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WP 17-07

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Abstract

Using a rich panel of owner-operated New York dairy farms, we provide new evidence on entrepreneurial behavior. We formulate a dynamic model of farms facing uninsured risks and financial constraints. Farmers derive nonpecuniary benefits from operating their businesses. We estimate the model via simulated minimum distance, matching both production and financial data. We find that financial factors and nonpecuniary benefits are of first-order importance. Collateral constraints and liquidity restrictions inhibit borrowing and the accumulation of capital. The nonpecuniary benefits to farming are large and keep small, low-productivity farms in business. Although farmers are risk averse, eliminating uninsured risk has only modest effects on capital and output.

JEL Classification: G31, G32, L26

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1 Introduction

The Statistics of US Businesses show that almost 80 percent of US businesses are single proprietorships, partnerships or S Corporations. What mechanisms best explain their behavior? While many researchers have focused on the importance of financial constraints, others have highlighted the role of nonpecuniary returns from running one's own business. Still other research has emphasized factors that encourage entrepreneurs to take risks. Assessing the relative importance of these mechanisms is a priority for policymakers. Compared with larger firms, small businesses are often viewed as more proficient at innovation and job creation, and also more likely to be hampered by financial constraints. Small firms are therefore seen as worth subsidizing. The value of such subsidies is less apparent, however, if entrepreneurs are driven mainly by nonpecuniary considerations. (Hurst and Pugsley, 2011, 2014).

In this paper we evaluate the importance of all these mechanisms by building and estimating a rich model of entrepreneurial behavior. Risk-averse entrepreneurs make borrowing, investment, production, dividend and liquidation decisions. They face uninsured risk, along with collateral and liquidity constraints, but also receive nonpecuniary benefits from operating their businesses. Older entrepreneurs retire, and entrepreneurs of any age can exit to wage work, albeit with liquidation costs. Limited liability and the outside option of wage work create incentives for risk-taking. We estimate the model's parameters using a detailed panel of family owned and operated dairy farms in New York State. Using a simulated minimum distance estimator, we match both the production and financial sides of the data. Counterfactual experiments allow us to quantify the effects of relaxing financial constraints, eliminating nonpecuniary benefits, and reducing or eliminating risk.

Our paper makes two key contributions. The first contribution is that, to the best of our knowledge, we are the first to formulate and estimate a model of entrepreneurial behavior that simultaneously accounts for financial constraints, nonpecuniary benefits and risk-taking. While (sometimes inconclusive) evidence exists for each of these mechanisms separately, to the best of our knowledge, we are the first to undertake a joint treatment. This is important, because none of these mechanisms can be measured correctly in isolation. For example, borrowing constraints that affect financial returns and nonpecuniary benefits both determine whether an enterprise remains in business.

Researchers have looked for financial constraints in a variety of settings. While Evans and Jovanovic (1989) and Blanchflower and Oswald (1998) find that wealthier individuals are more likely to become entrepreneurs, Hurst and Lusardi (2004) argue that a positive relationship between wealth and business creation exists only at the top of the wealth distribution.[1] Even if financial constraints do not restrict entry, they may restrict the operations of ongoing firms (Quadrini, 2009; Cagetti and De Nardi, 2006). The tendency of entrepreneurs to save at higher rates and invest much of their wealth in their own businesses suggests the presence of financial constraints (Quadrini, 2000, 2009; Cagetti and De Nardi, 2006; Herranz et al., 2015), as does evidence that inheritances improve their chances of survival (Holtz-Eakin et al., 1994).

There is both direct and indirect evidence that entrepreneurs are also motivated by nonfinancial considerations. Hurst and Pugsley (2011) tabulate responses from the Panel Study on Entrepreneurial Dynamics and find that nonpecuniary benefits (flexible hours, being one's own boss, etc.) are a primary motive behind business formation. In general, entrepreneurs report greater job satisfaction than wage workers, as documented by Blanchflower (2000) for the OECD, Anderson (2008) for Sweden, and Benz and Frey (2008) for Germany, UK and Switzerland.

Indirect evidence of nonpecuniary benefits is provided by the gap between the earnings of the self-employed and wage workers (Hamilton, 2000), and by the gap between the returns on undiversified entrepreneurial investment and publicly traded equities (Moskowitz and Vissing-Jørgensen, 2002).[2] Hall and Woodward (2010) find an extreme dispersion in the payoffs to startups, and consequently, a very small risk-adjusted return.

These income differentials, however, could be due to differences in risk-taking behavior between entrepreneurs and wage workers. Kihlstrom and Laffont (1979) construct a model where risk-loving individuals select into entrepreneurship, while Vereshchagina and Hopenhayn (2009) show that limited liability can encourage risk taking behavior among entrepreneurs even without a risk premium, indicating that nonpecuniary benefits cannot be measured accurately without accounting for attitudes for risk. More generally, as we mentioned above, none of our three mechanisms can be measured accurately without accounting for the others.

Our second main contribution is that, in contrast with most studies on entrepreneurship, we use detailed panel data to identify the dynamic mechanisms of the model. The data contain comprehensive information on the farms' real and financial activities, including input use, revenue, investment, borrowing and equity. Because they are drawn from a single region and industry, the data are less vulnerable to issues of unobserved

[1] Buera (2009) shows that a dynamic model with borrowing constraints has the opposite implication: the likelihood of becoming an entrepreneur is increasing in wealth at low levels of wealth, but decreasing in wealth when wealth is high

[2] Kartashova (2014) argues that this "private equity puzzle" does not exist outside the 1990s, a period of unusually high public equity returns.

heterogeneity.[3]

Our dataset allows us to estimate financial constraints from investment dynamics, rather than cross-sectional relationships. This is a quite different and arguably more direct source of identification. For example, using the parameters estimated by our model, we calculate revenue productivity shocks for each farm. These shocks can in turn be decomposed into a permanent farm-specific component, an aggregate shock tied closely to the price of milk, and an idiosyncratic transitory component. We find that periods of high aggregate productivity are also periods of high aggregate investment. Because aggregate productivity appears uncorrelated over time, this association suggests that high milk prices promote investment by increasing cash flow, as opposed to signalling higher future productivity. Volatile revenue shocks also help us assess attitudes toward risk, while farm exit decisions help us measure nonpecuniary benefits. This sort of identification is not available in cross-sectional datasets, such as the Survey of Consumer Finances or the Survey of Small Business Finances, on which most studies of entrepreneurship are based.

Our empirical methodology has many parallels with the literature on structural corporate finance (Pratap and Rendon, 2003; Hennessey and Whited, 2007; Strebulaev and Whited, 2012), which analyzes the real and financial decisions of large publicly traded corporations. However, the firms in our data are all family owned and operated, and hence not comparable to firms listed on the stock market. The closest counterparts to our analysis are arguably in the development literature, where structural models of entrepreneurship have been estimated with firm-level panel data, often from Townsend's Thai surveys.[4] Such firms are of course quite different in scale and operate in a radically different environment. Our work also resembles that of Caggese (2007, 2013), who calibrates and assesses his models with detailed data on Italian manufacturing firms.

Our main finding is that the effects of financial constraints and nonpecuniary benefits are of first-order importance but those of risk are not. Financial constraints exercise a significant influence along the intensive margin of operation, i.e., on investment and output. Collateral constraints hinder the accumulation of capital, especially among high-productivity farms that are seeking to expand. Liquidity constraints that force businesses to hold cash and divert resources from investment have similar effects, although their quantitative impact is much smaller. The effects of nonpecuniary benefits are manifested

[3]On the other hand, the average revenues of all US firms, and their distribution, are similar to those in our sample. We discuss these and other aspects of the external validity of our results in Section 6.

[4]Townsend et al. (1997) and Samphantharak and Townsend (2010) provide a description of the data. A recent study especially relevant to ours is Karaivanov and Townsend (2014), which also contains a literature review.

along the extensive margin, i.e., the decision to continue operations. The least productive farms in our data have very low financial returns. In the absence of significant nonfinancial rewards, their continued operation is hard to justify. Liquidation costs likewise affect the extensive margin by impeding the exit of unprofitable farms. We also find that liquidation costs amplify the effect of nonpecuniary benefits. Both work in the direction of discouraging exit of small, marginal farms. When combined, their effects are much larger than each in isolation.

In contrast, risk appears to play a minor role. The parameter estimates show that entrepreneurs are risk averse. Risk aversion, along with the nonpecuniary rewards to farming, combine to mitigate the appetite for risk-taking, despite limited liability and the ability to exit into wage work. On the other hand, while eliminating risk leads farms to expand along the intensive margin, the effect is quantitatively modest, especially compared to the effect of relaxing financial constraints. We reach similar similar conclusions regarding recent changes in US dairy policy. The 2014 Farm Bill replaced the previous system of price supports, which were too low to be effective, with a system of margin (milk prices net of feed costs) supports (Schnepf, 2014). We estimate what the impact of the margin supports program would have been had it existed during our 2001-2011 sample period, and we find that the insurance provided by the program would have had only a minor effect on farm operations. The premium charged for the margin supports would have had much larger, and negative, consequences.

Taken together, our results caution against the blanket subsidization of small firms and argue for a more nuanced approach. Low-productivity operations driven mainly by nonpecuniary concerns exist alongside high-productivity operations hindered by financial constraints. Relaxing the borrowing constraints may not have an expansionary effect across the board. Policies that encourage the formation of businesses as a way to spur innovation or growth may not achieve those results. Entrepreneurial policy may work better by helping the most promising entrepreneurs expand.

The rest of the paper is organized as follows. In section 2 we describe our data and perform some diagnostic reduced form exercises. Section 3 sets out the model and section 4 describes our estimation procedure. Section 5 presents our parameter estimates, assesses the model's fit, and discusses parameter identification. Section 6 elaborates on the mechanisms of the model, considering nonpecuniary benefits, financial constraints, and their interactions. We also discuss the external validity of our results. Section 7 evaluates the effects of uninsured risk in general and the effects of the 2014 Farm Bill in particular. Section 8 contains sensitivity analyses. We conclude in section 9.

2 Data and Descriptive Analysis

2.1 The DFBS

The Dairy Farm Business Summary (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 are extensively reviewed by the DFBS staff, who also construct income statements, balance sheets, cash flow statements, and a variety of productivity and financial measures (Cornell Cooperative Extension, 2006; Cornell Cooperative Extension, 2015b; Karzes et al., 2013). Participants can use these measures to compare their management practices with those of their peers. These diagnostics are an important benefit of participation in the survey, which is voluntary (Cornell Cooperative Extension, 2015a). We therefore expect the data to be of high quality, a supposition that is confirmed by internal data consistency checks. However, larger farms are over-represented, and the average farm in the DFBS data is larger than the population average for New York State.[5] As long as our structural model is specified correctly, our parameter estimates should be consistent even with a nonrepresentative sample. However, the results of the numerical experiments, which aggregate over the DFBS sample, are best interpreted as qualitative.

Our dataset is an extract of the DFBS covering the calendar years 2001-2011. This is an unbalanced panel of 541 distinct farms, with approximately 200 farms surveyed each year. Since our model is explicitly dynamic, we eliminate farms with observations for only one year. We also remove farms for which there is no information on the age of the operators, as we expect retirement considerations to influence both production and finance decisions on family operated farms. These filters leave us with a final sample of 363 farms and 2,222 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 farms.

[5] In 2011, average revenue in our sample was \$2,887,000, 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 505. However, the sample is very similar to state averages in terms of demographics: 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	1.79	2	0.87	6	1
Operator 1 Age	51.36	51	10.83	87	16
Youngest Operator Age	43.12	43	10.69	74	12
Herd Size (Cows)	374	186	434	3,656	20
Total Capital	3,329	1,932	3,622	28,247	212
Machinery	753	483	760	5,335	13
Real Estate	1,715	966	1,949	15,161	0
Livestock	861	432	1,030	9,027	39
Owned Capital	2,693	1,594	2,934	26,478	83
Machinery	562	360	576	3,776	3
Real Estate	1,296	756	1,509	14,196	0
Livestock	835	424	980	9,027	39
Owned/Total capital	0.84	0.87	0.12	1.00	0.26
Revenues	1,778	822	2,202	16,929	47
Total Expenses	1,510	675	1,900	15,685	43
Variable Inputs	1,389	613	1,769	15,203	36
Leasing and Interest	121	58	154	1,255	0
Total Assets	3,242	1,869	3,579	31,414	103
Cash	548	257	721	5,689	6
Total Liabilities	1,508	786	1,709	11,423	0
Net Worth	1,733	874	2,314	21,278	-734
Dividends	72	46	176	4,058	-2,327

Table 1: Summary Statistics from the DFBS

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

Table 1 provides summary statistics. A detailed data description is provided in Appendix A. The median farm is operated by two individuals and more than 80 percent of farms have two or fewer operators. The average age of the main operator is 51 years. For multioperator 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 eight 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 shows that these are substantial enterprises: the yearly revenues of the average farm are in the neighborhood of $1.8 million in 2011 terms. The distribution of revenues is heavily skewed to the right, with median farm revenues equal to less than half the mean. A large part of farm expenses are accounted for by variable inputs: intermediate goods and hired labor. Of these labor expenses are relatively small, accounting for about 14 percent of all expenditures on variable inputs. The remainder consists of intermediate goods and services 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 for the median farm.

Capital stock consists of machinery, real estate (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 13 percent of its capital, mostly real estate and machinery. (See Appendix A.) Livestock is almost always owned. Capital is by far the predominant asset, accounting for more than 85 percent of farm assets, while liquid assets (what we call cash) accounts for the rest.

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 \$1.7 million. Only 28 (or 1.3 percent) of all farm-years report negative net worth.

Farms generate relatively little disposable income. The average dividend remitted to the farm's owners is \$72,000, while the median is \$46,000. Because the farms' owner/operators also supply most of the labor, these returns are quite modest.

Much more of the farm's operating income is invested. 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 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) use data from the Longitudinal Research Database (LRD) to show that plant-level investment often occurs in large increments, suggesting a prominent role for fixed investment costs. For reference, Table 2 reproduces the statistics for gross investment rates shown in their Table 1. Investment spikes are much less frequent in the DFBS than in the LRD. The average investment rate is also a bit lower. Although the inaction rate is marginally higher in our sample, the comparison as a whole suggests 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 60 percent of

	DFBS	LRD
Average Investment Rate	0.087	0.122
Inaction Rate (< abs(0.01))	0.093	0.081
Fraction of Observations < 0	0.086	0.104
Positive Spike Rate (> 0.2)	0.077	0.186
Negative Spike Rate (< -0.2)	0.003	0.018
Serial Correlation	0.106	0.058

Table 2: Investment Rates

Notes: Column DFBS summarizes gross investment to owned capital ratios in the Dairy Farm Business Survey. Column LRD, taken from Cooper and Haltiwanger (2006, Table 1), shows corresponding statistics from the Longitudinal Research Database.

	Stanchion	Parlor
No. of Farms	146	217
No. of Operators	1	2
Total Capital	597	1,710
Herd Size (Cows)	52	181
Output/Capital	0.37	0.51
Intermed Goods/Capital	0.27	0.40
Investment/Capital	0.04	0.07
Debt/Assets	0.43	0.49
Cash/Assets	0.11	0.16

Table 3: Medians by Technology

Notes: Capital and herd size measured per operator.

the farms in our sample are parlor operations. Table 3 displays summary statistics for each technology group. Stanchions are smaller than parlors, both in herd size and capital stock per operator. They invest less, have lower debt-to-asset ratios, and hold less cash. Interestingly, they also have lower output to capital ratios, and use fewer intermediate goods per unit of capital. These differences are consistent with both heterogeneous production functions and with heterogeneous exposure to financial constraints that distort the mix of inputs. Our model and estimation will allow for both possibilities.

2.2 Productivity

2.2.1 Our Productivity Measure

We assume that farms utilize a Cobb-Douglas production function

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

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_i.[6] 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.[7] 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

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

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

Following Alvarez et al. (2012) and based on the descriptive statistics in Table 3, we allow for two production technologies. Using the structural estimation procedure described below, we find that for stanchion operations $\widehat{\alpha} = 0.135$ and $\widehat{\gamma} = 0.174$ and for milking parlors $\widehat{\alpha} = 0.107$ and $\widehat{\gamma} = 0.122$. In other words, parlor operators have higher returns to scale but lower returns to capital than stanchions. These estimates allow us to calculate total revenue 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 productivity measure can be decomposed into the individual fixed effect μ_i, a time-specific component, common to all farms, Δ_t, and the idiosyncratic

[6]More than two-thirds of our farms display no change in family size.

[7]The assumption of decreasing returns to scale in nonmanagement inputs is consistent 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."

i.i.d 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 has a mean of 0.812 but ranges from 0.072 to 1.273 with a standard deviation of 0.14, implying significant time-invariant differences in productivity across farms. The time effect Δ_t is constructed to be zero mean. This series is effectively uncorrelated and has a standard deviation of 0.059. The idiosyncratic residual ε_{it} can also be treated as uncorrelated, with a standard deviation of 0.070.

As a measure of revenue productivity, z_{it} captures variation in prices as well as productivity. Because dairy farmers are by and large price takers, however, price variation should affect only the aggregate component Δ_t. Figure 1 plots Δ_t against real milk prices in New York State (New York State Department of Agriculture and Markets, 2012). The aggregate shock follows milk prices very closely – the correlation is over 90 percent – which gives us confidence in our interpretation.[8] We thus feel comfortable assuming that the transitory shock ε_{it} and especially the fixed effect μ_i measure physical productivity.[9]

In Figure 1 we also 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 productivity measure. Cash flow varies quite significantly, indicating that farms face significant financial risk.

2.2.2 Productivity and Farm Characteristics

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. Ninety-eight

[8]The series in Figure 1 are consistent with the belief that that milk prices follow a three-year cycle. Nicholson and Stephenson (2014) find a stochastic cycle lasting about 3.3 years. While Nicholson and Stephenson 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[.]"

[9]Our assumption of perfect competition rules out the firm-level differences in market power or product demand emphasized by Foster et al. (2008). Hsieh and Klenow (2009, Appendix I) show that their framework for measuring productivity, with constant returns to scale in production and monopolistic competition ("diminishing returns in utility"), is isomorphic to our framework, with decreasing returns to scale in production and perfect competition.

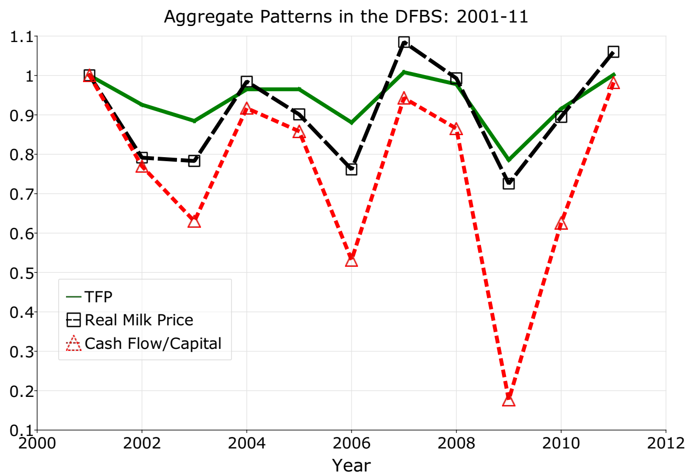

Figure 1: Aggregate Productivity, Real Milk Prices, and Cash Flow

percent of the stanchions are low-productivity farms, and almost eighty percent of the low-productivity farms are stanchions. eighty-two percent of the parlor operations are high-productivity farms, and almost all (ninety-eight percent) of the high-productivity farms are parlors.

Our convention will be to use thick solid lines to represent high-productivity farms and 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 several times larger than that of low-productivity farms.[10] This size advantage is increasing over time: high-productivity firms are growing while low-productivity firms are static. These differences will prove crucial to identifying our model.

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. In our model we will assume that all capital is owned. 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 percent vs. 30 percent). This could be due to differing production functions between stanchion and parlor farms, given that most high-productivity farms are parlors. Another explanation for this difference in input use could be financial constraints on the purchase of variable inputs. We will account for both possibilities in our model.

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

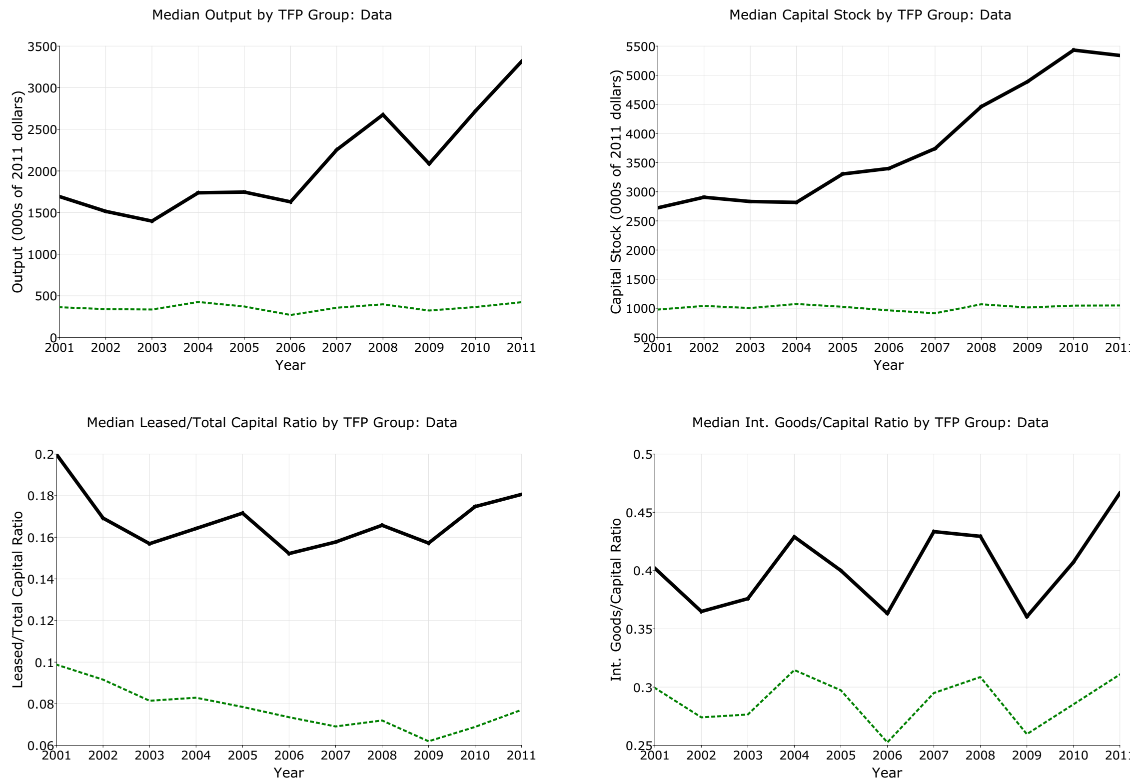

Figure 2: Production and Inputs by Productivity and Calendar Year

Notes: Thick, solid lines refer to high-productivity farms. Thinner, dashed lines refer to low-productivity farms.

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, cash flow and investment both fell during the recession of 2009. Given that the aggregate shocks are not persistent, high current productivity (and cash flow) does not indicate high expected productivity. The correlation of cash flow and investment thus suggests financial constraints, which are relaxed in periods of high output prices. However, the interpretation of cash flow regressions – much less simple correlations – is notoriously difficult (see for example Erickson and Whited, 2000, and Gomes, 2001, among others). We will formally assess the importance of financial constraints using our structural model.

The middle row shows investment rates and dividend payments. High-productivity farms invest at a higher rate and pay larger dividends to their owner/operators, than low productivity farms. Dividends and cash flow are strongly correlated for both types of farms. In general, dividend flows are quite modest, especially for low-productivity farms.

The bottom left panel of Figure 3 shows debt/asset ratios.[11] Although high-productivity farms begin the sample period with more debt, over the sample period they decrease their leverage, even as they expand their capital stocks.

In a static frictionless model, the optimal capital stock for a farm with productivity level μ_i is given by $k_i^* = [\kappa \exp(\mu_i)]^{1/\alpha}$, where κ is a positive constant.[12] 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 holds close to the optimal amount of capital throughout the sample period. In contrast, the capital stocks of high-productivity farms are initially almost half their optimal size, but grow rapidly. This difference can explain why large firms are more indebted and invest at higher rates.

While we do not seek a quantitative measure of allocative inefficiency, the bottom right panel of Figure 3 does suggest that financial constraints hinder the optimal 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.[13]

On the other hand, our findings seem at odds at with the evidence from the corporate finance literature that large firms are less financially constrained (Kaplan and Zingales, 1997; Whited and Wu, 2006; Hadlock and Pierce, 2010). This apparent discrepancy may be due to age and/or vintaging effects. Although larger farms appear more constrained, they also carry more debt. Because these farms are more likely to use parlor technologies, which are newer, they may simply have had less time to accumulate capital. It is also possible that many smaller farms cannot acquire the financing needed to install newer technologies and are thus effectively more constrained than the larger farms.[14]

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

[12] 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 $\kappa = \left(\frac{\gamma}{r+\delta-\varpi}\right)^{\alpha+\gamma}(1-\alpha-\gamma)^{1-\alpha-\gamma}E(\exp(\Delta_t\varepsilon_{it}))$.

[13] Protracted capital stock growth could also reflect capital adjustment costs, which we rule out by assumption. Capital adjustment costs cannot generate, however, the observed positive correlation between aggregate cash flow and aggregate investment. Because the aggregate productivity shocks appear to be serially uncorrelated, we do not believe the latter relationship is caused by current cash flow acting as a signal for future productivity.

[14] We are grateful to an anonymous referee for this insight.

Figure 3: Investment and Finances by Productivity and Calendar Year

Notes: Thick, solid lines refer to high-productivity farms. Thinner, dashed lines refer to low-productivity farms.

3 Model

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

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

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/nonpecuniary 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 are

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

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 productivity 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.

Because the farm enjoys limited liability, it may be able to void some of its debt via liquidation. This leads to enforceability problems of the sort described in Kehoe and Levine (1993). A family operating a farm thus makes an occupational decision at the beginning of each period. The family has three options: continued operation with full debt repayment, continued operation with reorganization, or liquidation followed by wage work.

If the family decides to repay its debt and continue operating, it will have two sources of funding: net worth, $e_q \equiv \tilde{a}_q - b_q$; and the age-$q$ proceeds from 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; withdrawals from cash reserves, contained in the second set of brackets; and additional borrowing, contained in the third set of brackets.

Operating farms face three financial constraints:

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

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

$$d_q \geq -c_0, \tag{10}$$

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 Kiyotaki 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 receive income throughout the year, in an annual model ζ is likely to exceed 1. The third constraint, given by equation (10), limits the farm's ability to raise funds by issuing new equity. We also require that

$$b_{q+1} \geq 0. \tag{11}$$

However, we allow farms to build up buffer stocks in the form of excess cash.

As alternatives to continued operation and full repayment, a farm can reorganize or liquidate. If it chooses the second option, reorganization, some of its debt is written down.[15] 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 (up to debt outstanding) are handed over to the bank.

[15]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 family then exits to wage work, with assets a_q where:

$$a_q = \max\{(1-\lambda)\tilde{a}_q - b_q, 0\}.$$

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 or if an ongoing operation decides to reduce its capital stock. While we allow the family to roll over debt (b_q can be bigger than $\tilde{a}_q$), Ponzi games are ruled out by requiring all debts to be resolved at retirement:

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

The interest rate realized on debt issued at age $q-1$, $\widehat{r}_q = \widehat{r}_q(s_q, r_q)$, depends on the state vector s_q (specified below) and the contractual interest rate r_q. If the farmer chooses to repay his debt in full, $\widehat{r}_q = r_q$. If the farmer chooses to default,

$$\widehat{r}_q = \frac{\min\{(1-\lambda)\tilde{a}_q, b_q\}}{b_q/(1+r_q)} - 1 = (1+r_q)\frac{\min\{(1-\lambda)\tilde{a}_q, b_q\}}{b_q} - 1.$$

The return on restructured debt is $\widehat{r}_q = (1+r_q)\hat{b}_q/b_q - 1$. We assume that loans are supplied by a risk-neutral competitive banking sector, so that

$$E_{q-1}(\widehat{r}_q(s_q, r_q)) = r, \tag{12}$$

where r is the risk-free rate.

The decision to default or renegotiate is best expressed recursively. To simplify matters, we assume that the decision to work for wages is permanent, so that the worker's only decision is how much to save. The value function for a worker is thus

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

A family that has decided to fully repay its debt and continue farming chooses how much income to withdraw from the farm (d_q) and how much new debt (b_{q+1}) to issue. It then allocates its financial resources between capital (k_q) and cash (ℓ_q). The cash, along with revenues earned as the year proceeds, are used to buy intermediate goods (n_q). The resulting value function is

$$V_q^F(e_q,\mu) = \max_{\{d_q, b_{q+1}, n_q \geq 0, k_q \geq 0\}} u(d_q) + \chi + \beta E_q \left(V_{q+1}(\tilde{a}_{q+1}, b_{q+1}, \mu)\right),$$
$$s.t. \text{ equations (4) - (6), (8) - (12),}$$

where $V_q(\cdot)$ denotes the continuation value prior to the age-q occupational choice:

$$V_q(\tilde{a}_q, b_q, \mu) = \max_{\{V^F, V^W\}} \left\{ V_q^F(\tilde{a}_q - \min\{b_q, \hat{b}_q\}, \mu),\ V_q^W(\max\{(1-\lambda)\tilde{a}_q - b_q, 0\}) \right\}.$$

The renegotiated debt level, $\hat{b}_q$, can then be expressed as

$$\hat{b}_q = \max\{b_q^*, (1-\lambda)\tilde{a}_q\},$$
$$V_q^F(\tilde{a}_q - b_q^*, \mu) \equiv\ V_q^W(\max\{(1-\lambda)\tilde{a}_q - b_q, 0\}),$$

so that $\hat{b}_q = \hat{b}_q(s_q)$, with $s_q = \{\tilde{a}_q, b_q, \mu\}$. The first line of the definition ensures that $\hat{b}_q$ is incentive-compatible for lenders: the bank can always force farms into liquidation, bounding $\hat{b}_q$ from below at $(1-\lambda)\tilde{a}_q$. However, if operators find liquidation sufficiently unpleasant, the bank may be able to extract a larger value of b_q^*. The second line ensures that such a payment is incentive-compatible for farmers, i.e., b_q^* is set so that farmers are indifferent between continued operation with equity level $\tilde{a}_q - b_q^*$ and liquidation followed by wage work. (We assume that once a farm chooses to renegotiate its debt, the bank holds all the bargaining power.) Holding initial net worth fixed, $\tilde{a}_q - b_q$, b_q^* will be largest – and renegotiation most preferable to liquidation – when the farm is highly productive (μ is large), or when the liquidation cost $\lambda\tilde{a}_q$ is large.

Solving for $\hat{b}_q(s_q)$ allows us to express the finance/occupation indicator $I_q^B \in \{$continue, restructure, liquidate$\}$ as the function $I_q^B(s_q)$. We can then divide the farm's optimal repayment amount by the loan's face value and compare the realized return on the loan, $\widehat{r}_q(s_q, r_q)$, to the contractual interest rate r_q:

$$\frac{1+\widehat{r}_q(s_q,r_q)}{1+r_q} = 1\{I_q^B(s_q) = \text{continue}\} + 1\{I_q^B(s_q) = \text{restructure}\} \cdot \frac{\hat{b}_q(s_q)}{b_q}$$
$$+ 1\{I_q^B(s_q) = \text{liquidate}\} \cdot \frac{\min\{(1-\lambda)\tilde{a}, b_q\}}{b_q}.$$

Inserting this result into equation (12), we can calculate the equilibrium contractual rate as[16]

$$1 + r_q = [1 + r] \,/\, E_{q-1} \left(\frac{1 + \widehat{r}_q(s_q, r_q)}{1 + r_q} \right). \tag{13}$$

A key feature of our model is limited liability. Dividends are bounded below by $-c_0$, the estimated value of which is small, limiting the amount the bank can extract through renegotiation. If the farm liquidates, the bank at most receives $(1 - \lambda)\tilde{a}_q$. Coupled with the option to become a worker, limited liability will likely lead the continuation value function, $V_q(\cdot)$, to be convex over the regions of the state space where farming and working have similar valuations (Vereshchagina and Hopenhayn, 2009).

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.

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. As we show in Section 8, the choice of w is largely a normalization of the occupation utility parameter χ. From the DFBS data we estimate the capital depreciation rate δ to be 5.55 percent and the appreciation rate ϖ to be 3.56 percent, as described in the appendix. 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, high loss rates are not implausible. We discuss a specification with $\lambda = 0.175$ in Section 8.

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

[16]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 rate only once, rather than at each potential value of r_q, as would be the case if debt incurred at age $q-1$ were denominated in age-$q-1$ terms. (In the latter case, b_q would be replaced with $(1 + r_q)b_{q-1}$.) This is a significant computational advantage.

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 91 and 92 cows per operator. As Section 2 suggests, this measure corresponds closely to the fixed productivity component μ_i. Then for each of these four age-size cells, for each of the years 2001 to 2011, we match the following sample moments:

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}.[17]

We match medians rather than means so that extreme realizations of firm-specific ratios, due mostly to small denominator values, do not distort our targets.

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 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 calendar 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

[17] 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.

$\{\Delta_t, \varepsilon_{jt}\}_t$. The residual shocks $\{\varepsilon_{jt}\}_{jt}$ are produced with a random number generator, assuming a normal distribution and using the standard deviation of ε_{iq} described immediately above. The aggregate shocks 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 the realization of summary statistic 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 $\{g^*_{mt}(\Omega)\}$ and $\{g_{mt}\}$.

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 nonparticipation, 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 $\bar{u} = \bar{u}(\Omega)$, the fraction of farms that exit in our simulations but not in the data. We then add to the SMD criterion the penalty $\Psi(\bar{u})$.[18]

Our SMD criterion function is

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

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 calculate standard errors.

5 Parameter Estimates, Goodness of Fit, and Identification

5.1 Parameter Estimates

Column (1) of Table 4 displays parameter estimates and asymptotic standard errors for the baseline specification. The estimated values of the discount factor β, 0.991, and the risk aversion coefficient ν, 4.14, 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 greatly value post-retirement consumption; in the period before retirement,

[18]We found that the penalty function $(36\bar{u})^2$ produced parameter estimates with reasonably low levels of counterfactual exit.

farmers consume only 1.1 percent of their wealth and save the rest.[19] The nonpecuniary benefit of farming χ, is expressed as a consumption decrement to the nonfarm wage w. Mechanically, we set

$$\chi = \frac{1}{1-\nu}\left(c_0 + w\right)^{1-\nu} - \frac{1}{1-\nu}\left(c_0 + w - \chi_C\right)^{1-\nu}$$

and estimate (and report) χ_C. This quantity can be interpreted as the equivalent variation for a switch from farming to wage work: how much consumption would a farmer surrender to avoid this switch? With w equal to \$15,000, the estimates imply that the psychic benefit from farming would offset a \$5,360 (35.7 percent) drop in consumption. Given the high estimated value of ν, this translates into a large drop in utility.[20] Even though the outside wage is modest, the income streams of low-productivity farms are so small and uncertain that some 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 77 percent. Table 1 shows that variable inputs in fact equal about 78 percent of revenues. The collateral constraint parameter ψ is 1.06, implying that each dollar of debt must be backed by a roughly equivalent amount of capital. The liquidity constraint parameter ζ is estimated to be about 2.83, implying that farms need to hold liquid assets equal to about four months of expenditures. Although these two constraints together significantly reduce the risk of insolvency, farms with adverse cash flow may find themselves extremely illiquid.

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

[20] In previous drafts of this paper, we expressed the nonpecuniary benefit as a consumption *in*crease. Given the curvature of the utility function, this results in a much higher value of consumption. In the case at hand, the utility lost by decreasing consumption by \$5,360 exceeds the utility gained by increasing consumption by \$100,000.

Parameter Description		Baseline (1)	$\lambda = 0.175$ (2)	$w = \$30K$ (3)	$\chi = 0$ (4)	$\psi = 0$ (5)	No Renegotiation (6)
		Specification					
Discount factor	β	0.991 (0.009)	0.991 (0.102)	0.991 (0.112)	0.996 (0.010)	0.996 (0.007)	0.991 (0.013)
Risk aversion	ν	4.143 (0.089)	4.113 (0.417)	4.130 (1.776)	4.806 (0.096)	5.095 (0.035)	4.115 (0.078)
Consumption utility shifter (in \$000s)	c_0	4.561 (0.097)	4.546 (1.299)	4.571 (4.199)	3.239 (0.097)	3.229 (0.080)	4.492 (0.016)
Retirement utility shifter (in \$000s)	c_1	20.89 (0.97)	20.77 (1.593)	20.77 (12.91)	16.99 (0.15)	16.53 (0.15)	20.76 (0.10)
Retirement utility intensity	θ	92.96 (3.94)	92.93 (17.92)	93.38 (18.39)	63.03 (0.96)	63.80 (0.67)	94.04 (1.35)
Nonpecuniary value of farming (consumption decrement in \$000s)	χ_C	5.365 (0.557)	6.156 (1.013)	21.87 (1.884)	0 (N.A.)	2.96 (0.122)	7.215 (0.275)
Returns to management: stanchions	α	0.135 (0.005)	0.135 (0.004)	0.135 (0.022)	0.159 (0.003)	0.157 (0.0007)	0.134 (0.0003)
Returns to management: parlors	α	0.107 (0.002)	0.108 (0.007)	0.107 (0.042)	0.184 (0.004)	0.183 (0.0007)	0.107 (0.002)
Returns to capital: stanchions	γ	0.174 (0.004)	0.174 (0.002)	0.174 (0.031)	0.161 (0.003)	0.162 (0.0008)	0.173 (0.004)
Returns to capital: parlors	γ	0.122 (0.003)	0.122 (0.016)	0.122 (0.049)	0.102 (0.002)	0.103 (0.002)	0.122 (0.002)
Strength of collateral constraint	ψ	1.062 (0.036)	1.063 (0.135)	1.063 (0.372)	0.763 (0.003)	0 (N.A.)	1.064 (0.045)
Degree of liquidity constraint	ζ	2.827 (0.113)	2.831 (0.208)	2.833 (2.281)	2.867 (0.060)	2.882 (0.054)	2.830 (0.056)

Table 4: Parameter Estimates

Notes: Standard errors in parentheses.

5.2 Goodness of Fit

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 30: this is the average age of the youngest operator in the junior cohort in 2001. Observations for age 31 correspond 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, although it understates the capital holdings of older farms and overstates dividend growth. However, it captures many of the differences between large and small farms and much of the year-to-year variation.

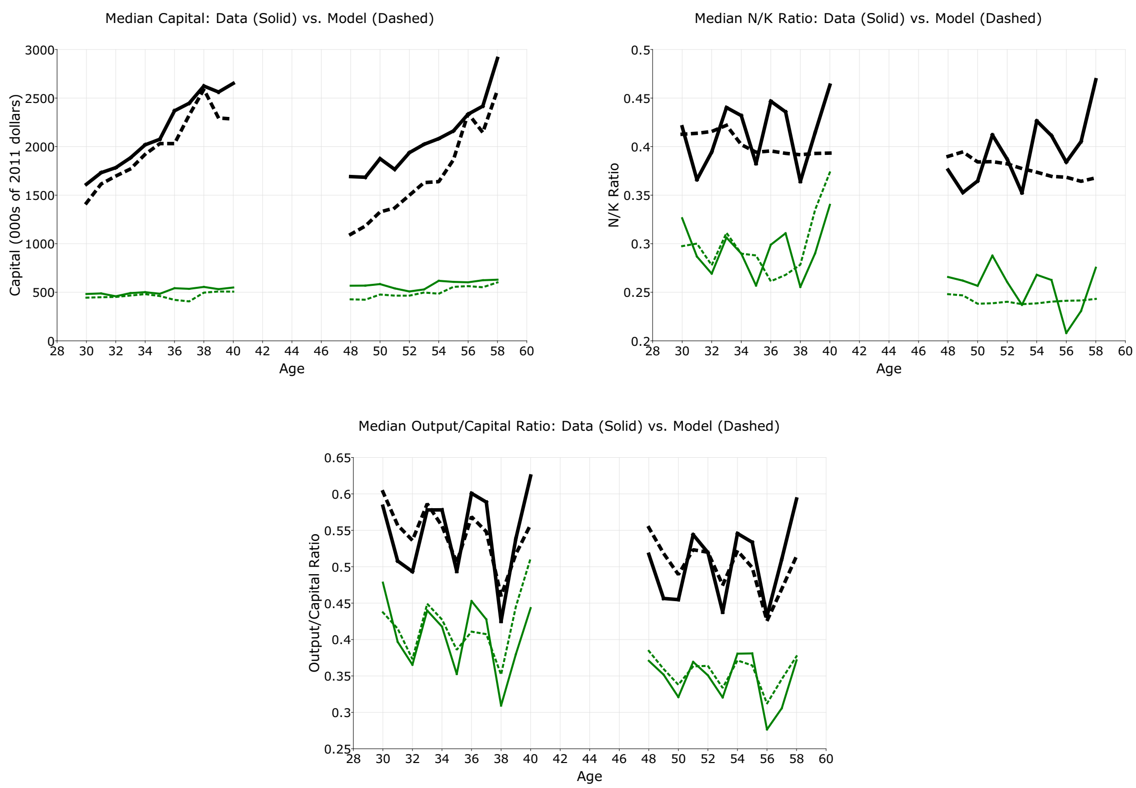

Figure 4: Model Fits: Production Measures

Notes: Solid lines refer to DFBS data, dashed lines to model simulations. Thicker black lines refer to farms with large herds, thinner green lines refer to farms with small herds.

Our estimation criterion includes a penalty for "false exits," simulated farms that exit when their data counterparts do not. False exit is uncommon, with a frequency of 2.1

percent. We also assess the model's fit of a number of untargeted cross-sectional moments. As shown in Appendix C, the model does a satisfactory job along this dimension as well.

5.3 Identification

Although all of the simulated moments depend on multiple model parameters, for some parameters identification is straightforward. 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. The parameter χ is identified by the counterfactual exit that would occur in its absence. The parameter ψ, measuring the strength of the collateral constraint, is identified by two features of the data: (1) high-productivity farmers expand their capital stock steadily over time, rather than all at once; and (2) for farms of all sizes, years of high income are years of high investment.

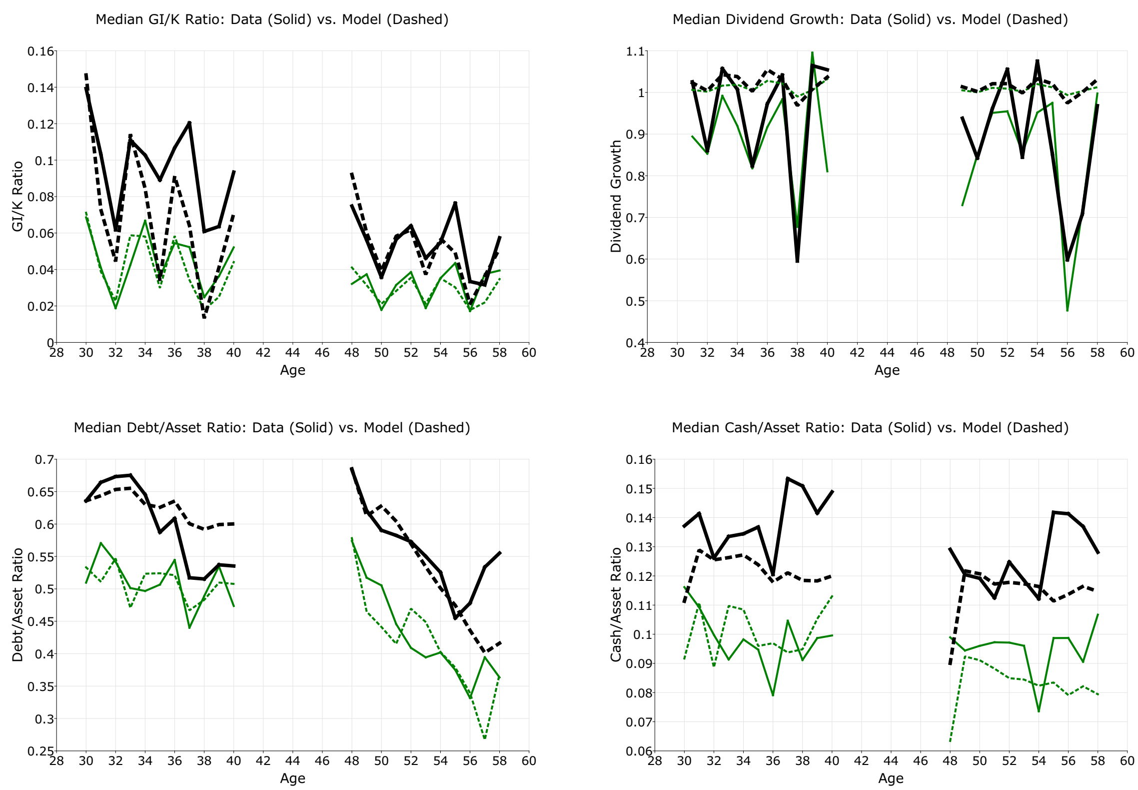

Figure 5: Model Fits: Financial Measures

Notes: Solid lines refer to DFBS data, dashed lines to model simulations. Thicker black lines refer to farms with large herds, thinner green lines refer to farms with small herds.

		Fraction Operating*	Assets	Debt	Debt/ Assets†	Cash/ Assets†	Capital	N/K†	Investment/ Capital (%)†	Dividend Growth Rate (%)‡	Optimal Capital
(1)	Baseline Model	1.000	1,964	1,052	0.536	0.114	1,593	0.378	6.59%	4.31%	2,833
(2)	$\beta = 0.95$	1.002	1,890	1,044	0.552	0.112	1,521	0.378	6.25%	3.46%	2,838
(3)	$\nu = 0.0$	0.928	2,610	1,268	0.486	0.115	2,218	0.365	7.86%	N.A.	3,080
(4)	$\nu = 6.0$	1.002	1,886	982	0.521	0.114	1,514	0.381	6.50%	4.12%	2,839
(5)	$c_0 = 200$	0.992	2,069	1,203	0.581	0.113	1,694	0.381	6.60%	5.67%	2,903
(6)	$c_0 = 0$	1.002	1,949	1,040	0.534	0.114	1,578	0.379	6.55%	4.29%	2,839
(7)	$\chi = 0$	0.920	2,104	1,140	0.542	0.114	1,704	0.381	6.75%	4.36%	3,070
(8)	$\lambda = 0$	0.965	1,959	1,059	0.541	0.116	1,607	0.379	6.40%	3.77%	2,751
(9)	$\lambda = \chi = 0$	0.780	2,302	1,282	0.557	0.117	1,895	0.386	6.51%	3.30%	3,327
(10)	$\psi = 0.5$	1.021	2,405	1,482	0.616	0.115	2,006	0.366	2.84%	3.36%	2,827
(11)	$\psi = 1.5$	1.000	1,515	636	0.420	0.118	1,157	0.419	8.43%	4.75%	2,833
(12)	$\zeta = 1$	0.995	1,671	809	0.484	0.244	1,111	0.363	7.30%	4.79%	2,845
(13)	$\zeta = 6$	1.001	2,089	1,158	0.554	0.060	1,819	0.377	6.08%	4.20%	2,838
(14)	No Aggregate Shocks	1.000	1,988	1,089	0.548	0.114	1,616	0.381	6.58%	4.43%	2,833
(15)	No Transitory Shocks	1.000	2,043	1,169	0.572	0.116	1,671	0.386	6.59%	4.22%	2,833

*Relative to baseline case. †Ratios of averages. ‡Mean growth rates for annual averages. N.A. indicates negative initial dividends.

Table 5: Comparative Statics

The identification of other parameters is more complicated and best illustrated through comparative statics. Table 5 shows averages of model-simulated data over the 11-year (pseudo-) sample period. Row (1) shows the statistics for the baseline model associated with the parameters in column (1) of Table 4, while subsequent rows show the statistics that arise as we vary different parameters or features of the model.

Row (2) shows the averages that result when the discount factor β is lowered to 0.95.[21] Farms hold less capital and invest less, as they place less weight on future returns. They take on more debt, for the same reason. Dividends grow more slowly, with the average growth rate falling from 4.31 to 3.46 percent.

Row (3) shows the effects of setting the curvature parameter ν to zero, so that preferences are linear in dividends. Linearity leads farmers to invest more aggressively in capital, as they are less concerned about uncertain returns and more willing to defer consumption. The average investment rate rises significantly, while the average capital stock increases from \$1.59 to \$2.22 million. Farms pay for this additional capital in several ways. Dividends are initially negative, as the farmers raise funds internally. Farms also raise more funds by borrowing. However, as Figure 6 shows, farms also deleverage more quickly in later years. This is because the borrowing rate $r = 0.04$ exceeds the discount rate of 0.009, and the opportunity cost of retained earnings – unsmoothed dividends – is zero.[22]

Row (4) shows the effects of raising ν from 4.14 to 6. Relative to the baseline case, the dividend growth rate is lower, as farms withdraw more funds up front. Debt is also lower, perhaps for precautionary reasons. The result is that the capital stock is lower in every period: the average stock falls to \$1.51 million.

Row (5) shows the effects of increasing the utility shifter c_0 to 200.[23] In addition to serving as a preference parameter, c_0 limits the ability of farms to raise funds from equity injections. A value of c_0 of 200 thus allows farmers to inject up to \$200,000 of personal funds into their farms each year. Capital and assets increase. Average dividends grow more quickly, as equity injections lead initial dividends to be low. Finally, increasing c_0 reduces risk aversion, encouraging farms to take on more debt. Row (6) shows the effects of changing c_0 in the opposite direction, to 0. Most variables move in the directions opposite to those in row (5).

[21] We restrict β to lie in the $(0, 1)$ interval.

[22] Row (3) also shows that the number of operating farms fall. This is an artifact of how we calculate the nonpecuniary benefit. When preferences are linear in consumption, the utility value of a \$5,360 drop in consumption is much smaller than in the baseline specification. With small nonpecuniary benefits, unproductive farms have less incentive to operate.

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

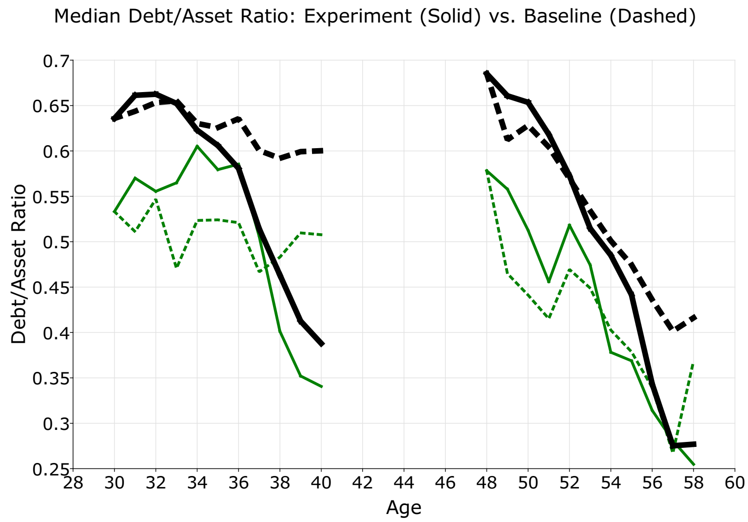

Figure 6: The Effects of Imposing Linear Utility on the Debt/Asset Ratio

Note: Solid lines refer to model simulations with $\nu = 0$, dashed lines to baseline simulations. Thicker lines refer to farms with large herds, thinner lines refer to farms with small herds.

Because the discount factor β, the risk coefficient ν, and the utility shifter c_0 affect similar summary statistics – dividend growth, capital, and debt – identification occurs jointly. It is informative to consider the simple unconstrained Euler Equation

$$(c_0 + d_t)^{-\nu} = \beta(1 + \iota_{t+1})(c_0 + d_{t+1})^{-\nu},$$

where ι denotes the returns the farm enjoys on its capital expenditures. An important feature of the data is that the average dividend growth rate is modest for both small and large farms. Moreover, because large farms are expanding while small farms are not, the model requires that the marginal product of capital be higher in large operations, to justify the different capital stock trajectories. This means that large farms have higher values of ι_{t+1}. In order for both types of farms to have flat dividend trajectories, ν must be large and c_0 must be small.[24] Given this requirement, the parameters further adjust to help the model match capital and debt. Another useful distinction is that raising c_0, which increases the scope for equity injections, is more effective in allowing farmers to acquire capital up front than is lowering ν. While the capital stock rises relative to the

[24] One shortcoming of the model is that it does not match the high volatility of dividend growth observed in the data. This is because values of ν that lead to low average dividend growth rates also dampen dividend growth variation. An interesting extension that we do not pursue here would be to introduce preferences (e.g., Epstein-Zin, 1989) that uncouple risk aversion and intertemporal substitutability.

baseline in both rows (3) and (5), the investment rate rises significantly in row (3) but rises only slightly in row (5).

The retirement parameters c_1 and θ are identified by life-cycle variation not shown in Table 5. As θ goes to zero and retirement utility vanishes, older farmers will have less incentive to invest in capital, and their capital stock will fall relative to that of younger farmers. Setting θ to zero also increases indebtedness, as farmers raise their average dividend (not shown) by over 40 percent.

6 Model Mechanisms

6.1 Nonpecuniary benefits

Our estimates imply that the nonpecuniary benefit from farming is equivalent to the flow utility lost by decreasing consumption from \$15,000 to \$9,640. 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. Row (7) of Table 5 shows the effects of setting χ to zero. In the absence of psychic benefits more farms liquidate, so that the average number of operating farms drops by 7 percent. Not surprisingly, it is the smaller, low-productivity farms that exit: the survivors in row (7) have more assets, debt and capital. Their optimal capital stock (recall Figure 3) rises from \$2.83 to \$3.07 million. Hamilton (2000) and Moskowitz and Vissing-Jørgensen (2002) find that many entrepreneurs earn below-market returns, suggesting that nonpecuniary benefits are large. (Also see Quadrini, 2009; and Hall and Woodward, 2010.) Similarly, 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 value of χ may reflect other considerations, such as efficiencies in home production or tax advantages.[25] It may also be the case that farm income is under-reported (Herrendorf and Schoellman, 2015). Furthermore, although \$15,000 is roughly equivalent to the Federal Poverty Line for a two-person household, it may overstate the outside earnings available to farmers. Poschke (2012, 2013) documents that the probability of entrepreneurship is "U-shaped" in an individual's prior nonentrepreneurial wage, and argues that many low-productivity entrepreneurs start and maintain their businesses because their outside options are even worse. Herrendorf and Schoellman (2016) conclude

[25]For example, farmers may be able to report (or misreport) personal consumption, such as the use of a farm vehicle, as operating expenditures. We are indebted to Todd Schoellman for this point.

that the low wages of agricultural workers reflect low levels of human capital.

On the other hand, there is considerable direct evidence suggesting that farming, and entrepreneurship in general, provides large nonpecuniary rewards. Recent surveys of national well-being, published by the Office for National Statistics in the U.K., show that the levels of life satisfaction of farmers and farm workers rank among the highest for all occupations and are substantially higher than the levels of life satisfaction reported by individuals in occupations with similar incomes such as construction and telephone sales (O'Donnell et al., 2014). Looking across all sectors, Hurst and Pugsley (2011) find that nonpecuniary considerations "play a first-order role in the business formation decision" and that many small businesses have "no desire to grow big." Both attitudes appear consistent with the behavior of the small farms in our sample.

6.2 Financial Constraints

Our model contains three important financial frictions: liquidation costs, collateral constraints and liquidity constraints. We consider the effects of each element on assets, debt, capital, investment, and exit.

6.2.1 Liquidation Costs

Row (8) 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.[26] 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 (9) shows that nonpecuniary benefits and liquidation costs reinforce each other; setting $\lambda = \chi = 0$ leads over 20 percent of the farms to exit.

Comparing row (8) to row (1) shows that the farms that remain after removing the liquidation cost have more capital and assets, but are not more productive. This suggests that the collateral and liquidity constraints devalue some productive farms. However, comparing row (9) to row (7) shows that in the absence of nonpecuniary benefits, the farms that remain after removing the liquidation costs are significantly more productive. Liquidation costs can thus generate financial inefficiency by discouraging the reallocation of capital and labor to more productive uses.

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

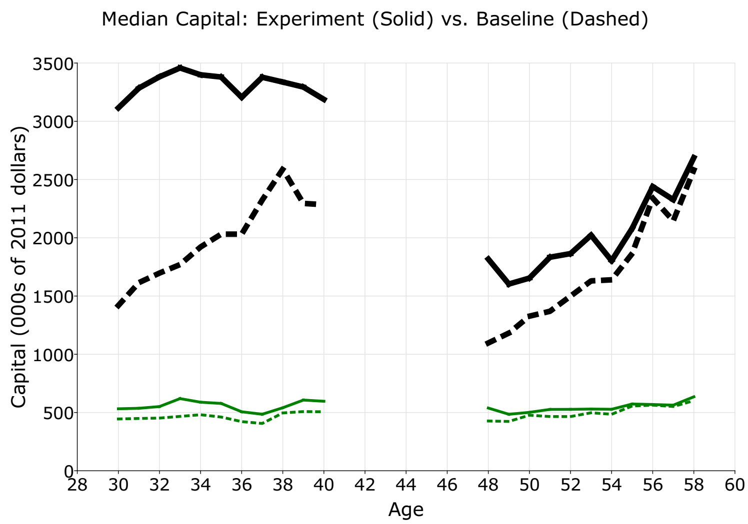

Figure 7: The Effects of Relaxing the Collateral Constraint on the Capital Stock

Note: Solid lines refer to model simulations with $\psi = 0.5$, dashed lines to baseline simulations. Thicker lines refer to farms with large herds, thinner lines refer to farms with small herds.

6.2.2 Collateral Constraints

Row (10) shows the effects of setting the collateral constraint ψ to 0.5, allowing each dollar of capital to back up to \$2 of debt. Farms respond to the relaxed constraint by borrowing more and acquiring more capital, with mean capital rising from \$1.59 million to \$2.01 million. Much of this additional capital is purchased up front; the investment rate falls from 6.6 percent to 2.8 percent. Figure 7, which compares capital stock trajectories, shows that the increase in initial capital is concentrated in the large/high-productivity farms, suggesting again that borrowing constraints are causing capital to be misallocated across farms.

Row (11) of Table 5 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 27 percent of its baseline value. Farms now accumulate their capital through retained earnings. With capital more difficult to fund, farms use more intermediate goods, so that the fall in output, 19 percent, is smaller than the fall in capital. All of these changes make farming less profitable, and fewer farms remain in operation.

6.2.3 Liquidity Constraints

Rows (12) and (13) of Table 5 illustrate the effects of the liquidity constraint, given by equation (9). Row (12) 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 15 percent, capital falls by over 30 percent, and the cash/asset ratio jumps from 0.114 to 0.244. 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 over 30 percent.

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 rise from their baseline value by 6.4 percent, while capital rises even more, by 14.2 percent.

6.3 Overview

To sum up: our estimates and comparative statics exercises indicate that financial factors play an important role in farm outcomes both at the intensive and extensive margin. The collateral and liquidity constraints hinder capital investment, reduce output and assets, and sometimes drive farms out of business.[27] Liquidation costs impede the exit of low productivity farms, by reducing the wealth they can carry into their new occupation.

Our analysis also reveals that nonpecuniary benefits are a significant motivating force. They keep farms in operation, despite low and uncertain revenue flows, reinforcing the effects of the liquidation costs. When both mechanisms are in place, only a few highly unproductive farms choose to exit.

6.4 External Validity

The questions of external validity that plague most empirical studies also apply to structural analyses of firm behavior, where nonlinear specifications and cross-industry heterogeneity are the norm (Strebulaev and Whited, 2012). In this section we explain why we believe our findings can be generalized beyond our dataset and beyond the dairy farm industry.

The Statistics of US Businesses (SUSB) generated by the US Census Bureau reveal

[27] 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; or Mendoza, 2010).

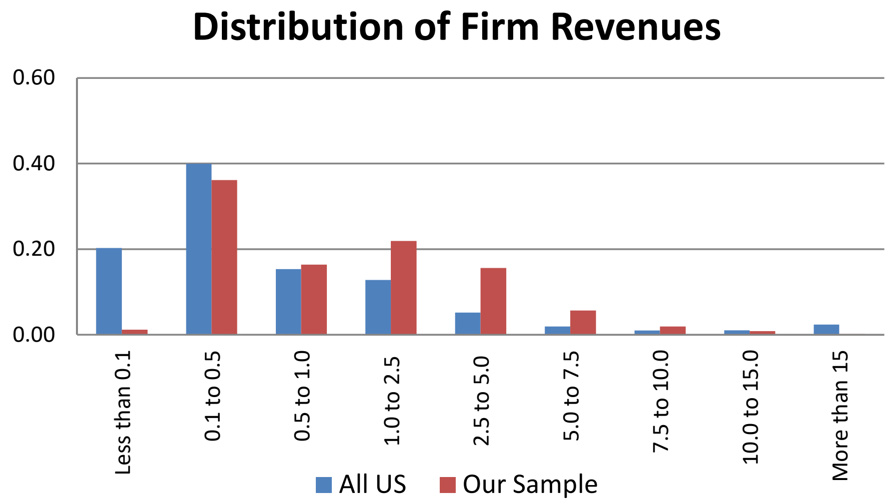

Figure 8: Distribution of Firm Revenues

important similarities between our data and all US businesses.[28] In 2012, 78 percent of all US firms (excluding government and nonprofit enterprises) were single-proprietor operations, partnerships or S Corporations. This is a group for which financial data are not readily available. Since all the farms in our sample are in this category, we can shed some light on an often neglected set of firms.

The revenues of the average firm in the US are not dissimilar to revenue of the average farm in our dataset.[29] Among single proprietorships, partnerships and S Corporations, average firm receipts were $2.76 million in 2012.[30] The farms in our dataset had average receipts of $2.89 million in 2011, the last year for which we have data.

The distribution of revenues in the US is also comparable with our data, as Figure 8 shows. Since the data are not separated by ownership type, it is not surprising that our sample under-represents firms receiving more than $15 million annually. It also under-represents very small enterprises, with less than $100,000 in annual revenue. However, it is quite similar in the middle of the distribution.

Our results also comport, while differing in sensible ways, with results from earlier studies. One of our key findings is that financial constraints, particularly collateral con-

[28]These data come from the publicly available datasets on the Census Bureau's website. http://www.census.gov/data/tables/2012/econ/susb/2012-susb-annual.html

[29]Since the Census Bureau does not publish further details about establishments in the SUSB we are unable to compare firms along other dimensions.

[30]Publicly available data for receipts of all US firms exists only for the Economic Census years, the last of which was 2012.

straints, inhibit investment. Recall that our estimate of the constraint parameter ψ in equation (8) is 1.06, implying that each dollar of debt must be backed by slightly more than a dollar of capital. Earlier studies report more stringent constraints. Looking at the decision to become an entrepreneur in the National Longitudinal Survey of Young Men, Evans and Jovanovic (1989) find ψ to be at least 2.37, implying that each dollar of debt be backed by over $2 of capital. Buera (2009) studies the same issue in the Panel Survey of Income Dynamics and finds a value for ψ of 1.26 in the constrained version of his estimates, and 101 in the unconstrained version. Working with the Survey of Small Business Finances (SSBF), Herranz et al. (2014) calibrate ψ to 6.[31]

Given that the firms in our sample are established businesses, it is not surprising that we find looser constraints than those estimated on firms that are starting up. While SSBF respondents are established firms, many are quite small and likely have less access to debt than our farms. Our conclusion that these constraints are important should be robust.

The other aspect of firm behavior our analysis highlights is the supplemental utility from self-employment. Such benefits are often referred to as "procedural utility," i.e., utility gained from procedures, rather than outcomes (Benz and Frey, 2008). As we discussed above, there is substantial indirect evidence of the nonpecuniary benefits of entrepreneurship from the studies on the returns to the self-employed relative to other groups. There is also a large body of direct evidence from survey literature where entrepreneurs report high levels of job satisfaction relative to wage work. These estimates all suggest that nonpecuniary benefits of entrepreneurship are widespread across industries and countries and not a special feature of agriculture.

Farmers willing to participate in the DFBS may well receive higher nonpecuniary benefits from their occupation than nonparticipants. Evidence of heterogeneity in the procedural utility from self-employment is found by Fuchs-Schuldeln (2009), who shows that job satisfaction from entrepreneurship is the largest for individuals who value independence. Binder and Coad (2013) find that self-employed individuals who moved from wage work experience larger changes in happiness levels than those who moved from unemployment. Our findings nonetheless accord with a large body of evidence.

To sum, our data are drawn from a set of firms that are similar to a large fraction of the firms in the United States, and our findings on financial constraints and nonpecuniary benefits are consistent with many earlier, albeit piecemeal, analyses. We therefore expect our results to be relevant across industries and regions.

[31] Evans and Jovanovic (1989) and Buera (2009) do not estimate ψ itself, but the parameter constraint $k \leq \phi a$. Assuming that capital is the sum of debt and assets, $k = a + b$, and we have $\psi = \phi/(\phi - 1)$. Herranz et. at. (2014) work with the constraint $b \leq \upsilon a$, with $\psi = \upsilon/(1 + \upsilon)$.

7 The Effects of Uninsured Risk

As discussed in Sections 5 and 5.3, our estimates suggest that our entrepreneurs are very risk averse, with a coefficient of relative risk aversion (ν) of about 4.14. This parameter is identified by the low observed dividend growth rates, as higher values of ν make entrepreneurs less willing to substitute dividends across time. Table 5 shows that linear utility would lead farmers to choose negative dividends at the beginning of the estimation period, resulting in counterfactually high dividend growth.

Section 2 showed that farmers face significant uninsured risk, which can be decomposed into an aggregate and an idiosyncratic component. Aggregate risk is in turn closely related to fluctuations in milk prices. This suggests a potentially useful role for government programs that insure farmers against milk price fluctuations, as envisaged by various dairy support programs.[32] Before considering the specific provisions of the latest program, as formulated in the 2014 Farm Bill, we first examine the effects of aggregate and idiosyncratic risk in general.

7.1 Full Insurance

Comparing row (14) of Table 5 to the baseline model in row (1) shows the effects of shutting down aggregate risk, keeping mean productivity constant. Such a change can be viewed as the introduction of complete insurance against aggregate shocks. Farms expand operations by increasing debt, and using it to finance purchases both fixed and variable inputs. The average capital stock increases by about 1.4 percent. This increase is modest, as the farms are still subject to idiosyncratic shocks and operators are risk averse.

Like the aggregate shock, the idiosyncratic shock is also i.i.d and has a similar standard deviation (6 percent compared to 7 percent for the aggregate shock). Row (15) shows that the effects of eliminating all transitory shocks (aggregate and idiosyncratic) are larger, but qualitatively similar, to the results shown in row (14). The average operation increases its capital stock by almost 5 percent and its debt by over 11 percent.

It is worth noting that the elimination of transitory risk, aggregate or idiosyncratic, has little effect on the extensive margin. The fraction of farms operating is virtually unchanged, as is their time-invariant productivity level, as measured by the optimal capital stock.

Rows (14) and (15) suggest that risk discourages investment, as reducing risk leads to

[32] Within the DFBS, the use of derivatives to reduce milk price risk is limited.

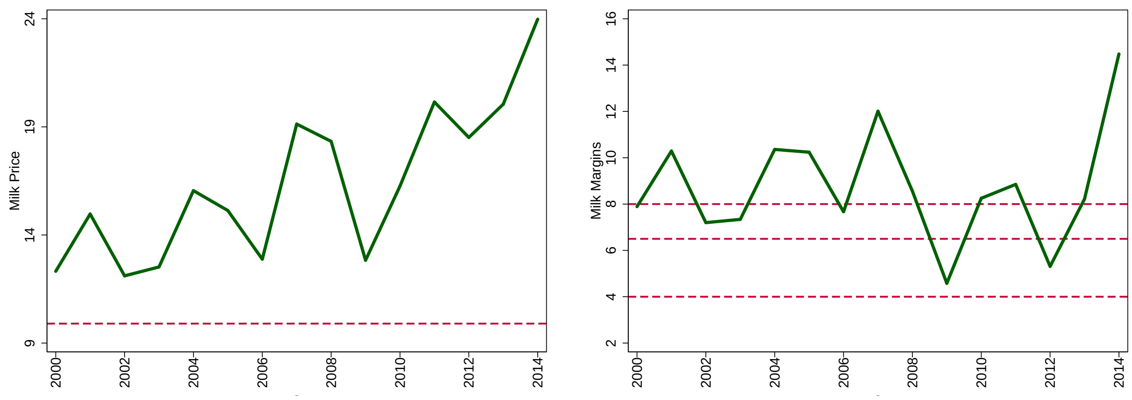

Figure 9: Milk Prices and Margins

higher capital. In addition to risk aversion, financial incentives induce farms to behave this way. 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 also argue that patient firms are less likely to seek risky investment projects; our estimated discount rate is 0.9 percent. Our data do not reject Vereshchagina and Hopenhayn's proposed mechanisms, but they suggest an environment where the mechanisms are unlikely to arise. Our results are more in line with Caggese (2012), who finds that risk discourages entrepreneurial innovation. On the other hand, risk discourages investment and production only modestly. As the previous section shows, collateral and liquidity constraints have much larger effects.

7.2 The Farm Bill of 2014

The dairy provisions of the Farm Bill of 2014 replaced a largely defunct dairy price support program. Although the former program guaranteed a statutory price for milk, either through direct purchase or through the purchase of other dairy products,[33] the support price of $9.90 per hundred pounds (cwt.) of milk was widely considered inadequate. As the left panel of Figure 9 shows, by 2000 the national average milk price, to which the support price was indexed, was always substantially higher than $9.90 per cwt., while still volatile.

This situation, coupled with an increase in feed costs, provided the impetus for a policy

[33]Our description of the dairy provisions of the 2014 Farm Bill and its predecessors borrows heavily from the discussion in Schnepf (2014).

	Capital	Debt	Debt/ Assets	Cash/ Assets	Investment/ Capital (%)	Optimal Capital
Baseline Model*	1,596	1,054	0.536	0.113	6.61%	2,833
Margin Support, No Premium	1,623	1,080	0.542	0.113	6.72%	2,832
Margin Support, Full Premium	1,509	978	0.523	0.112	6.41%	2,457

*Shock process revised to accommodate Farm Bill experiments. See Appendix D.

Table 6: Operational Effects of the 2014 Farm Bill

change toward margin support, rather than price support. The milk margin is defined as the difference between the price of milk and the weighted average of the prices of corn, soybean and alfalfa. The program offers a baseline margin support of $4.00 per cwt. for all participants and higher support levels in exchange for a premium. The right panel of Figure 9 shows nominal milk margins, as calculated by Schnepf (2014), between January 2000 and September 2014. Margin supports in the range of $4 to $8 would have kicked in several times in our sample period.

The close correlation between milk prices and the aggregate productivity shock, along with the assumption of constant input prices, imply that within our framework, the aggregate shock acts as a margin shock. We therefore model margin floors by eliminating the left-hand tail of the aggregate shock distribution. As Schnepf (2014) notes, the premium structure is intended to encourage farmers to choose a margin support level of $6.50 per cwt. This translates into truncating the aggregate shock distribution at the 9th percentile. Appendix D provides more details on the margin support program, the calculation of the truncation level, and the computational mechanics of truncating the distribution.

Table 6 shows the effects of a margin support program of $6.50. The first row of the table shows the no-farm bill benchmark.[34] The second row shows the effect of a $6.50 margin support that is provided to farmers for free. The effects of the margin support are modest. The capital stock increases by about 1.7 percent and debt by 2.5 percent. The extensive margin – the number of farms operating, not reported in the table – is essentially unchanged. Recalling row (14) of Table 5 shows that the effects of the margin support, which eliminates the worst downside risk, are similar to those of completely eliminating aggregate risk.

[34]Assessing the Farm Bill requires that we use a discretized shock process with many more grid points than in the baseline specification used to estimate the model. See Appendix D. Using a finer shock grid significantly increases computation time. However, the simulations generated by this case differ little from those of the baseline specification.

	Median	Mean	Min.	Max.	Correlation with μ
Margin Support, No Premium	4.06	4.92	0.18	24.08	0.63
Margin Support, Full Premium	-16.20	-18.75	-42.70	-0.91	-0.58

Table 7: Welfare Effects of the 2014 Farm Bill

Notes: Welfare measured as the increase in equity needed in the baseline model to achieve the welfare level found in each experiment. All numbers expressed as percentages of initial equity.

Row (3) of Table 6 shows the effects of coupling the margin support with the legislated premium (for large volumes) of $0.29 per cwt. Even though this premium equals only about 1.6 percent of the average milk price, it significantly reduces the scale of operations. Under our specification, returns to scale per operator are given by $1-\alpha$, with α estimated to be between 0.107 and 0.135 (see Table 4). This means that in the absence of frictions, the optimal scale of operations is quite sensitive to productivity, so that even a small fee can generate a significant contraction. The final column of Table 6 shows that the margin support premium reduces the optimal capital stock by more than 13 percent. The actual capital stock falls by about 5.5 percent, however, as most farms are below their efficient size.

The small (or negative) effects of the Farm Bill on production may be consistent with large increases in the farmers' welfare, given how risk averse they are. To study welfare effects, we compute the additional equity each farm would need in the baseline model to achieve the lifetime utility that it would get in the model with margin supports. This supplement is then expressed as a fraction of the farm's initial equity.

Table 7 summarizes the welfare effects of the margin support program, first without and then with premia. The first row of Table 7 shows that receiving free margin supports is equivalent to a once and for all 4 percent increase in equity for the median farm, equivalent to about $14,400. There is some variance in these benefits, with the largest being about 24 percent. Margin supports thus increase welfare, with the largest gains accruing to high-productivity farms, as shown by the positive correlation in the last column. However, the negative effects of the premium on production are matched by negative effects on welfare. The net effect of the Farm Bill with a premium is equivalent to a 16 percent fall in equity for the median farm. The average fall is about 19 percent, similar in magnitude to the 13 percent fall in optimal capital, whereas the largest losses are as much as 43 percent of initial equity. High-productivity farms face the largest losses.

In short, we find that the negative effects of the margin support premium outweigh the small positive effects of the support itself. It is possible that our model, which is calibrated to an annual frequency, understates the effects of the margin support program, which operates at a two-month frequency. Schnepf (2014) shows that milk margins change significantly from month to month. Moreover, the cash holdings observed in the DFBS, recorded at the beginnings and ends of calendar years, may understate farms' actual liquidity needs, which tend to be highest in the summer.[35] The combination of seasonal cash shortages and monthly margin fluctuations may enhance the impact of margin support. Finally, the distribution of aggregate shocks is based on data from our sample period of 2001-2011. As Figure 9 shows, milk margins fell below the floor in 2012. If the risk of low margins is greater than that found in our sample, margin supports will be more valuable than our estimates suggest.

8 Sensitivity Analyses

As we discussed above, nonpecuniary benefits (χ) and liquidation costs (λ) both discourage the exit of low-productivity farms, and are thus difficult to identify simultaneously. We also argued that the nonpecuniary benefit is positively related to the outside wage w: a low-productivity farm facing a high outside wage will remain in operation only if the nonpecuniary benefit to farming is also high. In this section we formally explore the sensititivity of our results to alternative values of λ, χ, and w, by changing these parameters and re-estimating the model. We also estimate versions of the model with no nonpecuniary benefits, no collateral constraint or no renegotiation. The parameter estimates for these alternative specifications can be found in rows (2)-(6) of Table 4. Table 8 compares predictions of a few key variables.

8.1 Liquidation Costs

Our benchmark estimate of λ, a loss rate of 0.35, is somewhat higher than those reported in the finance literature (see, e.g., Andrade and Kaplan, 1998; or Hennessy and Whited, 2007). When λ is cut in half, to 0.175, the estimated value of the nonpecuniary benefit χ_C increases by about 15 percent, from \$5,365 to \$6,155, so that the model continues to match the participation observed in the data. The other parameters of the model are essentially unaffected, and row (2) of Table 8 shows that the model-predicted

[35] Conversation with Wayne Knoblauch, April 20, 2015.

moments are unaffected as well.

8.2 Value of the Outside Wage

Doubling the outside wage w to \$30,000 (while leaving liquidation costs at their baseline value) also increases the estimated nonpecuniary benefit, by \$16,500, roughly the increase in w. As in the previous exercise, higher nonpecuniary benefits are needed to match the extensive margin, but the other parameters are unaffected.

8.3 Nonpecuniary Benefits

How do our results change if we eliminate nonpecuniary benefits? To answer this question, we re-estimate our model restricting χ to be zero, while keeping λ and w at their baseline values. The new parameter estimates are shown in the fourth column of Table 4. The parameters change in two notable ways: first, the value of the collateral constraint ψ falls from 1.06 to 0.76; and second, the returns to capital (γ) and the returns to scale ($1-\alpha$) both fall below their baseline values.

In the absence of nonpecuniary benefits, farmers need more pecuniary rewards to continue operating. A looser borrowing constraint allows them to attain their optimal capital stock more quickly – by borrowing more upfront – and to better smooth their dividends. Dividends both rise on average and become significantly less volatile: farming becomes safer and more profitable. Because improved access to funds would in isolation lead to counterfactually larger operations, the production parameters adjust to reduce the operations' optimal sizes.

The fourth row of Table 8 shows that these changes lead the investment rate to fall in half. This significantly worsens the fit of the model with respect to its investment targets, and the SMD criterion increases by 50 percent. In other words, without nonpecuniary benefits, our model cannot match investment rates and the extensive margin simultaneously.

These results suggest that nonpecuniary benefits are important to explaining the dynamics we observe in the data. While we would expect the value of these benefits to vary across industries, as a result of heterogeneous liquidation costs or outside options, our estimation shows that it is hard to deny their existence.

		Fraction Operating*	Capital	Debt/ Assets†	Invest-ment/ Capital (%)†	Dividend Growth Rate (%)‡	Optimal Capital
(1)	Baseline Model	1.000	1,593	0.536	6.59%	4.31%	2,833
(2)	$\lambda = 0.175$	1.001	1,588	0.534	6.59%	4.29%	2,811
(3)	$w = \$30,000$	1.001	1,584	0.534	6.61%	4.29%	2,820
(4)	$\chi = 0$	1.001	1,616	0.557	3.27%	2.09%	1,770
(5)	$\psi = 0$	1.010	1,630	0.560	3.23%	2.05%	1,790
(6)	No Renegotiation	0.975	1,619	0.543	6.45%	3.69%	2,730

*Relative to baseline case. †Ratios of averages. ‡Mean growth rates for annual averages.

Table 8: Robustness Exercises

8.4 Collateral Constraint

Setting the collateral constraint parameter ψ to 0.76 effectively eliminates the collateral constraint. This can be seen by comparing the fourth row of Table 8 to the fifth row, where ψ is set to zero. The two specifications generate very similar outcomes. In neither case does the model fit its investment targets well. Table 4 shows that the parameter estimates for the two specifications are also very similar.

8.5 Debt Renegotiation

In our baseline specification indebted farms can renegotiate their loans. This is consistent with the DFBS, where farms with negative net worth sometimes continue to operate. The bottom row of Table 8 shows results from a specification with no renegotiation, where farms with negative net worth must liquidate. The effects of this change are modest. The fraction of farms operating is only 2.5 percent smaller, and most other variables are similarly close to their baseline values. The most notable difference is that the optimal capital stock is \$0.1 million *smaller*, implying that the exiting farms are not from the bottom of the productivity distribution. Renegotiation thus plays a role in keeping productive farms alive. In most other respects, however, its effects are minor. The last column of Table 4 shows that the estimated value of the nonpecuniary benefit is higher in a model with no renegotiation. When farms with negative net worth are forced to exit, the model overstates exit rates. A higher nonpecuniary benefit encourages more farms to stay in business.

9 Conclusions

Although a wide range of policy measures are aimed at promoting entrepreneurial activity, there is still considerable debate about the forces that drive it. In this paper we use a dynamic model to assess how financial constraints, nonpecuniary benefits and risk jointly affect entrepreneurs. We build a life-cycle model that incorporates all three considerations – to our knowledge the first of its kind – and estimate it with a rich panel of owner-operated dairy farms in New York State. Using a simulated minimum distance estimator, we fit the model to real variables such as input use, capital and revenues, and to financial variables such as debt, dividends and cash holdings. Matching both production and financial variables allows us to disentangle the effects of real and financial factors.

Our principal finding is that the effects of financial constraints and nonpecuniary benefits are of first-order importance, but those of risk are not. Collateral constraints on investment and liquidity constraints on the purchase of intermediate goods restrict, sometimes significantly, capital holdings, input purchases and output. Nonpecuniary benefits and liquidation costs discourage low-productivity operators from exiting the industry. In contrast, eliminating aggregate risk has very modest effects on farm decisions. The insurance provided by the milk margin support program of the 2014 Farm Bill also provides limited benefits.

We find that much of the variation in farm productivity can be attributed to permanent idiosyncratic differences. While high-productivity farms grow steadily over the sample period, low-productivity farms appear to have been close to their optimal size throughout. This suggests that rather than maximizing the number of entrepreneurs, many of whom operate for nonpecuniary reasons, entrepreneurial policy may work better by helping the most promising entrepreneurs expand.

One reason our results are valuable is that detailed joint real and financial data for small firms are rarely available. But even though our data are especially well-suited to our approach, the firms that generate them are similar to many other US firms. We thus expect that our methodology and findings can be extended to a variety of settings.

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For Online Publication: Appendices

A Data Construction

Sample Selection: The table below describes the filters used to construct the sample. Since we are interested in the dynamic behavior of the enerprises, we also eliminate farms with only observation. Finally, we drop farms with missing information on the age of the youngest operator.

	# of Farms	# of Observations
Original Sample	541	2461
Drop farms with one observation	385	2305
Drop farms with missing age	363	2222

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 $\{g^*_{mt}(\Omega)\}$ and $\{g_{mt}\}$. Because the model gives farmers the option to become workers, we also need to match some measure of occupational choice. Let $\bar{u} = \bar{u}(\Omega)$ denote the fraction of farms that exit in our simulations but not in the data. We add to the SMD criterion the penalty $\Psi(\Omega) = (36\bar{u}(\Omega))^2$, a function that in estimation delivered reasonably low levels of counterfactual exit.

Suppose we have a sample of I conditionally (on the aggregate shocks) independent farms. Our SMD criterion function is

$$Q_I(\Omega) = \sum_{m=1}^{M} \sum_{t=1}^{T} \left(\frac{g^*_{mt}(\Omega)}{g_{mt}} - 1 \right)^2 + \Psi(\Omega). \tag{14}$$

It bears noting that the counterfactual exit penalty $\Psi(\Omega)$ is subject to sampling variation. The estimated productivity processes we feed into the model, as well as the initial values of the state vectors in the simulations, reflect sampling variation as well.

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 7.1) show that

$$\sqrt{I}\,(\Omega_I - \Omega_0) \rightsquigarrow \mathcal{N}(0, H^{-1}\Sigma H^{-1}), \tag{15}$$

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, setting the step size for each parameter equal to 0.1 percent of that parameter's absolute value. Unfortunately, there is no analytical expression for for the limiting variance Σ. We instead find Σ via a bootstrap procedure. In particular, we create $S = 49$ 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 variation in the aggregate shocks, and our standard errors are thus biased downward. 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 $D_s(\Omega_I)$, using the same step sizes as in the calculation of H_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.[36] 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 a one-step bootstrap, where Ω is re-estimated for each artificial sample s.[37] 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

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

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

[36] 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 multiplicative 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.

[37] See Andrews (2002). We are grateful to Lars Hansen for this suggestion.

	Medians		Means		Std. Deviation†		Autocorrelations†	
	Data	Model	Data	Model	Data	Model	Data	Model
Capital	1,114	970	1,823	1,593	1,919	1,576	0.98	0.99
Y/K	0.47	0.48	0.48	0.52	0.15	0.36	0.88	0.86
N/K	0.35	0.36	0.36	0.37	0.13	0.21	0.88	0.86
I/K	0.06	0.04	0.09	0.10	0.20	0.19	0.10	0.30
Debt/Assets	0.54	0.55	0.55	0.48	0.20	0.23	0.90	0.85
Cash/Assets	0.12	0.11	0.13	0.11	0.05	0.04	0.86	0.53
Dividend growth	0.93	1.01	0.69	1.03	4.28	0.09	0.03	0.11

*Standard deviations and autocorrelations use deviations from annual means.

Table 9: Data and Baseline Model Moments

to replicate S times, we replace it with its linear approximation:

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

C Goodness of Fit

Tables 9 and 10 compare data moments from the DFBS with moments for data generated by the baseline model. The criterion function targets yearly medians directly, but the model means and standard deviations are very similar to those in the data. A notable exception is the variablility of the growth rate of dividends, which is much larger in the data than in the model. This is partly due to the presence of outliers: dropping the top and bottom 1 percent of the sample gives us a standard deviation of 1.97, while keeping the mean virtually unchanged. However, as discussed in the main text (see footnote 24), our CRRA utility function cannot generate the low degree of interremporal substitutability implied by the low observed dividend growth rate and also generate the low degree of risk aversion implied by the high observed dividend volatility. Using Epstein-Zin type preferences would be an interesting extension.

The model also does a reasonable job in matching the autocorrelations found in the data. The cross correlations between the real and financial variables are mostly captured by the model as well.

	Capital	Y/K	N/K	I/K	Debt/ Assets	Cash/ Assets	Dividend Growth
Data							
Capital	1.00	0.33	0.36	0.04	0.13	0.19	0.01
Y/K		1.00	0.95	0.23	0.22	0.57	0.07
N/K			1.00	0.20	0.20	0.53	0.04
I/K				1.00	0.12	0.10	0.01
Debt/Assets					1.00	0.00	-0.01
Cash/Assets						1.00	0.06
Dividend Growth							1.00
Model							
Capital	1.00	0.02	0.07	-0.14	0.21	0.12	-0.05
Y/K		1.00	0.97	0.46	0.27	0.23	0.30
N/K			1.00	0.46	0.30	0.32	0.27
I/K				1.00	0.19	0.28	0.50
Debt/Assets					1.00	0.00	0.05
Cash/Asset						1.00	0.33
Dividend Growth							1.00

Table 10: Data and Baseline Model Cross Correlations

Notes: Correlations calculated using deviations from annual means.

D Modelling the 2014 Farm Bill

The 2014 Farm Bill program replaces the previous dairy support program, which guaranteed a minimum price for milk, with a guarantee of the milk margin, the difference between the price of milk and a weighted average of the prices of corn, soybean and alfalfa. As described by Schnepf (2014), the program provides a baseline margin support of \$4.00 per cwt. for all participants. Higher support levels (in \$0.50 increments) can be acquired in exchange for a premium. For the first 4 million lbs of output, the premium ranges from \$0.01 per cwt. for a margin of \$4.50 to \$0.475 for a \$8.00 margin. For additional output the premium ranges from \$0.02 to \$1.36 per cwt.

As discussed in the main text, we model margin floors by eliminating the left-hand tail of the aggregate shock distribution. Schnepf (2014) notes that the premium structure encourages farmers to choose a margin support level of \$6.50 per cwt. In the implementation of the margin support program, the milk margin is computed and compared to the margin floor every two months. At this frequency, during our sample period of 2001 to 2011 nominal milk margins fell beneath \$6.50 about 13.6 percent of the time. Real milk margins, measured in September 2014 dollars, fell beneath the floor about 7.6 percent of the time. At the annual frequency used in our model, both nominal and real milk margins fell below the \$6.50 floor once, in 2009, a rate of $1/11 = 9.09$ percent. We choose this annual figure as our truncation level.

Following standard practice, when solving the model numerically we replace the continuous processes for the productivity shocks with discrete approximations. We use the approach developed by Tauchen (1986) for discretizing Markov chains, simplified here to i.i.d. processes. Under Tauchen's approach one divides the support of the underlying continuous process into a finite set of intervals. The values for the discrete approximation come from the interiors of the intervals (demarcated by the midpoints, except at the upper and lower tails), and the transition probabilities are based on the conditional probabilities of each interval. To impose the cutoff, we construct the discretization for the aggregate shock so the bottom two states/intervals have a combined probability of 9.09 percent. We then set the truncated value for these states to equal the 9.09th percentile of the underlying continous distribution.

When finding the decision rules, we combine the aggregate and idiosyncratic shocks into a single transitory shock. In the baseline specification, which we use when estimating the model, we approximate the sum of the two-shock processes with an eight-state discretization. To model the elimination of certain shocks, we simply change the standard deviation of this combined process. However, to capture the Farm bill, we need to alter the distribution of the aggregate shock in isolation. We thus model the aggregate shock with its own eight-state discretization. To get the joint shock, we approximate the idiosyncratic shock with a four-state distribution, and convolute the aggregate and idiosyncratic shocks into a 32-state distribution. We construct the four-state discretization so that the standard deviation of the convoluted 32-state process is the same as the standard deviation of the eight-state shock used in the baseline model. Switching between the two discrete approximations affects the model's results only modestly (compare the first lines of Tables 5 and 6). Under either approximation, the shocks used in the simulations are a combination of idiosyncratic shocks from a random number generator and the aggregate shocks estimated from data. To simulate the Farm Bill, we simply truncate the aggregate shock for 2009 to the 9.09th percentile.

For large volumes, the premium for a margin support of \$6.50 is \$0.290 per cwt. This equals about 1.58 percent of the average real milk price over the 2001-2011 interval (\$18.34). We impose the premium by incrementing the logged productivity process by $\ln(0.9842)$, that is, by reducing the productivity level by 1.58 percent.