SEMINAR TITLE:

Income volatility, farm size and productivity growth: Two studies exploiting multiple years of farm micro data

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(Dr. Key is presenting both papers at his seminar on Tuesday, January 22nd.)

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Featured Article

The Income Volatility of U.S. Commercial Farm Households

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Abstract *This study uses a newly created panel dataset drawn from the 1997 to 2013 Agricultural Resource Management Survey to provide the first national estimates of income volatility for commercial farm households in the United States. Results show that the income of commercial farm households is substantially more volatile than that of all U.S. households – though the volatility of farm income is not more volatile than income from nonfarm self-employment. Using a regression analysis, we identify operator, operation, and regional characteristics associated with higher income volatility, providing information that could improve targeting of risk-mitigating programs. We find that farm income volatility has declined for farms specializing in program crops in recent decades, supporting the hypothesis that the expansion of the federal crop insurance program helped reduce farm income risk.*

Key words: Income volatility, income variation, farm income, off-farm income, risk.

JEL codes: I31, J31, Q12.

Farm income is highly variable due to fluctuations over time in both yields and prices. For the 1.4 million U.S. farmers who consider farming their primary occupation, variability of returns can be a challenging part of running their business and providing for their families. Indeed, large, unplanned income fluctuations can affect the ability of farmers to obtain credit, expand their operations, and repay debt. Farmers may try to cope with income variation by borrowing or liquidating their assets; they may adjust their off-farm labor supply in anticipation of, or to compensate for, unexpected income shocks. Farmers might also cope with risk by adjusting their inputs or altering their crop mix. Hence, the way farmers cope with income risk affects what, how, and how much they produce, and can have important implications for agricultural production, rural household welfare, and environmental quality.

Federal agricultural policies have long sought to shelter farmers from income fluctuations using price supports, direct income support, disaster assistance programs, and crop yield and revenue insurance programs. Trade and agricultural policies that are mainly framed as supporting producer incomes and internalizing externalities can have important risk-reducing benefits for farmers (Thompson et al. 2004). Even the largely decoupled production flexibility contract (PFC) payments introduced by the 1996 FAIR Act provided insurance value to farmers by offering a relatively stable source of income. The 2014 Farm Act significantly shifted federal agricultural spending towards programs aimed at reducing income risk (USDA Economic Research Service 2016). The act ended fixed annual payments to producers based on historical production, and created new programs tied to annual or multi-year fluctuations in prices, yields, or revenues. The new programs include those that pay producers when prices fall below a reference price or revenue level (Price Loss Coverage (PLC) and Agriculture Risk Coverage (ARC), respectively), and expanded crop insurance programs aimed at providing support for shallow revenue or yield losses.

Despite the important role of income volatility in determining farm household behavior and welfare, and despite the growing emphasis of federal programs on income risk reduction, there exists little empirical information about the extent of U.S. farm household income volatility, how this volatility varies across different types of households, or the role of government programs in mitigating farm household income volatility. This article has two main objectives. The first is to measure the income volatility of households that operate commercial farms in the United States. Key questions include how much does income vary from year to year after households have mitigated income variation through off-farm work, futures markets, contracts, etc.? And how does the income variability faced by farm households compare to that of all U.S. households? This information can help inform policymakers seeking to understand farm households' need for risk-mitigating programs.

The second objective of the paper is to identify how income volatility varies across different types of farm households. Information about how operator characteristics such as age, educational attainment, and marital status influence volatility could be useful in targeting information about risk management programs. Information about how volatility is correlated with farm commodity specialization and local economic conditions could help identify the types of producers who could benefit most from new risk mitigating programs or expanded insurance availability.

The dearth of information about farm household income variability is largely attributable to a lack of data tracking farm household income over time—that is, farm household panel data. Past studies of farm income variability at the national level have relied on either aggregate or cross-sectional data. Aggregate data can provide useful insight into how the sector as a whole fares from year to year, but can mask considerable variation at the farm level (Mishra and Sandretto 2002). In a given year, producers in one region might be thriving, whereas those in another region might be incurring losses from local drought or pest infestations.

Studies using cross-sectional data (e.g., Mishra and El-Osta 2001; Mishra et al. 2002) also only provide limited information about individual farm income variability. Inter-annual variation in commodity prices, policies, and yields can sometimes result in "boom" or "bust" cycles, causing the average income of farmers to change from year to year. Examining variation in income across farms at one point in time ignores this inter-annual variation, and therefore underestimates individual farm income variation.

The drawbacks associated with aggregate and cross-sectional data can be addressed with farm-level panel data spanning several years. We construct such a panel by matching observations of farms that were surveyed more than once between 1997 and 2013 by the USDA Agricultural Resource Management Survey (ARMS) —the most comprehensive survey of U.S. farm households. The panel nature of the data allows us to observe how farm and nonfarm income and program payments changed over time for the same household, which allows for an accurate assessment of inter-annual income fluctuations. Because the ARMS was not designed as a panel, the sample of repeat observations used in this study are not representative of the farm population as a whole. However, as we show, the farms we observe display characteristics that are very similar, on average, to commercial farms. Hence, the study provides insight into income volatility for the types of farms responsible for most agricultural production in the United States.

While the existing information about farm household income volatility is limited, there have been a number of studies that have used panel data to examine the income volatility of all U.S. households—usually seeking to identify how volatility varies across income categories and over time. Early studies focused on decomposing the cross-sectional variance in individual earnings into permanent and transitory components, and on identifying time trends using the Panel Study of Income Dynamics (Gottschalk and Moffitt 1994; Haider 2001) or the Current Population Survey (Cameron and Tracy 1998). More recent studies have examined trends in household income volatility using simple measures of volatility, which are usually a function of the change in income over consecutive years (e.g., Congressional Budget Office 2008; Dahl, DeLeire, and Schwabish 2011; Moffitt and Gottschalk 2011; Shin and Solon 2011; Ziliak, Hardy, and Bollinger 2011; Dynan, Elmendorf, and Sichel 2012).

In this study we adapt some of the measures of volatility used in the recent studies of all (mostly nonfarm) households to allow for the negative farm and total incomes experienced by some farm households. The measures allow us to compare the volatility of farm and off-farm income sources, and to compare the total income volatility of farm to all households. We use a regression analysis to determine how different farm and operator characteristics influence farm and total income volatility, and we investigate trends in volatility over time.

Data

The farm-level panel dataset is constructed with data from the 1997–2013 Agricultural Resource Management Surveys (ARMS). The ARMS is an annual USDA survey carried out by the National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) (USDA-ERS 2015a). Although the ARMS is not a panel survey, some farmers were surveyed multiple times over the eighteen year span due to either random chance or

Table 1 Number of Times the Same Farm Is Observed in ARMS between 1996 and 2013

Number of Times Observed	Distinct Farms	Percentage of Distinct Farms Observed
1	190,732	83.3
2	29,511	12.9
3	6,648	2.9
4	1,705	0.7
5	396	0.2
6	66	<0.1
7	13	<0.1
8	2	<0.1
Total	229,073	100.0

Source: Agricultural Resource Management Survey (ARMS), 1996-2013.

their agricultural importance within their state. We identify these repeat observations using the NASS operator identification number.[1]

Of a total of 229,073 farmers surveyed between 1996 and 2013, 37,945 were surveyed more than once. Of these repeat observations, 29,511 were surveyed twice, 6,648 three times, and 1,786 were surveyed four or more times (table 1). Our approach is to compare changes in real income across two periods.[2] For farmers who were sampled more than twice, each interior pair of years was used to create an observation.[3] We drop observations where the span between the observations is greater than 5 years in order to keep the time between observations relatively homogeneous, and omit 1996 due to insufficient observations. We also drop observations if the difference in operator age between two observations was more than 7 years (which would imply that a different person is operating the farm).[4] We limit the study to family farms—operations where the operator and the operator's family own the majority of the business. These family farms represent about 98% of all farms.

Finally, because the farm households that were surveyed at least twice between 1997 and 2013 tend to operate much larger farms and to produce more output than an average farm, we limit the sample to farms categorized by ERS as "commercial farms" in either year they were surveyed. According to the ERS farm typology in place for most of the study period, commercial farms include family farms with gross sales of at least $250,000 per year

[1]*The NASS uses a multipart method to track operations and operators over time. For family farm operations without hired professional managers, the principal operator is tracked over time. For "managed operations" that use hired farm managers, the operation is tracked and household information, including information on principal operator household income, is not collected in most years. Managed operations and non-family farms are not included in this study.*

[2]*All values are deflated to 2011 U.S. dollars using the Bureau of Economic Analysis' Gross Domestic Product Implicit Price Deflator, available online at: http://research.stlouisfed.org/fred2/series/GDPDEF/*

[3]*For example, a farmer surveyed in 1998, 2003, and 2006 would be included twice in the panel data set: once for the period between 1998 and 2003, and once for the period between 2003 and 2006.*

[4]*In most cases, the operator identification number is updated when there is a change in the principal operator. However, in some cases the operator identification number is not updated despite a change in the person making day-to-day decisions on the farm. This can occur in situations where the operation of the farm passes from one generation to another (e.g., from the father to the son).*

(Hoppe and MacDonald 2013). The final panel sample consists of 20,319 observations. Table 2 displays the distribution of the final sample across the two years that farms were observed.

All statistics are calculated using ARMS sampling weights that account for the probability of selection within a given year—giving a weight to an individual farm that is inversely proportional to their probability of selection and adjusting for nonresponse. These sample weights will also account for the probability of selection across the different years in our panel, placing a higher weight on observations from years with a smaller sample size.[5]

To account for the original ARMS sample design we bootstrap the standard errors presented in the summary statistics and regression results. The ARMS sample is stratified by sales class (and commodity) within individual estimate states or regions. We create 150 replicate weights that are stratified based on the sales class of the operation using the "bsweights" package developed by Kolenikov (2010). In our regressions, we also include fixed effects for both state and commodity type.

Table 3 displays some key household and farm characteristics for: (*a*) the panel sample, (*b*) all farms that were surveyed between 1997 and 2013, and (*c*) the subset of the full ARMS sample that are categorized as "commercial farms" according to the ERS farm typology (Hoppe and MacDonald 2013). As compared with the full ARMS sample (column 2), the panel sample of commercial farms (column 1) and the full sample of commercial farms (column 3) tend to operate much larger farms and produce more. The commercial farms received less income from off-farm sources and significantly more from farming. These farms also had an average household income that was more than twice that of the average farm. The panel sample has characteristics that are very similar to the full sample of commercial farms. The fact that the farms in the panel are comparable to commercial farms implies that our analysis should provide insight into the income volatility for the larger-scale operations that produce almost 80% of agricultural output.[6]

Measuring Income Volatility

To calculate farm, off-farm, and total household income using the ARMS data we employ the same methods used by the USDA ERS (USDA ERS 2015b). Farm income is defined as the sum of the operator household's share of farm business income (net cash farm income less depreciation), wages paid to the operator and other household members, and net rental income from renting farmland. In addition, some households report other farm-related income from operating a farm business other than the one being surveyed, and in-kind payments to household members for farm work.

Off-farm income comes from earned and unearned sources. Earned income includes compensation from wages and salaries for household members and net earnings from operating nonfarm businesses. Unearned income is derived from interest and dividends from investments, transfer payments

[5] *Because the population size of farms is relatively consistent throughout this period, the average sample weights in a year when 9,000 farms were sampled will be approximately twice that in a year when 18,000 farms were sampled.*

[6] *In 2010, commercial farms represented 9.9% of all farms and produced 79.0% of total output (Hoppe and MacDonald 2013).*

Table 2 Distribution of Final Sample Observations across Years

						Year 2								
Year 1	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**
1997	–	136	163												299
1998	199	78	112	140											529
1999	73	174	173	212	153										785
2000		41	278	253	207	257									1,036
2001			21	259	172	196	168								816
2002				74	376	333	287	223							1,293
2003					40	682	495	435	392						2,044
2004						162	820	408	469	382					2,241
2005							308	858	624	413	424				2,627
2006								143	875	596	421	539			2,574
2007									131	748	492	460	374		2,205
2008										89	802	557	500	353	2,301
2009											99	896	472	–	1,467
2010												102	–	–	102
Total	272	429	747	938	948	1,630	2,078	2,067	2,491	2,228	2,238	2,554	1,346	353	20,319

Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: This table shows the distribution of observations used in the analyses. The sample excludes pairs of observations collected more than five years apart.

Table 3 Summary Statistics for Panel, All ARMS Farms, and Commercial Farms, 1997–2013

	Panel sample Mean (Std. Dev.)	All ARMS farms Mean (Std. Dev.)	ARMS commercial farms Mean (Std. Dev.)
Farm income	140,140	11,864	153,210
	(377,487)	(171,714)	(549,144)
Off-farm income	49,971	76,199	53,239
	(101,249)	(132,791)	(167,232)
Total household income	190,111	88,064	206,449
	(393,860)	(215,621)	(579,980)
Farm assets	2,475,864	735,509	2,402,701
	(3,680,085)	(1,707,252)	(4,256,969)
Total assets	2,797,893	889,594	2,278,741
	(3,826,528)	(1,737,893)	(4,120,865)
Total debt	477,820	115,781	445,397
	(837,325)	(338,627)	(887,684)
Value of production	1,107,944	112,326	989,288
	(1,993,505)	(673,554)	(2,080,434)
Crop farm (1/0)	0.555	0.337	0.584
	(0.497)	(0.473)	(0.493)
Operator age	51.6	56.7	52.6
	(10.9)	(13.4)	(11.6)
Observations	20,319	261,146	105,464

Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: The "panel sample" consists of farms surveyed more than once between 1997 and 2013. "All ARMS farms" include all farms surveyed between 1997 and 2013. "All ARMS commercial farms" include all ARMS farms that are categorized "commercial" according to the ERS typology (Hoppe and MacDonald 2013). All values are deflated to 2011 dollars. Values for the panel sample are average values for the two years surveyed. All averages account for yearly sampling weights.

such as pensions and unemployment benefits from both private and public sources, and other off-farm income, such as gifts or bequests.

As enumerated later, farm income and total household income can be negative for some households in some years. Some commonly used measures of volatility, such as the coefficient of variation or the percentage change in income become nonsensical when income (or average income) is negative. In this section, we describe several measures of income volatility that allow for negative income values.

One such measure is the absolute value of the income change between periods, $|y_{it} - y_{is}|$, where y_{is} and y_{it} are the incomes of household i in years s and t. Another easily interpreted measure of income dispersion is the standard deviation of income: $\sqrt{\left(y_{is} - \bar{y}_i\right)^2 + \left(y_{it} - \bar{y}_i\right)^2}$, where $\bar{y}_i$ is average income in the years s and t. While these two measures describe the magnitude of income fluctuations over time, they do not take into account the size of the change relative to expected income. It is likely that a given income shock would have different welfare and behavioral implications depending on a household's expected income. For this reason, it is common to scale measures of income change by average income.

The absolute value of the arc percent change (AAPC) is one such income-scaled measure:

$$AAPC_i = 100 * \left| \frac{y_{it} - y_{is}}{\bar{y}_i} \right|. \tag{1}$$

The arc percentage change is often preferred to the percentage change as a measure of income volatility because the arc percentage change is symmetric regarding increases or decreases in income and it is bounded between -200 and 200 (Dyan, Elmendorf, and Sichel 2012; Hardy and Ziliak 2014). The second factor is particularly important when dealing with a skewed income distribution that includes large changes from year to year. The AAPC is bounded by 0 and 200.

The coefficient of variation (CV) is a second measure of income volatility that is scaled by average income. If the CV is large, then income varies widely relative to the mean, whereas if it is small then income usually falls within a narrow range around the mean. The absolute value of the coefficient of variation (ACV) of income allows for possible negative mean income values:

$$ACV_i = \left| \frac{\sqrt{(y_{is} - \bar{y}_i)^2 + (y_{it} - \bar{y}_i)^2}}{\bar{y}_i} \right|. \tag{2}$$

Unlike the AAPC, the ACV is not bounded. When households have a very small average income, the ACV can be extremely large, which can skew regression parameters.[7] To address this problem, we use the natural logarithm of the ACV as the dependent variable in the regressions. The log transformation reduces the influence of the outliers and makes data conform more closely to the normal distribution.

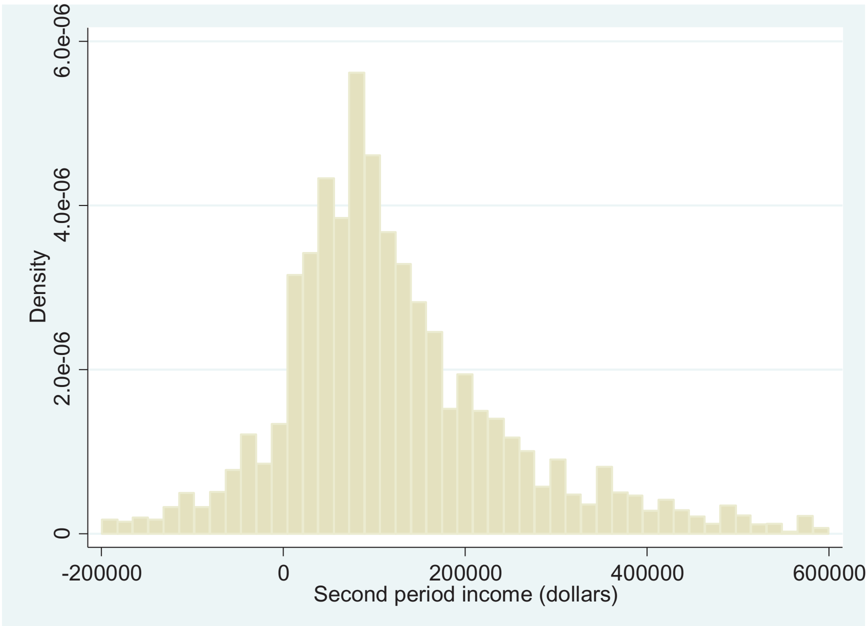
A measure that is commonly used to examine trends in volatility for the broad population of households is the standard deviation across households of the arc percentage change (SDAPC) (Dahl, DeLeire, and Schwabish 2011; Ziliak, Hardy, and Bollinger 2011; Dyan, Elmendorf and Sichel 2012). Unlike the previous measures, the SDAPC does not measure volatility for an individual household, but rather for the sample, or a subsample, at one point in time:

$$SDAPC_t = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(APC_{it} - \overline{APC}_t\right)^2}, \tag{3}$$

where $APC_{it} = \frac{(y_{it} - y_{is})}{0.5 \cdot (|y_{it}| + |y_{is}|)}$ and N is the number of households in the sample.

[7] *For instance, consider a small farm household that earns \$20,000 one year and suffers a loss of \$18,000 the next year. This corresponds with an average income of \$1,000 but a standard deviation of 26,870. The ACV is 26.9, which is unusually large.*

Figure 1 Second period total household income for households with first period total income between $75,000 and $125,000
Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: Positive and negative outliers are truncated in the figure for clarity.



Results

Income Volatility

To illustrate the scale of household income volatility for a typical commercial farm household, consider the distribution of second-period income for households that earned between $75,000 and $125,000 in the first period (figure 1).[8] The figure shows that the average second-period income centers on the average value of first-year income (about $100,000), but varies substantially. In fact, most households earn less than $75,000 or more than $125,000—the initial range of income in the first year. A significant share of households have net incomes less than $0 or more than $200,000 in the second period.

The high volatility of total household income illustrated in figure 1 is driven mainly by farm rather than off-farm income. For the same group of middle-income households (those that earned a total income between $75,000 and $125,000 in the first year), net farm income varies widely in the second period and a substantial share of households experienced negative net farm income (figure 2). In contrast, almost all second-period off-farm income was positive, and the distribution of off-farm income was clustered between $0 and $100,000 (figure 3).

The measures of income volatility defined in the previous section confirm that farm income is much more volatile than off-farm income (table 4, column 1). For the full panel sample, the median absolute change between periods for farm income is $117,693, which is 61% more than the median farm income ($73,144). In contrast, the median absolute change in off-farm

[8] *A total of 2,971 households representing 14.6% of the sample earned income in this range.*

Figure 2 Second period farm income for households with first period total income between \$75,000 and \$125,000
Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: Positive and negative outliers are truncated in the figure for clarity

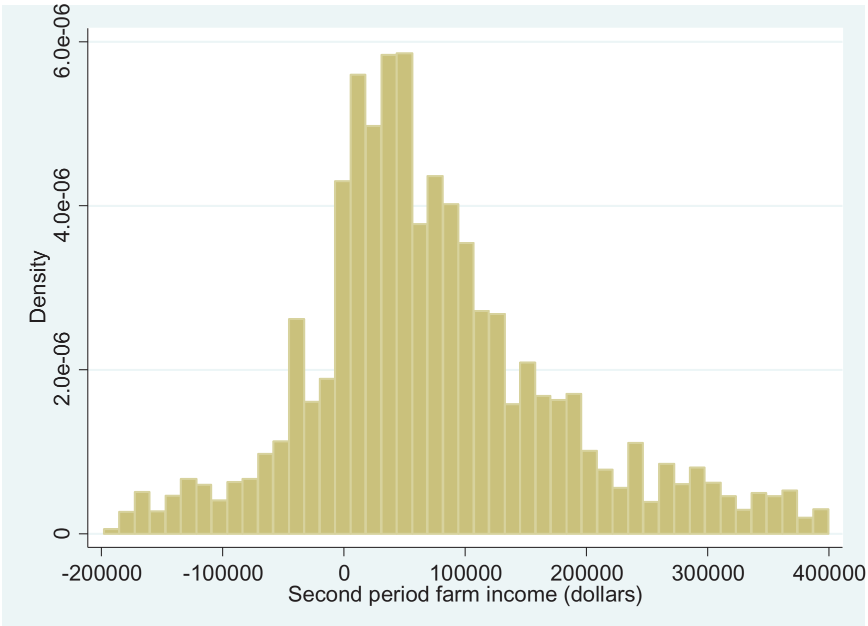
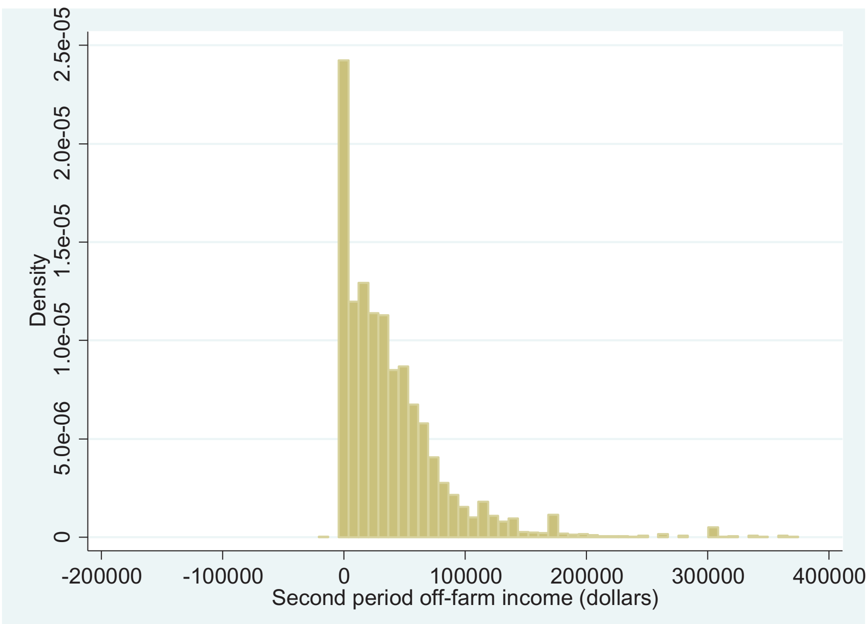


Figure 3 Second period off-farm income for households with first period total income between \$75,000 and \$125,000
Source: Agricultural Resource Management Survey (ARMS), 1997–2013
Note: Positive and negative outliers are truncated in the figure for clarity.



income is \$15,185, which is about half of median off-farm income (\$29,729). While 40% of households in the sample experienced negative farm income in at least one of the two periods, less than one tenth of one percent of the

Table 4 Volatility Measures of Crop, Livestock and All Farms, 1997–2013

	Full sample (Span = 1-5)	95% Confidence Interval for Selected Variables	Predicted value (Span = 1, Midyear = 2005)	Span = 2
Farm Income				
Median	73,144		73,458	69,032
Median absolute change between years	117,693		113,258	111,143
Mean	140,140	[133,848, 146,432]	146,707	142,239
Mean absolute change between years	264,937	[256,625, 273,249]	270,878	274,113
Share negative in at least one year	0.40		.42	0.40
Share negative in both years	0.08		.09	0.08
Mean absolute arc percent change	126.9	[125.5, 128.3]	125.4	126.6
Mean absolute coefficient of variation	1.37	[1.32, 1.41]	1.37	1.34
Std. dev. arc percentage change	143.5		n.a.	143.1
Off-farm Income				
Median	29,729		28,723	30,892
Median absolute change between years	15,185		13,974	15,496
Mean	49,971	[48,071, 51,871]	48,151	50,081
Mean absolute change between years	43,740	[41,647, 45,833]	39,999	43,409
Share negative in at least one year	0.00		0.00	0.00
Share negative in both years	0.00		0.00	0.00
Mean absolute arc percent change	95.9	[94.2, 97.6]	95.4	95.0
Mean absolute coefficient of variation	0.68	[0.67, 0.69]	0.68	0.71
Std. dev. arc percentage change	124.9		n.a.	124.2
Total Household Income				
Median	115,702		115,777	116,554
Median absolute change between years	127,052		119,421	121,397
Mean	190,111	[183,337, 196,885]	194,858	192,320
Mean absolute change between years	279,228	[270,683, 287,774]	283,625	287,786
Share negative in at least one year	0.29		0.29	0.30
Share negative in both years	0.04		0.04	0.04
Mean absolute arc percent change	110.4	[108.8, 112.0]	110.1	110.3

Continued

Table 4 *Continued*

	Full sample (Span = 1-5)	95% Confidence Interval for Selected Variables	Predicted value (Span = 1, Midyear = 2005)	Span = 2
Mean absolute coefficient of variation	1.11	[1.08, 1.15]	1.12	1.16
Std. dev. arc percentage change	131.5		n.a.	131.9
Observations	20,319		20,319	6,967

Source: Agricultural Resource Management Survey (ARMS), 1997–2013. Averages account for sampling weights.
Note: The standard deviation of the arc percentage change is not observed for individual households so is not predicted by the econometric model (column 3). Confidence intervals are created using bootstrapped standard errors.

sample had negative off-farm income in either period. Reflecting the greater variation in income relative to the mean, the AAPC in farm income averaged 127, compared to 96 for off-farm income.[9] Similarly, the ACV of farm income is 1.34 versus 0.72 for off-farm income.

As discussed in the data section, the sample is comprised of pairs of observations surveyed between one and five years apart. It is possible that the measures of income variability change with the time span between observations – presumably a longer span would cause a somewhat larger change in income, and therefore greater measured volatility. Almost all studies of U.S. household income volatility used data collected in consecutive years – that is, with a span equal to one. To better compare our estimates of farm household income volatility to estimates from other studies we adjust our estimates using the following model:

$$y_i = \alpha + \theta Span_i + \gamma Year_i + \epsilon_i, \tag{4}$$

where y_i is a measure of income or income volatility for household i, $Span_i$ is the number of years between surveys for that household, and $Year_i$ is the midpoint year between surveys. Including the span in the regression allows us to predict volatility when the span is one. Including the midpoint year allows us to control for possible volatility trends over time. Since the ARMS survey has more observations in the later years compared to the earlier years (as shown in table 2), if volatility were trending up or down, then the unequal number of surveys by year could influence the estimates.

Column 3 in table 4 presents the predicted values of various income and income volatility measures when the span = 1 and midpoint year = 2005. The predicted values in column 3 are very similar to the unadjusted values in column 1, suggesting that controlling for span and time trend has only a minimal effect on the estimates. We use the results in column 3 where possible to compare with the estimates for all households.

[9]*The absolute arc percent change can be interpreted as the absolute value of the arc percentaage change (which is similar to the percentage change). So a value of 127 means the absolute value of the change from year to year was about 125% larger than the mean value in the two years.*

Another way to demonstrate that the volatility measures are robust to span length is to compute the measures using only one span. Column 4 shows the estimates calculated for the subset of farms that are observed two years apart—the most common gap between observations—comprising 34.2% of the sample. The span = 2 estimates are very similar to the unadjusted and adjusted estimates for the full sample shown in columns 1 and 3.

Farm Households versus All U.S. Households

Our estimates show that commercial farm households have much more volatile income than the typical U.S. household. Using data from the Current Population Survey, Hertz (2006) reports that the median absolute change in U.S. household income between consecutive years was $11,345 in 2003–04, which was approximately 25% of median income at the time. In contrast, the farms in the ARMS panel had a predicted median absolute income change between consecutive years of $119,421, which was 103% of median income (table 4, column 3).

Farm households are also more likely to experience very large income changes than are typical U.S. households. Dahl, DeLeire, and Schwabish (2011) find that about 9% of all U.S. households had income changes of at least 50% between consecutive years. In contrast, we find that among the 85% of households with positive household income in the first year, two-thirds (66%) had a total household income change of at least 50%.[10]

Furthermore, Dynan, Elmendorf, and Sichel (2012) find the standard deviation of the arc percent change of household income averaged about 50% since the mid-1990s using data from the Panel Study of Income Dynamics. Dahl, DeLeire, and Schwabish (2011) find the same measure averaged around 30% using the Survey of Income and Program Participation and Social Security Administration data. These values are substantially below the 131% that we estimate (table 4, column 1), confirming that farm households have much more volatile income than typical households.

While the total household income of commercial farmers is more volatile than for the average U.S. household, the volatility of farm income does not appear to be more volatile than income from nonfarm self-employment. A Congressional Budget Office study (2008) found that the standard deviation of the arc percentage change in self-employment income ranged between 140 and 150 from 1992 to 2003, which is similar in magnitude to the variability of farm income (143).

The higher total income volatility of farm households is driven partly by the fact that farmers receive most of their income from on-farm sources—and, as we discussed above, this income is more volatile than off-farm income. However, there appears to be more to the story: the nonfarm income of farm households is also relatively volatile. For farm households, the standard deviation of the arc percent change of off-farm income is 125%—well above the total income volatility of all households (which is 30% to 50%). Similarly, among the 86% of farm households that reported positive off-farm income, 56% had off-farm income that changed by at least 50% (49% of those surveyed in consecutive periods also had large income changes). This is much higher

[10] *Only farms with positive income in the first period are considered because the percent change is not defined if first period income is negative or zero. This statistic is for all farms. For farms that were surveyed in consecutive years, we find that 58 percent had their income change by at least 50 percent.*

Table 5 Income Volatility by Farm and Operator Characteristics

	Total income		Farm income		Off-farm income	
	Mean	ACV	Mean	ACV	Mean	ACV
Farm asset category						
< $900K	129,275	1.04	82,771	1.39	46,503	0.66
$900K – $1.6M	146,412	1.09	102,065	1.33	44,347	0.66
$1.6M – $3.0M	187,763	1.15	142,067	1.38	45,696	0.68
> $3.0M	347,128	1.23	278,765	1.35	68,363	0.73
Highest education attained (1/0)						
Less than high school diploma	140,019	1.14	103,838	1.58	36,181	0.79
High school	168,515	1.13	128,142	1.34	40,372	0.70
Some college	180,733	1.09	134,880	1.34	45,853	0.66
Four or more years of college	239,472	1.11	169,474	1.39	69,999	0.65
Operator married (period 1)						
No	146,282	1.22	113,269	1.60	33,013	0.88
Yes	195,881	1.10	143,760	1.34	52,121	0.66
Farm Type						
Switched commodities	158,547	1.25	112,289	1.43	46,259	0.70
Cash grains	186,758	1.07	139,210	1.34	47,548	0.63
Rice	162,144	0.98	121,635	1.20	40,508	0.81
Cotton	291,248	1.03	225,533	1.12	65,715	0.68
High value	330,598	1.16	264,100	1.31	66,498	0.79
Other crops	203,165	1.15	157,088	1.30	46,077	0.72
Hogs	182,769	1.11	137,208	1.28	45,561	0.61
Poultry	95,864	0.93	47,537	1.52	48,326	0.62
Dairy	210,814	1.13	178,963	1.28	31,851	0.80
Cattle and general livestock	176,274	1.31	100,899	1.52	75,375	0.64

Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: ACV = Absolute Coefficient of Variation. Means and ACV account for sampling weights. Farm type is assigned based on a contribution of 50% or more to the total value of production.

than the 9% of all households who had their income change by at least 50% (Dahl, DeLeire, and Schwabish 2011). It is possible that farm households have particularly volatile off-farm income because their off-farm labor decisions are influenced by their highly volatile farm income. That is, farm households may make frequent adjustments to their off-farm employment to compensate for the large fluctuations in their farm income (Mishra and Goodwin 1997).

Factors Associated with Income Volatility

Table 5 shows how income and income volatility varies across different types of farm households. In terms of farm size (measured by farm assets) there is a clear positive correlation between farm size and off-farm income and total income volatility. However, there is no obvious relationship between farm size and farm income volatility. Income volatility of all types is lower for better-educated operators. However, this effect diminishes after an operator has some college. Married operators have substantially less off-farm, farm, and total income volatility than non-married operators.

The table also shows income volatility by commodity specialization, which is assigned if a commodity comprises 50% or more to the total value of production in both survey years. Farms that did not specialize in the same commodity category in both years are assigned to the "switched commodities" category. Poultry and cattle farms have the highest farm income volatility, while cotton farmers have the lowest, on average. Hog farmers have the lowest off-farm income volatility while dairy and rice farmers have the highest. In terms of total income volatility, poultry farmers have the lowest, while cattle farms have the highest.

The summary statistics provide information about income volatility for the average farm household with a particular characteristic. However, the statistics do not allow us to isolate the effect of particular farm or operator characteristics on volatility. For example, poultry farms have higher than average farm income volatility. However, poultry farms also have less-educated operators on average, and less well-educated operators have higher average farm income volatility. It is not clear whether the high farm income volatility for poultry farmers is due to the commodity specialization or other factors such as their operator education. To identify how farm and operator characteristics influence farm, off-farm, and total income variability we use a regression of the form:

$$Volatility_i = \alpha + \theta Span_i + \gamma Year_i + \boldsymbol{\beta X_i} + \delta \mathrm{State_i} + \epsilon_\mathrm{i}, \tag{5}$$

where $\boldsymbol{X_i}$ includes exogenous grower and operation characteristics and measures of local economic conditions, and $State_i$ is a state dummy variable that is included to account for soil quality, climate, and other time-invariant regional effects. The parameter γ on the mid-year variable indicates the annual rate of change in volatility.

A few earlier studies have used regression analyses to explore the volatility of farm business income using data from certain U.S. States, Canada, or Europe (e.g., Schurle and Tholstrup 1989; Purdy, Langemeier, and Featherstone 1997; Poon and Weersink 2011; Enjolras et al. 2014). A possible critique of these studies is that they included some regressors that are endogenously determined with income volatility. Potentially endogenous variables include measures of risk mitigation such as government program participation, farm enterprise diversification, borrowing, and off-farm labor participation. These variables are not only likely to affect income risk, but also to be influenced by income risk. For example, farmers who face higher production and income risks (e.g., from pest or weather hazards) are more likely to purchase crop insurance, diversify their production, borrow more, or work more off-farm. As a result, we might observe a positive correlation between income risk and these risk mitigation strategies in a regression, even though the strategies lower risk compared to what it would be otherwise. Therefore, it is impossible to meaningfully interpret the estimated parameters or determine the direction of causality when endogenous variables are included in the regression. For this reason, we include only plausibly exogenous variables that are likely to be determined independently of income risk.

Table 6 presents summary statistics for the variables used in the regression. As shown in the table, the average span between surveys was about 3 years. We use 10 commodity specialization categories, with those that switched specialization between survey years as the missing category. The majority of farms (61%) specialized in crop production. The sample is close to evenly divided among the four farm size (asset) categories. Most

Table 6 Summary of Regression Variables

Variable	Mean	Std. Dev.
Income volatility (Log of Abs. Coeff. of Var.)		
Total	−0.373	1.425
Farm	−0.096	1.422
Off-farm	−0.892	1.251
Mid-year between surveys	2005.5	3.228
Span between surveys	3.111	1.202
Farm Type (categorical)		
Switched commodities	0.119	0.323
Cash grains	0.289	0.453
Rice	0.014	0.119
Cotton	0.028	0.165
High value	0.090	0.287
Other crops	0.068	0.235
Hogs	0.050	0.217
Poultry	0.130	0.337
Dairy	0.123	0.328
Cattle and general livestock	0.089	0.285
Farm asset category		
< \$900K	0.303	0.460
\$900K – \$1.6M	0.259	0.438
\$1.6M – \$3.0M	0.245	0.430
> \$3.0M	0.193	0.394
Highest education attained (1/0)		
Less than high school diploma	0.062	0.242
High school	0.386	0.487
Some college	0.268	0.443
Four or more years of college	0.283	0.451
Operator age	51.56	10.90
Operator Married (period 1)	0.890	0.313
Population Interaction Index Change (2010–2000)	2280	3969
Observations	20,319	

Source: Agricultural Resource Management Survey (ARMS), 1997–2013. Means account for sampling weights.
Note: Farm type is assigned based on a contribution of 50% or more to the total value of production.

operators (94%) completed high school and 28% completed at least four years of college. Operators have an average age of 51.6. About 89% of the operators were married the first year they were surveyed.

We use a population trend measure to characterize local economic conditions.[11] Population trends within the county are measured using the difference in the Population Interaction Index (PII) between 2010 and 2000. The PII is derived from a gravitational model of population density that provides a continuous measure of proximity to nearby population centers (Ribaudo and Johansson 2007).

We use the natural logarithm of the absolute coefficient of variation (ACV) as our main measure of volatility. Using the ACV as the dependent variable produces similar results in terms of parameter significance and

[11] *A local area unemployment rate was also tried, but was not found to be statistically significant, so was dropped from the regression.*

sign, but the logarithm of the ACV permits interpreting the coefficients in terms of percentage change and better fits the data.[12] As a robustness check, we also estimate the model using the natural logarithm of absolute arc percentage change (AAPC) as the dependent variable. Because the AAPC is censored above 200 and below 0, we estimate a Tobit regression model. As a second robustness check, we estimate the model using the subset of observations which are observed two years apart (i.e., span = 2). The alternative specifications produce very similar results to the base specification.[13]

Researchers using ARMS normally account for the sample design in estimating variances using a jackknife method with replicate weights provided by the USDA/NASS. For the panel data this is an unattractive option because the replicate weights are designed for the cross-sectional sample. For this reason, we create sampling weights that are based on the average sampling weight assigned to the farm in each of the two years that it was sampled. We then use the "bsweights" package (Kolenikov 2010) to create 150 boostrap replicate weights, stratified based on the sales class of the operation. For each of our regressions, we use boostrapped standard errors based on the replicate weights.

Regression Results

Holding the other exogenous factors constant, the regression results indicate that specializing in certain commodities for both survey years is associated with significantly less volatile farm income than switching commodity specialization (the missing category; table 7). For example, specializing in rice, cotton, and high value crops was associated with at least 20% less volatile farm income.[14] High value crops (mainly fruits and vegetables) might display lower farm income variability because these crops are often produced under a marketing contract arrangement in which prices are negotiated before harvest, which lowers price risks for the farmer.

Specializing in poultry and dairy production was also associated with lower farm income variability. Poultry is produced almost exclusively under production contracts, which generally eliminates most price risk for the grower. Dairy producers are sheltered from some farm income risk by several federal programs that were functioning during most of the survey period. For example, under the Milk Income Loss Contract Program authorized by the 2002 Farm Bill, payments were made to dairy operations when milk prices fell below a certain level. In addition, the Dairy Product Price Support Program specified support prices for milk, and later (following the 2008 Farm Bill) manufactured milk-based products. Prices were supported by government purchases of these products.

In terms of farm size, larger farms (i.e., farms with more assets) generally earn more farm income and experience larger absolute changes in farm income that do smaller farms. However, as the regression shows, in proportion to average farm income, farm income volatility does not differ

[12]The ACV is not bounded and there are a number of outliers. Taking the natural log of the ACV reduces the influence of outliers and makes the data more normal in shape, thus satisfying the assumptions of an OLS regression.

[13]Results of the robustness checks are available from the authors upon request.

[14]Because the volatility measures are in logarithmic form, the percentage change in the volatility measures given a one unit change in the independent variable is calculated as $100 \cdot (\exp(\beta) - 1)$, where β is the estimated coefficient.

Table 7 Regression Analysis: What Factors Explain Income Variation?

VARIABLES	(1) Total Income	(2) Farm Income	(3) Off-farm Income
Mid-year	−0.0187***	−0.0156***	−0.0180***
	(0.00595)	(0.00546)	(0.00527)
Year span	0.00726	0.00836	0.0284**
Commodity specialization:	(0.0146)	(0.0151)	(0.0134)
Cash Grains	−0.0520	−0.0770	−0.146***
	(0.0555)	(0.0538)	(0.0564)
Rice	−0.244*	−0.304**	−0.0218
	(0.129)	(0.129)	(0.124)
Cotton	−0.177*	−0.438***	−0.130
	(0.104)	(0.0889)	(0.0981)
High-value crops	−0.149**	−0.222***	0.174**
	(0.0639)	(0.0645)	(0.0677)
Other crops	−0.0509	−0.160**	−0.0149
	(0.0736)	(0.0734)	(0.0680)
Hogs	0.0203	−0.0315	−0.228**
	(0.0865)	(0.102)	(0.0897)
Poultry	−0.305***	−0.165**	−0.219***
	(0.0713)	(0.0658)	(0.0624)
Dairy	−0.174***	−0.323***	0.168***
	(0.0658)	(0.0644)	(0.0610)
Other livestock	−7.37e-05	−0.112	−0.164**
Farm assets:	(0.0905)	(0.0809)	(0.0804)
$900,000 - $1.6m	0.0730	−0.0283	0.0262
	(0.0516)	(0.0451)	(0.0449)
$1.6m - $3.0m	0.167***	0.0532	0.108**
	(0.0522)	(0.0499)	(0.0463)
More than $3.0m	0.203***	−0.0136	0.224***
Operator education:	(0.0523)	(0.0461)	(0.0444)
High school	−0.142	−0.0719	−0.239***
	(0.103)	(0.0925)	(0.0770)
Some college	−0.200**	−0.0946	−0.323***
	(0.0996)	(0.0943)	(0.0811)
College or more	−0.239**	−0.0929	−0.392***
Operator age in first year:	(0.102)	(0.0953)	(0.0773)
50-65	−0.0467	−0.0533	0.0254
	(0.0358)	(0.0373)	(0.0349)
>65	0.0282	0.135***	−0.213***
	(0.0508)	(0.0472)	(0.0460)
Operator Married: Year 1	−0.292***	−0.194***	−0.507***
	(0.0537)	(0.0575)	(0.0398)
Population Interaction Change	−7.56e-06**	1.48e-06	−2.67e-06
	(3.85e-06)	(4.37e-06)	(3.85e-06)
Constant	37.88***	31.69***	35.82***
	(11.96)	(10.96)	(10.57)
Observations	20,265	20,243	19,058
R-squared	0.027	0.023	
State FEs	Yes	Yes	Yes

Source: Authors' calculations using data from the Agricultural Resource Management Survey (ARMS).
Note: State-clustered standard errors appear in parentheses. Asterisks indicate the following:
**** = p<0.01, ** = p<0.05, and * = p<0.1).*

significantly across farm sizes. In contrast, the riskiness of off-farm income does increase substantially with farm size: the largest farms (those with at least $2.6 million in assets) have off-farm income volatility that is 25% greater than small farms. It is possible that larger farms, with more assets and higher average incomes, are able to indulge in riskier off-farm investments. Alternatively, these households with large farm businesses are more likely to use the off-farm labor market as a response to farm income shocks rather than as a constant source of income.

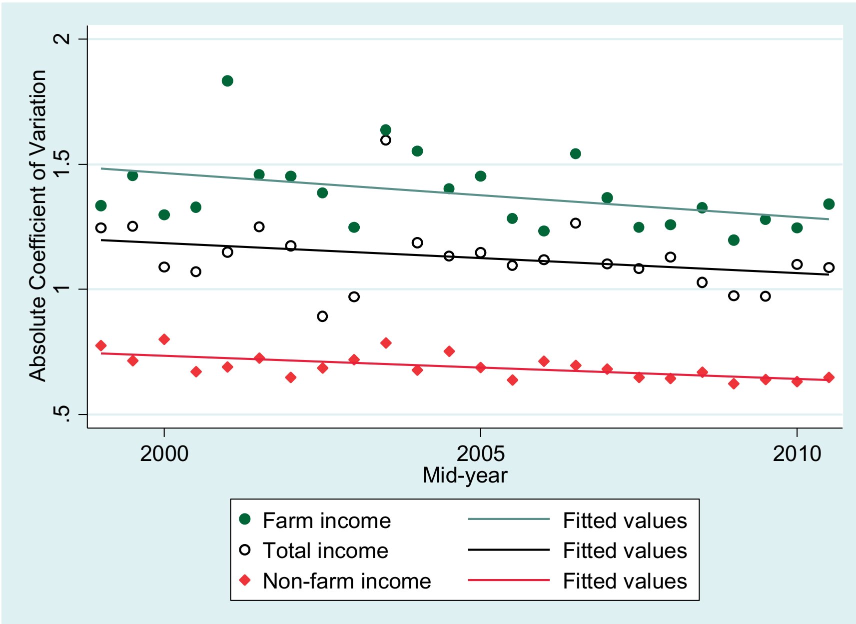
The income sources of farm households differ from all households in ways that can explain the difference in total income volatility. Households operating large farms have a greater share of their total income coming from farm income, which is riskier than off-farm income, and they have more volatile off-farm income. These two factors combine to make total household income more volatile for larger farms compared to smaller farms: households with at least $3.0 million in farm assets have total income volatility that is 22% greater than the smallest farms. The higher volatility means that households operating larger farms are more likely to experience years with negative income despite having higher average income. The probability of having negative household income in at least one of the two observed periods is 17% for the smallest farms compared to 33% for the largest farms.

The finding that larger (and higher average income) farms have more volatile household income contrasts with (mostly) nonfarm households, where studies have consistently found less income volatility among higher-wage earners and higher-income households (Hertz 2006; Dahl, DeLeire, and Schwabish 2011; Moffitt and Gottschalk 2011; Shin and Solon 2011; Hardy and Ziliak 2014).

Results also indicate that off-farm income and total income volatility are substantially lower if the principal operator has more education. Operators with a college degree had total household income volatility that was 27% lower and off-farm income volatility that was 39% lower than those who did not graduate from high school. Operators with some college education had total income that was 22% lower and off-farm income that was 38% lower. Compared to having only a high school diploma, having four years of college reduced total income volatility by 10% and off-farm income volatility by 16%. Higher income volatility for less educated farmers is consistent with findings for all households (Ziliak, Hardy, and Bollinger 2011; Dynan, Elmendorf, and Sichel 2012). Individuals with less education may have more volatile income because they have less employment security. This study covers a period that spanned the Great Recession—during which less-educated workers faced larger increases in unemployment (and hence, negative off-farm income shocks) than better-educated workers (Hout and Cumberworth 2012).

Operators older than 65 had farm income volatility that was 14% higher than operators younger than 50, holding other factors constant. On the other hand, those over 65 had off-farm income volatility that was 23% lower than those under 50; their off-farm income might be less volatile because older farmers are more likely to be retired from off-farm occupations, and to qualify for stable retirement annuities and Social Security payments. Older farmers' farm income might be more volatile because of large negative changes in farm income as they transition out of farm work and into retirement. Alternatively, farm income risk might be higher for older farmers because their more stable off-farm income allows them to take more risks on-farm.

Figure 4 Trends in the absolute coefficient of variation of farm, off-farm and total income
Source: Agricultural Resource Management Survey (ARMS), 1997–2013.
Note: Each data point represents the average income volatility for each survey midpoint in the sample. The survey midpoint is defined as (year 2 – year 1)/2.



Marital status had a large effect on income volatility. Being married was associated with a 66% decrease in off-farm income volatility and a 34% decrease in total household income volatility. Compared to single individuals, married couples likely have a larger share of household labor earning income from less volatile off-farm sources, which reduces total income variability.

The local economic conditions, as measured by the population interaction index, had a significant influence on total household income volatility. Living in an area with an increasing/decreasing population density was associated with lower/higher levels of total income volatility. The finding that farmers who reside in counties with declining populations have more volatile income suggests that programs aimed at supporting the rural economy may also be effective at decreasing income volatility for farm households—in addition to traditional farm policies aimed at reducing farm income risk.

Trends in Income Volatility

The negative and significant coefficients on the mid-year variable (the midpoint between the two years the farm was surveyed) indicates that the volatility of farm income declined about 1.6% per year, while total income and off-farm income declined by 1.8% per year. These regression results, which control for changes in the composition of the panel sample over time are also evident in a plot of farm, off-farm and total income volatility (ACV) over the span of the dataset (figure 4). Because each observation is a single measure of income volatility between two years, we use the midpoint of those two years as the date on the graphs. Hence, each point represents the average ACV for all the farms at that midpoint. The figure also shows an estimated linear trend for each income component. The graph shows a declining trend in volatility for all income types.

Studies of the volatility trends in the United States find more income variability in the 1980s than in the 1970s, and flat trends in variability during the 1980s and early 1990s—though these studies differ in their findings in more recent periods (Congressional Budget Office 2008; Dahl, DeLeire, and Schwabish 2011; Moffitt and Gottschalk 2011; Shin and Solon 2011; Ziliak, Hardy, and Bollinger 2011; Dynan, Elmendorf, and Sichel 2012). However, because farms are influenced by different economic conditions and policies than nonfarm households, it is plausible that farm households would have experienced different trends in income volatility.

It is possible that farm policies have been increasingly effective in reducing the income volatility of farmers over the study period because of increasing resources being directed towards the federal crop insurance program. Over this period the number of acres enrolled beyond the most basic catastrophic coverage level increased from 117 million acres in 1996 to 280 million acres in 2013 and federal subsidies to purchase insurance increased from $720 million to $6.6 billion in constant 2009 dollars over the same period (RMA 2015).

To test the hypothesis that farm policies have contributed to the decline in income volatility, we create a new category of farms that specialize in program crops—the crops that receive the bulk of farm payments and federal crop insurance subsidies. Farms in the "program crops" include those specializing in "cash grains," rice, and cotton. This category does not include farm specializing in any of the livestock commodities, high value crops (fruits and vegetables), or "other crops." We interact the program crop indicator with the time (mid-year) variable to see if volatility changed over time at a different rate for this group. Results show that program crop producers saw their farm income volatility decline about 2% per year more rapidly than other types of farms—which saw no statistically significant decline in volatility over time (table 8). For off-farm income (and total income) the negative trends in volatility were not associated with specializing in program crops.

The finding that program crop producers have lower farm income volatility but not lower off-farm volatility is consistent with the hypothesis that changes in federal farm programs contributed to lower farm income volatility over time. However, there are other possible factors that could have contributed this trend. For example, it is possible that changes in farming technologies and practices used on program crops (e.g., increased use of genetically engineered crops, no-till farming, GPS technologies, precision agriculture, irrigation, etc.) reduced yield variation over time.

Young Beginning Farmers

Finally, we consider the effect of farming experience on income volatility. It is plausible that farm income volatility is higher for new farmers, and that over time farmers learn techniques that allow them to mitigate their income risks. To test whether beginning farmers have more variable income, we include an indicator for whether a farmer has no more than 10 consecutive years of farming experience (the USDA definition of a beginning farmer) in the main regression model. We find that the coefficient on the indicator

Table 8 Regression with Program Crop Indicator Interacted with Time Trend

VARIABLES	(1) Total Income	(2) Farm Income	(3) Off-farm Income
Mid-year	−0.0160**	−0.00850	−0.0173***
	(0.00655)	(0.00678)	(0.00633)
Year span	0.00756	0.00912	0.0285**
	(0.0146)	(0.0151)	(0.0135)
Program crops * Mid-year	**-0.00798**	**-0.0209***	**-0.00190**
Commodity specialization:	**(0.0137)**	**(0.0122)**	**(0.0111)**
Cash Grains	15.96	41.91*	3.674
	(27.45)	(24.57)	(22.25)
Rice	15.76	41.66*	3.797
	(27.46)	(24.57)	(22.24)
Cotton	15.83	41.53*	3.688
	(27.42)	(24.56)	(22.25)
High-value crops	−0.150**	−0.225***	0.174**
	(0.0638)	(0.0647)	(0.0678)
Other crops	−0.0509	−0.160**	−0.0148
	(0.0736)	(0.0735)	(0.0679)
Hogs	0.0193	−0.0341	−0.228**
	(0.0863)	(0.102)	(0.0896)
Poultry	−0.305***	−0.165**	−0.219***
	(0.0714)	(0.0661)	(0.0624)
Dairy	−0.173***	−0.322***	0.168***
	(0.0659)	(0.0646)	(0.0609)
Other livestock	0.000156	−0.111	−0.164**
Farm assets:	(0.0905)	(0.0811)	(0.0803)
$900,000 - $1.6m	0.0721	−0.0307	0.0260
	(0.0514)	(0.0451)	(0.0450)
$1.6m - $3.0m	0.167***	0.0524	0.108**
	(0.0520)	(0.0499)	(0.0465)
More than $3.0m	0.202***	−0.0145	0.224***
Operator education:	(0.0521)	(0.0461)	(0.0444)
High school	−0.142	−0.0716	−0.239***
	(0.102)	(0.0916)	(0.0770)
Some college	−0.200**	−0.0937	−0.323***
	(0.0992)	(0.0936)	(0.0812)
College or more	−0.239**	−0.0924	−0.391***
Operator age in first year:	(0.101)	(0.0945)	(0.0773)
50-65	−0.0472	−0.0546	0.0253
	(0.0356)	(0.0372)	(0.0350)
>65	0.0280	0.135***	−0.213***
	(0.0508)	(0.0472)	(0.0460)
Operator Married: Year 1	−0.293***	−0.197***	−0.507***
	(0.0536)	(0.0574)	(0.0401)
Population Interaction Change	−7.52e-06*	1.58e-06	−2.67e-06
	(3.84e-06)	(4.39e-06)	(3.84e-06)
Constant	32.44**	17.46	34.50***
	(13.18)	(13.58)	(12.71)
Observations	20,265	20,243	19,058
R-squared	0.027	0.023	
State Fes	Yes	Yes	Yes

Source: Authors' calculations using data from the Agricultural Resource Management Survey (ARMS).
Note: State-clustered standard errors appear in parentheses. Asterisks indicate the following:
**** = $p<0.01$, ** = $p<0.05$, and * = $p<0.1$).*

variable is not statistically significantly different from zero, indicating that beginning farmers as a group do not have more volatile income than more experienced farmers, after controlling for age and other characteristics.[15]

However, beginning farmers are a diverse group. If we focus instead on young beginning farmers (those under age 50) we find a very different result. We find that being a young and beginning farmer is associated with a 36% increase in farm income volatility and a 20% increase in total income volatility after controlling for other operator and operation characteristics. We find no statistically significant difference for off-farm income volatility.

The USDA has a number of programs that target beginning farmers, including Farm Service Agency (FSA) "Beginning Farmer" direct and guaranteed loan programs, which are aimed, in part, at helping beginning farmers to start or expand their operations. The finding that young beginning farmers have particularly variable income could serve as additional justification for federal loan program support for beginning farmers.

Conclusion

This study used a newly-created panel dataset drawn from the 1997 to 2013 Agricultural Resource Management Survey to provide the first national estimates of income volatility for commercial farm households. Because each household in the sample is observed at least twice, the data allowed us to obtain a more accurate measure of household income fluctuations than would be possible using cross-sectional or aggregate income data.

The data show that commercial farm households have much more variable household income than do typical U.S. households. The median change in total income between consecutive years was about eight times larger for the farm households than the typical U.S. household. The household income for farmers is highly volatile mainly because farm income varies much more than off-farm income—though the variability of farm income is comparable to that of the self-employment income of non-farm households.

Recent decades have seen a shift in agricultural spending towards programs that reduce farm income risk. This shift includes increases in federal subsidies for crop insurance that resulted in increases in coverage and acres enrolled. In more recent years, crop insurance programs have expanded to non-traditional program crops and livestock. In addition, the 2014 Farm Act ended fixed annual payments to producers based on historical production, and created new programs tied to annual or multi-year fluctuations in prices, yields, or revenues. Policymakers seeking to further expand the farm safety net could benefit from information about the types of producers who are most vulnerable to household income risk.

This study identified some farm household characteristics associated with greater household income variability. In particular, we found that income volatility increases with farm size—unlike for typical U.S. household for which income volatility declines with average income. Total household income is more volatile on larger farms because operators of larger farms derive a greater share of household income from the farm, and because they have more volatile off-farm income. We also found that household income

[15] *The beginning farmer variable has been generated by ERS only since 2005, so the sample used in the regression only includes 8,702 observations. Results are not shown in table 8, but are available from authors upon request.*

is more volatile when the principal operator has less education, is unmarried, or is a young and beginning farmer.

Local economic conditions also appear to influence income volatility: a higher local population density growth rate decreases total income volatility. This suggests that, in addition to traditional risk mitigation farm policies, economic development programs aimed at depressed areas of the rural economy may be effective at reducing income volatility for farm households.

The study also shed light on recent trends in farm income volatility. Results indicate that the volatility of farm income declined about 1.6% per year, while total income and off-farm income declined by 1.8% per year between 1997 and 2013. We also find that those specializing in program crops (the commodities associated with the bulk of agricultural program payments) saw a significantly greater decline in volatility than those not specializing in program crops. These results are consistent with the hypothesis that the shift in federal spending toward risk-mitigating agricultural policies has lowered farm income variability. However, there are other possible factors, such as changes in farming technologies that could have contributed to this trend.

The results illustrate the magnitude of the temporal income fluctuations experienced by commercial-scale farm households. Agricultural programs play an important and valuable role in helping farmers cope with these fluctuations. While income volatility appears to have declined over the last two decades, the paper demonstrates that even with increased spending on risk-mitigating agricultural programs, most commercial farm households continue to face substantial income risk.

References

Cameron, S., and J. Tracy. 1998. *Earnings Variability in the United States: An Examination Using Matched-CPS Data*. Unpublished paper, Federal Reserve Bank of New York.

Congressional Budget Office. 2008. Recent Trends in the Variability of Individual Earnings and Household. Available at: http://www.cbo.gov/publication/41714.

Dahl, M., T. DeLeire, and J. Schwabish. 2011. Estimates of Year-to-Year Volatility in Earnings and in Household Incomes from Administrative, Survey, and Matched Data. *Journal of Human Resources* 46 (4): 750–74.

Dynan, K., D. Elmendorf, and D. Sichel. 2012. The Evolution of Household Income Volatility. *The B.E. Journal of Economic Analysis and Policy* 12 (2): 1–40.

Enjolras, G., F. Capitanio, M. Aubert, and F. Adinolfi. 2014. Direct Payments, Crop Insurance and the Volatility of Farm Income. Some Evidence in France and in Italy. *New Medit: A Mediterranean Journal of Economics, Agriculture and Environment* 13 (1): 31–40.

Gottschalk, P., and R. Moffitt. 1994. The Growth of Earnings Instability in the U.S. Labor Market. *Brookings Papers on Economic Activity* 2: 217–72.

Haider, S. 2001. Earnings Instability and Earnings Inequality of Males in the United States, 1967-1991. *Journal of Labor Economics* 19: 799–836.

Hardy, B., and J. Ziliak. 2014. Decomposing Trends in Income Volatility: The "Wild Ride" at the Top and Bottom. *Economic Inquiry* 52 (1): 459–76.

Hertz, T. 2006. *Understanding Mobility in America.* The Center for American Progress. Discussion Paper.

Hoppe, R., and J. MacDonald. 2013. *Updating the ERS Farm Typology*. Washington DC: U.S. Department of Agriculture, Economic Information Bulletin No. EIB-110.

Hout, M., and E. Cumberworth. 2012. *The Labor Force and the Great Recession.* Stanford, CA: The Russel Sage Foundation and the Stanford Center on Poverty and Inequality.

Kolenikov, S. 2010. Resampling Variance Estimation for Complex Survey Data. *Stata Journal* 10 (2): 165–99.

Mishra, A., and H. El-Osta. 2001. A Temporal Comparison of Sources of Variability in Farm Household Income. *Agricultural Finance Review* 61 (2): 181–98.

Mishra, A., and B. Goodwin. 1997. Farm Income Variability and the Supply of off-Farm Labor. *American Journal of Agricultural Economics* 79 (8): 880–7.

Mishra, A., and C. Sandretto. 2002. Stability of Farm Income and the Role of Nonfarm Income in US Agriculture. *Review of Agricultural Economics* 24 (1): 208–21.

Mishra, A., H. El-Osta, M. Morehart, J. Johnson, and J. Hopkins. 2002. *Income, Wealth, and the Economic Well-Being of Farm Households.* Washington DC: U.S. Department of Agriculture, Economic Research Service, Agricultural Economic Report No. 812.

Moffitt, R., and P. Gottschalk. 2011. *Trends in the Transitory Variance of Male Earnings in the US, 1970–2004*. Working papers, The Johns Hopkins University, Department of Economics, No. 578.

Poon, K., and A. Weersink. 2011. Factors Affecting Variability in Farm and Off-farm Income. *Agricultural Finance Review* 71 (3): 379–97.

Purdy, B., M. Langemeier, and A. Featherstone. 1997. Financial Performance, Risk, and Specialization. *Journal of Agricultural and Applied Economics* 27 (1): 149–61.

Ribaudo, M., and R. Johansson. 2007. Nutrient Management Use at the Rural-Urban Fringe: Does Demand for Environmental Quality Play a Role? *Review of Agricultural Economics* 29: 689–99.

Schurle, B., and M. Tholstrup. 1989. Farm Characteristics and Business Risk in Production Agriculture. *North Central Journal of Agricultural Economics* 11 (2): 183–8.

Shin, D., and G. Solon. 2011. Trends in Men's Earnings Volatility: What Does the Panel Study of Income Dynamics Show? *Journal of Public Economics* 95 (7): 973–82.

Thompson, S., P.M. Schmitz, N. Iwai, and B. Goodwin. 2004. The Real Rate of Protection: The Income and Insurance Effects of Agricultural Policy. *Applied Economics* 36 (16): 1851–8.

United States Department of Agriculture (USDA), Economic Research Service (ERS). 2015a. ARMS Farm Financial and Crop Production Practices. Available at: http://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices.aspx (accessed May 11, 2015).

——. 2015b. Farm Household Well-being: Income and Wealth in Context. Available at: http://www.ers.usda.gov/topics/farm-economy/farm-household-well-being/income-and-wealth-in-context.aspx (accessed May 19, 2015).

——. 2016. Projected Spending under the 2014 Farm Bill. Available at: http://www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/projected-spending-under-the-2014-farm-bill.aspx (accessed June 3, 2016).

U.S. Department of Agriculture, Risk Management Agency (RMA). 2015. Summary of Business. Available at: http://www.rma.usda.gov/data/sob.html (accessed December 1, 2015).

Ziliak, J., B. Hardy, and C. Bollinger. 2011. Earnings Volatility in America: Evidence from Matched CPS. *Labour Economics* 18 (6): 742–54.

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Farm size and productivity growth in the United States Corn Belt[☆]

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ABSTRACT

In recent decades, agricultural production in the U.S. has continued to shift to large-scale operations, raising concerns about the economic viability of small and midsized farms. To understand whether economies of size provided an incentive for the consolidation of production, the study estimates the total factor productivity (TFP) of five size classes of grain-producing farms in the U.S. Heartland (Corn Belt) region. Using quinquennial Agricultural Census data from 1982 to 2012 the study also compares TFP growth rates across farm sizes to gain insight into whether observed productivity differences are likely to persist. The finding of a strong positive relationship between farm size and TFP suggests that consolidation of production has contributed to recent aggregate productivity growth in the crop sector. The study estimates the extent to which sectoral productivity growth can be attributed to structural change versus other factors including technological change. The study also explores some tradeoffs associated with policies that raise the productivity of small versus large farms.

1. Introduction

Over the past several decades, there have been pronounced structural changes in the U.S. farm sector – with production shifting steadily to larger operations. Between 1982 and 2007, the midpoint farm size – the size at which half of all land is on bigger farms and half is on smaller farms – almost doubled from 589 to 1105 acres (MacDonald et al., 2013). At the same time, the midpoint acreage more than doubled in each of the five major field crops: corn, cotton, rice, soybeans, and wheat. Additionally, the share of output from farms with sales of at least $1 million increased from less than 30% in 1987 to over 60% in 2007 (Sumner, 2014).

The shift in production to large farms has raised questions about the economic viability of small and mid-sized producers, and the rural communities that depend on these farm households. These and other concerns have helped spur Federal efforts to target resources toward smaller-scale operations through loan, risk management, marketing, and educational programs (USDA, 2017). The extent to which farming is characterized by economies of size – that is, how much average unit costs decrease as farm size increases – is likely to influence the rate and extent of future consolidation.[1] The first objective of this study is to estimate the total factor productivity (TFP) and unit costs of crop farms of different sizes to understand how productivity and costs vary. This analysis focuses on operations located in the U.S. Heartland (Corn Belt) region that specialize in major field crops.

To gain further insight into the long-run economic viability of small farms, the study also estimates how productivity has changed over time for crop farms of different sizes. It is possible that some recent technological advances (e.g., very large combine harvesters, precision agriculture technologies, improved seed varieties) have raised the productivity of larger operations more than smaller operations. This has implications for whether small farms can persist as viable economic units. Economies of size give large-scale operations a competitive advantage – allowing production at a lower unit cost. If new technological advances favor larger operations, economies of size will increase over time and likely hasten the demise of small family farms. On the other hand, if small farms can increase productivity at a faster rate than large farms, it may be possible to reduce smaller farms' competitive disadvantage and potentially slow or even reverse the consolidation of production. This study is the first to inform this issue by estimating long-run trends in productivity for crop farms of different sizes.

The second objective of this study is to estimate how much of the

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[1] Economies of size is defined by how average (unit) costs change when production increases. More precisely, a firm is said to display economies of size if a one percent increase in output results in a less than one percent increase in average costs. Economies of scale – a closely related to but distinct concept – is defined by how output changes when all inputs are increased in the same proportion. That is, a firm is said to display increasing returns to scale if a one percent increase in all inputs results in a more than one percent increase in output. The concepts are closely related as a cost-minimizing firm exhibits increasing returns to scale if and only if it simultaneously exhibits increasing returns to size (Chambers, 1988, pp. 21–77).

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past aggregate productivity growth can be attributed to structural change (changes in the farm size distribution) versus other factors, including technological change. The recent consolidation of agricultural production has coincided with substantial growth in agricultural productivity: between 1982 and 2012, aggregate TFP increased by 46% – an average annual growth rate of about 1.3% (ERS-USDA (2017)). In explaining the drivers of this productivity growth, most research has focused on technical progress and the role of research and development in promoting technological advances (e.g., Wang et al., 2015; Alston et al., 2010). Little research has examined the contribution of structural change to aggregate productivity growth. If large farms are more productive than smaller farms, as we find in this study, the widespread shift in production towards larger farms could explain a portion of the aggregate productivity growth observed over the past several decades (Huffman and Evenson, 2001). Additionally, understanding the extent to which structural change has explained past productivity growth can shed light on future productivity potential. If the scope for further consolidation of production is now less that it was in the past – because most output is now produced by large farms – then aggregate TFP growth will likely slow in the years ahead unless the rate of technological progress increases.

The third objective of this study is to better understand the relationship between farm size and aggregate productivity growth. The paper develops a new method for estimating aggregate agricultural productivity growth based on the share of production of farms in different size categories, shifts in the distribution of production across farms of different sizes, and changes in the productivity of different sized operations. This allows us to estimate how targeted policies that raise the productivity of farms of a particular size would affect aggregate TFP growth. Results show that targeting small operations would result in much less aggregate productivity growth than similar policies targeting larger operations, mainly because larger farms had higher average sales shares. However, the relative cost-effectiveness of targeted policies, in terms of raising aggregate productivity growth, depends on whether the policy costs are proportional to farm output or the number of farms targeted.

2. Methodology

2.1. Empirical framework

There are two main approaches that can be used to compare the productivity *change over time* of farms of a similar size. If panel data were available, one approach is to assign farms to time-invariant size categories – for example, according to a farm's initial size. Calculating TFP change for each farm would allow for a straightforward comparison of average productivity change across farm size categories. If stochastic production function or data envelope analyses were performed, it would be possible to disaggregate TFP change for each size category into technical change, and technical and scale efficiency change (Färe et al., 1994; Orea, 2002).

This approach has significant shortcomings if a substantial portion of farms transition between size categories over the study period: e.g., some small farms become large and some large become small. Using a sales-based farm size measure, Burns and Kuhns (2016) showed that over five years about 42% of midsize farms transitioned into either small or large farms. They also report five-year transition rates for small and large farms ranging between 21% and 33%. When farm size is fluid, as is likely the case over long periods of time, placing farms in time-invariant categories does not permit a valid comparison of the productivity growth of similarly-sized operations.

Another drawback of this approach, because it relies on panel data, is the potential for sample attrition bias. U.S. crop farms are characterized by five-year attrition rates of about 35–50%, depending on the size of the operation, crop specialization, and operator's age, among other factors (Key and Roberts, 2006).[2] Hence, only a fraction of farms would continue to be observed over a long period, such as the 30-year span considered in this analysis. The farms that remain in business over a long period would likely be very different from the population as a whole – and would have different levels of productivity. Hence, assertions about the population as whole from a sample of surviving farms could suffer from sample attrition bias unless this can be adequately addressed by the empirical model.

The second main approach for making productivity growth comparisons across farm size is to categorize observations by size in each year. This cohort approach can use repeated cross-section or panel data to estimate changes in productivity by farm size groups (Morrison Paul et al., 2004). If the surveys are representative in each period, this approach is not vulnerable to sample attrition bias.

The drawback to this cohort approach is that the farm size categories are fixed, so estimates of scale efficiency change for the farms in each size category will be close to zero (except, perhaps, for the largest farm size category, which typically is unbounded from above). Hence, this approach mostly ignores an important source of aggregate productivity growth: economies of size resulting from a shift in the farm size distribution.

To illustrate the limitation of the cohort approach consider a simple example where there are two farm size categories, small and large, and size economies such that small farms have a TFP index value of 1 and large farms have a TFP of 2. Also assume for simplicity that there is no technical change over the study period, but there is a shift in production from small to large farms. If initially 50% of output is produced by each type of farm, then aggregate TFP in the first period is 1.5 ($=0.50\cdot 1 + 0.50\cdot 2$). If production shifts so that in the second period small farms produce 25% of output and large farms produce 75%, then aggregate productivity increases to 1.75 ($=0.25\cdot 1 + 0.75\cdot 2$). Because there was no technical change, a cohort analysis that compared the productivity change of farms of the same size would estimate zero productivity growth for small and large farms, even though aggregate productivity increased substantially. Hence simply comparing the productivity of farms in the same size category does not reveal the contribution of increasing farm size to aggregate productivity growth.

In this study, we develop a framework for estimating the contribution of structural change to aggregate productivity growth using cohort data. Let the aggregate TFP in any period be approximated by the sales-weighted average TFP of S size categories:

$$TFP = \theta_1\cdot TFP_1 + \theta_2\cdot TFP_2 ... + \theta_s\cdot TFP_s ... + \theta_S\cdot TFP_S, \tag{1}$$

where θ_s is the share of total sales produced by farms in category s and is the average TFP of farms in category s. It follows that the change in the aggregate TFP between two periods is:

$$\begin{aligned}\Delta TFP = {} & (\Delta\theta_1\cdot\overline{TFP}_1 + \Delta\theta_2\cdot\overline{TFP}_2 ... + \Delta\theta_s\cdot\overline{TFP}_s ... + \Delta\theta_S\cdot\overline{TFP}_S)\\ & + (\Delta TFP_1\cdot\bar{\theta}_1 + \Delta TFP_2\cdot\bar{\theta}_2 ... + \Delta TFP_s\cdot\bar{\theta}_s ... + \Delta TFP_S\cdot\bar{\theta}_S),\end{aligned} \tag{2}$$

where Δ indicates the change between periods and the overbar represents the average of the two periods. The first term in parentheses is the contribution to aggregate TFP change from the change in the farm size distribution. The second term in parentheses is the contribution to aggregate TFP from the change in TFP from farms within each size category, where $\Delta TFP_s\cdot\bar{\theta}_s$ is the contribution from the TFP change of farms in size category s.

Note that the change in TFP for each size category, ΔTFP_s, could be decomposed into changes in scale efficiency, technical efficiency and technical change. However, since the size categories are fixed, scale

[2] Attrition rates are high in studies that use Census of Agriculture data in part because farms can only be tracked over time with an operator identification number. When an operator retires from farming and sells his farm business or passes it on to his children the operator ID will often change and this will be recorded as a farm exit. Additionally, the attrition rate is high because farmers who do not respond to the Census will be classified as having exited.

efficiency change will be negligible, except perhaps for the largest category. To keep the analysis simple, and to focus attention of the importance of changes in the size distribution, we do not disaggregate TFP change for each category.

In this study, we measure TFP using a Fisher index. A Fisher TFP index is a measure of outputs produced per unit of inputs, with prices used to weight the outputs and inputs. To compare TFP over time the weights (prices) should remain fixed in an index. The Laspeyres TFP index uses the initial year prices (t = 1) as weights: $TFP_{Lt} = \sum_{m=1}^{M} p_{m1}y_{mt}/\sum_{k=1}^{K} w_{k1}x_{kt}$. The Paasche index uses the final year prices (t = T) as weights: $TFP_{Pt} = \sum_{m=1}^{M} p_{mT}y_{mt}/\sum_{k=1}^{K} w_{kT}x_{kt}$. The Fisher index, is defined as the geometric mean of the Laspeyres and Paasche indexes ($TFP_{Ft} = \sqrt{TFP_{Lt}\cdot TFP_{Pt}}$). The Fisher index numerically approximates and has similar theoretical properties to the Törnqvist index, but has the advantage over the Törnqvist index in this application of being defined for zero-quantities (Diewert, 1978; Dumagan, 2002).

2.2. Defining farm size

An important consideration in measuring the relationship between farm size and productivity is how to measure farm size. The quantity produced, or when considering farms that produce more than one output, the value of sales, are commonly used to define farm size and to create farm size categories. However, it has long been recognized that using output or sales to define size may lead to a spurious correlation between farm size and productivity (Stigler, 1946). Correlation results because output, and therefore also sales, varies a lot from year-to-year and across farms due to random weather shocks, pests, etc. A farm having an unusually good (bad) harvest will have unusually high (low) sales and therefore unusually high (low) productivity. Hence sales and productivity may be correlated even if there is no difference in the underlying technology.[3]

Because this study focuses on crop farms, harvested acres are used to measure farm size. In contrast to sales, the amount of land farmed does not vary a lot from year-to-year due to random yield shocks (except in extreme cases of crop failure, crop acreage is determined before yields are realized). Because land is an input – and thus inversely correlated to TFP – errors in measuring land could cause a spurious negative correlation between size and productivity (Benjamin, 1995; Carletto et al., 2013). However, in the U.S., crop acreage is generally accurately measured and is well known by the farmer, so measurement error is likely small.[4]

3. Data

Data for study are drawn from the quinquennial Agriculture Censuses conducted from 1982 to 2012. The Census is administered by the USDA National Agriculture Statistics Service with the aim of collecting information from all agricultural operations that produce, or would normally produce and sell, at least $1000 of agricultural products per year. To create a homogeneous sample and to reduce the influence of climate, soil and other regional effects, observations are limited to the "Heartland" farm production region. This region is defined by the USDA and consists of a set of contiguous counties, including all of Iowa, Illinois, and Indiana, and parts of Minnesota, South Dakota, Nebraska, Missouri, Kentucky, and Ohio (Heimlich et al., 2000). The Heartland region contains 22% of all U.S. farms and 27% of cropland and produces 23% of U.S. farm output. To further increase the homogeneity of the sample we only include farms specializing in corn (for grain), wheat, soybeans, sorghum (for grain), barley, and oats.[5] Specialization is defined as having at least 90% of sales and 90% of harvested acres in these crops. This eliminates livestock operations and farms that grow other crops that might have substantially different production technologies.[6]

Outputs include the observed quantities produced of the six field crops listed above plus "other outputs", which is the residual value of production (total production minus the value of the six major crops). To weight the outputs in the Fisher index we use each crop's average annual price corresponding to the year of the Census (1982–2012). Crop prices are from the USDA National Agricultural Statistics service (NASS).

Inputs include land, labor, machinery, and other variable inputs. Land is the reported total acres harvested on the farm. Labor expenses include the costs of hired and contract labor plus the estimated opportunity cost of the operator's labor and other unpaid labor, including family labor. Hired and contract labor expenses are collected by the Census. To estimate the opportunity cost of the operator's labor, we first estimate the number of hours the operator worked on-farm by subtracting the number of days that the operator reported working off-farm from 240 days (full time work). The estimated on-farm work days are then multiplied by a daily wage rate based on the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey. The Census does not collect information about non-operator household labor or other unpaid labor so this is estimated using data from the Agricultural Resource Management Survey (ARMS). Using a sample from ARMS with similar characteristics, we regress unpaid labor on operator labor and measures of farm size and then use the estimated parameters to predict unpaid labor for the Census sample (see Appendix A for details). Unpaid labor is valued using the same wage as the operator.[7]

Machinery expenses are based on the reported value of owned machinery and equipment used on-farm plus machinery and equipment rental expenses. The Census collects information on equipment rental expenses and the value of machinery used on farm. The value of machinery that is used on-farm is converted to an annual expense rate using a capitalization value of 0.15. Other variable input expenses include the reported amount paid for fertilizer, chemicals, fuel, utilities and seeds.

To calculate the Fisher index, input expenses (labor, machinery and other inputs) are converted to a quantity indexes, by dividing by an appropriate input price index. For labor we use the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey; for machinery, the NASS Prices Paid Index for

[3] This can be a problem even when farms are placed in discrete size categories. For example, consider two farms with identical technologies that use the same inputs and that would normally produce at a level near the size category cutoff. Suppose one farm experiences good weather and hence high sales (and high productivity) and is therefore categorized as a "large" farm; the other experiences bad weather and hence low sales (and low productivity) and is placed in the "small" size category. The data would seem to indicate a positive correlation between size and productivity even though there is, in fact, no difference in the technologies between the differently-sized operations.

[4] Planted acres would likely be less correlated to yields than harvested acres, but information on planted acres is not available. Land value might be a better measure of farm size since than acreage. However, land value is poorly measured in the Census, which introduces a negative spurious correlation between size and productivity. Similarly, the total value of productive assets might be preferable to acreage as a measure of farm size. However, asset value is also poorly measured because it is difficult for farmers to estimate and because non-response rates tend to be high on questions about assets.

[5] These are all the main crops grown in the Heartland region, except for hay, which is not included in the analysis because it includes several plant species that are not identified in the Census – making it impossible to accurately assign a price. Corn and sorghum that is grown for silage or greenchop are not included among the major outputs because the quantity produced is less accurately measured than when grown for grain.

[6] Inconsistent Census data on livestock inputs is another reason livestock producers are not included in the analysis. Several livestock commodities (hogs, poultry, and eggs) are frequently grown under a production contract arrangement in which the contractor provides most of the inputs (e.g., feed and young animals). Since the 2002 Census, expenses paid by the contractor were not accounted for, making it impossible to compare inputs for these products across the study period.

[7] On average, unpaid labor represents only 18% of the value of total labor inputs. The main results of the paper are not sensitive to whether unpaid labor is included in total labor.

Table 1
Sample characteristics by farm size category.

	Acres harvested				
	0–100	100–250	250–500	500–1000	1000+
Outputs (bu.)					
Corn (grain)	2336	9970	23,366	48,030	124,251
Wheat	133	365	705	1291	3734
Soybeans	808	3115	6864	13,542	32,698
Sorghum (grain)	2	10	31	67	243
Barley	1	4	10	20	46
Oats	20	61	92	93	108
Inputs					
Land (harv. acres)	45	167	365	711	1752
Labor ($)	8445	11,005	14,429	21,379	47,663
Machinery ($)	5301	11,594	20,655	37,371	90,392
Variable inputs ($)	5815	20,394	44,362	92,951	281,082
Major crop sales ($)	14,163	56,737	129,633	275,174	814,438
Corn yields (bu./acre)	114	124	129	133	134
Number of farms	277,089	193,048	163,395	134,255	78,755
Census respondents	81,247	60,927	59,260	68,884	64,945

Source: Author's calculations using 1982–2012 Census of Agriculture data.
Notes: Variable inputs include fertilizer, chemicals, fuel, utilities and seeds. Major crops include corn (for grain), wheat, soybeans, sorghum (for grain), barley, and oats. Sample consists of crop farms located in Heartland region. See text for details about sample creation. The National Agricultural Statistics Service reports a probability weight for each observation to correct for undercoverage and nonresponse. These weights are used in this study to estimate sample statistics and regression coefficients. The weight is used to calculate the implied "Number of farms" represented by the census respondents.

Machinery; and for other inputs, the NASS Farm Sector Prices Paid Index. These price indexes, along with a land price (the annualized average value of farm real estate per acre in the Heartland region) are also used for the initial and final year weights in the Laspeyres and Paasche indexes used to compute the Fisher index.

In this study, we place farms into five size categories based on number of acres harvested: 0–100, 100–250, 250–500, 500–1000, and over 1000 (Table 1). The farms in the sample produce primarily corn and soybeans, with the other crops representing a small fraction of total output. Farms vary widely in size: the average farm in the smallest category harvested 45 acres and had about $14,000 in major crop sales, whereas the average farm in the largest category harvested 1752 acres and had over $814,000 in major crop sales. Corn yields increased monotonically with farm size, with the largest farms producing about 18 percent more per acre than the smallest farms.

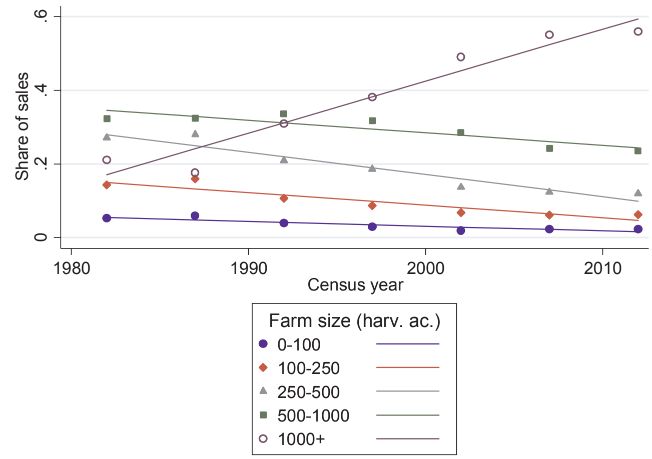

Fig. 1. Share of sales by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average sales share for each size category in each year and an estimated linear trend.

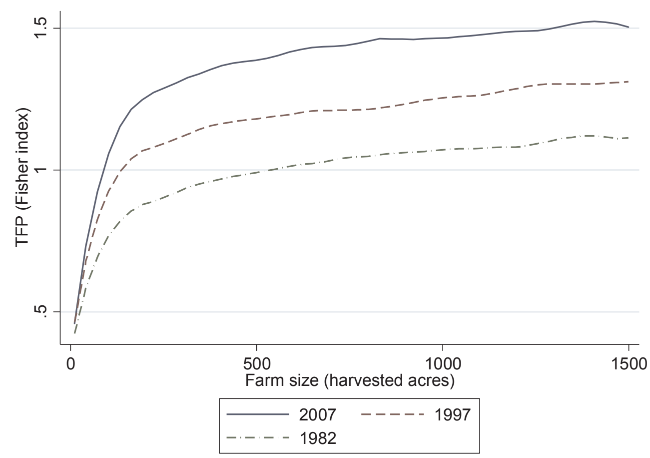

Fig. 2. Estimated relationship between TFP and farm size, farms harvesting fewer than 1500 acres.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the results of a kernel-weighted local polynomial regression of a Fisher TFP index on farm size in each year. The Fisher TFP index is a measure of the quantity of output produced relative to the quantity of inputs used – see text for details. An increase in the TFP index from 1 to 1.5 would imply a 50% increase in total factor productivity.

4. Results

4.1. Trends in sales and TFP

The dramatic change in the farm size distribution between 1982 and 2012 is illustrated in Fig. 1. The figure shows the share of sales for each size category in each Census year, along with a fitted linear trend line. The study period saw production concentrating in the hands of the largest farms. Operations with more than 1000 acres increased their predicted share of total production from 17% in 1982 to 59% in 2012. In contrast, over the same period, the share of total production declined for the four smaller farm size categories. Midsized farms (250–500 acres) experienced the largest decline in market share, with their share falling from about 30% to 10%.

Increasing returns to size can be illustrated by plotting the results of a kernel-weighted local polynomial regression of the TFP index on farm size (acres harvested) (Fig. 2). The estimated relationship is graphed for 1982, 1997, and 2007 (1987 and 2002 were excluded for visual clarity). The graph shows data for 2007 rather than 2012 because there was an extreme drought in the Heartland region in 2012, which lowered productivity substantially that year. The figure shows TFP increasing with farm size, over the size range shown (up to 1500 acres). The figure also shows that TFP increased between each of the three Censuses, at all farm sizes.

To gain insight into how productivity changed over time by farm size, we first examine trends in corn yields (Fig. 3). Corn is by far the most widely produced crop in the Heartland region, which provides a large sample for comparisons. To account for the fact that 2012 was an exceptional drought year in the Heartland which resulted in unusually low yields, we calculate a linear trend without using the 2012 observations. Between 1982 and 2007, predicted corn yields for the smallest farms increased at an average rate of 1.00 bushels per year. In contrast, for the four largest size categories expected corn yields increased at an average rate of 1.14–1.18 bushels per acre per year. Over 30 years, this amounts to an increased corn yield differential between smallest and the larger farms of 4.2–5.4 bu/ac (as a reference, small farms had predicted yields in 2012 of 137 bu/ac and large farms 159 bu/ac).

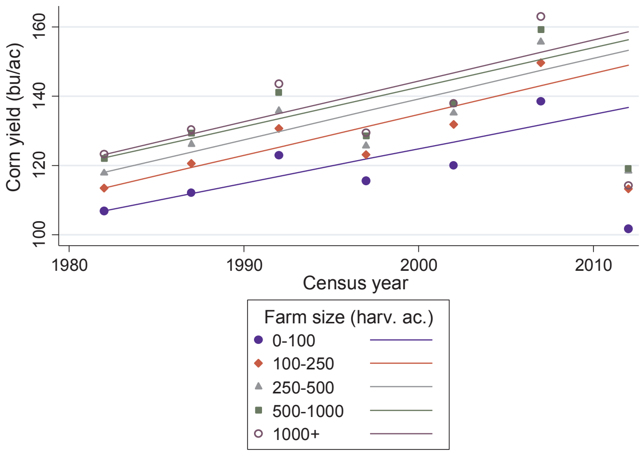

Fig. 3. Corn yields by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average corn yields for farms growing corn in each size category in each year and it shows an estimated linear trend, which is estimated without using the 2012 data.

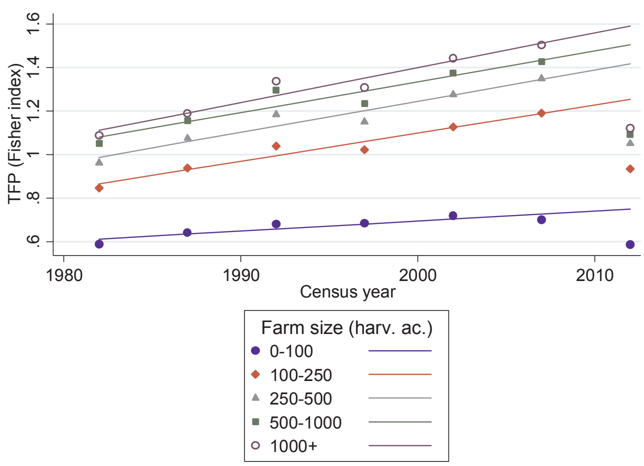

Fig. 4. TFP by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average TFP index for each size category in each year and an estimated linear trend. The trend is estimated without using the 2012 data. The Fisher TFP index is a measure of the quantity of output produced relative to the quantity of inputs used – see text for details. An increase in the TFP index from 1 to 1.5 would imply a 50% increase in total factor productivity.

A more complete picture of productivity change can be seen comparing TFP trends from 1982 to 2012 for each farm size category (Fig. 4). As with the corn yields, we account for the drought year by fitting a linear trend to TFP without using the 2012 data. Even more pronounced than with corn yields, the rate of growth in TFP is slower for the smallest size group (estimated TFP changes are reported in the first column of Table 3.) While the predicted TFP for farms in the four largest size categories increased by 47–59% between 1982 and 2012, TFP for the smallest farms increased by only 17%. Hence, the difference in productivity between farms with fewer than 100 acres and all other farms widened between 1982 and 2012. If this trend continues, it suggests that farms in the smallest size category will see a further deterioration in their competitive position and their share of total output will likely continue to shrink. We explore the factors underlying the lagging productivity growth of the smallest farms in the next section.

4.2. Technology and size economies

Using information on input expenditures from the Census, we can compare unit costs across farm size categories and over time to gain insight into the factors driving returns to size (Table 2). Unit costs are calculated as the input expenses divided by a Fisher output index. Input expenses for labor, machinery and variable inputs are described in the data section. For land, input expenses are estimated by multiplying harvested acres by an estimated national average rental rate.

Consistent with size economies, unit costs declined with farm size. In 2012, small farms (less than 100 acres) spent $2.96 per unit, midsize farms (250–500 acres) $1.72 per unit, and large farms (at least 1000 acres) $1.61 per unit. Over half of the $1.35 unit cost difference between the smallest and largest farms was attributable to labor costs and 27% was due to a capital costs – compared to only 8% and 11% for land and variable inputs, respectively. Hence, the available technology allowed large farms to use labor and capital much more cost effectively than small farms; the size advantage was limited for land and variable inputs. The relatively small differences in land productivity across size categories imply small differences in yields (assuming land prices do not vary by size). This is confirmed by the data on corn yields, which show relatively small differences across farm sizes (Fig. 3).

What explains the lower unit costs of labor and capital for larger farms? The unit labor cost advantages for larger farms likely stem from characteristics of the farm labor market and the availability of labor-saving technologies. Partly because of transaction costs associated with employing and supervising hired labor, most production in the U.S. occurs on farms that are family-owned and operated (Cochrane, 1993). Labor-saving technologies allow farms with a limited amount of family labor to produce at a larger, more efficient scale. Labor-saving technologies include large tractors, harvesters and other equipment that reduce the amount of labor required per acre. In addition, genetically engineered seeds can allow for fewer applications of herbicides and pesticides, which also reduces unit labor costs (Gardner et al., 2009).

Lower capital costs per unit may exist because capital equipment is "lumpy" and large pieces of equipment and machinery can be operated more cost effectively on large operations. Moving and setting up large pieces of equipment is costly, and these costs can be minimized when fields are large and contiguous – conditions more prevalent on large operations (MacDonald et al., 2013). Larger farms may also be able to use capital more efficiently by reducing the time that costly capital equipment is idle. Large farms are able to more fully employ equipment without having to incur the transactions costs associated with renting in equipment. Small farms could in theory purchase large-scale equipment and rent it out rather than idle it, but there are transactions costs associated with renting out equipment and limits to how many farms can enter the rental market.

Consistent with the slower TFP growth rates for the smallest farms that was shown in Fig. 3, the data also show an increasing divergence in unit costs. Between 1982 and 2012, nominal unit costs increased by $0.32–0.39 for farms with more than 100 acres compared to $0.62 for the smallest farms, a difference of $0.23–$0.30 (bottom row, Table 2).[8] This increasing divergence in unit costs was driven by changes in labor and variable input unit costs: the difference between smallest and largest farms increased by $0.13 for unit labor costs and by $0.11 for variable input costs; there was little divergence in machinery or land unit costs (last column, Table 2).

The increasing unit cost divergence for the smallest farms suggests that some of the new technologies that were adopted between 1982 and 2012 that allowed farmers to use labor and variable inputs (seed, fertilizer, pesticides, and energy) more efficiently were less well-suited for

[8] Unit costs were abnormally high in 2012 because the drought in the Heartland lowered output. However, we use the 2012 data because we are mainly interested in differences between small and large farms, rather than levels.

Table 2
Input costs per unit by farm size, 1982 and 2012.

	Farm size (harvested acres)					
	0–100 (1)	100–250 (2)	250–500 (3)	500–1000 (4)	1000+ (5)	Difference between (1) and (5)
Labor						
1982	0.72	0.28	0.17	0.12	0.11	0.61
2012	0.81	0.24	0.13	0.10	0.08	0.74
2012–1982	0.10	−0.04	−0.04	−0.02	−0.03	0.13
Machinery						
1982	0.51	0.30	0.24	0.20	0.15	0.35
2012	0.55	0.31	0.25	0.23	0.19	0.36
2012–1982	0.04	0.01	0.01	0.03	0.04	0.01
Land						
1982	0.64	0.59	0.56	0.54	0.53	0.11
2012	0.79	0.72	0.69	0.68	0.69	0.10
2012–1982	0.15	0.13	0.13	0.14	0.16	−0.01
Variable inputs						
1982	0.47	0.44	0.43	0.42	0.43	0.04
2012	0.80	0.69	0.65	0.64	0.65	0.15
2012–1982	0.33	0.25	0.22	0.22	0.22	0.11
Total unit costs						
1982	2.34	1.61	1.40	1.27	1.22	1.12
2012	2.96	1.96	1.72	1.65	1.61	1.35
2012–1982	0.62	0.35	0.32	0.38	0.39	0.23

Source: Author's calculations using 1982 and 2012 Census of Agriculture data.
Note: Variable inputs include fertilizer, chemicals, fuel, utilities and seeds. Unit costs are input costs (in nominal dollars) divided by a Fisher output index. Sample consists of crop farms located in Heartland region. See text for details about sample creation.

and consequently less likely to be adopted by the smallest operations. New labor and variable input saving technologies include larger combines and harvesters that allow farmers to cultivate more land with the same amount of labor. Other innovations include GPS-equipped precision agriculture technologies that allow farmers to more closely match input applications to the crops' needs, which can reduce the amount of seed, fertilizer and pesticides used. Using information about crop yields, terrain topography, organic matter content, moisture levels, nitrogen levels, etc., on-board computers can operate variable rate controllers on farm equipment to optimize the application of inputs. GPS-guided autopilot systems also allow farmers to reduce skips and overlap when planting and applying agrochemicals, which also reduces variable input costs. The fact that the smallest farms have lagged larger farms in reducing variable input costs is consistent with the lower adoption rates of precision farming technologies by smaller operations that have been reported in other studies (Schimmelpfennig, 2016; Daberkow and McBride, 2003).

4.3. *Size economies and aggregate TFP change*

How much of the past aggregate productivity growth can be attributed to structural change versus size-specific TFP growth? Following (2) we use the estimated average sales share, change in shares, average TFP, and change in TFP for each size category to calculate the aggregate TFP change in percentage terms (baseline scenario, Table 3). To reduce the influence of outlier years, we use the predicted value of the sales shares and TFP levels (that is, the fitted values from the linear trends shown in Figs. 1 and 3). The aggregate TFP of crop farms in the Heartland grew an estimated 63.7% (= 52.9 + 10.8) between 1982 and 2012, or 1.5% per year. This estimate is slightly higher than the 1.3% annual growth rate estimated by the USDA for the entire U.S. agricultural sector (ERS-USDA, 2017). Productivity growth for crop farms in the Heartland region may have exceeded the national average in part to the extent that crop production experienced more rapid TFP growth than livestock production. Alternatively, because farmland in the Heartland region is relatively flat and contiguous, farmers could more efficiently use large-scale farm equipment and advanced precision agriculture technologies (MacDonald et al., 2013).

We estimate that 17% (= 10.8/63.7) of aggregate productivity growth between 1982 and 2012 was attributable to the shift to larger and more productive operations. Put another way, by 2012, total output was 7.1% (= 1.637/1.529) greater because of the farm size distributional changes than it would have been with no distributional changes.

The remaining 83% (= 52.9/63.7) of aggregate TFP growth was due to the increasing TFP of the average farm in each size category. This TFP growth was due to factors other than farm size change – including technical change (the adoption of more productive technologies) and technical efficiency change (greater ability to achieve maximum output given a set of inputs and the technology). The magnitude of these other sources of aggregate productivity growth increased steadily with farm size (column 3, Table 3). TFP growth for the smallest farms contributed 0.6 percentage points to aggregate TFP growth whereas TFP growth for the largest farms contributed 22.4 percentage points. The contribution increased with farm size mainly because larger farms had higher average sales shares. For example, farms with less than 100 acres produced only 3% of total output on average from 1982 to 2012, compared to 38% for farms with at least 1000 acres. Consequently, increases in TFP for larger operations resulted in a greater expansion of output and a bigger contribution to aggregate TFP growth.

4.4. *Targeted policies to increase productivity*

If policymakers have the objective of slowing the rate of consolidation of production, one approach would be to devise policies that raise the productivity of smaller farms. Raising the productivity of smaller farms could make them more profitable, presumably causing fewer to exit the industry. Such productivity-enhancing policies might include targeted subsidized loans or tax breaks for purchasing new machinery and equipment, or targeted agricultural extension assistance. A potential drawback with targeting small farms, as opposed to larger farms, is that smaller operations produce relatively little output, so effect of the targeted policy on aggregate productivity growth would be limited.

To illustrate how targeted policies differentially affect aggregate

Table 3
Percent change in aggregate TFP (1982–2012): Contributions from changes in productivity and size distribution.

Farm size (harvested acres)	Percent change in TFP $100\frac{\Delta TFP_S}{TFP}$ (1)	Average sales share $\bar{\theta}_S$ (2)	Contribution to aggregate TFP change due to change in TFP $100\frac{\Delta TFP_S}{TFP}\cdot\bar{\theta}_S$ (3)	Change in Sales Share $\Delta\theta_S$ (4)	Average TFP as a percent of Initial TFP $100\frac{\overline{TFP_S}}{TFP}$ (5)	Contribution to aggregate TFP change due to change in sales share $\Delta\theta_S\cdot 100\frac{\overline{TFP_S}}{TFP}$ (6)	Total contribution to aggregate TFP change (3) + (6)
Baseline scenario: Estimates based on observed data							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			52.9			10.8	63.7
Scenario 1: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 0–100 acres							
0–100	**26.8**	0.03	**0.9**	−0.04	**86.9**	**−3.4**	**−2.5**
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			**53.2**			**10.7**	**63.9**
Scenario 2: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 250–500 acres							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	**62.4**	0.19	**11.8**	−0.18	**152.6**	**−27.5**	**−15.7**
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			**54.8**			**9.8**	**64.6**
Scenario 3: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 1000+ acres							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	**68.6**	0.38	**26.2**	0.42	**171.3**	**72.5**	**98.7**
All farms			**56.7**			13.5	**70.2**

Source: Author’s calculations using 1982–2012 Census of Agriculture data.
Note: ΔTFP_S is the change in predicted TFP for farms in size category s between 1982 and 2012, TFP is the predicted initial aggregate TFP for all farms, and $\overline{TFP_S}$ is the average of the 1982 and 2012 predicted TFP for farms in size category s.
The bold font indicates the values that are different from the baseline scenario.

productivity depending on the size of the farms targeted, consider the effect of a hypothetical policy that increased the productivity growth of targeted farms by 10 percentage points while having no effect on the farm size distribution.[9] We estimate the effects of the policy in 2012, assuming it had been implemented in 1982. If the smallest farms (less than 100 acres) were targeted, this policy would have increased the TFP of these farms by 26.8% instead of 16.8%, and their average TFP (as a percent of initial total TFP) would have increased from 83.1 to 86.9 (scenario 1: Table 3). The policy would have had two effects on aggregate TFP. First, the contribution to aggregate TFP for the average farm with less than 100 acres would have increased 0.3 percentage points (from 0.6 to 0.9). Second, gains from structural change would have been smaller. As farms left the smallest category, aggregate TFP would have dropped by 3.4 points instead of 3.2 (the increase in TFP from growth in the other size categories would have been the same). In total, aggregate productivity growth would have increased by only 0.2 percentage points.

The effect of a similar policy that targets midsized farms (250–500 acres) is shown in scenario 2. The 10 percentage point increase in the productivity growth rate means midsized farms would have contributed 11.8 percentage points to the total aggregate growth (up from 9.9 points). However, because midsized farms were more productive on average over the period, structural change would have contributed a smaller amount to aggregate productivity growth (9.8 points compared to 10.8). In sum aggregate productivity would have increased by only 0.9 percentage points.

In comparison, consider a hypothetical policy that raised the productivity growth of the largest farms by 10 percentage points (scenario 3, Table 3). The contribution to aggregate TFP from farms with more than 1000 acres would have increased by 3.8 percentage points (from 22.4 to 26.2). As farms shifted into the largest category between 1982 and 2012, the gains from structural change would have been greater than before – productivity would have increased by 72.5 percentage points compared to 69.8 in the baseline – an increase of 2.7 points. The net effect would have been an increase in aggregate TFP of 6.5 percentage points.

Hence, the policy targeting the largest farms would have increased aggregate TFP 32 times more than a similar policy targeting the smallest farms and 7 times more than the policy targeting midsized farms. The magnitude of the difference in the policy effects between the largest farms and the smaller farms would have been even greater had we considered the effects of the policies on structural change. Targeting the small and midsized farms would have likely slowed the shift in production to larger farms. Since larger farms are more productive, slowing the shift to larger farms would have reduced aggregate productivity growth. In contrast, targeting the largest farms would have increased the rate of consolidation, which would have increased the rate of aggregate productivity growth.

The net effect of targeting farms of different sizes on aggregate productivity growth is shown column 1 of Table 4. While the effect on aggregate productivity growth increases with the size of farm targeted, the cost-effectiveness of the targeted policies – defined in terms of aggregate productivity gains per policy dollar – depends on policy costs. If

[9] The evolution of the size distribution would likely change in response to the policy. However, this change is difficult to predict and therefore is not modeled here. We discuss the likely implications of the effect of the policy on the size distribution later in the section.

Table 4
Aggregate productivity increases from targeted productivity-enhancing policies relative to the farm and sales shares.

Targeted Farm size (harvested acres)	Percentage point increase in aggregate productivity (1)	Average share of farms, 1982–2012 (2)	Average share of sales, 1982–2012 (3)	Percentage point increase in aggregate productivity per farm share (4)	Percentage point increase in aggregate productivity per sales share (5)
0–100	0.2	0.33	0.03	1	7
100–250	0.5	0.23	0.10	2	5
250–500	0.9	0.19	0.19	5	5
500–1000	2.4	0.16	0.29	15	8
1000 +	6.5	0.09	0.38	70	17

Source: Author's calculations using 1982 and 2012 Census of Agriculture data.
Note: The "percentage point increase in aggregate productivity" is the estimated additional increase resulting from a policy that increases the productivity growth of targeted farms by 10 percentage points from 1982 to 2012. The table shows the effects of five distinct policies each targeting one of the five farm-size categories (see Table 3 and text for more details).

policy costs are roughly proportional to the number of farms targeted – which might be approximately the case with targeted agricultural extension policies – then targeting small farms would likely be much less cost-efficient than targeting larger farms. This can be seen in Table 4. Between 1982 and 2012, the smallest farms represented about a third of all crop farms in the Heartland region (column 2), which would make it very costly to provide extension or other similar types of policies to this group. Put another way, targeting the smallest farm category would results in very little increase in aggregate output per farm (column 4). In contrast, the largest farms represented only 9% of all farms over this period, so targeting these farms would have resulted in a large increase in aggregate output per farm. In fact, the aggregate productivity gain per farm share is 70 times greater for the largest farms compared to the smallest farms.

On the other hand, if policy costs are roughly proportional to farm output – which might be the case with loan or risk management polices – then cost-effectiveness is less closely correlated with farm size.[10] As discussed earlier, larger farms produced a greater share of aggregate output between 1982 and 2012 than did smaller farms (column 3). If policy costs are proportional to output, then it would be substantially less costly to target a smaller farm size category. For smaller farm categories, a targeted policy has a smaller effect on aggregate output, but also a lower cost – so the effect on cost effectiveness is ambiguous. This is shown in column 5: the percentage point increases in total output per sales share for the smallest four farm size categories are roughly the same. The largest farms are roughly two to three times more cost effective than the smaller farms – which is a much less extreme difference.

5. Conclusion

This study used quinquennial Agricultural Census data collected from 1982 to 2012 to estimate the TFP of five size classes of grain-producing farms in the U.S. Corn Belt. We found strong evidence of economies of size in each Census year. The productivity differences across farm size categories are reflected in substantially higher unit costs of the smallest operations. These findings support the hypothesis that economies of size was a contributing factor behind the consolidation of commodity crop production that occurred in the U.S. over the last 30 years.

Findings also indicate that the smallest crop farms (less than 100 harvested acres) fell further behind large farms in terms of productivity in recent decades. Between 1982 and 2012, TFP growth rates were similar across farm size classes except for the smallest, which had a significantly slower growth rate. If past trends continue, this suggests that the productivity disadvantages for smaller operations will persist, and in the case of the smallest farms, will expand.

Consistent with slower TFP growth for the smallest farms, the study found that the difference in unit costs between the smallest farms and larger farms increased over the study period. Most of the unit cost divergence can be explained by changes in the unit costs of labor and variable inputs (seeds, fertilizer, pesticides, and energy). This suggests that some technological advances in recent decades, such as very large combine harvesters and precision agriculture technologies, lowered unit labor and variable input costs less for the smallest farms. Lower adoption rates of precision agricultural technologies on the smallest farms, which have been observed in other studies, might explain why the labor and variable input costs disparities increased, and why the farm productivity growth of the smallest farms has lagged behind that of larger operations.

Because of size economies, crop farm consolidation contributed significantly to aggregate agricultural productivity growth in the Corn Belt. Between 1982 and 2012, the share of output produced by crop farms with at least 1000 acres increased from 17% to 59%. Using a new method for disaggregating TFP growth, we estimate that the aggregate TFP of specialized crop farms in the Heartland region increased by 64% or 1.5% per year between 1982 and 2012, and that about one-sixth of this growth was attributable to the shift in production to larger more productive farms. Hence, while technological change and technical efficiency change were the most important sources of aggregate productivity growth in recent decades, the contribution from the farm size distribution change was substantial.

The data provide no indication yet of a slowdown in crop consolidation or productivity growth in the Heartland region. However, with most output in the region now produced by large farms, it is plausible that the pace of consolidation will slow in the coming decades. A slowdown in the rate of productivity growth in hog production after 2004 was observed in the U.S. hog sector following a rapid shift in production to very large farms – a size at which returns to scale were close to constant (McBride and Key, 2013). If the rate of consolidation of crop production slows in the coming decades, then aggregate TFP growth rates will likely decline as well, unless the rate of technological progress increases.

Finally, this study illustrated some of the tradeoffs associated with productivity growth policies that target farms of a particular size. Policies that raise the productivity of small farms could increase the economic viability of these farms and potentially slow the rate of consolidation. However, the study showed that targeting small farms would result in relatively little in aggregate productivity growth compared to targeting larger farms. For example, a hypothetical productivity-enhancing policy targeting farms with at least 1000 acres of cropland would have increased aggregate productivity 32 times more than a similar policy targeting farms having less than 100 acres and 7 times more than a policy targeting farm having between 250 and 500

[10] Loan or risk management programs could plausibly have costs that are roughly proportional to output. This would be the case for loan programs if most of the program costs (e.g., default costs) are proportional to the loan amount, and the loan amount is roughly proportional to farm size. This would be the case for risk management programs if the costs (indemnity payments) are proportional to the amount of cropland insured, which in turn is proportional to total output.

acres.

At the same time, the cost effectiveness of targeted policies in terms of aggregate productivity gains per policy dollar depends on the policy costs. If costs are roughly proportional to the number of farms targeted – which might be the case with targeted agricultural extension policies – then targeting smaller farms would likely be substantially less efficient than targeting larger farms (or not targeting at all by farm size). On the other hand, if policy costs are roughly proportional to farm output – which might be the case with loan or risk management polices – then the efficiency costs of targeting smaller farms would likely be much smaller.

Appendix A. Estimating unpaid labor input for Census of Agriculture

Before 2012, no questions were asked on the Census of Agriculture about the quantity of non-operator family labor or other unpaid labor that worked on-farm. To address this missing data issue, we estimate the quantity of unpaid farm labor using information from the Agricultural Resource Management Survey (ARMS). The ARMS is a detailed survey of a representative sample of U.S. farm households conducted annually since 1996 by the USDA Economic Research Service and NASS. The ARMS collects the same information as the Census but also includes more detailed questions about production costs, assets, and off-farm employment. Relevant to this study, the ARMS also asks about the amount of unpaid time the operator's spouse and family and other operators spend working on the farm. This information allows us to predict the quantity of unpaid labor used on farm as a function of highly correlated variables that are observed in the Census: the operators' on-farm labor, and the size of the farm (defined by harvested acres and value of production).

To estimate the parameters in the predictive model, we first create an ARMS sample to match the Census sample. We do this by limiting the ARMS sample using the same criteria used in this study: being located in the Heartland region and specializing in production of the major commodity crops (see data section for details). We use ARMS data collected from 1996 to 2012 – all the survey years available that overlap with the Census data. The matched sample includes 21,912 observations. As expected, the ARMS data reveal that the unpaid farm labor hours increases with farm size and the operator's farm labor (Table A1). On average, operators work on farm about 3.4 times as many hours as unpaid labor, and this ratio decreases with farm size. The data show that the labor productivity of operator and unpaid labor (as measured by value of production per hour) increases dramatically with farm size.

We take advantage of the fact that unpaid labor hours is correlated with the operators' hours and with farm size to estimate the quantity of unpaid farm labor. We regress unpaid labor on operator hours, harvested acres, the natural log of harvested acres, value of production, and a time trend. The linear regression model has an R-squared of 0.38 and all the variable coefficients are significant at the 99% level. We use the estimated coefficients with the Census data variables to predict unpaid labor time for each farm in the Census sample. The opportunity cost of unpaid labor is estimated as the predicted quantity of unpaid labor (in days) multiplied by the same daily wage rate used for hired and operator labor (based on the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey).

Using the Census data, the productivity of estimated unpaid labor (A Fisher output index divided by unpaid labor days) increases over time because of the negative time trend coefficient and because the positive operator labor coefficient – as operator's labor productivity increases, unpaid labor productivity also increases. Because unpaid labor is a small share (18%) of total farm labor (which also includes hired, contract and operator labor), including the unpaid labor estimates has a very small effect on the results presented in the paper.

Table A1
Operator labor and unpaid labor quantities for crop producers in the Heartland.

	Acres harvested				
	0–100	100–250	250–500	500–1000	1000+
Operator labor (h)	799	1388	1918	2484	2871
Unpaid labor (h)	178	287	472	684	1343
Value of production ($)	16,748	62,038	139,435	290,380	749,637
VOP/operator labor ($/h)	21	45	73	117	261
VOP/unpaid labor ($/h)	94	217	295	425	558
ARMS respondents	2190	3060	3568	4865	8229

Source: Author's calculations using 1996–2012 USDA Agricultural Resource Management Survey. See Appendix A for details about sample creation.

References

Alston, J., Anderson, M., James, J., Pardey, P., 2010. Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending. Springer, New York.

Benjamin, D., 1995. Can unobserved land quality explain the inverse productivity relationship. J. Dev. Econ. 46 (1), 51–84.

Burns, C., Kuhns, R., 2016. The Changing Organization and Well-Being of Midsize U.S. Farms, 1992–2014. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-219) (October).

Carletto, C., Savastano, S., Zezza, A., 2013. Fact or artifact: the impact of measurement errors on the farm size-productivity relationship. J. Dev. Econ. 103, 254–261.

Chambers, R.G., 1988. Applied Production Analysis: A Dual Approach. Cambridge University Press, New York.

Cochrane, W., 1993. The Development of American Agriculture: A Historical Analysis, second ed. University of Minnesota Press, Minneapolis.

Daberkow, S., McBride, W., 2003. Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the U.S. Precis. Agric. 4, 163–177.

Diewert, W., 1978. Superlative index numbers and consistency in aggregation. Econometrica 46, 883–900.

Dumagan, J., 2002. Comparing the superlative Törnqvist and Fisher ideal indexes. Econ. Lett. 76, 251–258.

ERS-USDA, 2017. Indices of output, input, and total factor productivity for the United States, 1948-2013, table 1a. Accessed 1/12/17 from: < https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/ > .

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. Am. Econ. Rev. 84 (1), 66–83.

Gardner, J., Nehring, R., Nelson, C., 2009. Genetically modified crops and household labor savings in US crop production. Agbioforum 12 (3&4), 303–312.

Heimlich, R., Farm Resource Regions. Agricultural Information Bulletin No. AIB-760, August 2000. Accessed 1/11/17 from: < https://www.ers.usda.gov/publications/pub-details/?pubid=42299 > .

Huffman, W., Evenson, R., 2001. Structural and productivity change in US agriculture, 1950–1982. Agricultural Economics 24 (2), 127–147.

Key, N., Roberts, M.J., 2006. Government Payments and Farm Business Survival. Am J Agric Econ 88 (2), 382–392.

MacDonald, J.M., Korb, P., Hoppe, R., 2013. Farm Size and the Organization of U.S. Crop

Farming. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-152) (August).
McBride, W., Key, N., 2013. U.S. Hog Production from 1992 to 2009: Technology, Restructuring, and Productivity Growth. U.S. Department of Agriculture, Economic Research Service, Economic Research Report, (ERR-158) (October).
Morrison Paul, C., Nehring, R., Banker, D., Somwaru, A., 2004. Scale economies and efficiency in US agriculture: are traditional farms history? J. Prod. Anal. 22 (3), 185–205.
Orea, L., 2002. Parametric decomposition of a generalized Malmquist productivity index. J. Prod. Anal. 18 (1), 5–22.
Schimmelpfennig, D., 2016. Farm Profits and Adoption of Precision Agriculture. Economic Research Report, ERR-217, U.S. Department of Agriculture, Economic Research Service.
Sumner, D.A., 2014. American farms keep growing: size, productivity, and policy. J. Econ. Perspect. 28 (1), 147–166.
Stigler, G., 1946. Labor productivity and size of farm: a statistical pitfall. J. Farm Econ. 48 (3), 821–825.
USDA, 2017. Resources for Small and Mid-Sized Farmers. United States Department of Agriculture. Accessed 1/18/17 from: < https://www.usda.gov/wps/portal/usda/usdahome?contentidonly=true&contentid=small-midsized-farmer-resources.xml > .
Wang, S.L., Heisey, P., Schimmelpfennig, D., Ball, E., 2015. Agricultural Productivity Growth in the United States: Measurement, Trends, and Drivers. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-189) (July).

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Farm size and productivity growth in the United States Corn Belt[☆]

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ABSTRACT

In recent decades, agricultural production in the U.S. has continued to shift to large-scale operations, raising concerns about the economic viability of small and midsized farms. To understand whether economies of size provided an incentive for the consolidation of production, the study estimates the total factor productivity (TFP) of five size classes of grain-producing farms in the U.S. Heartland (Corn Belt) region. Using quinquennial Agricultural Census data from 1982 to 2012 the study also compares TFP growth rates across farm sizes to gain insight into whether observed productivity differences are likely to persist. The finding of a strong positive relationship between farm size and TFP suggests that consolidation of production has contributed to recent aggregate productivity growth in the crop sector. The study estimates the extent to which sectoral productivity growth can be attributed to structural change versus other factors including technological change. The study also explores some tradeoffs associated with policies that raise the productivity of small versus large farms.

1. Introduction

Over the past several decades, there have been pronounced structural changes in the U.S. farm sector – with production shifting steadily to larger operations. Between 1982 and 2007, the midpoint farm size – the size at which half of all land is on bigger farms and half is on smaller farms – almost doubled from 589 to 1105 acres (MacDonald et al., 2013). At the same time, the midpoint acreage more than doubled in each of the five major field crops: corn, cotton, rice, soybeans, and wheat. Additionally, the share of output from farms with sales of at least $1 million increased from less than 30% in 1987 to over 60% in 2007 (Sumner, 2014).

The shift in production to large farms has raised questions about the economic viability of small and mid-sized producers, and the rural communities that depend on these farm households. These and other concerns have helped spur Federal efforts to target resources toward smaller-scale operations through loan, risk management, marketing, and educational programs (USDA, 2017). The extent to which farming is characterized by economies of size – that is, how much average unit costs decrease as farm size increases – is likely to influence the rate and extent of future consolidation.[1] The first objective of this study is to estimate the total factor productivity (TFP) and unit costs of crop farms of different sizes to understand how productivity and costs vary. This analysis focuses on operations located in the U.S. Heartland (Corn Belt) region that specialize in major field crops.

To gain further insight into the long-run economic viability of small farms, the study also estimates how productivity has changed over time for crop farms of different sizes. It is possible that some recent technological advances (e.g., very large combine harvesters, precision agriculture technologies, improved seed varieties) have raised the productivity of larger operations more than smaller operations. This has implications for whether small farms can persist as viable economic units. Economies of size give large-scale operations a competitive advantage – allowing production at a lower unit cost. If new technological advances favor larger operations, economies of size will increase over time and likely hasten the demise of small family farms. On the other hand, if small farms can increase productivity at a faster rate than large farms, it may be possible to reduce smaller farms' competitive disadvantage and potentially slow or even reverse the consolidation of production. This study is the first to inform this issue by estimating long-run trends in productivity for crop farms of different sizes.

The second objective of this study is to estimate how much of the

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[1] Economies of size is defined by how average (unit) costs change when production increases. More precisely, a firm is said to display economies of size if a one percent increase in output results in a less than one percent increase in average costs. Economies of scale – a closely related to but distinct concept – is defined by how output changes when all inputs are increased in the same proportion. That is, a firm is said to display increasing returns to scale if a one percent increase in all inputs results in a more than one percent increase in output. The concepts are closely related as a cost-minimizing firm exhibits increasing returns to scale if and only if it simultaneously exhibits increasing returns to size (Chambers, 1988, pp. 21–77).

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past aggregate productivity growth can be attributed to structural change (changes in the farm size distribution) versus other factors, including technological change. The recent consolidation of agricultural production has coincided with substantial growth in agricultural productivity: between 1982 and 2012, aggregate TFP increased by 46% – an average annual growth rate of about 1.3% (ERS-USDA (2017)). In explaining the drivers of this productivity growth, most research has focused on technical progress and the role of research and development in promoting technological advances (e.g., Wang et al., 2015; Alston et al., 2010). Little research has examined the contribution of structural change to aggregate productivity growth. If large farms are more productive than smaller farms, as we find in this study, the widespread shift in production towards larger farms could explain a portion of the aggregate productivity growth observed over the past several decades (Huffman and Evenson, 2001). Additionally, understanding the extent to which structural change has explained past productivity growth can shed light on future productivity potential. If the scope for further consolidation of production is now less that it was in the past – because most output is now produced by large farms – then aggregate TFP growth will likely slow in the years ahead unless the rate of technological progress increases.

The third objective of this study is to better understand the relationship between farm size and aggregate productivity growth. The paper develops a new method for estimating aggregate agricultural productivity growth based on the share of production of farms in different size categories, shifts in the distribution of production across farms of different sizes, and changes in the productivity of different sized operations. This allows us to estimate how targeted policies that raise the productivity of farms of a particular size would affect aggregate TFP growth. Results show that targeting small operations would result in much less aggregate productivity growth than similar policies targeting larger operations, mainly because larger farms had higher average sales shares. However, the relative cost-effectiveness of targeted policies, in terms of raising aggregate productivity growth, depends on whether the policy costs are proportional to farm output or the number of farms targeted.

2. Methodology

2.1. Empirical framework

There are two main approaches that can be used to compare the productivity *change over time* of farms of a similar size. If panel data were available, one approach is to assign farms to time-invariant size categories – for example, according to a farm's initial size. Calculating TFP change for each farm would allow for a straightforward comparison of average productivity change across farm size categories. If stochastic production function or data envelope analyses were performed, it would be possible to disaggregate TFP change for each size category into technical change, and technical and scale efficiency change (Färe et al., 1994; Orea, 2002).

This approach has significant shortcomings if a substantial portion of farms transition between size categories over the study period: e.g., some small farms become large and some large become small. Using a sales-based farm size measure, Burns and Kuhns (2016) showed that over five years about 42% of midsize farms transitioned into either small or large farms. They also report five-year transition rates for small and large farms ranging between 21% and 33%. When farm size is fluid, as is likely the case over long periods of time, placing farms in time-invariant categories does not permit a valid comparison of the productivity growth of similarly-sized operations.

Another drawback of this approach, because it relies on panel data, is the potential for sample attrition bias. U.S. crop farms are characterized by five-year attrition rates of about 35–50%, depending on the size of the operation, crop specialization, and operator's age, among other factors (Key and Roberts, 2006).[2] Hence, only a fraction of farms would continue to be observed over a long period, such as the 30-year span considered in this analysis. The farms that remain in business over a long period would likely be very different from the population as a whole – and would have different levels of productivity. Hence, assertions about the population as whole from a sample of surviving farms could suffer from sample attrition bias unless this can be adequately addressed by the empirical model.

The second main approach for making productivity growth comparisons across farm size is to categorize observations by size in each year. This cohort approach can use repeated cross-section or panel data to estimate changes in productivity by farm size groups (Morrison Paul et al., 2004). If the surveys are representative in each period, this approach is not vulnerable to sample attrition bias.

The drawback to this cohort approach is that the farm size categories are fixed, so estimates of scale efficiency change for the farms in each size category will be close to zero (except, perhaps, for the largest farm size category, which typically is unbounded from above). Hence, this approach mostly ignores an important source of aggregate productivity growth: economies of size resulting from a shift in the farm size distribution.

To illustrate the limitation of the cohort approach consider a simple example where there are two farm size categories, small and large, and size economies such that small farms have a TFP index value of 1 and large farms have a TFP of 2. Also assume for simplicity that there is no technical change over the study period, but there is a shift in production from small to large farms. If initially 50% of output is produced by each type of farm, then aggregate TFP in the first period is 1.5 ($=0.50\cdot 1 + 0.50\cdot 2$). If production shifts so that in the second period small farms produce 25% of output and large farms produce 75%, then aggregate productivity increases to 1.75 ($=0.25\cdot 1 + 0.75\cdot 2$). Because there was no technical change, a cohort analysis that compared the productivity change of farms of the same size would estimate zero productivity growth for small and large farms, even though aggregate productivity increased substantially. Hence simply comparing the productivity of farms in the same size category does not reveal the contribution of increasing farm size to aggregate productivity growth.

In this study, we develop a framework for estimating the contribution of structural change to aggregate productivity growth using cohort data. Let the aggregate TFP in any period be approximated by the sales-weighted average TFP of S size categories:

$$TFP = \theta_1\cdot TFP_1 + \theta_2\cdot TFP_2 ... + \theta_s\cdot TFP_s ... + \theta_S\cdot TFP_S, \tag{1}$$

where θ_s is the share of total sales produced by farms in category s and is the average TFP of farms in category s. It follows that the change in the aggregate TFP between two periods is:

$$\begin{aligned}\Delta TFP = {} & (\Delta\theta_1\cdot\overline{TFP}_1 + \Delta\theta_2\cdot\overline{TFP}_2 ... + \Delta\theta_s\cdot\overline{TFP}_s ... + \Delta\theta_S\cdot\overline{TFP}_S) \\ & + (\Delta TFP_1\cdot\bar{\theta}_1 + \Delta TFP_2\cdot\bar{\theta}_2 ... + \Delta TFP_s\cdot\bar{\theta}_s ... + \Delta TFP_S\cdot\bar{\theta}_S),\end{aligned} \tag{2}$$

where Δ indicates the change between periods and the overbar represents the average of the two periods. The first term in parentheses is the contribution to aggregate TFP change from the change in the farm size distribution. The second term in parentheses is the contribution to aggregate TFP from the change in TFP from farms within each size category, where $\Delta TFP_s\cdot\bar{\theta}_s$ is the contribution from the TFP change of farms in size category s.

Note that the change in TFP for each size category, ΔTFP_s, could be decomposed into changes in scale efficiency, technical efficiency and technical change. However, since the size categories are fixed, scale

[2] Attrition rates are high in studies that use Census of Agriculture data in part because farms can only be tracked over time with an operator identification number. When an operator retires from farming and sells his farm business or passes it on to his children the operator ID will often change and this will be recorded as a farm exit. Additionally, the attrition rate is high because farmers who do not respond to the Census will be classified as having exited.

efficiency change will be negligible, except perhaps for the largest category. To keep the analysis simple, and to focus attention of the importance of changes in the size distribution, we do not disaggregate TFP change for each category.

In this study, we measure TFP using a Fisher index. A Fisher TFP index is a measure of outputs produced per unit of inputs, with prices used to weight the outputs and inputs. To compare TFP over time the weights (prices) should remain fixed in an index. The Laspeyres TFP index uses the initial year prices (t = 1) as weights: $TFP_{Lt} = \sum_{m=1}^{M} p_{m1}y_{mt} / \sum_{k=1}^{K} w_{k1}x_{kt}$. The Paasche index uses the final year prices (t = T) as weights: $TFP_{Pt} = \sum_{m=1}^{M} p_{mT}y_{mt} / \sum_{k=1}^{K} w_{kT}x_{kt}$. The Fisher index, is defined as the geometric mean of the Laspeyres and Paasche indexes ($TFP_{Ft} = \sqrt{TFP_{Lt} \cdot TFP_{Pt}}$). The Fisher index numerically approximates and has similar theoretical properties to the Törnqvist index, but has the advantage over the Törnqvist index in this application of being defined for zero-quantities (Diewert, 1978; Dumagan, 2002).

2.2. Defining farm size

An important consideration in measuring the relationship between farm size and productivity is how to measure farm size. The quantity produced, or when considering farms that produce more than one output, the value of sales, are commonly used to define farm size and to create farm size categories. However, it has long been recognized that using output or sales to define size may lead to a spurious correlation between farm size and productivity (Stigler, 1946). Correlation results because output, and therefore also sales, varies a lot from year-to-year and across farms due to random weather shocks, pests, etc. A farm having an unusually good (bad) harvest will have unusually high (low) sales and therefore unusually high (low) productivity. Hence sales and productivity may be correlated even if there is no difference in the underlying technology.[3]

Because this study focuses on crop farms, harvested acres are used to measure farm size. In contrast to sales, the amount of land farmed does not vary a lot from year-to-year due to random yield shocks (except in extreme cases of crop failure, crop acreage is determined before yields are realized). Because land is an input – and thus inversely correlated to TFP – errors in measuring land could cause a spurious negative correlation between size and productivity (Benjamin, 1995; Carletto et al., 2013). However, in the U.S., crop acreage is generally accurately measured and is well known by the farmer, so measurement error is likely small.[4]

3. Data

Data for study are drawn from the quinquennial Agriculture Censuses conducted from 1982 to 2012. The Census is administered by the USDA National Agriculture Statistics Service with the aim of collecting information from all agricultural operations that produce, or would normally produce and sell, at least $1000 of agricultural products per year. To create a homogeneous sample and to reduce the influence of climate, soil and other regional effects, observations are limited to the "Heartland" farm production region. This region is defined by the USDA and consists of a set of contiguous counties, including all of Iowa, Illinois, and Indiana, and parts of Minnesota, South Dakota, Nebraska, Missouri, Kentucky, and Ohio (Heimlich et al., 2000). The Heartland region contains 22% of all U.S. farms and 27% of cropland and produces 23% of U.S. farm output. To further increase the homogeneity of the sample we only include farms specializing in corn (for grain), wheat, soybeans, sorghum (for grain), barley, and oats.[5] Specialization is defined as having at least 90% of sales and 90% of harvested acres in these crops. This eliminates livestock operations and farms that grow other crops that might have substantially different production technologies.[6]

Outputs include the observed quantities produced of the six field crops listed above plus "other outputs", which is the residual value of production (total production minus the value of the six major crops). To weight the outputs in the Fisher index we use each crop's average annual price corresponding to the year of the Census (1982–2012). Crop prices are from the USDA National Agricultural Statistics service (NASS).

Inputs include land, labor, machinery, and other variable inputs. Land is the reported total acres harvested on the farm. Labor expenses include the costs of hired and contract labor plus the estimated opportunity cost of the operator's labor and other unpaid labor, including family labor. Hired and contract labor expenses are collected by the Census. To estimate the opportunity cost of the operator's labor, we first estimate the number of hours the operator worked on-farm by subtracting the number of days that the operator reported working off-farm from 240 days (full time work). The estimated on-farm work days are then multiplied by a daily wage rate based on the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey. The Census does not collect information about non-operator household labor or other unpaid labor so this is estimated using data from the Agricultural Resource Management Survey (ARMS). Using a sample from ARMS with similar characteristics, we regress unpaid labor on operator labor and measures of farm size and then use the estimated parameters to predict unpaid labor for the Census sample (see Appendix A for details). Unpaid labor is valued using the same wage as the operator.[7]

Machinery expenses are based on the reported value of owned machinery and equipment used on-farm plus machinery and equipment rental expenses. The Census collects information on equipment rental expenses and the value of machinery used on farm. The value of machinery that is used on-farm is converted to an annual expense rate using a capitalization value of 0.15. Other variable input expenses include the reported amount paid for fertilizer, chemicals, fuel, utilities and seeds.

To calculate the Fisher index, input expenses (labor, machinery and other inputs) are converted to a quantity indexes, by dividing by an appropriate input price index. For labor we use the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey; for machinery, the NASS Prices Paid Index for

[3] This can be a problem even when farms are placed in discrete size categories. For example, consider two farms with identical technologies that use the same inputs and that would normally produce at a level near the size category cutoff. Suppose one farm experiences good weather and hence high sales (and high productivity) and is therefore categorized as a "large" farm; the other experiences bad weather and hence low sales (and low productivity) and is placed in the "small" size category. The data would seem to indicate a positive correlation between size and productivity even though there is, in fact, no difference in the technologies between the differently-sized operations.

[4] Planted acres would likely be less correlated to yields than harvested acres, but information on planted acres is not available. Land value might be a better measure of farm size since than acreage. However, land value is poorly measured in the Census, which introduces a negative spurious correlation between size and productivity. Similarly, the total value of productive assets might be preferable to acreage as a measure of farm size. However, asset value is also poorly measured because it is difficult for farmers to estimate and because non-response rates tend to be high on questions about assets.

[5] These are all the main crops grown in the Heartland region, except for hay, which is not included in the analysis because it includes several plant species that are not identified in the Census – making it impossible to accurately assign a price. Corn and sorghum that is grown for silage or greenchop are not included among the major outputs because the quantity produced is less accurately measured than when grown for grain.

[6] Inconsistent Census data on livestock inputs is another reason livestock producers are not included in the analysis. Several livestock commodities (hogs, poultry, and eggs) are frequently grown under a production contract arrangement in which the contractor provides most of the inputs (e.g., feed and young animals). Since the 2002 Census, expenses paid by the contractor were not accounted for, making it impossible to compare inputs for these products across the study period.

[7] On average, unpaid labor represents only 18% of the value of total labor inputs. The main results of the paper are not sensitive to whether unpaid labor is included in total labor.

Table 1
Sample characteristics by farm size category.

	Acres harvested				
	0–100	100–250	250–500	500–1000	1000 +
Outputs (bu.)					
Corn (grain)	2336	9970	23,366	48,030	124,251
Wheat	133	365	705	1291	3734
Soybeans	808	3115	6864	13,542	32,698
Sorghum (grain)	2	10	31	67	243
Barley	1	4	10	20	46
Oats	20	61	92	93	108
Inputs					
Land (harv. acres)	45	167	365	711	1752
Labor ($)	8445	11,005	14,429	21,379	47,663
Machinery ($)	5301	11,594	20,655	37,371	90,392
Variable inputs ($)	5815	20,394	44,362	92,951	281,082
Major crop sales ($)	14,163	56,737	129,633	275,174	814,438
Corn yields (bu./acre)	114	124	129	133	134
Number of farms	277,089	193,048	163,395	134,255	78,755
Census respondents	81,247	60,927	59,260	68,884	64,945

Source: Author's calculations using 1982–2012 Census of Agriculture data.
Notes: Variable inputs include fertilizer, chemicals, fuel, utilities and seeds. Major crops include corn (for grain), wheat, soybeans, sorghum (for grain), barley, and oats. Sample consists of crop farms located in Heartland region. See text for details about sample creation. The National Agricultural Statistics Service reports a probability weight for each observation to correct for undercoverage and nonresponse. These weights are used in this study to estimate sample statistics and regression coefficients. The weight is used to calculate the implied "Number of farms" represented by the census respondents.

Machinery; and for other inputs, the NASS Farm Sector Prices Paid Index. These price indexes, along with a land price (the annualized average value of farm real estate per acre in the Heartland region) are also used for the initial and final year weights in the Laspeyres and Paasche indexes used to compute the Fisher index.

In this study, we place farms into five size categories based on number of acres harvested: 0–100, 100–250, 250–500, 500–1000, and over 1000 (Table 1). The farms in the sample produce primarily corn and soybeans, with the other crops representing a small fraction of total output. Farms vary widely in size: the average farm in the smallest category harvested 45 acres and had about $14,000 in major crop sales, whereas the average farm in the largest category harvested 1752 acres and had over $814,000 in major crop sales. Corn yields increased monotonically with farm size, with the largest farms producing about 18 percent more per acre than the smallest farms.

4. Results

4.1. Trends in sales and TFP

The dramatic change in the farm size distribution between 1982 and 2012 is illustrated in Fig. 1. The figure shows the share of sales for each size category in each Census year, along with a fitted linear trend line. The study period saw production concentrating in the hands of the largest farms. Operations with more than 1000 acres increased their predicted share of total production from 17% in 1982 to 59% in 2012. In contrast, over the same period, the share of total production declined for the four smaller farm size categories. Midsized farms (250–500 acres) experienced the largest decline in market share, with their share falling from about 30% to 10%.

Increasing returns to size can be illustrated by plotting the results of a kernel-weighted local polynomial regression of the TFP index on farm size (acres harvested) (Fig. 2). The estimated relationship is graphed for 1982, 1997, and 2007 (1987 and 2002 were excluded for visual clarity). The graph shows data for 2007 rather than 2012 because there

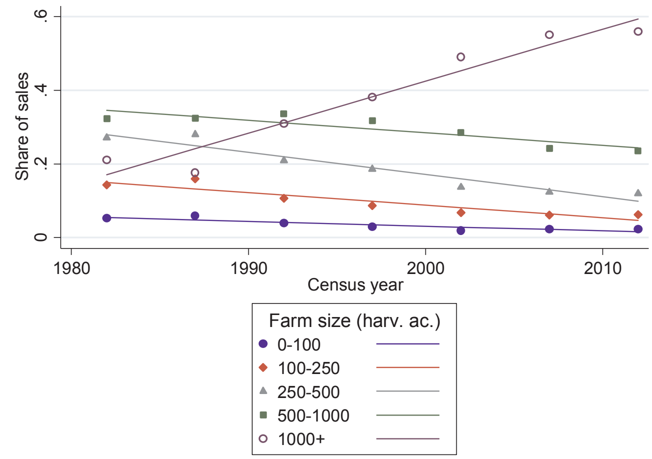

Fig. 1. Share of sales by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average sales share for each size category in each year and an estimated linear trend.

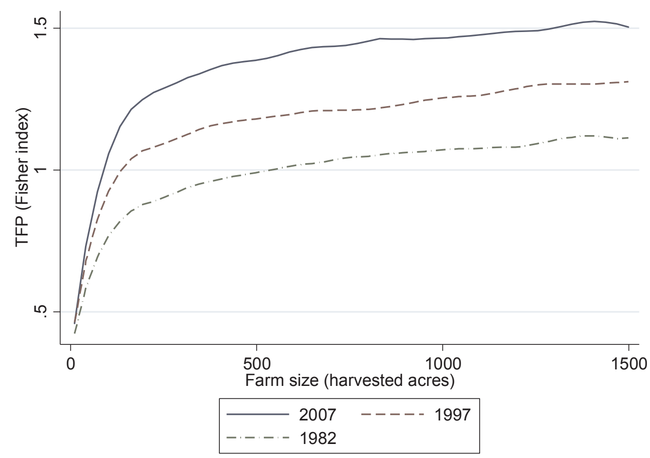

Fig. 2. Estimated relationship between TFP and farm size, farms harvesting fewer than 1500 acres.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the results of a kernel-weighted local polynomial regression of a Fisher TFP index on farm size in each year. The Fisher TFP index is a measure of the quantity of output produced relative to the quantity of inputs used – see text for details. An increase in the TFP index from 1 to 1.5 would imply a 50% increase in total factor productivity.

was an extreme drought in the Heartland region in 2012, which lowered productivity substantially that year. The figure shows TFP increasing with farm size, over the size range shown (up to 1500 acres). The figure also shows that TFP increased between each of the three Censuses, at all farm sizes.

To gain insight into how productivity changed over time by farm size, we first examine trends in corn yields (Fig. 3). Corn is by far the most widely produced crop in the Heartland region, which provides a large sample for comparisons. To account for the fact that 2012 was an exceptional drought year in the Heartland which resulted in unusually low yields, we calculate a linear trend without using the 2012 observations. Between 1982 and 2007, predicted corn yields for the smallest farms increased at an average rate of 1.00 bushels per year. In contrast, for the four largest size categories expected corn yields increased at an average rate of 1.14–1.18 bushels per acre per year. Over 30 years, this amounts to an increased corn yield differential between smallest and the larger farms of 4.2–5.4 bu/ac (as a reference, small farms had predicted yields in 2012 of 137 bu/ac and large farms 159 bu/ac).

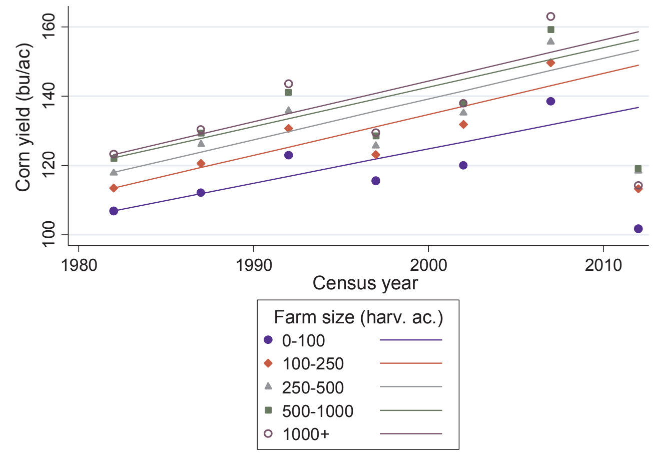

Fig. 3. Corn yields by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average corn yields for farms growing corn in each size category in each year and it shows an estimated linear trend, which is estimated without using the 2012 data.

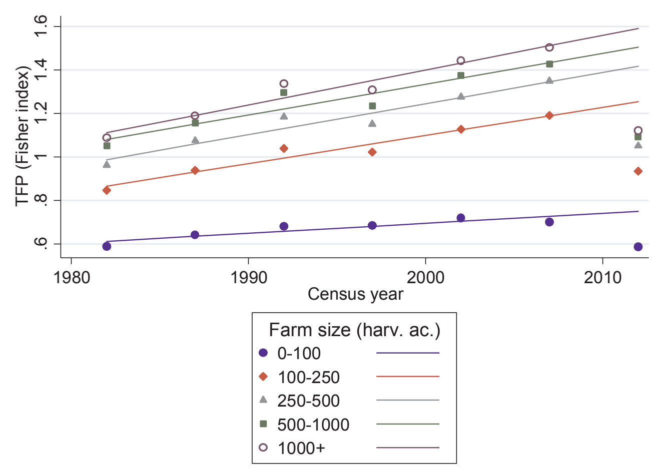

Fig. 4. TFP by farm size category: 1982–2012.
Source: Author's calculations using 1982–2012 Census of Agriculture data. Note: The figure shows the average TFP index for each size category in each year and an estimated linear trend. The trend is estimated without using the 2012 data. The Fisher TFP index is a measure of the quantity of output produced relative to the quantity of inputs used – see text for details. An increase in the TFP index from 1 to 1.5 would imply a 50% increase in total factor productivity.

A more complete picture of productivity change can be seen comparing TFP trends from 1982 to 2012 for each farm size category (Fig. 4). As with the corn yields, we account for the drought year by fitting a linear trend to TFP without using the 2012 data. Even more pronounced than with corn yields, the rate of growth in TFP is slower for the smallest size group (estimated TFP changes are reported in the first column of Table 3.) While the predicted TFP for farms in the four largest size categories increased by 47–59% between 1982 and 2012, TFP for the smallest farms increased by only 17%. Hence, the difference in productivity between farms with fewer than 100 acres and all other farms widened between 1982 and 2012. If this trend continues, it suggests that farms in the smallest size category will see a further deterioration in their competitive position and their share of total output will likely continue to shrink. We explore the factors underlying the lagging productivity growth of the smallest farms in the next section.

4.2. Technology and size economies

Using information on input expenditures from the Census, we can compare unit costs across farm size categories and over time to gain insight into the factors driving returns to size (Table 2). Unit costs are calculated as the input expenses divided by a Fisher output index. Input expenses for labor, machinery and variable inputs are described in the data section. For land, input expenses are estimated by multiplying harvested acres by an estimated national average rental rate.

Consistent with size economies, unit costs declined with farm size. In 2012, small farms (less than 100 acres) spent $2.96 per unit, midsize farms (250–500 acres) $1.72 per unit, and large farms (at least 1000 acres) $1.61 per unit. Over half of the $1.35 unit cost difference between the smallest and largest farms was attributable to labor costs and 27% was due to a capital costs – compared to only 8% and 11% for land and variable inputs, respectively. Hence, the available technology allowed large farms to use labor and capital much more cost effectively than small farms; the size advantage was limited for land and variable inputs. The relatively small differences in land productivity across size categories imply small differences in yields (assuming land prices do not vary by size). This is confirmed by the data on corn yields, which show relatively small differences across farm sizes (Fig. 3).

What explains the lower unit costs of labor and capital for larger farms? The unit labor cost advantages for larger farms likely stem from characteristics of the farm labor market and the availability of labor-saving technologies. Partly because of transaction costs associated with employing and supervising hired labor, most production in the U.S. occurs on farms that are family-owned and operated (Cochrane, 1993). Labor-saving technologies allow farms with a limited amount of family labor to produce at a larger, more efficient scale. Labor-saving technologies include large tractors, harvesters and other equipment that reduce the amount of labor required per acre. In addition, genetically engineered seeds can allow for fewer applications of herbicides and pesticides, which also reduces unit labor costs (Gardner et al., 2009).

Lower capital costs per unit may exist because capital equipment is "lumpy" and large pieces of equipment and machinery can be operated more cost effectively on large operations. Moving and setting up large pieces of equipment is costly, and these costs can be minimized when fields are large and contiguous – conditions more prevalent on large operations (MacDonald et al., 2013). Larger farms may also be able to use capital more efficiently by reducing the time that costly capital equipment is idle. Large farms are able to more fully employ equipment without having to incur the transactions costs associated with renting in equipment. Small farms could in theory purchase large-scale equipment and rent it out rather than idle it, but there are transactions costs associated with renting out equipment and limits to how many farms can enter the rental market.

Consistent with the slower TFP growth rates for the smallest farms that was shown in Fig. 3, the data also show an increasing divergence in unit costs. Between 1982 and 2012, nominal unit costs increased by $0.32–0.39 for farms with more than 100 acres compared to $0.62 for the smallest farms, a difference of $0.23–$0.30 (bottom row, Table 2).[8] This increasing divergence in unit costs was driven by changes in labor and variable input unit costs: the difference between smallest and largest farms increased by $0.13 for unit labor costs and by $0.11 for variable input costs; there was little divergence in machinery or land unit costs (last column, Table 2).

The increasing unit cost divergence for the smallest farms suggests that some of the new technologies that were adopted between 1982 and 2012 that allowed farmers to use labor and variable inputs (seed, fertilizer, pesticides, and energy) more efficiently were less well-suited for

[8] Unit costs were abnormally high in 2012 because the drought in the Heartland lowered output. However, we use the 2012 data because we are mainly interested in differences between small and large farms, rather than levels.

Table 2
Input costs per unit by farm size, 1982 and 2012.

	Farm size (harvested acres)					
	0–100 (1)	100–250 (2)	250–500 (3)	500–1000 (4)	1000+ (5)	Difference between (1) and (5)
Labor						
1982	0.72	0.28	0.17	0.12	0.11	0.61
2012	0.81	0.24	0.13	0.10	0.08	0.74
2012–1982	0.10	−0.04	−0.04	−0.02	−0.03	0.13
Machinery						
1982	0.51	0.30	0.24	0.20	0.15	0.35
2012	0.55	0.31	0.25	0.23	0.19	0.36
2012–1982	0.04	0.01	0.01	0.03	0.04	0.01
Land						
1982	0.64	0.59	0.56	0.54	0.53	0.11
2012	0.79	0.72	0.69	0.68	0.69	0.10
2012–1982	0.15	0.13	0.13	0.14	0.16	−0.01
Variable inputs						
1982	0.47	0.44	0.43	0.42	0.43	0.04
2012	0.80	0.69	0.65	0.64	0.65	0.15
2012–1982	0.33	0.25	0.22	0.22	0.22	0.11
Total unit costs						
1982	2.34	1.61	1.40	1.27	1.22	1.12
2012	2.96	1.96	1.72	1.65	1.61	1.35
2012–1982	0.62	0.35	0.32	0.38	0.39	0.23

Source: Author's calculations using 1982 and 2012 Census of Agriculture data.
Note: Variable inputs include fertilizer, chemicals, fuel, utilities and seeds. Unit costs are input costs (in nominal dollars) divided by a Fisher output index. Sample consists of crop farms located in Heartland region. See text for details about sample creation.

and consequently less likely to be adopted by the smallest operations. New labor and variable input saving technologies include larger combines and harvesters that allow farmers to cultivate more land with the same amount of labor. Other innovations include GPS-equipped precision agriculture technologies that allow farmers to more closely match input applications to the crops' needs, which can reduce the amount of seed, fertilizer and pesticides used. Using information about crop yields, terrain topography, organic matter content, moisture levels, nitrogen levels, etc., on-board computers can operate variable rate controllers on farm equipment to optimize the application of inputs. GPS-guided autopilot systems also allow farmers to reduce skips and overlap when planting and applying agrochemicals, which also reduces variable input costs. The fact that the smallest farms have lagged larger farms in reducing variable input costs is consistent with the lower adoption rates of precision farming technologies by smaller operations that have been reported in other studies (Schimmelpfennig, 2016; Daberkow and McBride, 2003).

4.3. *Size economies and aggregate TFP change*

How much of the past aggregate productivity growth can be attributed to structural change versus size-specific TFP growth? Following (2) we use the estimated average sales share, change in shares, average TFP, and change in TFP for each size category to calculate the aggregate TFP change in percentage terms (baseline scenario, Table 3). To reduce the influence of outlier years, we use the predicted value of the sales shares and TFP levels (that is, the fitted values from the linear trends shown in Figs. 1 and 3). The aggregate TFP of crop farms in the Heartland grew an estimated 63.7% (=52.9 + 10.8) between 1982 and 2012, or 1.5% per year. This estimate is slightly higher than the 1.3% annual growth rate estimated by the USDA for the entire U.S. agricultural sector (ERS-USDA, 2017). Productivity growth for crop farms in the Heartland region may have exceeded the national average in part to the extent that crop production experienced more rapid TFP growth than livestock production. Alternatively, because farmland in the Heartland region is relatively flat and contiguous, farmers could more efficiently use large-scale farm equipment and advanced precision agriculture technologies (MacDonald et al., 2013).

We estimate that 17% (=10.8/63.7) of aggregate productivity growth between 1982 and 2012 was attributable to the shift to larger and more productive operations. Put another way, by 2012, total output was 7.1% (=1.637/1.529) greater because of the farm size distributional changes than it would have been with no distributional changes.

The remaining 83% (=52.9/63.7) of aggregate TFP growth was due to the increasing TFP of the average farm in each size category. This TFP growth was due to factors other than farm size change – including technical change (the adoption of more productive technologies) and technical efficiency change (greater ability to achieve maximum output given a set of inputs and the technology). The magnitude of these other sources of aggregate productivity growth increased steadily with farm size (column 3, Table 3). TFP growth for the smallest farms contributed 0.6 percentage points to aggregate TFP growth whereas TFP growth for the largest farms contributed 22.4 percentage points. The contribution increased with farm size mainly because larger farms had higher average sales shares. For example, farms with less than 100 acres produced only 3% of total output on average from 1982 to 2012, compared to 38% for farms with at least 1000 acres. Consequently, increases in TFP for larger operations resulted in a greater expansion of output and a bigger contribution to aggregate TFP growth.

4.4. *Targeted policies to increase productivity*

If policymakers have the objective of slowing the rate of consolidation of production, one approach would be to devise policies that raise the productivity of smaller farms. Raising the productivity of smaller farms could make them more profitable, presumably causing fewer to exit the industry. Such productivity-enhancing policies might include targeted subsidized loans or tax breaks for purchasing new machinery and equipment, or targeted agricultural extension assistance. A potential drawback with targeting small farms, as opposed to larger farms, is that smaller operations produce relatively little output, so effect of the targeted policy on aggregate productivity growth would be limited.

To illustrate how targeted policies differentially affect aggregate

Table 3
Percent change in aggregate TFP (1982–2012): Contributions from changes in productivity and size distribution.

Farm size (harvested acres)	Percent change in TFP $100\frac{\Delta TFP_S}{TFP}$ (1)	Average sales share $\bar{\theta}_S$ (2)	Contribution to aggregate TFP change due to change in TFP $100\frac{\Delta TFP_S}{TFP}\cdot\bar{\theta}_S$ (3)	Change in Sales Share $\Delta\theta_S$ (4)	Average TFP as a percent of Initial TFP $100\frac{\overline{TFP_S}}{TFP}$ (5)	Contribution to aggregate TFP change due to change in sales share $\Delta\theta_S\cdot 100\frac{\overline{TFP_S}}{TFP}$ (6)	Total contribution to aggregate TFP change (3) + (6)
Baseline scenario: Estimates based on observed data							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			52.9			10.8	63.7
Scenario 1: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 0–100 acres							
0–100	**26.8**	0.03	**0.9**	−0.04	**86.9**	**−3.4**	**−2.5**
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			**53.2**			**10.7**	**63.9**
Scenario 2: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 250–500 acres							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	**62.4**	0.19	**11.8**	−0.18	**152.6**	**−27.5**	**−15.7**
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	58.6	0.38	22.4	0.42	164.9	69.8	92.2
All farms			**54.8**			**9.8**	**64.6**
Scenario 3: Hypothetical 10 pct. pt. increase in “Percent change in TFP” for farms with 1000+ acres							
0–100	16.8	0.03	0.6	−0.04	83.1	−3.2	−2.6
100–250	47.5	0.10	4.7	−0.10	129.4	−13.3	−8.6
250–500	52.4	0.19	9.9	−0.18	146.7	−26.4	−16.5
500–1000	51.8	0.29	15.3	−0.10	157.7	−16.0	−0.7
1000+	**68.6**	0.38	**26.2**	0.42	**171.3**	**72.5**	**98.7**
All farms			**56.7**			13.5	**70.2**

Source: Author’s calculations using 1982–2012 Census of Agriculture data.
Note: ΔTFP_S is the change in predicted TFP for farms in size category s between 1982 and 2012, TFP is the predicted initial aggregate TFP for all farms, and $\overline{TFP_S}$ is the average of the 1982 and 2012 predicted TFP for farms in size category s.
The bold font indicates the values that are different from the baseline scenario.

productivity depending on the size of the farms targeted, consider the effect of a hypothetical policy that increased the productivity growth of targeted farms by 10 percentage points while having no effect on the farm size distribution.[9] We estimate the effects of the policy in 2012, assuming it had been implemented in 1982. If the smallest farms (less than 100 acres) were targeted, this policy would have increased the TFP of these farms by 26.8% instead of 16.8%, and their average TFP (as a percent of initial total TFP) would have increased from 83.1 to 86.9 (scenario 1: Table 3). The policy would have had two effects on aggregate TFP. First, the contribution to aggregate TFP for the average farm with less than 100 acres would have increased 0.3 percentage points (from 0.6 to 0.9). Second, gains from structural change would have been smaller. As farms left the smallest category, aggregate TFP would have dropped by 3.4 points instead of 3.2 (the increase in TFP from growth in the other size categories would have been the same). In total, aggregate productivity growth would have increased by only 0.2 percentage points.

The effect of a similar policy that targets midsized farms (250–500 acres) is shown in scenario 2. The 10 percentage point increase in the productivity growth rate means midsized farms would have contributed 11.8 percentage points to the total aggregate growth (up from 9.9 points). However, because midsized farms were more productive on average over the period, structural change would have contributed a smaller amount to aggregate productivity growth (9.8 points compared to 10.8). In sum aggregate productivity would have increased by only 0.9 percentage points.

In comparison, consider a hypothetical policy that raised the productivity growth of the largest farms by 10 percentage points (scenario 3, Table 3). The contribution to aggregate TFP from farms with more than 1000 acres would have increased by 3.8 percentage points (from 22.4 to 26.2). As farms shifted into the largest category between 1982 and 2012, the gains from structural change would have been greater than before – productivity would have increased by 72.5 percentage points compared to 69.8 in the baseline – an increase of 2.7 points. The net effect would have been an increase in aggregate TFP of 6.5 percentage points.

Hence, the policy targeting the largest farms would have increased aggregate TFP 32 times more than a similar policy targeting the smallest farms and 7 times more than the policy targeting midsized farms. The magnitude of the difference in the policy effects between the largest farms and the smaller farms would have been even greater had we considered the effects of the policies on structural change. Targeting the small and midsized farms would have likely slowed the shift in production to larger farms. Since larger farms are more productive, slowing the shift to larger farms would have reduced aggregate productivity growth. In contrast, targeting the largest farms would have increased the rate of consolidation, which would have increased the rate of aggregate productivity growth.

The net effect of targeting farms of different sizes on aggregate productivity growth is shown column 1 of Table 4. While the effect on aggregate productivity growth increases with the size of farm targeted, the cost-effectiveness of the targeted policies – defined in terms of aggregate productivity gains per policy dollar – depends on policy costs. If

[9] The evolution of the size distribution would likely change in response to the policy. However, this change is difficult to predict and therefore is not modeled here. We discuss the likely implications of the effect of the policy on the size distribution later in the section.

Table 4
Aggregate productivity increases from targeted productivity-enhancing policies relative to the farm and sales shares.

Targeted Farm size (harvested acres)	Percentage point increase in aggregate productivity (1)	Average share of farms, 1982–2012 (2)	Average share of sales, 1982–2012 (3)	Percentage point increase in aggregate productivity per farm share (4)	Percentage point increase in aggregate productivity per sales share (5)
0–100	0.2	0.33	0.03	1	7
100–250	0.5	0.23	0.10	2	5
250–500	0.9	0.19	0.19	5	5
500–1000	2.4	0.16	0.29	15	8
1000+	6.5	0.09	0.38	70	17

Source: Author's calculations using 1982 and 2012 Census of Agriculture data.
Note: The "percentage point increase in aggregate productivity" is the estimated additional increase resulting from a policy that increases the productivity growth of targeted farms by 10 percentage points from 1982 to 2012. The table shows the effects of five distinct policies each targeting one of the five farm-size categories (see Table 3 and text for more details).

policy costs are roughly proportional to the number of farms targeted – which might be approximately the case with targeted agricultural extension policies – then targeting small farms would likely be much less cost-efficient than targeting larger farms. This can be seen in Table 4. Between 1982 and 2012, the smallest farms represented about a third of all crop farms in the Heartland region (column 2), which would make it very costly to provide extension or other similar types of policies to this group. Put another way, targeting the smallest farm category would results in very little increase in aggregate output per farm (column 4). In contrast, the largest farms represented only 9% of all farms over this period, so targeting these farms would have resulted in a large increase in aggregate output per farm. In fact, the aggregate productivity gain per farm share is 70 times greater for the largest farms compared to the smallest farms.

On the other hand, if policy costs are roughly proportional to farm output – which might be the case with loan or risk management polices – then cost-effectiveness is less closely correlated with farm size.[10] As discussed earlier, larger farms produced a greater share of aggregate output between 1982 and 2012 than did smaller farms (column 3). If policy costs are proportional to output, then it would be substantially less costly to target a smaller farm size category. For smaller farm categories, a targeted policy has a smaller effect on aggregate output, but also a lower cost – so the effect on cost effectiveness is ambiguous. This is shown in column 5: the percentage point increases in total output per sales share for the smallest four farm size categories are roughly the same. The largest farms are roughly two to three times more cost effective than the smaller farms – which is a much less extreme difference.

5. Conclusion

This study used quinquennial Agricultural Census data collected from 1982 to 2012 to estimate the TFP of five size classes of grain-producing farms in the U.S. Corn Belt. We found strong evidence of economies of size in each Census year. The productivity differences across farm size categories are reflected in substantially higher unit costs of the smallest operations. These findings support the hypothesis that economies of size was a contributing factor behind the consolidation of commodity crop production that occurred in the U.S. over the last 30 years.

Findings also indicate that the smallest crop farms (less than 100 harvested acres) fell further behind large farms in terms of productivity in recent decades. Between 1982 and 2012, TFP growth rates were similar across farm size classes except for the smallest, which had a significantly slower growth rate. If past trends continue, this suggests that the productivity disadvantages for smaller operations will persist, and in the case of the smallest farms, will expand.

Consistent with slower TFP growth for the smallest farms, the study found that the difference in unit costs between the smallest farms and larger farms increased over the study period. Most of the unit cost divergence can be explained by changes in the unit costs of labor and variable inputs (seeds, fertilizer, pesticides, and energy). This suggests that some technological advances in recent decades, such as very large combine harvesters and precision agriculture technologies, lowered unit labor and variable input costs less for the smallest farms. Lower adoption rates of precision agricultural technologies on the smallest farms, which have been observed in other studies, might explain why the labor and variable input costs disparities increased, and why the farm productivity growth of the smallest farms has lagged behind that of larger operations.

Because of size economies, crop farm consolidation contributed significantly to aggregate agricultural productivity growth in the Corn Belt. Between 1982 and 2012, the share of output produced by crop farms with at least 1000 acres increased from 17% to 59%. Using a new method for disaggregating TFP growth, we estimate that the aggregate TFP of specialized crop farms in the Heartland region increased by 64% or 1.5% per year between 1982 and 2012, and that about one-sixth of this growth was attributable to the shift in production to larger more productive farms. Hence, while technological change and technical efficiency change were the most important sources of aggregate productivity growth in recent decades, the contribution from the farm size distribution change was substantial.

The data provide no indication yet of a slowdown in crop consolidation or productivity growth in the Heartland region. However, with most output in the region now produced by large farms, it is plausible that the pace of consolidation will slow in the coming decades. A slowdown in the rate of productivity growth in hog production after 2004 was observed in the U.S. hog sector following a rapid shift in production to very large farms – a size at which returns to scale were close to constant (McBride and Key, 2013). If the rate of consolidation of crop production slows in the coming decades, then aggregate TFP growth rates will likely decline as well, unless the rate of technological progress increases.

Finally, this study illustrated some of the tradeoffs associated with productivity growth policies that target farms of a particular size. Policies that raise the productivity of small farms could increase the economic viability of these farms and potentially slow the rate of consolidation. However, the study showed that targeting small farms would result in relatively little in aggregate productivity growth compared to targeting larger farms. For example, a hypothetical productivity-enhancing policy targeting farms with at least 1000 acres of cropland would have increased aggregate productivity 32 times more than a similar policy targeting farms having less than 100 acres and 7 times more than a policy targeting farm having between 250 and 500

[10] Loan or risk management programs could plausibly have costs that are roughly proportional to output. This would be the case for loan programs if most of the program costs (e.g., default costs) are proportional to the loan amount, and the loan amount is roughly proportional to farm size. This would be the case for risk management programs if the costs (indemnity payments) are proportional to the amount of cropland insured, which in turn is proportional to total output.

acres.

At the same time, the cost effectiveness of targeted policies in terms of aggregate productivity gains per policy dollar depends on the policy costs. If costs are roughly proportional to the number of farms targeted – which might be the case with targeted agricultural extension policies – then targeting smaller farms would likely be substantially less efficient than targeting larger farms (or not targeting at all by farm size). On the other hand, if policy costs are roughly proportional to farm output – which might be the case with loan or risk management polices – then the efficiency costs of targeting smaller farms would likely be much smaller.

Appendix A. Estimating unpaid labor input for Census of Agriculture

Before 2012, no questions were asked on the Census of Agriculture about the quantity of non-operator family labor or other unpaid labor that worked on-farm. To address this missing data issue, we estimate the quantity of unpaid farm labor using information from the Agricultural Resource Management Survey (ARMS). The ARMS is a detailed survey of a representative sample of U.S. farm households conducted annually since 1996 by the USDA Economic Research Service and NASS. The ARMS collects the same information as the Census but also includes more detailed questions about production costs, assets, and off-farm employment. Relevant to this study, the ARMS also asks about the amount of unpaid time the operator's spouse and family and other operators spend working on the farm. This information allows us to predict the quantity of unpaid labor used on farm as a function of highly correlated variables that are observed in the Census: the operators' on-farm labor, and the size of the farm (defined by harvested acres and value of production).

To estimate the parameters in the predictive model, we first create an ARMS sample to match the Census sample. We do this by limiting the ARMS sample using the same criteria used in this study: being located in the Heartland region and specializing in production of the major commodity crops (see data section for details). We use ARMS data collected from 1996 to 2012 – all the survey years available that overlap with the Census data. The matched sample includes 21,912 observations. As expected, the ARMS data reveal that the unpaid farm labor hours increases with farm size and the operator's farm labor (Table A1). On average, operators work on farm about 3.4 times as many hours as unpaid labor, and this ratio decreases with farm size. The data show that the labor productivity of operator and unpaid labor (as measured by value of production per hour) increases dramatically with farm size.

We take advantage of the fact that unpaid labor hours is correlated with the operators' hours and with farm size to estimate the quantity of unpaid farm labor. We regress unpaid labor on operator hours, harvested acres, the natural log of harvested acres, value of production, and a time trend. The linear regression model has an R-squared of 0.38 and all the variable coefficients are significant at the 99% level. We use the estimated coefficients with the Census data variables to predict unpaid labor time for each farm in the Census sample. The opportunity cost of unpaid labor is estimated as the predicted quantity of unpaid labor (in days) multiplied by the same daily wage rate used for hired and operator labor (based on the Bureau of Labor Statistics Average Hourly Earnings from the Current Employment Statistics survey).

Using the Census data, the productivity of estimated unpaid labor (A Fisher output index divided by unpaid labor days) increases over time because of the negative time trend coefficient and because the positive operator labor coefficient – as operator's labor productivity increases, unpaid labor productivity also increases. Because unpaid labor is a small share (18%) of total farm labor (which also includes hired, contract and operator labor), including the unpaid labor estimates has a very small effect on the results presented in the paper.

Table A1
Operator labor and unpaid labor quantities for crop producers in the Heartland.

	Acres harvested				
	0–100	100–250	250–500	500–1000	1000+
Operator labor (h)	799	1388	1918	2484	2871
Unpaid labor (h)	178	287	472	684	1343
Value of production ($)	16,748	62,038	139,435	290,380	749,637
VOP/operator labor ($/h)	21	45	73	117	261
VOP/unpaid labor ($/h)	94	217	295	425	558
ARMS respondents	2190	3060	3568	4865	8229

Source: Author's calculations using 1996–2012 USDA Agricultural Resource Management Survey. See Appendix A for details about sample creation.

References

Alston, J., Anderson, M., James, J., Pardey, P., 2010. Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending. Springer, New York.

Benjamin, D., 1995. Can unobserved land quality explain the inverse productivity relationship. J. Dev. Econ. 46 (1), 51–84.

Burns, C., Kuhns, R., 2016. The Changing Organization and Well-Being of Midsize U.S. Farms, 1992–2014. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-219) (October).

Carletto, C., Savastano, S., Zezza, A., 2013. Fact or artifact: the impact of measurement errors on the farm size-productivity relationship. J. Dev. Econ. 103, 254–261.

Chambers, R.G., 1988. Applied Production Analysis: A Dual Approach. Cambridge University Press, New York.

Cochrane, W., 1993. The Development of American Agriculture: A Historical Analysis, second ed. University of Minnesota Press, Minneapolis.

Daberkow, S., McBride, W., 2003. Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the U.S. Precis. Agric. 4, 163–177.

Diewert, W., 1978. Superlative index numbers and consistency in aggregation. Econometrica 46, 883–900.

Dumagan, J., 2002. Comparing the superlative Törnqvist and Fisher ideal indexes. Econ. Lett. 76, 251–258.

ERS-USDA, 2017. Indices of output, input, and total factor productivity for the United States, 1948-2013, table 1a. Accessed 1/12/17 from: < https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/ > .

Färe, R., Grosskopf, S., Norris, M., Zhang, Z., 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. Am. Econ. Rev. 84 (1), 66–83.

Gardner, J., Nehring, R., Nelson, C., 2009. Genetically modified crops and household labor savings in US crop production. Agbioforum 12 (3&4), 303–312.

Heimlich, R., Farm Resource Regions. Agricultural Information Bulletin No. AIB-760, August 2000. Accessed 1/11/17 from: < https://www.ers.usda.gov/publications/pub-details/?pubid=42299 > .

Huffman, W., Evenson, R., 2001. Structural and productivity change in US agriculture, 1950–1982. Agricultural Economics 24 (2), 127–147.

Key, N., Roberts, M.J., 2006. Government Payments and Farm Business Survival. Am J Agric Econ 88 (2), 382–392.

MacDonald, J.M., Korb, P., Hoppe, R., 2013. Farm Size and the Organization of U.S. Crop

Farming. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-152) (August).
McBride, W., Key, N., 2013. U.S. Hog Production from 1992 to 2009: Technology, Restructuring, and Productivity Growth. U.S. Department of Agriculture, Economic Research Service, Economic Research Report, (ERR-158) (October).
Morrison Paul, C., Nehring, R., Banker, D., Somwaru, A., 2004. Scale economies and efficiency in US agriculture: are traditional farms history? J. Prod. Anal. 22 (3), 185–205.
Orea, L., 2002. Parametric decomposition of a generalized Malmquist productivity index. J. Prod. Anal. 18 (1), 5–22.
Schimmelpfennig, D., 2016. Farm Profits and Adoption of Precision Agriculture. Economic Research Report, ERR-217, U.S. Department of Agriculture, Economic Research Service.
Sumner, D.A., 2014. American farms keep growing: size, productivity, and policy. J. Econ. Perspect. 28 (1), 147–166.
Stigler, G., 1946. Labor productivity and size of farm: a statistical pitfall. J. Farm Econ. 48 (3), 821–825.
USDA, 2017. Resources for Small and Mid-Sized Farmers. United States Department of Agriculture. Accessed 1/18/17 from: < https://www.usda.gov/wps/portal/usda/usdahome?contentidonly=true&contentid=small-midsized-farmer-resources.xml > .
Wang, S.L., Heisey, P., Schimmelpfennig, D., Ball, E., 2015. Agricultural Productivity Growth in the United States: Measurement, Trends, and Drivers. U.S. Department of Agriculture, Economic Research Service, Economic Research Report (ERR-189) (July).