n_q \geq 0, k_q \geq 0\}} u(d_q) + \chi + \beta E_q\left(V_{q+1}(\tilde{a}_{q+1}, b_{q+1}, \mu)\right), \\ & s.t. \text{ equations (4) - (6), (8) - (10),} \end{aligned}$$

where $V_{q+1}(\cdot)$ is the continuation value prior to the time-$q+1$ occupational choice:

$$\begin{aligned} & V_{q+1}(\tilde{a}_{q+1}, b_{q+1}, \mu) = \\ & \quad \max\left\{V_{q+1}^F(\tilde{a}_{q+1} - \min\{b_{q+1}, \hat{b}_{q+1}\}, \mu),\ V_{q+1}^W(\max\left\{(1-\lambda)\tilde{a}_{q+1} - b_{q+1}, 0\right\})\right\}. \end{aligned}$$

We require that the renegotiated debt level $\hat{b}_{q+1}$ be incentive-compatible:

$$\begin{aligned} \hat{b}_{q+1} &= \max\{b_{q+1}^*, (1-\lambda)\tilde{a}_{q+1}\}, \\ V_{q+1}^F(\tilde{a}_{q+1} - b_{q+1}^*, \mu) &\equiv V_{q+1}^W(\max\left\{(1-\lambda)\tilde{a}_{q+1} - b_{q+1}, 0\right\}), \end{aligned}$$

so that $\hat{b}_{q+1} = \hat{b}_{q+1}(s_{q+1})$, with $s_{q+1} = \{\tilde{a}_{q+1}, b_{q+1}, \mu\}$. The first line of the definition ensures that $\hat{b}_{q+1}$ is incentive-compatible for lenders: the bank can always force the farm into liquidation, bounding $\hat{b}$ from below at $(1-\lambda)\tilde{a}_{q+1}$. However, if the family finds

liquidation sufficiently unpleasant, the bank may be able to extract a larger payment b^*_{q+1}. The second line ensures that such a payment is incentive-compatible for farmers, i.e., farmers must be no worse off under this deal than they would be if they liquidated and switched to wage work.

A key feature of this renegotiation is limited liability. If the farm liquidates, the bank at most receives $(1-\lambda)\tilde{a}_{q+1}$, and under renegotiation dividends are bounded below by $-c_0$. Our estimated value of c_0 is small, implying that new equity is expensive and not an important source of funding. Coupled with the option to become a worker, limited liability will likely lead the continuation value function, $V_{q+1}(\cdot)$, to be convex over the regions of the state space where farming and working have similar valuations (Vereshchagina and Hopenhayn, 2009).

The debt contract also bounds repayment from above: the farm can always honor its contract and pay back b_{q+1}. Solving for $\hat{b}_{q+1}$ allows us to express the finance/occupation indicator $I^B_q \in \{\text{continue, restructure, liquidate}\}$ as the function $I^B_q(s_q)$. It immediately follows that

$$\begin{aligned}\frac{1+\widehat{r}_q(s_q,r_q)}{1+r_q} &= 1\{I^B_q(s_q)=\text{continue}\}+\\ &\quad 1\{I^B_q(s_q)=\text{liquidate}\}\cdot\frac{\min\{(1-\lambda)\tilde{a},b_q\}}{b_q}+\\ &\quad 1\{I^B_q(s_q)=\text{restructure}\}\cdot\frac{\min\{\hat{b}_q(s_q),b_q\}}{b_q}.\end{aligned}$$

Inserting this result into equation (10), we can calculate the equilibrium contractual rate as[17]

$$1+r_q=[1+r]\,/\,E_{q-1}\left(\frac{1+\widehat{r}_q(s_q,r_q)}{1+r_q}\right). \tag{11}$$

4 Econometric Strategy

We estimate our model using a form of Simulated Minimum Distance (SMD). In brief, this involves comparing summary statistics from the DFBS to summary statistics calculated from model simulations. The parameter values that yield the "best match" between the DFBS and the model-generated summary statistics are our estimates.

[17] The previous equation shows that the ratio $\frac{1+\widehat{r}_q(s_q,r_q)}{1+r_q}$ is independent of the contractual rate r_q. Finding r_q thus requires us to calculate the expected repayment rates only once, rather than at each potential value of r_q, as would be the case if time-t debt were denominated in time-t terms. (In the latter case, b_{q+1} would be replaced with $(1+r_q)b_q$.) This is a significant computational advantage.

Our estimation proceeds in two steps. Following a number of papers (e.g., French, 2005; De Nardi, French and Jones, 2010), we first calibrate or estimate some parameters outside of the model. In our case there are four parameters. We set the real rate of return r to 0.04, a standard value. We set the outside wage w to an annual value of \$15,000, or 2,000 hours at \$7.50 an hour. To a large extent, the choice of w is a normalization of the occupation utility parameter χ, as the parameters affect occupational choice the same way. Using DFBS data, we set the capital depreciation rate δ to 5.56% and the appreciation rate ϖ to 3.59%. The liquidation loss, λ, is set to 35 percent. This is at the upper range of the estimates found by Levin, Natalucci and Zakrajšek (2004). Given that a significant portion of farm assets are site-specific, higher loss rates are not implausible. We discuss alternative values of λ below.

In the second step, we estimate the parameter vector $\Omega = (\beta, \nu, c_0, \chi, c_1, \theta, \alpha, \gamma, n_0, \lambda, \zeta, \psi)$ using the SMD procedure itself. To construct our estimation targets, we sort farms along two dimensions, age and size. There are two age groups: farms where the youngest operator was 39 or younger in 2001; and farms where the youngest operator was 40 or older. This splits the sample roughly in half. We measure size as the time-averaged herd size divided by the time-averaged number of operators. Here too, we split the sample in half: the dividing point is between 86 and 87 cows per operator. As Section 2 suggests, this measure corresponds closely to the fixed TFP component μ_i. Then for each of these four age-size cells, for each of the years 2001 to 2011, we match:

1. The median value of capital per operator, k.
2. The median value of the output-to-capital ratio, y/k.
3. The median value of the variable input-to-capital ratio, n/k.
4. The median value of the gross investment-to-capital ratio.
5. The median value of the debt-to-asset ratio, $b/\tilde{a}$
6. The median value of the cash-to-asset ratio, $\ell/\tilde{a}$.
7. The median value of the dividend growth rate, d_t/d_{t-1}.[18]

For each value of the parameter vector Ω, we find the SMD criterion as follows. First, we use α and γ to compute z_{it} for each farm-year observation in the DFBS, following

[18] Because profitability levels, especially for large farms, are sensitive to total returns to scale $1 - \alpha$, we match dividend growth, rather than levels. Both statistics measure the desire of farms to smooth dividends, which in turn affects their ability to fund investment through retained earnings.

equation (1). We then decompose z_{it} according to equation (2). This yields a set of fixed effects $\{\mu_i\}_i$ and a set of aggregate shocks $\{\Delta_t\}_t$ to be used in the model simulations, and allows us to estimate the means and standard deviations of μ_i, Δ_t, and ε_{iq} for use in finding the model's decision rules. Using a bootstrap method, we take repeated draws from the joint distribution of $s_{i0} = (\mu_i, a_{i0}, b_{i0}, q_{i0}, t_{i0})$, where a_{i0}, b_{i0} and q_{i0} denote the assets, debt and age of farm i when it is first observed in the DFBS, and t_{i0} is the year it is first observed. At the same time we draw ϑ_i, the complete set of dates that farm i is observed in the DFBS.

Discretizing the asset, debt, equity and productivity grids, we use value function iteration to find the farms' decision rules. We then compute histories for a large number of artificial farms. Each simulated farm j is given a draw of s_{j0} and the shock histories $\{\Delta_t, \varepsilon_{jt}\}_t$. The residual shocks $\{\varepsilon_{jt}\}_{jt}$ are produced with a random number generator, using the standard deviation of ε_{iq} described immediately above. The aggregate shocks we use are those observed in the DFBS. Combining these shocks with the decision rules allows us to compute that farm's history. We then construct summary statistics for the artificial data in the same way we compute them for the DFBS. Let g_{mt}, $m \in \{1, 2, ..., M\}$, $t \in \{1, 2, ..., T\}$, denote a summary statistic of type m in calendar year t, such as median capital for young, large farms in 2007. The model-predicted value of g_{mt} is $g^*_{mt}(\Omega)$. We estimate the model by minimizing the squared proportional differences between $\{g^*_{mt}(\Omega)\}$ from $\{g_{mt}\}$.

Because the model gives farmers the option to become workers, we also need to match some measure of occupational choice. We do not attempt to match observed attrition, because the DFBS does not report reasons for non-participation, and a number of farms exit and re-enter the dataset. In fact, when data for a particular farm-year are missing in the DFBS, we treat them as missing in the simulations, using our draws of ϑ_i. However, we also record the fraction of farms that exit in our simulations but not in the data. We use this fraction to calculate a penalty that is added to the SMD criterion, $\Psi(\Omega)$.

Our SMD criterion function is

$$\sum_{m=1}^{M} \sum_{t=1}^{T} \aleph_m^2 \left(\frac{g^*_{mt}(\Omega)}{g_{mt}} - 1 \right)^2 + \Psi(\Omega).$$

Our estimate of the "true" parameter vector Ω_0 is the value of Ω that minimizes this criterion. Appendix B contains a detailed description of how we set the weights $\{\aleph_m\}$ and calculate standard errors.

5 Parameter Estimates and Identification

5.1 Parameter Estimates and Goodness of Fit

Table 6 displays the parameter estimates and asymptotic standard errors. The estimated values of the discount factor β, 0.987, and the risk aversion coefficient ν, 3.0, are both within the range of previous estimates (see, e.g., the discussion in De Nardi et al., 2010). The retirement parameters imply that farms value post-retirement consumption; in the period before retirement, farmers consume only 1.3% of their wealth, saving the rest.[19] The non-pecuniary benefit of farming, χ, is expressed as a consumption increment to the non-farm wage w. With w equal to \$15,000, the estimates imply that the psychic benefit from farming is equivalent to the utility gained by increasing consumption from \$15,000 to \$148,000. Even though the outside wage is modest, the income streams from low productivity farms are small and uncertain that enough that operators would exit if they did not receive significant psychic benefits.

The returns to management and capital are both fairly small, implying that the returns to intermediate goods, $1 - \alpha - \gamma$, are between 69 and 72 percent. Table 1 shows that variable inputs in fact equal about 77.5% of revenues. The collateral constraint parameter ψ is 0.942, implying that each dollar of debt must be backed by 94 cents of capital. The liquidity constraint parameter ζ is estimated to be about 2.5, implying that farms need to hold liquid assets equal to about 5 months of expenditures. Although these two constraints together significantly reduce the risk of insolvency, farms with adverse cash flow may find themselves extremely illiquid.

Figures 4 and 5 compare the model's predictions to the data targets. To distinguish the younger and older cohorts, the horizontal axis measures the average operator age of a cohort at a given calendar year. The first observation on each panel starts at age 29: this is the average age of the youngest operator in the junior cohort in 2001. Observations for age 30 corresponds to values for this cohort in 2002. When first observed in 2001, the senior cohort has an average age of 48. As before, thick lines denote large farms, and thin lines denote smaller farms. For the most part the model fits the data well. The model understates the spending on variable inputs by large farms, overstates the cash holdings

[19] This can be found by solving for the value of the optimal retirement assets a^r in the penultimate period of the operator's economically active life, $\max_{a^r \geq 0} \left\{ \frac{1}{1-\nu} \left(c_0 + x - a^r\right)^{1-\nu} + \beta \frac{\theta}{1-\nu} \left(c_1 + \frac{a^r(1+r)}{\theta} \right)^{1-\nu} \right\}$, and finding $\partial a^r(x)/\partial x|_{a^r=(a^r)^*}$. A derivation based on a similar specification appears in De Nardi et al. (2010).

Parameter Description		Parameter Estimate	Standard Error
Discount factor	β	0.987	3.69×10^{-5}
Risk aversion	ν	3.00	0.046
Consumption utility shifter	c_0	6.08	0.139
Retirement utility shifter	c_1	25.44	11.48
Retirement utility intensity	θ	76.76	351.4
Non-pecuniary value of farming (as a consumption increment)	χ	133.1	796.1
Returns to management: small herds	α	0.153	0.0001
Returns to management: large herds	α	0.161	0.0005
Returns to capital: small herds	γ	0.158	0.002
Returns to capital: large herds	γ	0.117	0.0006
Strength of collateral constraint	ψ	0.942	0.874
Degree of liquidity constraint	ζ	2.50	0.426

Table 6: Parameter Estimates

of small farms, and overstates dividend growth. However, the model captures many of the differences between large and small farms, and much of the year-to-year variation.

5.2 Identification

The model's parameters are identified from aggregate averages. Some linkages are straightforward. For example, the production coefficients α and γ are identified by expenditure shares, and the extent to which farm size varies with productivity. The cash constraint ζ is identified by the observed cash/asset ratio.[20]

The identification of the preference parameters is less straightforward. Table 7 shows comparative statics for our model, which we find by repeating the model simulations while changing parameters in isolation. The numbers in the table are averages of the model-simulated data over the 11-year (pseudo-) sample period.

Row (1) shows data for the baseline model, associated with the parameters in Table 6. Row (2) shows the averages that arise when the discount factor β is reduced to 0.975. Lowering β leads farms to hold less capital and invest less, as they place less weight on future returns. In addition, β is identified by the dividend growth rate rate, as lower values of β lead to slower growth.

[20] The cash holdings observed in the DFBS, recorded at the beginning and ends of calendar years, may understate farms' actual liquidity needs, which tend to be highest in the summer. (Conversation with Wayne Knoblauch, April 20, 2015.)

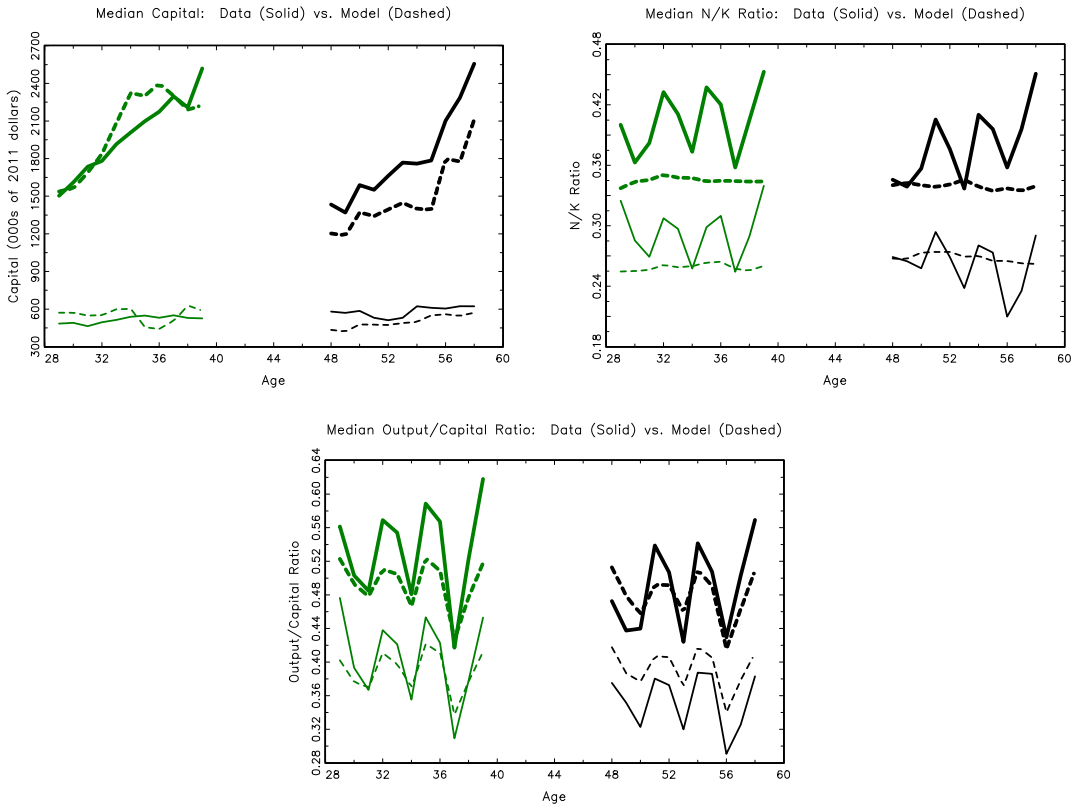

Figure 4: Model Fits: Production Measures

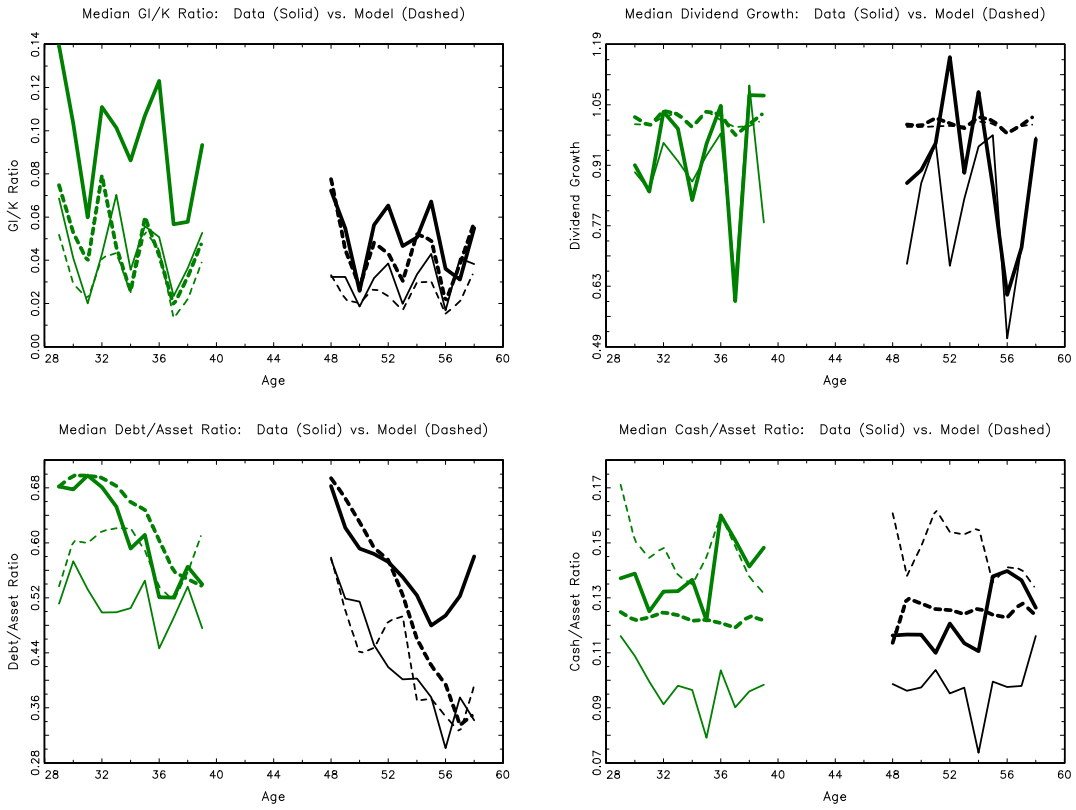

Figure 5: Model Fits: Financial Measures

Rows (3) and (4) show the effects of changing the risk coefficient ν. When $\nu = 0.0$, farmers are risk-netural. This leads them to hold less debt, as the borrowing rate $r = 0.04$ exceeds the discount rate, and the utility cost of retained earnings – unsmoothed dividends – is small. Dividends are low and grow at the counterfactually rapid rate of 29.5%. Risk-neutrality also leads farmers to invest more aggressively in capital, as they are less concerned about its stochastic returns. With fewer precautionary motives, cash holdings fall from 14.5 percent to 12.5 percent of total assets. With no risk-aversion and constant marginal utility, the baseline consumption value of being a farmer, \$133,000, leads all farmers to remain in operation; the fraction of operating farms, 0.553, is at its highest possible level. In contrast, increasing ν to 4.0 (row (4)) leads more farms to exit the industry. The utility shifter c_0 is identified by similar mechanics.

The retirement parameters c_1 and θ are identified by life cycle variation not shown in Table 7. As θ goes to zero, so that retirement utility vanishes, older farmers will have less incentive to invest in capital, and their capital holdings will fall relative to those of younger farmers. Setting θ to zero also increases debt-holding, as farmers become more inclined to carry debt into retirement. As Figure 5 shows, the variation in the capital stock between old and young farmers is small, causing the estimate of θ to be imprecise.

The parameter χ is identified by occupational choice, namely the estimation criterion that farms observed in the DFBS in a given year also be operating and thus observed in the simulations. While the standard errors suggest weak local identification of χ, row (5) shows that the effect of setting χ to zero is large. Eliminating the psychic benefits of farming leads many farms to liquidate; the fraction of farms operating (and observed in the DFBS) drops from 54 to 50 percent. Not surprisingly, it is the smaller, low-productivity farms that exit: the surviving farms in row (5) have more assets, debt and capital. Their optimal capital stock (recall Figure 3) rises from \$2.7 to \$2.9 million. Hamilton (2000) and Moskowitz and Vissing-Jørgensen (2002) find that many entrepreneurs earn below-market returns, suggesting that non-pecuniary benefits are large. (Also see Quadrini, 2009.) Figure 3 shows that many low-productivity farms have dividend flows around the outside salary of \$15,000. Moreover, these flows are uncertain, while the outside salary is not. This is consistent with a high value of χ. The high estimated value of ν also implies that large increases in consumption have only modest effects on flow utility, implying that the consumption increment underlying χ will be large.

		Fraction Operating	Assets	Debt	Debt/ Assets	Cash/ Assets	Capital	N/K	Investment/ Capital (%)	Dividend* Growth (%)	Optimal Capital
(1)	Baseline Model	0.544	1,837	1,024	0.510	0.145	1,468	0.304	6.44	4.03	2,703
(2)	$\beta = 0.975$	0.546	1,822	1,036	0.527	0.143	1,457	0.302	5.84	3.66	2,693
(3)	$\nu = 0.0$	0.553	1,996	874	0.416	0.125	1,649	0.284	8.03	29.5	2,669
(4)	$\nu = 4.0$	0.532	1,798	979	0.492	0.145	1,422	0.306	6.59	3.93	2,713
(5)	$\chi = 0$	0.499	1,971	1,107	0.526	0.136	1,576	0.315	6.95	3.77	2,921
(6)	$\lambda = 0$	0.494	1,929	1,053	0.492	0.144	1,550	0.306	5.12	3.76	2,752
(7)	$\lambda = \chi = 0$	0.394	2,275	1,279	0.541	0.129	1,842	0.321	5.83	2.96	3,352
(8)	$c_0 = 2,000$	0.553	2,092	1,006	0.388	0.120	1,743	0.285	5.48	NA	2,669
(9)	$\psi = 0.5$	0.553	1,976	1,182	0.536	0.152	1,595	0.304	3.17	2.92	2,671
(10)	$\psi = 1.5$	0.519	1,318	499	0.328	0.170	948	0.434	11.53	4.95	2,745
(11)	$\zeta = 1$	0.524	1,666	855	0.467	0.245	1,127	0.326	9.28	4.73	2,700
(12)	$\zeta = 4$	0.547	1,801	982	0.484	0.113	1,490	0.312	6.30	3.93	2,697
(13)	No Renegotiation	0.513	1,879	1,025	0.489	0.149	1,506	0.305	4.57	3.53	2,654
(14)	No Reneg., $\nu = 0$	0.545	2,027	883	0.417	0.127	1,678	0.291	6.03	29.0	2,647

*Growth rate based on changes in median dividends. N.A. indicates negative initial dividends.

Table 7: Comparative Statics

Although our model includes limited liability and occupational choice, most low-productivity farms enter our sample with low levels of indebtedness and (relative to the productivity fixed effect μ_i) high capital stocks (see Figures 2 and 3). In such circumstances the risk-taking incentives described by Vereshchagina and Hopenhayn (2009) are less likely to apply. Vereshchagina and Hopenhayn (2009) also argue that patient firms are less likely to seek risky investment projects; our estimated discount rate is 1.3%.

The high estimated value of χ may also reflect other considerations, such as tax advantages to continued operations.[21] Although \$15,000 is a low salary, for some farmers the outside employment opportunties may be even less remunerative, as well as uncertain.

Row (5) also shows that eliminating non-pecuniary benefits raises the N/K ratio from 0.304 to 0.319. This likely reflects selection effects, as the production technology for large farms places more weight on intermediate goods.[22] On the other hand, the cash/assets ratio falls, even though the baseline model leads small farms tend to hold more cash. When χ is present, small farms hold cash reserves to avoid being forced out of business. Setting $\chi = 0$ removes this precautionary motive. It also raises the debt/asset ratio from 0.510 to 0.526. In addition to composition effects, some of this increase may also reflect a greater willingness to take on debt.

The parameter ψ, measuring the strength of the collateral constraint, is identified by several factors. Tighter collateral constraints: reduce debt holding; induce more farms to close; reduce the average capital stock; and force farmers to build up their capital stock over time, rather than acquiring it immediately. We will discuss the effects of ψ, and the other financial constraints, in more detail in the next section.

6 The Effects of Financial Constraints

In the previous section, we found that nonpecuniary benefits are large and have large effects. In this section we assess the importance of financial constraints. Our model contains five important financial elements: liquidation costs, limits on new equity, collateral constraints, liquidity constraints, and the ability to renegotiate debt. We consider the effects of each of these elements on assets, debt, capital and investment.

[21] We are indebted to Todd Schoellman for this point.

[22] In a frictionless static world, with full debt financing ($r = 0.04$), the N/K ratio would be 0.261 for small-herd farms and 0.368 for large farms.

6.1 Liquidation Costs

Row (6) shows the effects of setting the liquidation cost λ to zero. Eliminating the liquidation cost *reduces* the number of operating farms, by allowing farmers to retain more of their wealth after exiting.[23] Liquidation costs thus provide another explanation of why entrepreneurs may persist despite low financial returns. The effect of setting $\lambda = 0$ is in many ways similar to that of eliminating the psychic benefit χ. This lack of identification is one reason why we calibrate rather than estimate λ. Row (7) shows that non-pecuniary benefits and liquidation costs reinforce each other; setting $\lambda = \chi = 0$ leads a large number farms to exit the industry.

Comparing row (6) to row (1), and row (7) to row (5), shows that the farms that remain after the elimination of the liquidation costs are significantly larger and more productive. Liquidation costs thus lead to financial inefficiency, by discouraging the reallocation of capital and labor to more productive uses.

6.2 Equity Injections

In addition to serving as a preference parameter, c_0 limits the ability of farms to raise funds from equity injections. Row (8) shows the effects of increasing c_0 to 2,000, allowing farmers to inject up to \$2 million of personal funds into their farms each year.[24] Because farmers have a discount rate of 1.3 percent, as opposed to the risk-free rate of 4 percent, they greatly prefer internal funding to debt. Increasing c_0 to 2,000 thus results in a dramatic decrease in debt, along with as significant increases in capital and assets. The reduced cost of funds also leads to a different input mix. Because capital becomes cheaper relative to intermediate goods, the N/K ratio falls from 30.4 to 28.5 percent. Greater access to equity also raises the value of farming, so that no operators exit.[25]

6.3 Collateral Constraints

Row (9) shows the effects of setting the collateral constraint ψ to 0.5, allowing each dollar of capital to back up to 2 dollars of debt. Farms respond to the relaxed constraint by borrowing more and acquiring more capital, with the median value rising from \$1.47

[23] Recall that we assume that liquidation costs are not imposed upon retiring farmers.

[24] We also increase the retirement shifter c_1 by an equivalent amount.

[25] Increasing c_0 also reduces fluctuations in the marginal utility of consumption, $u'(c_0 + d)$, making farming a more appealing choice. On the other hand, c_0 decreases the incremental utility associated with farming, which is calculated as $u(w + c_0 + 133) - u(w + c_0)$.

million to \$1.60 million. Much of this additional capital is purchased up front; the investment rate falls from 6.4% to 5.5%. As with equity, expanding access to debt raises the value of farming, and virtually all farmers stay in business.

Row (10) shows the effects of the opposite experiment, setting ψ to 1.5. Tightening the constraint this much leads farms to drastically reduce their capital stock, by 35% of its baseline value. Farms then rebuild their capital stock through retained earnings. With capital more difficult to fund, farms use more intermediate goods, so that the fall in output, 21%, is much less than the fall in capital. All of these changes make farming less profitable, and fewer farms remain in operation. Although the estimated parameter has a relatively large standard error, it is clear that variations in ψ affect the behavior of farms a great deal.

6.4 Liquidity Constraints

Rows (11) and (12) illustrate the effects of the liquidity constraint given by equation (9). Row (11) of Table 7 shows what happens when we tighten this constraint by reducing ζ to 1. Even though fewer farms remain in business, the average scale of operations declines. While total assets fall by around 10 percent, capital falls by over 23%, and the cash/asset ratio jumps from 0.145 to 0.245. Rather than holding their assets in the form of capital, farms are obliged to hold it in the form of liquid assets used to purchase intermediate goods. Output falls by nearly 20%.

Loosening the liquidity constraint ($\zeta = 4$) allows farms to hold a larger fraction of their assets in productive capital, raising the assets' overall return. Total assets fall from their baseline value, while capital rises. Needing fewer liquid assets, intermediate goods are more desirable, and the N/K ratio rises. Output increases by 3%, twice the increase in capital.

6.5 Renegotiation of Debt Contracts

Finally we explore the role of contract renegotiation in our model. Row (13) of Table 7 shows the effects of eliminating renegotiation and requiring farms with negative net worth to liquidate. The fraction of farms observed drops by 5.7 percent. Any farms that enter the DFBS with negative net worth are forced out immediately in our simulations. In addition, the inability to renegotiate significantly reduces the value of farming, causing a number of farms to exit.

Row (14) shows the effects of jointly elimination renegotiation and setting the risk

	Median	Std. Dev	Maximum	Minimum
ω_{it}: Small Farms	1.04	0.19	3.42	0.00
ω_{it}: Large Farms	0.96	0.13	1.54	0.26
Regression Coefficients: Dependent Variable = $(\omega_{it} - 1)^2$				
	Coefficient	Std. Error	Coefficient	Std. Error
z_{it}	-0.014*	0.005	-0.016*	0.005
Total Assets×Small	-0.010*	0.000		
Total Assets×Large	-0.010*	0.000		
Net Worth×Small			0.001	0.001
Net Worth×Large			-0.009*	0.002
Individual Effects	Yes		Yes	
Time Dummies	Yes		Yes	

Table 8: Input Distortions with Simulated Data

coefficient ν to zero. Without consumption smoothing motives, farming becomes much more desirable, and farms exit only when their net worth is negative. Comparing this experiment to the one in row (3) shows that about only 1.4 percent of farms are forced out by a strict default requirement. The ability to renegotiate is less valuable when there are no dividend smoothing motives. Comparisons to row (3) also reveal that when preferences are linear, eliminating renegotiation causes the optimal capital stock to *fall*, from \$2.67 to \$2.65 million: the exiting farms are not from the bottom of the productivity distribution. Renegotiation can therefore play an important role in keeping productive farms alive.

6.6 Cross-sectional Evidence

While the comparative statics presented above give a good picture of the behavior of the average farm, it is also interesting to also study the cross sectional variation. Another way to assess the importance of the model's financial mechanisms to repeat the regressions in Tables 4 and 5 on simulated data. Such an exercise also provides useful out-of-sample validation. The results are presented in Tables 8 and 9 respectively.

Table 8 shows that the model generates distortions similar to those in the actual data. The dispersion of distortions is larger for small farms than for large ones. Firms with higher assets still come closer to their optimal input mix. On the other hand, the effects of net worth are less clear cut than in the data. Table 9 shows that our model also generates a positive relation between cash flow and investment, even after controlling for productivity. The fixed component of productivity μ_i is an important determinant of productivity for small farms, although its effect is very small for large farms.

Dependent Variable: Gross Investment/Capital				
	Coefficient	Std. Error	Coefficient	Std. Error
Operator Age	-0.000*	0.000	0.003*	0.000
Cash Flow/Capital×Small	1.147*	0.008	3.019*	0.022
Cash Flow/Capital×Large	2.418*	0.006	7.807*	0.012
z_{it}×Small			-5.871*	0.061
z_{it}×Large			-21.612*	0.042
μ_i×Small	0.166*	0.002		
μ_i×Large	-0.022*	0.001		
Fixed Effects	No		Yes	
Time Effects	Yes		Yes	

Table 9: Investment-Cash Flow Regressions with Simulated Data

6.7 Overview

To sum up: our estimates and policy exeriments suggest that financial factors play an important role in farm outcomes. Our model is rich enough to distinguish between many types of constraints and quantify their importance. Increasing the availability of either debt or equity funding allows farms to significantly expand their operations. The liquidity constraint on variable inputs also seems important, in the sense that tightening it can reduce assets, capital and output of farms substantially. Similar borrowing constraints have been shown to play an important role in financial crises in Latin America and East Asia (see for example Pratap and Urrutia 2012, Mendoza 2010). The model futher suggests that the ability to renegotiate debt allows productive farms to remain operational. On the other hand, liquidation costs discourage low-productivity farms from exiting. In our model, the reallocation effect of liquidation costs appears as significant as the borrowing restrictions.

Our exercises also reveal important interactions between financial factors and occupational choice. High non-pecuniary benefits encourage cautious financial behavior. Tighter collateral or liquidity constraints reduce the value of farming, and encourage exit. Liquidation costs, on the other hand, discourage farms from shutting down.

7 Conclusion

Using a rich panel of New York State dairy farms, we assess the importance of financial constraints and nonpecuniary considerations for a group of established entrepreneurs. Our data allow us to disentangle financial and technological factors, and to control for

firm-specific factors. This in turn allows us to analyze our entrepreneurs at a much higher level of precision than is standard in the literature.

After a descriptive analysis, we estimate a structural model of farm investment, liquidity and production decisions. Farms face uninsured idiosyncratic and aggregate risks. They have a limited ability to issue new equity, are required to back much of their debt with capital, and are forced to hold cash to cover variable expenditures. Their debt contracts account for liquidation costs and allow for renegotiation. Farmers choose their occupation, and can exit farming through retirement as well as liquidation. The combination of occupational choice and bankruptcy protection introduces the possibility of risk-seeking behavior (Vereshchagina and Hopenhayn, 2009). Using a simulated minimum distance estimator, we find that our model can account for a significant portion of the time series and cross sectional variation in the data.

Our model allows us to quantify the importance of each type of financial constraint. The collateral constraints significantly constrict capital holdings. We also find that the short-term borrowing constraint on the purchase of variable inputs exerts a strong influence on investment, asset accumulation and liquidity management decisions of farms. The renegotiability of the debt contract allows productive farms to remain operational when they experience transitory setbacks. As in the data, our model also predicts that financial health is important for farm investment and its ability to use inputs optimally. Relaxing the collateral and liquidity constraints allows farms to expand and makes farming a more attractive occupation.

We find that high-productivity farms are further below their optimal scale than low-productivity farms, suggesting a significant misallocation of resources. Moreover, our estimates indicate that the non-pecuniary benefits of farming are an important reason many farms remain operational. Removing them (or equivalently, improving outside opportunities for farmers) would lead many operations in the lower tail of the productivity distribution to shut down. Liquidation costs also discourage exit, suggesting that they too could hinder the reallocation of capital. The high costs of exiting in turn encourage cautious financial behavior. More generally, our model suggests that financial constraints and occupational choice interact in important ways.

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A Data Construction

Sample Selection: The table below describes the filters used to construct the sample. The outlier farms eliminated were those whose time averaged herd size was in the top and bottom 2.5th percentile respectively. Since we are interested in the dynamic behavior of the enerprises, we also eliminate farms with only one observation. Finally, we drop farms with missing information on the age of the youngest operator.

	# of Farms	# of Observations
Original Sample	541	2461
Trim top and bottom 2.5%	508	2261
Drop farms with one observation	357	2110
Drop farms with missing age	338	2037

Owned Capital: The sum of the beginning of period market value of the three categories of capital stock owned by a farm: real estate and land, machinery and equipment and livestock.

Depreciation and Appreciation Rates: The depreciation rate δ_j for each type of capital stock j is calculated as

$$\delta_j = \frac{1}{T} \frac{\sum_i \text{Depreciation}_{jit}}{\sum_i \text{Market Value of Owned Capital}_{jit}}$$

where i indexes farms and $T = 11$ (2001-2011).

Analogously, the appreciation rate ϖ_j for each type of capital stock j is given by

$$\varpi_j = \frac{1}{T} \frac{\sum_i \text{Appreciation}_{jit}}{\sum_i \text{Market Value of Owned Capital}_{jit}}$$

The actual depreciation rate δ is the weighted average of each δ_j,the weights being the average share of each type of capital stock in owned capital. The appreciation rate ϖ is calculated similarly.

Leased Capital: The market value of leased capital ($MVLK$) of type j for farm i at time t is calculated as

$$MVLK_{jit} = \frac{\text{Leasing Expenditures}_{jit}}{r + \delta_j - \varpi_j + \pi}$$

where r is the risk free rate of 4 percent and π is the average inflation rate through the period. The market value of all leased capital is the sum of the market value of all types of leased capital.

Total Capital : Owned Capital + Leased Capital

Investment: Sum of net investment and depreciation expenditures in real estate, livestock and machinery.

Total Output: Value of all farm receipts.

Total Expenditure: Expenses on hired labor, feed, lease and repair of machinery and real estate, expenditures on livestock, crop expenditures, insurance, utilities and interest.

Variable Inputs: Total expenditures less expenditures on interest payments and leasing expenditures on machinery and real estate

Total Assets: Beginning of period values of the current assets (cash in bank accounts and accounts receivable), intermediate assets (livestock and machinery) and long term assets (real estate and land).

Total Liabilities: Beginning of period values of current liabilities (accounts payable and operating debt), intermediate and long term liabilities.

Dividends: Net income (total receipts-total expenditures) less retained earnings and equity injections.

Cash: Total assets less owned capital.

B Econometric Methodology

We estimate the parameter vector $\Omega = (\beta, \nu, c_0, \chi, c_1, \theta, \alpha, \gamma, n_0, \lambda, \zeta, \psi)$ using a version of Simulated Minimum Distance. To construct our estimation targets, we sort farms along two dimensions, operator age and size (cows per operator). Along each dimension, we divide the sample in half. Then for each of these four age-size cells, for each of the years 2001 to 2011, we match:

1. The median value of capital per operator, k.

2. The median value of the output-to-capital ratio, y/k.

3. The median value of the variable input-to-capital ratio, n/k.

4. The median value of the gross investment-to-capital ratio.

5. The median value of the debt-to-asset ratio, $b/\tilde{a}$

6. The median value of the cash-to-asset ratio, $\ell/\tilde{a}$.

7. The median value of the dividend growth rate, d_t/d_{t-1}.

Let g_{mt}, $m \in \{1, 2, ..., M\}$, $t \in \{1, 2, ..., T\}$, denote a summary statistic of type m in calendar year t, such as median capital for young, large farms in 2007, calculated from the DFBS. The model-predicted value of g_{mt} is $g^*_{mt}(\Omega)$. We estimate the model by minimizing the squared proportional differences between $\{g^*_{mt}(\Omega)\}$ from $\{g_{mt}\}$. Because the model gives farmers the option to become workers, we also need to match some measure of occupational choice. We thus record the fraction of farms that exit in our simulations but not in the data, and the fraction to calculate a penalty, $\Psi_I(\Omega)$, that is added to the SMD criterion.

Our SMD criterion function is

$$Q_I(\Omega) = \sum_{m=1}^{M} \sum_{t=1}^{T} \aleph_m^2 \left(\frac{g^*_{mt}(\Omega)}{g_{mt}} - 1 \right)^2 + \Psi_I(\Omega), \tag{12}$$

where $\Psi(\Omega)$ is a penalty imposed when farms exit in the simulations, but not in the DFBS. The weights $\{\aleph_m\}$ are normalized to 1, with two exceptions. We set the weight on dividend growth rates to 2; and we set the weight on cash/asset ratios to 1/4. The dividend growth rate measures the willingness of farmers to fund investment internally by withholding dividends. If the dividend smoothing motive is strong, equity funding will be driven by cash flow rather than variations in dividends. Given the paper's focus on the links between financial conditions and investment, we place a high priority on matching the dividend smoothing motive, and have thus placed additional weight on deviations in dividend growth rates. We view matching the cash/asset ratio, especially the way it varies by farm size, as a lower priority. We thus place lower weight on deviations in the cash/asset ratios.

Our estimate of the "true" parameter vector Ω_0 is the value of Ω that minimizes the criterion function $Q_I(\Omega)$. Let Ω_I denote this estimate. Our approach for calculating the

variance-covariance matrix of Ω_0 follows standard arguments for extremum estimators. Suppose that

$$\sqrt{I} D_I(\Omega_0) \equiv \sqrt{I} \frac{\partial Q_I(\Omega_0)}{\partial \Omega} \rightsquigarrow \mathcal{N}(0, \Sigma),$$

so that the gradient of $Q_I(\Omega)$ is asymptotically normal in the number of cross-sectional observations. With this and other assumptions, Newey and McFadden (1994, Theorem 3.1) show that

$$\sqrt{I}\,(\Omega_I - \Omega_0) \rightsquigarrow \mathcal{N}(0, H^{-1}\Sigma H^{-1}), \tag{13}$$

where

$$H = \text{plim} \frac{\partial Q_I(\Omega_0)}{\partial \Omega \partial \Omega'}.$$

We estimate H as H_I, the numerical derivative of $Q_I(\Omega)$ evaluated at Ω_I. Unfortunately, there is no analytical expression for for the limiting variance Σ. We instead find Σ via a bootstrap procedure. In particular, we create S artificial samples of size I, each sample consisting of I bootstrap draws from the DFBS. Each draw contains the entire history of the selected farm. In this respect, we follow Kapetanios (2008), who argues that this is a good way to capture temporal dependence in panel data bootstraps. Our bootstrap procedure does not account for aggregate shocks, and thus our standard errors abstract from aggregate variation. For each bootstrapped sample $s = 1, 2, \ldots, S$, we generate the artificial criterion function $Q_s(\Omega_I)$, in the same way we constructed $Q_s(\Omega_I)$ using the DFBS data. The function $Q_s(\Omega_I)$ is then run through a numerical gradient procedure to find $D_s(\Omega_I)$. The estimated parameter vector Ω_I is used for every s, but the simulations used to construct $Q_s(\cdot)$ employ different random numbers, to incorporate simulation error.[26] Finding the variance of $D_s(\Omega_I)$ across the S subsamples yields Σ_S, an estimate of Σ/I (not Σ).

An alternative interpretation of our approach is to treat it as an approximation to the "complete" bootstrap, where Ω is re-estimated for each artificial sample s.[27] Let G_I denote the vector containing all the summary statistics used in $Q_I(\cdot)$. The first-order condition for minimizing $Q_I(\cdot)$ implies that

$$D_I(\Omega_I) = D(\Omega_I, G_I) = 0,$$

[26] Because $g^*_{mt}()$ is found via simulation rather than analytically, the variance Σ must account for simulation error. In most cases the adjustment involves a multiplicate adjustment (Pakes and Pollard, 1989; Duffie and Singleton, 1993; Gouriéroux and Monfort, 1996). Because each iteration of our bootstrap employs new random numbers, no such adjustment is needed here.

[27] We are grateful to Lars Hansen for this suggestion.

Implicit differentiation yields

$$\frac{\partial \Omega_I}{\partial G_I} \approx -H_I^{-1} \frac{\partial D(\Omega_I, G_I)}{\partial G_I}.$$

Because the mapping from G_I to Ω_I – the minimization of $Q_I(\Omega)$ – is too time-consuming to replicate S times, we replace it with its linear approximation:

$$\begin{aligned} V(\Omega_I) &\approx \frac{\partial \Omega_I}{\partial G_I} V(G_I) \frac{\partial \Omega_I}{\partial G_I'} = H_I^{-1} \frac{\partial D(\Omega_I, G_I)}{\partial G_I} V(G_I) \frac{\partial D(\Omega_I, G_I)}{\partial G_I'} H_I^{-1} \\ &\approx H_I^{-1} \Sigma_S H_I^{-1}. \end{aligned}$$