Consolidation and Its Efficiency Effects: Evidence from the Dairy Industry

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Abstract: This paper examines the efficiency effects of horizontal consolidation in the dairy industry. Efficiency is measured in terms of both the returns to scale and economies of scale. In dairy farming, doubling farm size leads to 12-14% productivity gain and 4-5% cost decline. This suggests that efficiency gains from increasing the size of the capital investment are higher than the gains from input cost savings via capital-labor substitution. Finally, consolidation leads to a nonlinear efficiency gain where the gains for farms with 1000 or more cows approximate to zero.

JEL classification codes: D24, L11, L22, Q13

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1 Introduction

Williamson (1968) firmly established consolidation as a trade-off between potential efficiency gains from scale economies and potential consumer welfare loss from increasing market power. Despite a growing literature since then, there are still under investigated questions. Retrospective empirical analysis of horizontal consolidation is one of them (Whinston 2007).[1] Without detailed cost and production data, it is difficult to empirically separate the effects of consolidation on market power and on efficiency. Hence the limited empirical evidence on the effects of horizontal consolidations (Whinston 2007).

With this paper, I contribute to this under-investigated area by retrospectively examining efficiency effects of horizontal consolidation in the dairy industry. The dairy industry is an ideal empirical laboratory for three reasons.

First, the dairy industry has a partial antitrust exemption. Dairy farms are permitted to form dairy cooperatives and collectively bargain for higher prices. As a result, even a small dairy farm can achieve market power via cooperative membership, without necessarily increasing its market share.[2] To put it differently, consolidation does not necessarily imply market power for dairy farms.[3] Therefore, in this empirical setting I can focus on the efficiency effects of consolidation, without the market power effects convoluting the results.

Second, the nature of the available data allow me to avoid certain econometric problems. Most of the existing productivity studies do not have quantity data on an output. These studies proxy the output with revenue data—adjusted by various price indices. Studies with revenue-based productivity estimations have well-established econometric problems (Foster

[1] Some papers in this area are Prager (1992); Kim and Singal (1993); Baker (1999); Ravenscraft and Long (2000); Focarelli and Panetta (2003); Pesendorfer (2003); Peters (2006).

[2] The details of the dairy industry are in section 2.

[3] When dairy farms are members of a cooperative, the cooperative bargains for prices on their behalf. This is independent of a dairy farm's size. Therefore, consolidation among dairy farms that belong to cooperatives would not change their bargaining power.

et al. 2008). This paper sidesteps those econometric problems for two reasons: (1) this is an extensively regulated industry with reported and reliable output data; and (2) the output, milk, is a homogenous good that is easy to measure and consistently compare across different producers.

Third, consolidation has been a major trend in the dairy industry, especially, since the 1990s. While the number of farms has declined, the average farm size has increased. These developments allow a retrospective look at the effects of the consolidation on efficiency.

To investigate the relationship between efficiency and consolidation, I first decide on an efficiency measure. Two of the well established measurements are returns to scale (RTS) and economies of scale (EOS). RTS is a measure of *productivity*, EOS is a measure of *cost efficiency*, and theoretically these concepts are mirror images. However, this equivalency holds only under special circumstances. Because the dairy industry does not satisfy all of the equivalency requirements, I use both measurements. This paper examines the relationship between productivity (RTS) and farm size as well as cost efficiency (EOS) and farm size. For both analyses, farm size proxies for consolidation.

The results show that, after controlling for many demographic characteristics, doubling farm size is associated with a 12–14% increase in farm productivity (RTS) and with a 4–5% decline in unit milk cost (EOS). Both RTS and EOS show efficiency gains from consolidation, however, the magnitudes are different. Additionally, this is not a linear relationship. Consolidation does not lead to same efficiency gains for all farms regardless of their initial size. The quantile regression results show that more productive farms tend to gain very little from increasing their size even further. More productive farms are already the larger farms. Therefore, as farm size gets larger, the impact of further consolidation declines, and eventually disappears. In fact, when the focus is just the farms with more than 1,000 cows, the relationship between farm size and efficiency (both RTS and EOS) becomes statistically insignificant.

These results alone cannot establish a causal direction, as there may be confounding effects. It may be that more efficient farms get larger (reverse causation) or that a third factor, such as managerial ability, causes both outcomes simultaneously. To control for these confounding effects and identify the correct causal direction, I use instrumental variable regressions. Here, the goal is to use multiple strong instruments to show that, regardless of the instrument choice, the coefficients hover around the same magnitude and significance. The instrumental variable results confirm the previous OLS results and establish that increasing farm size leads to efficiency increases.

The main dataset I use for the above analyses come from the Agricultural Resource Management Survey. To my knowledge, this is the first time all three latest ARMS dairy commodity surveys (2000, 2005, and 2010) are used to analyze the efficiency effects of consolidation in the dairy industry. This analysis makes two contributions: first, it expands the empirical evidence pool for retrospective horizontal consolidation analysis; and second, it establishes an empirical relationship between returns to scale and economies of scale. Though earlier work established the theoretical equivalency of these two concepts, there is no empirical study showing their relationship.

The rest is organized as follows: section 2 looks at the U.S. Dairy Industry background, section 3 describes the empirical motivations behind this paper, section 4 establishes the equivalency of RTS and EOS in the dairy industry, section 5 describes the data and presents empirical results, and section 6 concludes.

2 Dairy Industry Background

United States is the second largest milk producer in the world (UN, Food and Agriculture Organization 2012). In 2011, the total cash receipts from all U.S. dairy products were over 39.5 billion dollars, corresponding to approximately 9.5% of all the U.S. agricultural sector (USDA, Economic Research Service 2013). There are four main supply chain participants in the dairy industry: producers (dairy farms), dairy cooperatives, manufacturing plants, and retailers. Dairy farms and dairy cooperatives (in terms of cooperatives' contribution to farms' market power) are the focus of this paper.

2.1 Dairy farms

Milk production starts in dairy farms. This is where dairy cows are housed, fed, and milked.[4] In its infancy, dairy farming was very localized. Because of its perishability, raw milk did not travel long distances. Most of the farms were small and doing subsistence farming. Over time, dairy production transformed from being a local subsistence farming to a regional, and for some products, a national industry.

Major technological innovations such as milking parlors, mechanized milking machines, and refrigerated trucks transformed dairy production from subsistence farming to a commercial activity. Milking parlors are raised platforms over which the cows are milked with milking machines.[5] Milking machines are vacuuming tubes, attached to a cow's udders during milking. Both of these technological innovations lead to farmers' improved ability to milk more number of cows, at a faster speeds. Today, with parlors and milking machines, a farmer's milking rates increased from six cows an hour to over hundred cows an hour (Woodside Farm

[4]In the U.S., dairy farming is still considered a family business. Over 90% of dairy farms are still family owned—though may not be family operated.

[5]There are five major parlor types: side opening parlor, fishbone parlor, parallel parlor, swing parlor, and carousel parlor.

Creamery 2010).

Refrigerated trucks, were most effective in transforming local farming into regional industries. One of the biggest problems in the dairy industry has been the perishability of the product. Even with pasteurization, milk products could not travel long distances. Refrigerated trucks changed this reality, to a certain extend. Pasteurized and packaged milk is now able to travel hundreds of miles a day between states, creating a more regional market for milk products.

Besides these technological advancements, dairy cooperatives have been the second major force in transforming dairy farming.

2.2 Dairy cooperatives

Toward the end of the 19th century, farmers in all agricultural fields started forming collective bargaining organizations, called cooperatives. The goal of these organizations was to negotiate better terms of trade for their members, against the manufacturers. However, in 1890, the Congress passed an antitrust law, the Sherman Act, which declared agricultural cooperatives illegal cartels. Dairy farms were the ones affected most from this law. By the enactment of the Sherman Act, nearly seven out of every ten agricultural cooperatives were dairy cooperatives (Varney 2010). The Congress passed the Capper-Volstead Act in 1922, to solve this problem and provide agricultural producers an exemption. This act gave farmers a partial antitrust exemption to collectively set prices and market their products under an umbrella organization called a dairy cooperative.

A dairy cooperative is a business that is owned and operated by the dairy farmers, who benefit from the cooperative's services as members (Dept. of Agriculture 2005). They have two fundamental marketing goals: to get favorable terms of trade and prices for their members, and to guarantee an outlet for members' milk, no matter what the demand-supply conditions are (Cotterill 1987). Their operation is egalitarian; each farm has one vote. This means, the smallest farm has equal voting power as the largest farm. These two properties of a cooperative—bargaining on behalf of its members and operating with a one-farm-one-vote rule—mean, cooperative membership allows a farm to achieve high levels of market power, independent of its size.

3 Motivation

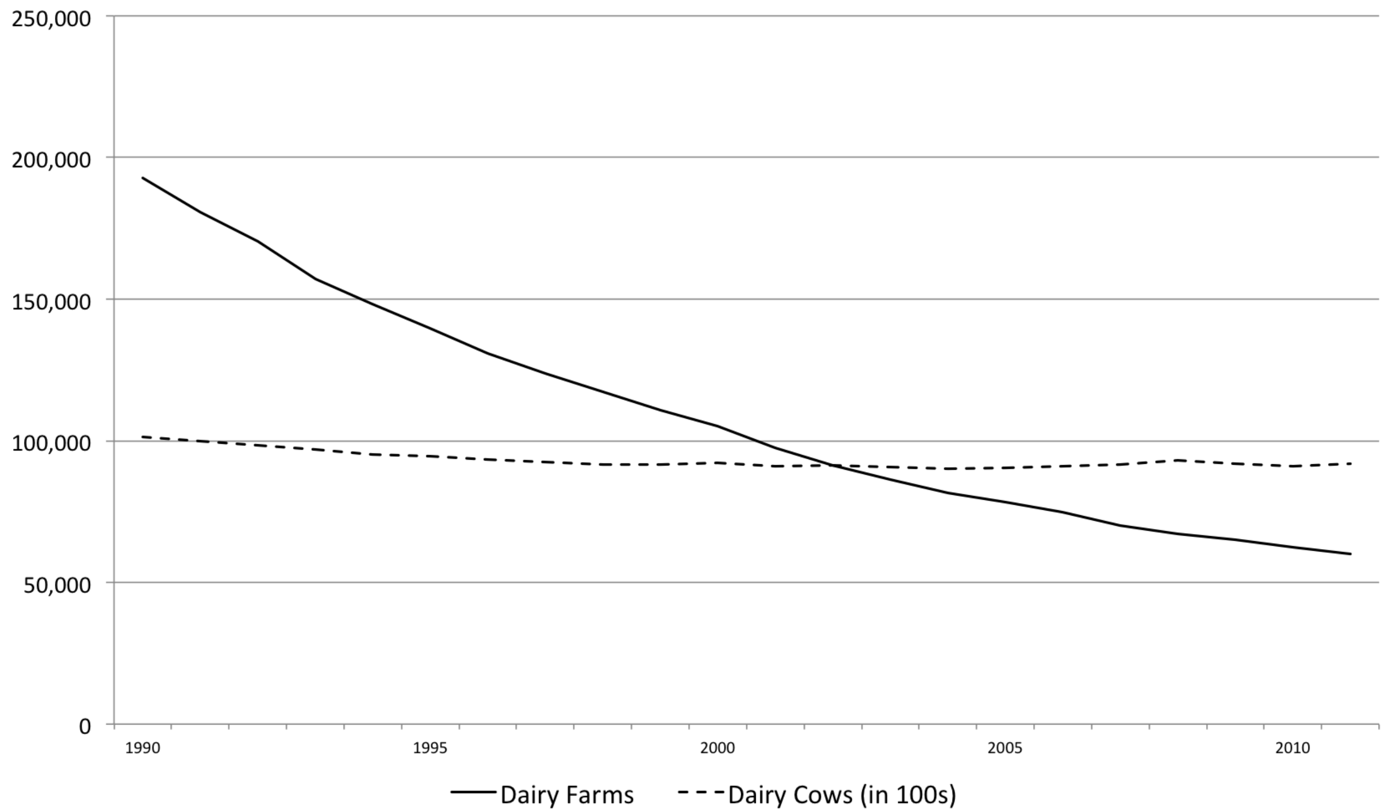
Since 1990s, we have observed three empirical patterns related to the dairy farms and cooperatives: (1) there are big consolidations in dairy farming; (2) the majority of dairy farms belong to dairy cooperatives and these cooperatives are what determine farms' market power, not farms' size; and (3) there is a positive relationship between a farm's size and its efficiency. The next three subsections will present these empirical patterns.

3.1 Consolidation in dairy farming

The dairy industry has been experiencing extensive consolidation waves (Blayney 2002). The main trend has been fewer number of larger size farms. As Figure 1 shows, in the last 20 years the number of dairy farms decreased from over 192,000 to 60,000. A 69% decline. However, the size of dairy cow inventory in the country did not change significantly. The total inventory of dairy cattle has been hovering around 9,2–10 million. As a result, the average farm size almost tripled in 20 years. This is an indication of buyouts and growth, as well as exits taking place among dairy farms, leading to consolidation.

The distribution of U.S. milk production also highlights a shift in production, from small farms to large farms. Currently, over 30% of all U.S. milk comes from farms that have more

Figure 1: Changes in the Number of Dairy Farms and Dairy Cattle Inventory in the U.S.



Source: Quick Stat and archived documents (USDA, National Agricultural Statistics Service 2013) than 2,000 dairy cows (excluding calves, heifers, and bulls). Table 1 shows the shift in milk production sources. Since 2003, total milk production from farms with more than 1,000 cows increased from approximately 32% to 48% of the U.S. total output. The number of farms is declining, while an increasing share of milk production is coming from large farms. This evidence supports the idea that there is significant consolidation in the dairy industry, where merging and/or exiting small farms leave us with larger size farms.

Table 1: Percent of U.S. Milk Production By Farm Size Group

Herd Size	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
less than 29	1.5	1.4	1.3	1.2	1.3	1.2	1.2	1.1
30–49	5.7	5.4	5.1	4.9	4.0	3.9	3.8	3.5
50–99	16.5	15.5	15.2	14.3	12.0	11.5	11.4	10.4
100–199	14.8	14.3	13.5	13.0	12.0	11.8	11.6	11.3
200–499	16.2	16.0	15.3	15.0	13.7	13.1	12.5	12.7
500–999	13.8	14.1	14.3	14.3	12.3	12.5	12.6	13.0
1,000–1,999	13.4	13.3	13.4	13.9	16.1	15.5	15.7	15.5
2,000+	18.1	20.0	21.9	23.4	28.6	30.5	31.2	32.5

Source: USDA NASS; *Farms, Land in Farms, and Livestock Operations*, 2004–11.

3.2 Consolidation and farms' market power

The majority of dairy farms belong to a dairy cooperative. And this rate has been increasing since the earliest data available from the 1987. Table 2 shows the percent of milk handled by cooperatives in the U.S. Now, suppose there are two equal size farms that belong to the same cooperative. Then further suppose that either one of the farms bought out the other one, or one of the farms exited, and the other one captured the exiting farm's market share. Neither of these scenarios would change the market power of the consolidated farm that stayed in the market. Because these farms' market power is equal to the market power of their cooperative. Therefore, dairy farm consolidation does not necessarily lead to a change in farm's market power.

Table 2: Cooperative share of total milk handled in the U.S.

Year	**Share of Total Milk Handled**
1987	76%
1992	82%
1997	83%
2002	85%
2007	84%

Source: USDA Rural Development Cooperatives, *Cooperative Share of milk marketed by producers.*

3.3 Consolidation and farm efficiency

In this industry, the consolidation movement among dairy farms indicates potential economic benefits from increasing farm sizes. A quick look at farms' cost structures can give us some insights as to what farms might be gaining by getting larger. Figure 2 shows an Epanechnikov kernel-weighted local polynomial regression of unit milk cost on log output of milk produced in 2005.[6] Unit cost is calculated as total production cost, plus the hauling cost, divided by the total pound of milk produced in a farm in that year. Total cost includes user cost of capital, labor cost (including benefits), materials cost (such as feed, seed, fertilizer costs, etc.), energy cost (fuel and electricity), and hauling cost (milk, grain, and manure hauling). Each of these components are inflated to 2010 prices by using the appropriate price indices.[7] The pooled sample for all three years also shows a very similar pattern but I chose the year

[6] Throughout the paper log denotes the natural logarithm.

[7] Details of the variable constructions and price adjustments are in the subsection A.2.

2005 for expositional clarity.

Figure 2: Unit Milk Cost & log Output Relationship (2005)

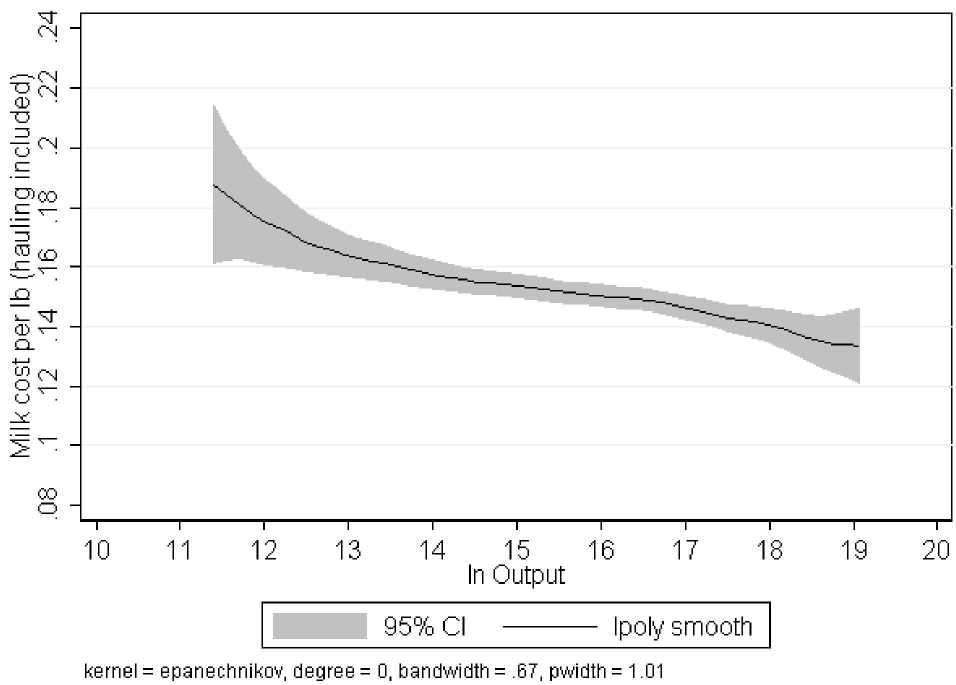


Figure 2 shows an approximately 30% decline in unit cost as total output reaches the highest levels. This relationship is even starker if we look at bigger and smaller farms separately. Figure 3 and Figure 4 show the same cost-output relationship for small and large farms, separately. A small farm is defined as a farm with less than seven hundred cows (including milk cows, heifers, dry cows, and breeding bulls) and a big farm has more than seven hundred cows.[8,9]

Looking at the small and large farms separately highlights a conjecture. Main cost declines comes from smaller farms getting bigger, their cost savings are over 32%. Large farms already

[8]Environmental Protection Agency defines farms with more than seven hundred cows as Concentrated Animal Feeding Operations, therefore I use this definition as the benchmark.

[9]In terms of herd size, small and large farms do not overlap. However, in Figure 3 and Figure 4, the graphs are overlapping for some output levels. This is because, in the small-farm sample, there are a few outlier farms with output levels that correspond to or surpasses output levels of some farms in the large-farm sample.

Figure 3: Unit Milk Cost & log Output in Smaller Farms

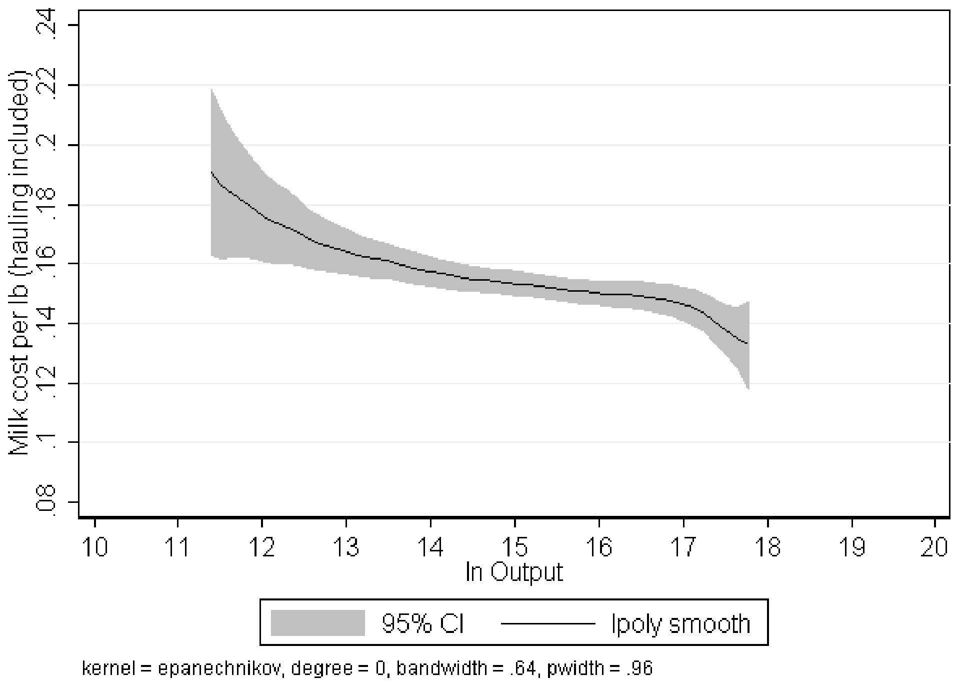
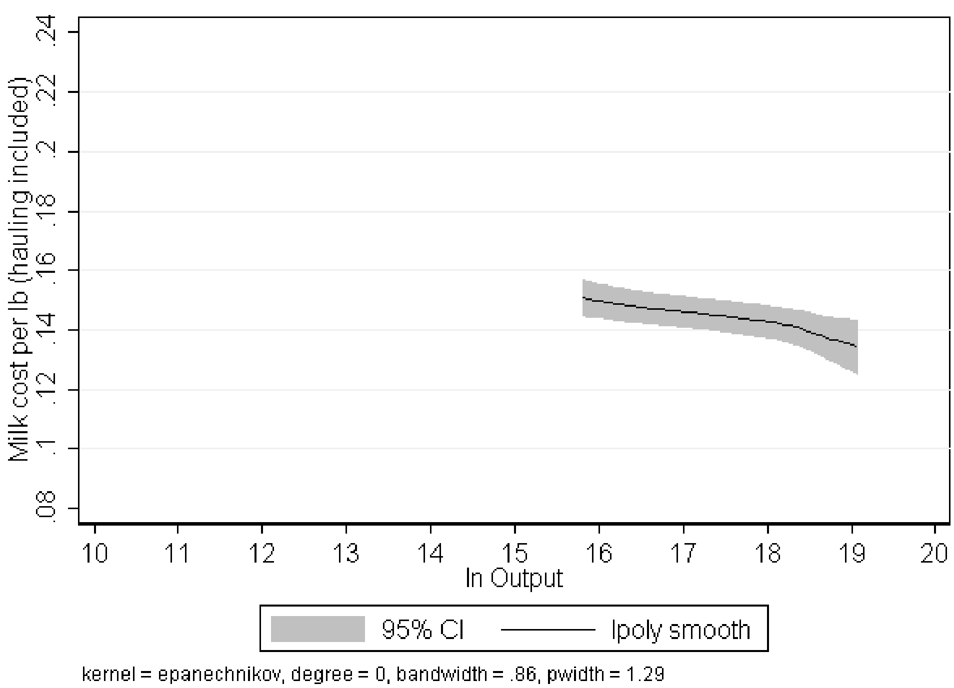


Figure 4: Unit Milk Cost & log Output in Large Farms



start from a lower cost level. So, for them, getting even bigger creates modest cost savings, less than 13% decline in unit cost. These results would be even stronger if I were to look at very small farms (farms with less than two hundred cows).

These figures suggests that, especially for smaller farms, there is a lot of efficiency gains to make from increasing farm size. In other words, consolidation may have important efficiency effects for dairy farms. However, a simple local linear relationship with a single year graph could be deceptive. Hence, the rest of the paper takes a more serious look at this relationship between farm size and productivity (as well as farm size and cost efficiency), and shows that there is a non-spurious causal relationship from size to productivity and cost efficiency.

4 Efficiency in the Dairy Industry: Returns to Scale and Economies of Scale

Before going into the details of the estimations, I first operationalize the concept of efficiency. This paper uses two related concepts of efficiency: returns to scale (RTS) and economies of scale (EOS). RTS can be informally defined as the proportional change in a farm's output, given a proportional change in all of the inputs used. EOS, on the other hand, is the proportional change in a farm's long-term average cost, given a proportional change in the output it produces.

If farms operate in a competitive input market environment, in other words, a farm's input usage rates do not affect its input prices, these concepts are mirror images. In such a competitive market, if a firm has increasing returns to scale (for a region over its production set), then that firm also has economies of scale over the same area of the production curve. Similarly, decreasing returns to scale will indicate diseconomies of scale over the same region of the production set.

Suppose, there is a single output and multiple-input production function $Q = f(x_1, x_2, x_3, ..., x_n)$, where Q is the output and x_i are the inputs where $i = 1, ...n$. Then we have,

$$\xi_{eos} = \frac{1 - \xi_{rts}}{\xi_{rts}} + \frac{\sum_{i=1}^{n}(x_i)^2 \frac{\partial r(x_i)}{\partial x_i}}{\xi_{rts} TC}, \quad (1)$$

where ξ_{eos}, ξ_{rte}, $r(x_i)$, and TC denote economies of scale, returns to scale, input prices, and the total cost respectively. If the input markets are perfectly competitive, the input prices do not depend on the quantity firms use. In other words, $\frac{\partial r(x_i)}{\partial x_i} = 0$; and as a result, the second term in Equation 1 disappears. The following relationship emerges between the economies of scale and returns to scale:

$$\xi_{eos} = \frac{1 - \xi_{rts}}{\xi_{rts}}. \quad (2)$$

Therefore, in these markets the increasing, decreasing, or constant returns to scale ($\xi_{rts} > 1$, $\xi_{rts} < 1$, $\xi_{rts} = 1$) correspond to economies of scale, diseconomies of scale, or neither ($\xi_{eos} > 0$, $\xi_{eos} < 0$, $\xi_{eos} = 0$).[10] However, if some of the input markets are not competitive, this relationship breaks down (Gelles and Mitchell 1996; Bell 1988).

Dairy markets well demonstrate how we do not have perfect competition in all of the input markets. I assume in dairy production there are four inputs: capital, labor, materials, and energy. For the equivalence between RTS and EOS to hold, all of these input markets would need to be perfectly competitive. However, this is not the case in at least two input markets for dairy farms: capital and labor input markets. I focus on these inputs, because I only have input price data for labor and capital. Even if the other input markets are competitive, the capital and labor input prices change based on a farm's usage level of them. Figure 5 and Figure 6 show that, in capital and labor input markets, farms are not always price takers. Their input usage rates affect the input prices they pay.

Farms that use larger amounts of capital tend to pay lower capital prices (measured as the

[10] Details of this derivation are in subsection A.1.

interest rate on loans), as indicated in Figure 5. There are potentially two reasons for this. First, capital markets are integrated, therefore there is no local market where one players' usage can drive the prices up. Second, a farm having high levels of capital means a higher collateral for additional borrowing. Hence, higher capital user farms can get lower interest rate loans.

On the other hand, farms using higher levels of labor input pay higher hourly labor prices, as Figure 6 shows. There may be two reasons for this outcome as well. First, farm labor is a local market with labor supply limitations. Therefore, a farm using high rates of labor can drive the local prices up and lead to an increase in labor costs. Second, most small farms tend to use family labor and/or small amounts of outside labor. Only with increasing size, does a farm acquire additional full-time labor. These large farms tend to have more specialized and more highly educated workers. Such workers will have salaries higher than a hourly part-time worker will have. Therefore, the average hourly labor rates may end up being higher for farms that use more labor input.

In the dairy industry, neither capital nor labor input markets are perfectly competitive. In this setting, the RTS and EOS may or may not be overlapping. As a result, to examine the effects of the recent consolidation movements, I analyze a relationship between farm size and productivity as well as farm size and cost efficiency.

5 Empirical Evidence

In this section, I examine the relationship between consolidation—measured as increasing farm size—and efficiency in dairy farms. By using cooperatives, farms can achieve higher market power without consolidation. Therefore, I focus on the efficiency effects of consolidation; more specifically, I analyze whether consolidation leads to efficiency gains in dairy

Figure 5: Capital Price & log Capital

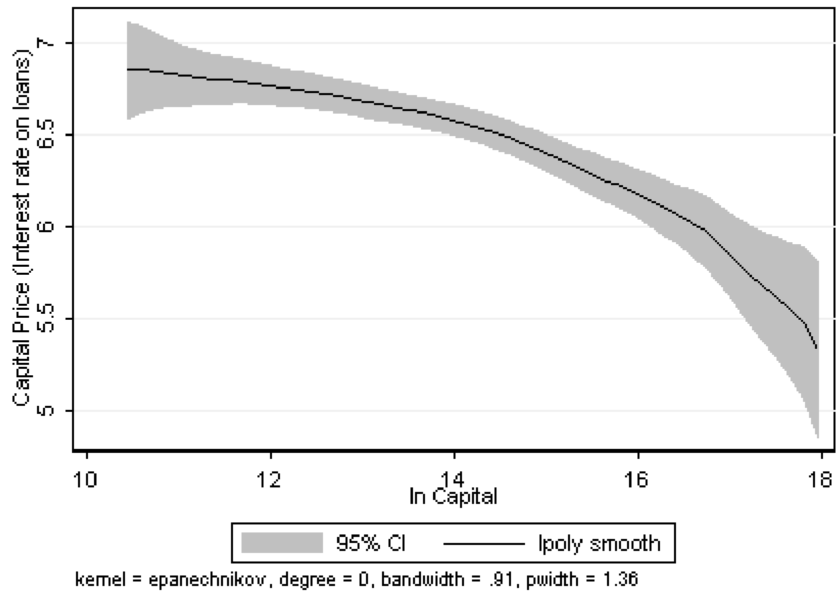
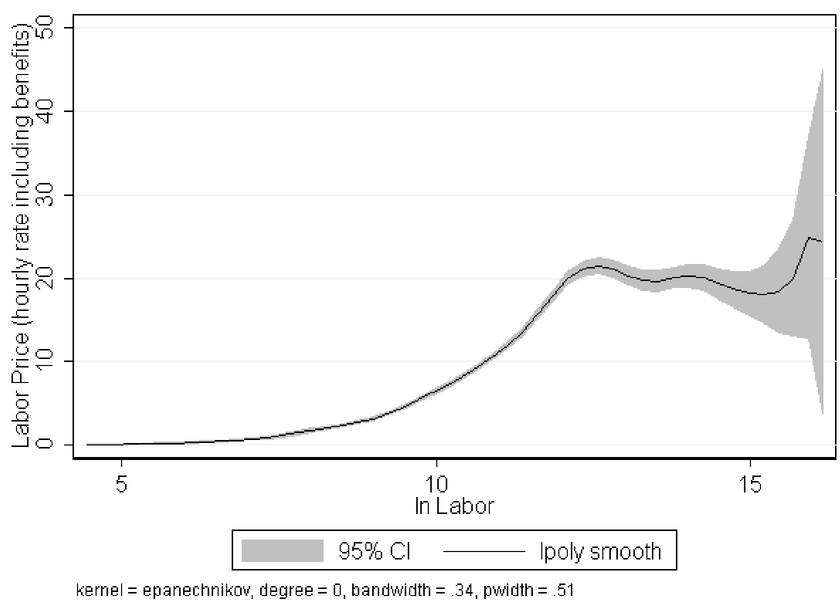


Figure 6: Labor Price & log Labor



farms.

Simultaneous analysis of RTS and EOS sheds some light on the origin of these efficiency gains. Results showing returns to scale would indicate that productivity gains may be from adopting new milking technologies that comes with increasing farm size. Such as large milking parlors and increasing number of automatic milking machines. On the other hand, results showing that increasing farm size leads to a cost decline would indicate effective input substitution at the farms. Farms may be adopting efficiency improving input substitution practices, such a capital-labor substitution, by installing automatic feeders instead of manual feeding.

5.1 Data description

The dataset I employ is the confidential Agricultural Resource Management Survey (ARMS). This is one of the best national scale agricultural data sources available. This paper uses the *Dairy Commodity Survey* of the ARMS data. The dairy commodity survey focuses solely on dairy farms and collects data on the specifics of dairy production processes. The dataset covers the years 2000, 2005, and 2010. It is a representative sample of more than 3,330 dairy farms across 25 states.

Given the depth and scope of the data, other studies also use it. Some recent papers using the ARMS data are Tauer and Mishra (2006); Mosheim and Lovell (2009); MacDonald et al. (2007). Unlike this paper, these studies employ either a cost of production accounting or a cost function estimation using 2005 and earlier ARMS data. This paper uses all three years of available ARMS data (2000, 2005, and 2010), and analyzes both productivity and cost efficiency relationship with consolidation.

I cleaned the data in two ways: First, I only select farms that self identify as dairy farms.

Second, I calculate the farm income breakdowns, and I drop any farm from the sample if less than 80% of its income is from the milk revenues.[11] Table 3 and Table 4 show descriptive statistics of the final sample.

Table 3 shows that the demographics of the dairy farms have not changed significantly from 2000 to 2010. Farms have approximately the same average age, silo capacity, and daily milking operation time. Similarly, the average level of production inputs have also not changed in major ways. However, the farms' average herd and land size (measured as total acreage) have increased since the 2000. An average farm is almost twice as large in 2010 than it was in year 2000. Correspondingly, the unit milk cost declined over the same time period.

This dataset has many advantages. It is one of the two nationally representative agricultural datasets available. The other source is the Census of Agriculture (COA). However, unlike the COA, ARMS dairy commodity survey has a dairy industry focus. The questionnaires are tailored for dairy farming. The data detail cost and production structure of this industry specifically. Furthermore, output variables are measured in terms of quantity instead of sales values. Studies such as Foster et al. (2008) show that employing price indices can introduce bias in productivity estimations. This study, therefore, is less prone to such estimation problems.

ARMS does have some characteristics that create challenges for estimation. It is repeated cross-section data, so I cannot follow a farm over time and cannot directly observe entry and exit. The cross-section nature of the data prevents me from using some of the latest econometric tools developed for the productivity estimation. Additionally, though there is

[11] Here the goal is to ensure that the sample consists of only the farms focused solely on milk production. This allows me to drop from the sample farms with large feed productions or cattle sales. To see if this sample cleaning has any significant effect on the results, I replicate all of the analysis with the full sample as well. The results are qualitatively the same, therefore I conclude that the results are not sensitive to this sample selection.

Table 3: Descriptive Statistics–1

Variables	**2000**	**2005**	**2010**
Milk Price* (per lb)	0.166	0.163	0.166
	(0.030)	(0.019)	(0.027)
N of Obs.	724	1226	1105
Milk Cost* (per lb)	0.165	0.146	0.129
	(0.127)	(0.053)	(0.062)
N of Obs.	729	1228	1105
Total Land Owned (acres)	392.906	649.771	504.023
	(365.235)	(1244.134)	(791.536)
N of Obs.	733	1229	1105
Farm Size (Herd Size)	221.208	460.962	433.087
	(413.059)	(793.988)	(1085.987)
N of Obs.	733	1229	1105
Age of the Farm	24.090	23.668	27.111
	(73.474)	(14.611)	(17.887)
N of Obs.	733	1220	1081
Milking Operation (Hr/Day)	7.142	10.053	8.676
	(5.102)	(6.460)	(6.308)
N of Obs.	732	1228	1102
log Silo Capacity	9.316	9.919	9.686
	(0.925)	(1.072)	(1.121)
N of Obs.	725	1229	1105

*Milk prices and costs are adjusted with various price indices from NASS Quickstats. Standard deviations are in parentheses. Details of variable construction are in subsection A.2.

Table 4: Descriptive Statistics–2

Variables	**2000**	**2005**	**2010**
log Milk Output (lb)	14.285	15.096	14.741
	(1.178)	(1.344)	(1.424)
N of Obs.	733	1228	1105
log Capital	13.041	13.705	13.422
	(0.952)	(1.131)	(1.197)
N of Obs.	733	1214	1101
log Labor	8.625	9.015	8.885
	(0.672)	(0.923)	(0.967)
N of Obs.	726	1229	1105
log Materials	11.779	12.581	12.024
	(1.364)	(1.473)	(1.547)
N of Obs.	729	1229	1105
log Energy	9.542	10.199	9.907
	(1.686)	(1.263)	(1.303)
N of Obs.	727	1206	1093

Standard deviations are in parentheses. Details of variable construction are in subsection A.2.

extensive data on inputs and cost of production, input price data for materials and energy are not available at the farm level. As a result, to test the consolidation and efficiency relationship, I avoid the structural estimation methods because of this dataset's pitfalls. Instead, I pursue empirical strategies that use the advantages of this dataset.

5.2 The impact of farm size on productivity and cost efficiency

Until the end of the 1970s, the productivity literature was an active research field.[12] Yet with the 1980s, productivity research slowed and many of the earlier discussions languished. Productivity discussions only came back into focus with new micro-datasets, and the econometric advances of Olley and Pakes (1996) and many that followed afterward (Levinsohn and Petrin 2003; Syverson 2004; Ackerberg et al. 2006; Foster et al. 2008; Syverson 2011).

The key requirement for these new methodologies is using panel data. Unfortunately, the agriculture industry in general lacks good panel data. A few local-level panel datasets exist. However, to my knowledge, there is no panel dataset at the national scale, besides the census of agriculture. And though the agricultural census can be compiled as a panel dataset, it does not contain very detailed information on specific aspects of dairy production. As a result, in this paper—instead of trying to measure productivity levels precisely—I calculate farm productivity levels and focus on identifying the relationship between farm size and productivity (as well as farm size and cost efficiency).

First, I start with analyzing returns to scale in dairy farming. Initially, I estimate two different production functions—with the Cobb-Douglas and Translog functional forms. Here the goal is to examine the output elasticities and check to see whether there are increasing returns to scale ($\xi_{rts} > 1$). Following Eslava et al. (2004) and Syverson (2004), I construct a KLEM (capital, labor, energy, and materials) production function. I first use the Cobb-

[12] e.g. (Solow 1957; Nerlove 1963; Griliches 1963; Griliches and Jorgenson 1966)

Douglas form,

$$\begin{aligned} Q &= F(K, L, M, E; \beta)\omega, \\ \log Q_{it} &= \beta_k \log K_{it} + \beta_l \log L_{it} + \beta_m \log M_{it} + \beta_e \log E_{it} + \log \omega_{it}, \end{aligned} \tag{3}$$

where β_k, β_l, β_m, and β_e are output elasticities.[13]

To relax the output elasticities and elasticities of factor substitution, I also use a translog (transcendental logarithmic) function following Christensen and Greene (1976). The translog function has the form,

$$\log Q = \alpha_0 + \sum_i \alpha_i \log(i) + \frac{1}{2} \sum_i \alpha_{ii} (\log(i))^2 + \sum_i \sum_j \alpha_{ij} \log(i) \log(j) + \log \omega, \tag{4}$$

where $i \neq j$, $i, j = K, L, M, E$, and the residual is $\log \omega$.

In both estimations, the addition of the output elasticities—$(\beta_k + \beta_l + \beta_m + \beta_e)$ and $(\alpha_k + \alpha_l + \alpha_m + \alpha_e)$—gives a value for returns to scale.[14] Table 5 gives the output elasticities of inputs for both the Cobb-Douglas and the translog functions in the first six columns. The last three columns gives us the input cost shares in the data.

These output elasticities are the rates at which each of these inputs contribute to the output. In both the Cobb-Douglas and translog estimations, capital input contributes approximately 25–30% of the output. This rate is higher than the capital cost share in the data, which is 20%. Labor only contributes 6–11% percent to the output according to Cobb-Douglas and translog estimations. In the data, labor cost accounts for around 15% of the total cost. The largest contribution to the output comes from materials. Materials include feed, veterinary expenditures, medicine for the cows, seed, and chemical expenditures. And both in cost

[13]Here and throughout the paper log denotes natural logarithm.

[14]I assume the same functional form for all farms because in the dairy industry most farms, small or large, use similar technologies.

Table 5: Output Elasticity of Inputs

	Cobb-Douglas			Translog			Input Cost Shares		
	2000	2005	2010	2000	2005	2010	2000	2005	2010
β_k (capital)	0.327	0.322	0.275	0.268	0.279	0.239	0.200	0.164	0.178
β_l (labor)	0.097	0.055	0.111	0.056	0.062	0.119	0.149	0.165	0.164
β_m (materials)	0.520	0.541	0.515	0.527	0.594	0.523	0.580	0.609	0.582
β_e (energy)	0.078	0.136	0.179	0.123	0.122	0.185	0.071	0.062	0.076
Returns to Scale	1.022	1.054	1.080	0.974	1.057	1.066	1.000	1.000	1.000
Adj. R^2	0.865	0.932	0.928	0.877	0.940	0.933			
Number of Obs.	733	1,229	1,105	733	1,229	1,105	733	1,229	1,105

Standard errors in parentheses. Here with an output elasticity I imply the % change in output levels given a 1% change in any of the factors of production, capital, labor, energy, or materials. This table only shows the marginal effects for the translog function, not the coefficients of the factors of production. The detailed results including standard errors and coefficients for the translog function estimation are in the appendix.

shares and in estimations, output elasticity of materials is around 55–60%. Finally, the energy input contributes around 10–12% of the output production. This rate is higher than the cost share of energy input, which is around 6–7%. Most importantly the returns to scale values are above one. This indicates that there is evidence for increasing returns to scale in dairy farming.

Let's take this indicative evidence and increase the depth of the analysis. The OLS estimates of a production function has well established selection and simultaneity problems (Olley and Pakes 1996). As a result, I turn to a two-stage analysis.

In the first stage, I calculate farms' total factor productivity (TFP)[15] values by using average input cost shares as output elasticities à la Baily et al. (1992) and Syverson (2004).[16,17] In

[15] There are different concepts of productivity, for instance labor productivity or capital productivity. However, two farms using the same technology might use capital and labor in different intensities. And if I only look at a single input productivity, I might mistakenly take different input usage intensity as productivity differences. In order to prevent this and use a productivity concept that is not dependent on observable input usage intensity, I use the total factor productivity concept—TFP—similar to Syverson (2011).

[16] Here, I use the TFP calculated with input cost shares, in order to avoid estimated dependent variable problems. However, all of these estimations were also ran with an initial production function estimation. The results with the estimated dependent variable, though omitted in the paper, were qualitatively equivalent, after correcting for the standard errors.

[17] In order to use input cost shares, I need to first establish that output elasticities are equal to input cost shares. And theoretically, output elasticities of a Cobb-Douglas production function are equal to that firm's input cost shares, if I assume constant returns to scale. The following is the derivation of this equality. Suppose the production function is a two-input—Capital and Labor—Cobb-Douglas:

$$Q = Q(K, L) = AL^{\alpha_l} K^{\alpha_k}. \tag{5}$$

I build the Lagrangian to get the first order conditions,

$$\begin{aligned}
\mathcal{L} &= P_k K + P_l L - \lambda(Q(K, L) - Q) \\
&= P_k K + P_l L - \lambda(AL^{\alpha_l} K^{\alpha_k} - Q) \\
\frac{\partial \mathcal{L}}{\partial L} &= P_l - A\alpha_l \lambda K^{\alpha_k} L^{\alpha_l - 1} \\
\lambda &= \frac{P_l L^{1-\alpha_l}}{A\alpha_l K^{\alpha_k}} \\
\frac{\partial \mathcal{L}}{\partial K} &= P_k - A\alpha_k \lambda K^{\alpha_k - 1} L^{\alpha_l} \\
\lambda &= \frac{P_k K^{1-\alpha_k}}{A\alpha_k L^{\alpha_l}} \\
\frac{P_l L^{1-\alpha_l}}{A\alpha_l K^{\alpha_k}} &= \frac{P_k K^{1-\alpha_k}}{A\alpha_k L^{\alpha_l}}.
\end{aligned} \tag{6}$$

the second stage, I use this TFP variable as the dependent variable in productivity-size regressions.

I also analyze the farm size and productivity relationship via its mirror image—farm size and cost efficiency. For this, I run a simple linear regression, where log unit cost is the dependent variable and farm size is the independent variable of interest. Here, the cost variable includes capital, labor, materials, energy, and hauling costs.

In both the productivity and the cost regressions, there are various demographic variables as controls. I control for farm age, because older farms may have more knowledge accumulation about efficient milk production. I also control for whether there is a hired manager running the farm; professional managers might be better-equipped to operate a farm more efficiently. For similar reasons, I control for the education level of the farmer. Finally, all of the regressions also include year, state, and year-state dummies to control for unobservable year, state, and year-state effects.

In the first three columns of Table 6, the dependent variable is the TFP calculated with the average input cost shares. The fourth through sixth columns establish a relationship between cost efficiency and farm size, where the dependent variable is log unit cost (\$/lb). In both sets of regressions, I start out with a very simple model and move to the full model with complete sets of year and state dummies. In these regressions, the main variable of interest is the farm size, which proxies for farm consolidation. The full model in Table 6 shows that, doubling farm size is associated with a 13% productivity gain. Similarly, doubling farm size is associated with a 4% cost decline. In other words, Table 6 shows that dairy industry

If I assume constant returns to scale, then I have $\alpha_k = 1 - \alpha_l$. Plugging this back into the above equation I get,

$$\begin{aligned} \frac{P_l L^{1-\alpha_l}}{A(1-\alpha_k)K^{\alpha_k}} &= \frac{P_k K^{1-\alpha_k}}{A\alpha_k L^{\alpha_l}} \\ \alpha_k &= \frac{P_k K}{P_k K + P_l L}. \end{aligned} \tag{7}$$

This means the output elasticity of capital (α_k) is equal to the cost share of the capital input. The output elasticity of labor (α_l) will be similarly the share of the labor in the total cost.

Table 6: Productivity-Size and Cost Efficiency-Size Relationships (OLS)

Dependent Var:	Productivity log TFP			Cost Efficiency log Unit Cost (lb)		
log Farm Size	0.118***	0.123***	0.135***	–0.007	–0.017***	–0.045***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Farm Age		0.000	–0.001		0.001**	0.001***
		(0.001)	(0.001)		(0.000)	(0.000)
Cooperative Member		–0.005	–0.007		–0.007	–0.021
		(0.017)	(0.018)		(0.017)	(0.018)
Hired Manager		0.023	0.015		0.054	0.055
		(0.44)	(0.042)		(0.037)	(0.035)
Operator's Education		–0.056***	–0.074***		0.106***	0.118***
(Some College)		(0.020)	(0.019)		(0.020)	(0.019)
Operator's Education		–0.069***	–0.082***		0.136***	0.133***
(College Graduate)		(0.024)	(0.024)		(0.024)	(0.023)
Constant	2.444***	2.471***	2.364***	–1.981***	–2.042***	–1.701***
	(0.033)	(0.038)	(0.090)	(0.031)	(0.037)	(0.073)
Year Dummies	N	N	Y	N	N	Y
State Dummies	N	N	Y	N	N	Y
Year-State Dummies	N	N	Y	N	N	Y
Observations	2,974	2,941	2,941	3,039	3,006	3,006

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

consolidation (increasing farm size) is associated with both increasing productivity and cost efficiency.

There may be confounding effects influencing the OLS results. Next, I turn to instrumental variable (IV) estimation to be able to establish a causal relationship and its direction. The first analysis is one productivity effects (TFP) of farm size, and then for the cost efficiency effects.

For the TFP-size relationship, one major concern may be reverse causation. Instead of increasing farm size causing increasing productivity, it may be that more productive farms get larger. Second, there may be an unobserved third factors, such as managerial ability or parental knowledge transmission, causing these phenomena to occur simultaneously. I seek an instrumental variable that is correlated with farm size, but otherwise unrelated to farm productivity and the unobservables. I use ZIP code-averaged log real estate tax per cow and ZIP code-averaged log feed costs.[18] These results are shown in the first two columns of Table 7, respectively. The first stage F-test suggests that these are strong instruments.[19] Testing the validity of these or any instruments, however, is notoriously difficult. My approach is to look for strong instruments, which would affect the coefficients in the opposite direction in the event of a potential endogeneity problem.

The first instrument is ZIP-code-averaged log real estate tax per cow. I calculate this variable by taking the total real estate tax paid by a farm, divide it by the number of cows the farm owns, and take the ZIP-code average of this value. I argue for the exogeneity of this instrument, because the real estate tax rates are determined by local governments for reasons other than a farm's productivity. It is even less likely that the ZIP-code-averaged log real estate per cow values to be correlated with an individual farm's productivity.

[18] I also have a third IV estimation as a robustness check. I use two instruments—state-averaged log real estate per cow and state-averaged log feed cost—and the results are very similar and shown in Table A1.

[19] An F-test from the first-stage test that is below 10 implies a weak instrument (Bound et al. 1995).

On the other hand, high real estate taxes may encourage farms to substitute away from land, reducing land-per-cow ratios. This may directly affect farm productivity—through a mechanism other than size—since farms with lower land-per-cow ratios are more mechanized and, hence, productive. Note, however, that this channel of direct impact would exert *upward* bias on the second-stage coefficient. (The sign of this potential bias will be useful below.) The results in the first column of Table 7 shows that this instrument preserves the relationship between size and productivity. A doubling of the farm size, leads to a 14% increase in productivity, similar to the OLS result.

The other instrument is ZIP-code-averaged log feed costs. This is similarly a strong instrument with a first stage F-statistic of 53.14. It is correlated with size because larger farms spend larger amounts on feed. This instrument likewise has a plausible degree of exogeneity, because feed input markets are fairly competitive, and these are ZIP-code-averaged values. It might, however, also potentially be endogenous, because a farmer can affect its feed cost by acquiring a larger land and producing its own feed. This potential channel of endogeneity would lead to larger land-per-cow ratios and reduce productivity. In other words, any direct effect of this instrument on productivity might be realized by exerting a *downward* bias on the second-stage coefficient estimate. As shown in the second column of Table 7, a doubling of farm size leads to a 12% increase in productivity.

The possible biases in each of these instruments go in opposite directions. Yet, both IV regressions give very similar second-stage results. This suggests that either there is no endogeneity problem or if there is any potential endogeneity bias it is small in magnitude in *both* instruments.

In the cost regressions, I am similarly concerned with potential confounding effects such as unobserved managerial ability or reverse causation. So, I need an instrument that is correlated with farm size, but is uncorrelated with production cost and the unobservables in

Table 7: Productivity-Size and Cost Efficiency-Size Relationships (IV)

	Productivity		**Cost Efficiency**	
Dependent Var:	log TFP		log Unit Cost (lb)	
log Farm Size	0.147***	0.124***	–0.050***	–0.040***
	(0.023)	(0.017)	(0.011)	(0.015)
Farm Age	–0.000	–0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Cooperative Member	–0.008	–0.007	–0.024	–0.021
	(0.018)	(0.018)	(0.018)	(0.018)
Hired Manager	0.006	0.011	0.058	0.051
	(0.44)	(0.046)	(0.036)	(0.037)
Operator's Education	–0.077***	–0.067***	0.116***	0.116***
(Some College)	(0.021)	(0.020)	(0.019)	(0.020)
Operator's Education	–0.086***	–0.069***	0.132***	0.130***
(College Graduate)	(0.027)	(0.026)	(0.024)	(0.024)
Constant	2.295***	2.431***	–1.663***	–1.735***
	(0.163)	(0.131)	(0.087)	(0.109)
Year Dummies	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y
Year-State Dummies	Y	Y	Y	Y
Observations	2,938	2,814	3,002	3,006
1^{st}-Stage F-test	44.40	53.14	88.13	63.45

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the error term. Here, I use ZIP-code-averaged log silo capacity and ZIP-code-averaged log acres of land operated by a farm as the instruments.[20]

ZIP-code-averaged log silo capacity is a strong instrument with an F-test result of 88.13. In a dairy farm, silos are used to store feed for cows. A farm with a large herd, would need a larger silo capacity. However, silos are large capital investments and do not change from year to year. If a dairy farm builds a large silo capacity, that occurs many years in advance with the expectation of growth. Therefore, this instrument is plausibly exogenous to the farm cost or current unobservable such as managerial ability. The instrumental variable results are very similar to the OLS results. As shown in the third column of Table 7, a doubling of farm size leads to a 5% decrease in unit cost.

Similarly, the operated land size is correlated with farm size, because larger farms need larger land for cows. However, it is unlikely to be correlated with individual farms' costs. Unlike in other agricultural sub sectors like fruits and vegetables, dairy production mostly does not depend on land.[21] Plus land values are not included in the capital cost variable and I use ZIP-code-average values for all farms. Therefore, this is a valid instrument as well as a strong one. The results support this view, as the IV coefficient is very similar to the OLS results. A doubling of farm size causes a 4% decline in unit milk cost.

The previous two sets of results establish that there are efficiency gains to make from increasing farm size. Lastly I look at the linearity of this relationship. I examine whether the efficiency-size relationship is uniform across different farm sizes.

Earlier, I conjectured that as a farm's size increases, the impact of getting even bigger on productivity declines. The motivational graph, Figure 4, indicates a non-linear relationship.

[20] Again there is an additional IV estimation in the appendix to ensure that it is not these particular instrumental variables that drive the results. In Table A1, the regression in the second column has two instruments—ZIP-code-averaged log silo capacity andZIP-code-averaged log land. The results hold.

[21] Except for feed growing purposes, however, most farms purchase at least a large portion of their feed from input suppliers instead of growing all of it themselves.

Table 8: Quantile Regressions of Productivity and Cost Efficiency

Dependent Var.	log TFP			Unit Cost (lb)		
	10%	50%	90%	10%	50%	90%
log Farm Size	0.168***	0.132***	0.109***	–0.005	–0.036***	–0.096***
	(0.011)	(0.008)	(0.017)	(0.009)	(0.006)	(0.009)
Farm Age	–0.001	–0.001	–0.001	0.001	0.001	0.002**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Cooperative Member	0.032	–0.025**	–0.052	0.049**	–0.006	–0.036*
	(0.021)	(0.012)	(0.034)	(0.027)	(0.014)	(0.019)
Hired manager	–0.059	0.041	0.018	0.102**	0.023	0.024
	(0.074)	(0.052)	(0.065)	(0.051)	(0.020)	(0.042)
Operator's Education	–0.038	–0.052***	–0.103***	0.119***	0.101***	0.086***
(Some College)	(0.036)	(0.016)	(0.032)	(0.041)	(0.022)	(0.023)
Operator's Education	–0.054	–0.046**	–0.109**	0.134***	0.103***	0.091***
(College Graduate)	(0.041)	(0.024)	(0.048)	(0.046)	(0.026)	(0.022)
Constant	1.872***	2.339***	2.869***	–2.185***	–1.655***	–1.025***
	(0.071)	(0.124)	(0.132)	(0.135)	(0.092)	(0.079)
Year Dummies	Y	Y	Y	Y	Y	Y
State Dummies	Y	Y	Y	Y	Y	Y
Year-State Dummies	Y	Y	Y	Y	Y	Y
Observations	2,941	2,941	2,941	3,006	3,006	3,006
Pseudo R-Square	0.211	0.194	0.167	0.165	0.164	0.155

*** significant at the 1% level, **significant at the5% level, *significant at 10% level. Std. Errors are bootstrapped for the entire estimation, not just the second stage.

Highest efficiency gains from increasing size were realized for smaller farms. Here, I take a more detailed look at this potential non-linearity, by first analyzing quantile regressions for the 10^{th}, 50^{th}, and 90^{th} quantiles.[22]

The first three columns in Table 8 give the results for a quantile regression with the productivity (TFP) as the dependent variable. The last three columns show a quantile regression with the unit cost as the dependent variable. Both sets of these results confirm a non-linear relationship between size and productivity. The effect of increasing size on productivity declines as a farm gets larger. For the farms at the 10^{th} productivity quantile, doubling farm size leads to a 17% increase in productivity, whereas this value goes down to 10% for the farms in the 90^{th}.

The results are similar and even stronger for the cost efficiency-size relationship. Farms at the 90^{th} quantile of milk cost—meaning highest cost, lowest efficiency farms—have the largest cost declines from increasing farm size. Whereas for farms that are already quite efficient, I see no statistically significant impact from further increasing farm size. In other words, for both the productivity and the cost efficiency side there is an upper bound for efficiency gains from increasing farm size. At some point, the efficiency gains tapper off.

To examine this effect from a different perspective I look at these relationships with only a large-farm sample; only farms with more than one thousand cows. Table 9 shows the OLS results for the relationship between farm size and productivity in the first column and the farm size and cost efficiency in the second column. In both regressions, the coefficients are statistically insignificant. Meaning the effect of size on efficiency disappears as the farms get very large.

[22] I estimated the same model with additional quantile cut of values, such as 25%, 50%, 75%, and the results were very similar in magnitude and significance.

Table 9: Productivity-Size and Cost Efficiency-Size Relationships (For Farms with >1000 Cows)

Dependent Var:	**Productivity** log TFP	**Cost Efficiency** Unit Cost (lb)
log Farm Size	0.079	–0.061
	(0.058)	(0.044)
Farm Age	–0.002	0.001
	(0.002)	(0.001)
Cooperative Member	–0.053	–0.033
	(0.081)	(0.049)
Hired Manager	0.010	–0.017
	(0.113)	(0.64)
Operator's Education	–0.173	0.116
(Some College)	(0.118)	(0.092)
Operator's Education	-0.257^{**}	0.171^{*}
(College Graduate)	(0.120)	(0.095)
Constant	2.857^{***}	-1.505^{***}
	(0.441)	(0.341)
Year Dummies	Y	Y
State Dummies	Y	Y
Year-State Dummies	Y	Y
Observations	270	272

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6 Conclusion

In the last few decades, the size distribution of dairy farms has been changing substantially. There are large consolidation movements in the dairy industry. In this paper, I investigate the impact of this horizontal consolidation on efficiency.

The dairy industry provides a unique setting for this analysis. Dairy farms are legally allowed to collective bargain and market their products via cooperatives. These dairy cooperatives give, even the smallest farm, a large market power. This aspect of this industry creates an clean empirical setting to study the efficiency impacts of horizontal consolidation. With the market power effects of consolidation mostly controlled for, I focus on the efficiency effects. I hypothesize that with consolidation farms are achieving efficiency gains.

The empirical evidence in this paper suggests that there are both increasing returns to scale and economies of scale in dairy farming. Dairy farms can increase their productivity 12–14% by doubling their size. With the same size increase their unit cost will decline 4–5%. Therefore, the efficiency returns from increasing the size of the capital investment is higher than returns from labor-capital substitution. In other words, a farm achieve higher efficiency from setting up a larger parlor with more number of milking machines compared with replacing human feeding with automated feeding machines.

Additionally, this is not a linear relationship for all farm sizes. Most of the efficiency gains occur when small farms increase their size. As consolidating farms get larger, their gains from further increasing their scale declines. For farms with more than one thousand cows, there is no statistically significant relationship between increasing farm size and efficiency (RTS and EOS).

In conclusion, consolidations lead to a non-linear productivity and efficiency increase in dairy farms. These efficiency effects start out high for smaller farms, they decline as the farm sizes increase, and eventually disappear once a dairy farm reaches a certain size—around one thousand cows.

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A Technical Appendix

A.1 The duality of returns to scale and economies of scale

Derivations below are heavily drawn from Gelles and Mitchell (1996). Suppose, I have a single-output and a multiple-input production function, where x_i are the inputs and Q is the output. The production function is:

$$Q = f(x_1, x_2, x_3..., x_n) = exp\Big[h(\log x_1, \log x_2, ..., \log x_n)\Big]. \tag{A.1}$$

It is more convenient to use the log form of the production function, therefore I have:

$$lnQ = h(lnx_1, lnx_2, lnx_3, ..., lnx_n). \tag{A.2}$$

Then, returns to scale (ξ_{rts}) is the proportional change in output given a proportional change in all inputs. I can write returns to scale as

$$\xi_{rts} = \frac{dQ/Q}{dx_i/x_i}, \tag{A.3}$$

, where $\frac{dx_i}{x_i}$ represents the same proportional change in all inputs, independent of i. Now, let's differentiate equation (A.2):

$$\begin{aligned} \frac{d\log Q}{dx_i} &= \sum_{i=1}^{n} \frac{d}{dx_i}\Big[h(.)\Big] \\ \frac{\partial \log Q}{\partial Q}\frac{\partial Q}{\partial x_i} &= \sum_{i=1}^{n} \frac{\partial h(.)}{\partial \log x_i}\frac{\partial \log x_i}{\partial x_i} \\ \frac{dQ/Q}{dx_i/x_i} &= \sum_{i=1}^{n} \frac{\partial h(.)}{\partial \log x_i}. \end{aligned} \tag{A.4}$$

Therefore, I can denote the returns to scale as

$$\xi_{rts} = \sum_{i=1}^{n} h_i, \text{where } h_i(.) \equiv \frac{\partial h(.)}{\partial \log x_i}. \tag{A.5}$$

Now, let's look at economies of scale. This concept is about changing average costs given changes in inputs. Roughly, economies of scale is the proportional change in long run average cost given a proportional change in all inputs. Take a cost function, where $r(x_i)$ is input price for input, x_i, for all i=1,..., n. Here, input prices are a function of the amount of input purchased (though I have not ruled out the possibility of perfectly competitive input markets, that is $\frac{\partial r(x_i)}{\partial x_i} = 0$). Firms minimize cost, given their production constraint:

$$\begin{aligned} \min \quad & \sum_{i=1}^{n} r(x_i)x_i \\ \text{s.t.} \quad & h(\log x_1, \log x_2, \log x_3, ..., \log x_n) \geq \log Q \end{aligned} \tag{A.6}$$

I build the Lagrangian, and look at the input constraints:

$$\begin{aligned} \mathcal{L} &= \sum_{i=1}^{n} r(x_i)x_i - \lambda \left(h(\log x_1, \log x_2, \log x_3, ..., \log x_n) - \log Q \right) \\ \frac{\partial \mathcal{L}}{\partial x_i} &= r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i} - \lambda \frac{\partial h(.)}{\partial x_i} \\ 0 &= r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i} - \lambda \frac{\partial h(.)}{\partial \log x_i} \cdot \frac{\partial \log x_i}{\partial x_i} \\ 0 &= r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i} - \lambda h_i(.)(\frac{1}{x_i}) \\ \lambda h_i(.)(\frac{1}{x_i}) &= r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i} \end{aligned} \tag{A.7}$$

I multiply both sides with x_i then sum over i to find λ :

$$\begin{aligned}
\lambda h_i(.) &= x_i r(x_i) + (x_i)^2 \frac{\partial r(x_i)}{\partial x_i} \\
\sum_{i=1}^{n} \lambda h_i(.) &= \sum_{i=1}^{n} \left(x_i r(x_i) + (x_i)^2 \frac{\partial r(x_i)}{\partial x_i} \right) \\
\lambda \sum_{i=1}^{n} h_i(.) &= \sum_{i=1}^{n} x_i r(x_i) + \sum_{i=1}^{n} (x_i)^2 \frac{\partial r(x_i)}{\partial x_i}
\end{aligned} \tag{A.8}$$

Here, I have two important results. The first result comes from the final line in equation (A.7). The second, important, result comes from equation (A.8) after plugging in total cost ($TC = \sum_{i=1}^{n} x_i r(x_i)$) and returns to scale ($\xi_{rts} = \sum_{i=1}^{n} h_i(.)$). These two results to keep in mind are,

$$h_i(.)(\frac{1}{x_i}) = \frac{r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i}}{\lambda} \tag{A.9}$$

$$\lambda = \frac{TC + \sum_{i=1}^{n} (x_i)^2 \frac{\partial r(x_i)}{\partial x_i}}{\xi_{rts}} \tag{A.10}$$

Now, I go back to the Lagrangian, and look at the constraint with respect to λ:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \lambda} &= h(lnx_1, lnx_2, lnx_3, ..., lnx_n) - lnQ \\
lnQ &= h(lnx_1, lnx_2, lnx_3, ..., lnx_n)
\end{aligned} \tag{A.11}$$

I take the derivative of both sides with respect to x_i:

$$\begin{aligned}
\frac{\partial \log Q}{\partial x_i} &= \frac{\partial h(.)}{\partial x_i} \\
\frac{\partial \log Q}{\partial x_i} &= \frac{\partial h(.)}{\partial \log x_i} \cdot \frac{\partial \log x_i}{\partial x_i} \\
\frac{\partial \log Q}{\partial x_i} &= \frac{r(x_i) + x_i \frac{\partial r(x_i)}{\partial x_i}}{\lambda} \quad \text{by equation (A.9)} \\
\frac{\partial \log Q}{\partial x_i} &= \frac{\partial TC/\partial x_i}{\lambda} \\
\lambda &= \frac{\partial TC}{\partial lnQ}
\end{aligned} \tag{A.12}$$

Economies of scale is the elasticity of average cost with respect to the output. However, so far the equations above are functions of total cost. So, before showing the relationship between economies of scale and returns to scale, I will first establish the relationship between the elasticity of total cost and the average cost.

The elasticity of total cost with respect to output is

$$\begin{aligned}
\xi_{tc} &= \frac{dTC/dQ}{TC/Q} \\
&= \frac{\partial TC}{\partial \log Q} \frac{\partial \log Q}{\partial Q} \frac{Q}{TC} \\
&= \frac{\partial TC/\partial \log Q}{TC},
\end{aligned} \tag{A.13}$$

where ξ_{tc} = denotes the elasticity of total cost. Below, is the relationship between the elasticity of total cost and the economies of scale:

$$
\begin{aligned}
\xi_{eos} &= \frac{dAC/dQ}{AC/Q} \\
&= \frac{d(TC/Q)}{dQ}\frac{Q}{(TC/Q)} \\
&= \Big[\frac{(\partial TC/\partial Q)Q - TC}{Q^2}\Big]\frac{Q^2}{TC} \\
&= \frac{\partial TC/\partial Q}{TC/Q} - 1 \\
&= \xi_{tc} - 1
\end{aligned}
\tag{A.14}
$$

Therefore, I know that:

$$
\begin{aligned}
\xi_{eos} &= \frac{\partial TC/\partial \log Q}{TC} - 1 \quad \text{by equation (A.13)} \\
&= \frac{\lambda}{TC} - 1 \quad \text{by equation (A.12)} \\
\lambda &= (\xi_{eos} + 1)TC
\end{aligned}
\tag{A.15}
$$

Finally, I will combine the results in equations (A.10) and (A.15) to establish the relationship between returns to scale and economies of scale.

$$
\begin{aligned}
(\xi_{eos} + 1)TC &= \frac{TC + \sum_{i=1}^{n} x_i^2 \frac{\partial r(x_i)}{\partial x_i}}{\xi_{rts}} \\
\xi_{eos} &= (\frac{1}{\xi_{rts}} - 1) + \frac{\sum_{i=1}^{n} x_i^2 \frac{\partial r(x_i)}{\partial x_i}}{\xi_{rts}}
\end{aligned}
\tag{A.16}
$$

The equation (A.16) shows us a relationship between ξ_{rs} and ξ_{es}, which depends on the input markets. If all the input markets are perfectly competitive, then $\frac{\partial r(x_i)}{\partial x_i} = 0$ for all i, therefore the second term will disappear. In this setting, increasing, decreasing, or constant returns to scale have direct implications for economies of scale, diseconomies of scale, or neither (respectively). There is a duality between economies of scale and returns to scale. However, if one or more of the input markets are not competitive, then this duality breaks down.

A.2 Production function variable construction

I use a single-output, four-input production function. The input variables are capital, labor, energy, and materials. Below are the variable construction for inputs used in the production function estimation:

Output: The ARMS reports total pound of milk production for each farm. So, without using price deflators and revenue variable, I simply look at the quantity of milk produced.

Capital: This is one of the most controversial inputs in productivity literature. In an ideal world, I would have data on all the productive capital quantities, and I would aggregate them based on their production contribution. However, in reality, it is almost never possible to find data on the number of (or hours of) machines used in the production, and even if I do there is still the problem of aggregating them to a single capital index. So, I use the perpetual inventory method à la Olley and Pakes (1996), who assume a fixed depreciation rate for the capital input. Capital input is $K_{t+1} = (1 - \delta) * K_t + I_t$, where K and I denote capital and investment respectively. These capital and investment values are in constant prices—in this paper they are constant 2010 prices inflated with appropriate prices indices.

ARMS has a breakdown of capital components. I have data on estimated values of all of the buildings, equipment, cars, tractors, and trucks used in milk production as well as the value of breeding livestock at hand for the beginning of each year. And for each of these components, I also have investment values—if there were any investment made. Land, operator's house, or other dwellings—basically all the non-productive capital—is excluded from this variable.

Additionally, I collected depreciation data from the Bureau of Economic Analysis (BEA). For buildings, I used "Private nonresidential structures, farm", and for equipment, I used "Agricultural machinery, except tractors" rates (BEA 2012). For livestock, the IRS tax guidelines explained that new breeding stock could be depreciated the first year they are acquired (IRS 2012). So for the newly purchased breeding stock I used average depreciation values reported in the data, but I did not depreciate the livestock value at hand. Then, I aggregated these values with equal weights. In the end, the capital variable is,

$$\begin{aligned} K_t = [((1-\delta^{building}) * K_{t-1}^{building} + I_{t-1}^{building}) + \\ ((1-\delta^{equipment}) * K_{t-1}^{equipment} + I_{t-1}^{equipment}) + (K_{t-1}^{livestock} + I_{t-1}^{livestock}), \end{aligned} \tag{A.17}$$

where δ_i is the depreciation rate for each component.

- $K^{building}$: The market value of all farm buildings including barns, cribs, equipment shops, grain bins, greenhouses, silos, storage sheds, etc., except the operator's house.
- $K^{equipment}$: The market value of the farm share of all trucks, cars, tractors, machinery, tools, equipment, and implements owned by a farm.
- $K^{livestock}$: The market value of the farm share of all breeding livestock owned and located on a farm.

Capital Cost: Again in an ideal world, I would have information about the rental rate of each capital component and would aggregate these based on their production contribution. However, it was not possible to find this information, because most companies own their capital items. Therefore, I developed a rental rate they are paying to themselves. Following OECD (2001), I calculate "user cost of capital (UCC)". $UCC = V * (\delta + r)$ where UCC is the user cost of capital, V is the constant price value of an asset, δ is the depreciation rate, and r is the real interest rate. Here again depreciation rates are the ones used in the capital variable construction. This time breeding stock purchases are depreciated by livestock depreciation rates. For the real interest rate, I used the USDA definition used in capital recovery cost estimations. The real interest rate is then the long-run rate of return to farm assets out of current income—10-year moving average (USDA Economic Research Service 2012). The final equation is,

$$\begin{aligned} UCC = V_{building} * (r + \delta_{building}) + V_{breedingstock} * (r + \delta_{livestock}) + \\ V_{equipment} * (r + \delta_{equipment}) + V_{livestock} * (r) \end{aligned} \tag{A.18}$$

Labor: Because this is a detailed dairy farm survey, the questionnaire asks for the total worked hours as estimated weekly hours of labor. Here, labor hours are: Labor = total full-time hours (excludes the operator and unpaid hours) + total part-time hours (excludes operator and unpaid hours) + total operator hours (paid or unpaid) + total unpaid hours (excludes paid labor and operator hours).

Labor Cost: The questionnaire asks for the total labor expenditure (total of cash wages, contract labor, custom work, and benefits paid). This value does not cover the unpaid work. However, because the unpaid hours for the operator are not separately identified in the data, I cannot only look at the paid labor hours. Therefore, the labor cost only covers the paid labor time.

Materials: Materials is the sum of feed expenditure, seed expenditure, grazing expenditure, fertilizer expenditure, and finally chemical expenditure. I had to use expenditure totals as materials input, because it is not possible to find farm level input cost data to separate materials used from materials cost. These values are inflated to 2010 prices with appropriate price indices. Materials include seed expenditures, grazing, and fertilizer expenditures, because otherwise I would be excluding the homegrown feed expenditures. Because, it is mostly the small farmers who grow their own feed, this would be biasing the results.

Materials Cost: This is the same calculation as materials variable.

Energy: Energy is the sum of all fuel (gas, natural gas, LP, etc.) and electricity expenditure inflated to 2010 prices with the appropriate price indices. Again, because it is not possible to find information on quantities of energy units used for production or farm level fuel prices, I use expenditure totals as energy input.

Energy Cost: This is the same calculation as energy variable.

Price Indices Used: All prices are inflated to 2010 prices using the appropriate price indices. Most of the price indices are collected from the USDA National Agricultural Statistics Service (NASS) as indices of prices paid by the producers.The baseline of the price indices is 1990–1992, and I used indices from years 2000, 2005, and 2010. These numbers are specific to dairy producers.

- Milk Cow Replacement Price Index (US National Agricultural Statistics Service 2012)
- Feed Price Index (US National Agricultural Statistics Service 2012)
- Seed Price Index (US National Agricultural Statistics Service 2012)
- Chemicals Price Index (US National Agricultural Statistics Service 2012)
- Fertilizer Price Index (US National Agricultural Statistics Service 2012)
- Grass Price Index (US National Agricultural Statistics Service 2012)
- Labor Price Index (US National Agricultural Statistics Service 2012)
- Tractor Price Index (US National Agricultural Statistics Service 2012)
- Machinery Price Index (US National Agricultural Statistics Service 2012)
- Dairy Price Index (US Census Bureau 2012)
- Crop Price Index (US National Agricultural Statistics Service 2012)
- Fuel Price Index (US National Agricultural Statistics Service 2012)

- Electricity Price Index, Consumer Price Index (all urban consumers, city average) (US Bureau of Labor Statistics 2012)
- Construction Price Index (US National Agricultural Statistics Service 2012)

A.3 Additional IV regressions

In addition to the instrumental variables used in Table 7, I use two more sets of instrumental variables to run robustness checks. The first column in Table A1 is the productivity-size, and the second column is cost efficiency-size IV regressions. In the first regression, I use two variables to instrument for the potentially endogenous variable, farm size. These instruments are log real estate tax per cow and log total feed cost, averaged over state. For the second regression, I similarly use two instruments, log total land owned and log silo capacity averaged over the ZIP code. Given the 1^{st}-state F tests all of these instruments are strong.

Results confirm our original findings in direction with slight differences in magnitude. Consolidation, measured as increasing farm size, leads to 8% increase in productivity and 5% decline in farm costs.

Table A1: Productivity-Size and Cost Efficiency-Size Relationships (Additional IV)

Dependent Var:	**Productivity** log TFP	**Cost Efficiency** log Unit Cost (lb)
log Farm Size	0.079**	–0.049***
	(0.041)	(0.010)
Farm Age	–0.000	0.001***
	(0.000)	(0.000)
Cooperative Member	–0.003	–0.024
	(0.018)	(0.018)
Hired Manager	0.059	0.057
	(0.55)	(0.036)
Operator's Education	–0.054**	0.115***
(Some College)	(0.024)	(0.019)
Operator's Education	–0.050	0.131***
(College Graduate)	(0.034)	(0.023)
Constant	2.727***	–1.672***
	(0.174)	(0.084)
Year Dummies	Y	Y
State Dummies	Y	Y
Year-State Dummies	Y	Y
Observations	2,941	3,002
1^{st}-Stage F-test	43.77	99.68

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.