Vertical Disintegration and the Shifting Boundary of the Farm Business: Implications for Agricultural Productivity

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Abstract

Agricultural production in the United States has undergone significant vertical disintegration over the past half-century, with farmers increasingly outsourcing production activities to specialized service providers. This article provides the first systematic evidence of the relationship between support service intensity and farm productivity. Using restricted-access data from the Longitudinal Business Database to overcome suppression in public-use statistics, we measure local service activity with information from administrative tax filings. Our cross-sectional analysis of data from 2002 to 2017 reveals a persistent, statistically significant positive relationship between the size of the crop services sector and county-level crop yields measured in dollars (all crops) and bushels (corn, soybeans, wheat) per acre. Crucially, longitudinal analysis of the determinants of yield growth between 2002 and 2022 demonstrates that crop service intensity predicts subsequent yield growth conditional on base-year yield, indicating that the link between support services and productivity is substantive, rather than a statistical artifact of service providers selecting into high productivity areas. We discuss the implications of this relationship on the measurement of total factor productivity.

Key words: agricultural services; vertical integration; agricultural inputs; productivity

JEL classification: Q12, L22, O47

1. Introduction

Organizational change has long been recognized as a driver of agricultural productivity growth, with particular attention in recent decades focused on the implications of increased vertical integration and supply chain coordination. Nevertheless, many agricultural production sectors have been characterized by the opposing process of vertical *dis*-integration, whereby production activities historically undertaken directly by farm businesses are instead purchased from specialized input suppliers. Despite this now well-documented evo-

lution in the organization of agricultural production in the United States, direct empirical evidence linking the growth of upstream service industries to agricultural productivity remains scarce. Using restricted-access microdata for establishments providing support services for crop production, this article presents the first estimates of this relationship.

Vertical disintegration in agricultural production was anticipated by Davis (1957, p. 300), who described the "gradual dispersion of functions from the farm to business." The economic logic underlying this transformation was first articulated by Stigler (1951), who argued that vertical disintegration is a natural consequence of market growth: as industries expand, specialized firms can achieve scale economies in particular functions, leading to the emergence of dedicated supplier industries. Although Stigler's framework suggests that vertical disintegration may increase productivity, empirical research on the organizational determinants of productivity growth in the agricultural sector has largely focused on technology adoption (*what* inputs are used) or outsourcing (*who* manages those inputs), while ignoring the market structure that allows entire service industries to emerge and grow so that outsourcing in agriculture is possible at scale.

For example, a substantial literature examines the underlying motivations for the growing prominence of vertical integration (e.g., Frank and Henderson 1992; Hennessy 1996; Reimer 2006), and more recently supply chain coordination (e.g., Sexton and Xia 2018; Maples, Lusk, and Peel 2019; Zilberman, Lu, and Reardon 2019), in agriculture. A related body of work examines agricultural contracting, analyzing the structure of contractual arrangements between farmers and intermediaries and the allocation of risk and incentives within these relationships (Knoeber and Thurman 1995; Hueth and Ligon 1999; Goodhue 2000). Empirical work has documented the productivity effects of these arrangements, e.g, researchers estimating the effect of contracting and vertical integration in livestock sectors find that these forms of coordination improve productivity (Key and McBride 2003; Morrison Paul et al. 2004; MacDonald and McBride 2009).

Yet, much less attention has focused directly on the productivity implications of vertical disintegration via the outsourcing of agricultural production activities to specialized input suppliers. Although the relationship between outsourcing and firm performance has been studied extensively outside of agriculture, neither theory nor empirical evidence provides unambiguous predictions. Lahiri (2016) reviews 57 studies across industries and finds inconsistent results. Outsourcing effects range from positive to negative to nonexistent, depending on measurement approaches, industry, and organizational context. The only study examining agricultural outsourcing and productivity is Lu, Du, and Qiu (2022), who find mixed effects of mechanization services in China.

To address this gap in the literature, we estimate the relationship between access to businesses providing support services for crop production and crop yields in the United States.[1] We combine county-level data from the Census of Agriculture with establishment-level payroll data from the Longitudinal Business Database (LBD), using total payroll in crop support service industries as a proxy for the intensity of service provision within counties.[2] The LBD contains administrative records derived from Internal Revenue Service payroll tax filings, allowing us to overcome the disclosure suppression that renders publicly available data sources inadequate for this analysis. Because the relationship between support services and productivity may vary across crop types, we separately examine corn, soybean, and wheat yields, as well as aggregate crop sales per acre, using both cross-sectional and longitudinal specifications.

A considerable challenge to interpreting estimated relationships is the strong likelihood that local agricultural productivity influences the equilibrium level of support service pro-

[1] Total factor productivity estimates are not available at the county level. We focus on crop yield as a key dimension of productive efficiency that provides a starting point for future research.

[2] *Support activities for crop production* are formally defined in the North American Industry Classification System (NAICS) at the four-digit level (1151) and includes the following six-digit industries: Cotton ginning (115111); Soil preparation, planting, and cultivating (115112); Crop harvesting, primarily by machine (115113); Postharvest crop activities (except cotton ginning (115114); Farm labor contractors and crew leaders (115115); and Farm management services (115116). *Support activities for crop production* together with *Support activities for animal production* (1152) define the entire Agricultural support services sector and provide the sampling frame for the Census of Agricultural Services.

vision. While an approach based on a natural experiment or instrumental variable might offer a stronger causal claim, shocks to the organizational boundaries of the farm that are both plausibly exogenous and generalizable to national agricultural production are notoriously difficult to identify. Given the absence of prior empirical studies investigating the role of support services, the theoretical ambiguity of how crop service intensity affects yield, and the lack of an obviously valid instrument, we instead prioritize providing an econometrically feasible estimate of this relationship. Specifically, we leverage the longitudinal structure of our data to regress yield growth on support service intensity controlling for base-year productivity so that the estimated relationship is robust to the static selection of crop service providers into high productivity areas.

In a preview of our results, we find a persistent and statistically significant positive relationship between the size of the crop services sector and crop yields. In every Census of Agriculture year between 2002 and 2017, counties with larger crop service payrolls exhibited higher crop yields, with estimated elasticities of 0.02–0.063 for corn, 0.007–0.028 for soybeans, and 0.024–0.048 for wheat. We further find that the relationship varies systematically with scale but in opposite directions for wheat and corn: for wheat, the association between services and yields is larger in counties with more harvested acres, while for corn the relationship diminishes as harvested acreage increases. Finally, our longitudinal analysis estimating yield growth between 2002 and 2022 reveals that crop service intensity predicts future yield growth controlling for initial crop productivity. Notably, however, the association has weakened over time, which coincides with declining new business formation in the crop services sector. This pattern is consistent with productivity gains from outsourcing reaching their limits as the sector matures and economies of scale are exhausted.

Thus, the contributions of this work are fivefold. First, we demonstrate that using restricted Federal administrative data can overcome a fundamental measurement problem: approximately 76 percent of the U.S. counties with at least one crop services provider have suppressed data in publicly available sources, yet these counties account for approxi-

mately half of national crop production. Second, we introduce important new information on the equilibrium relationship between crop support services and crop yield in U.S. agriculture, as well as its evolution over the past two decades. Third, we document how the services-yield relationship varies by crop type and farm scale, revealing important heterogeneity. Fourth, we demonstrate that the positive association between support services and crop yields is robust to a longitudinal specification that controls for initial productivity and therefore reflects a substantive relationship rather than mere correlation arising from the selection of crop service providers into high-productivity areas. Fifth, we identify specific implications for agricultural total factor productivity (TFP) growth accounting frameworks, highlighting how the current treatment of purchased production services may lead to systematic biases in quality adjustment and input share calculations. As this study represents an initial attempt to document the potential effects of vertical disintegration within agricultural production, there are clear opportunities for future refinement of both data and methods; nonetheless, these results indicate that existing productivity frameworks are incomplete without further consideration of the agricultural services sector.

The remainder of the article is organized as follows. The next section establishes context for our analysis where we document vertical disintegration via growth of the agricultural services sector and describe agricultural productivity trends. We then provide an overview of existing theoretical and empirical research that investigates the relationship between outsourcing and productivity. Next, we describe our data and empirical methodology and present results from cross-sectional and longitudinal analyses. The final section discusses implications for productivity measurement and directions for future research.

2. Agricultural Service Industry and Productivity Trends

Previous work has described the evolution of the crop support services sector over the past half century (Dunn 2024; Babkin et al. 2022; Dunn and Hueth 2017). In this section, we briefly summarize these findings and put them in the context of vertical disintegration and

farm productivity. We begin by documenting the increasing importance of the agricultural services industry (and where possible, the crop services sector specifically) from three different perspectives: industry size, farm expenditures, and capital ownership.

2.1. The Growth of Agricultural Services

The agricultural services sector has expanded substantially over the past half century. In 2022, the Census Bureau conducted a Census of Agricultural Services for the first time since 1978, revealing that the real value of sales increased 143 percent over the period for the sector as a whole, and 146 percent for crop services specifically (throughout this article, all dollar values and percent changes are in real terms after price-adjusting reported nominal values to the 2023 level using the GDP price index published by the Bureau of Economic Analysis). Payroll to workers exhibited similar growth: 126 percent for agricultural services and 136 percent for crop services. Administrative data from the Quarterly Census of Employment and Wages (QCEW) shows even larger increases: 263 percent for agricultural services payroll and 288 percent for crop services between 1978 and 2022. By comparison, the real value of farm sales increased only 12 percent over the same period.

Farm expenditure patterns reflect this shifting boundary between farm and non-farm production activities. According to the Census of Agriculture, farms spent $10.5 billion on contract labor in 2022, compared to $2.9 billion in 1982, a 256 percent increase. Over this period, expenditures on contract labor as a share of total labor expenses rose from 11.6 percent to 19.5 percent (solid line in Figure 1). Farm expenditures on custom work and custom hauling experienced similar growth, increasing from $5.4 billion in 2002 to $10.4 billion in 2022, with the share of farm spending on outsourced capital rising from 16.4 percent to 18.4 percent (dotted line in Figure 1).

The shift in capital ownership has been equally striking. Using the Fixed Asset Investment Tables published by the Bureau of Economic Analysis (BEA), the value of tractors and other agricultural machinery owned by farms fell from $252.5 billion in 1978 to $239.6

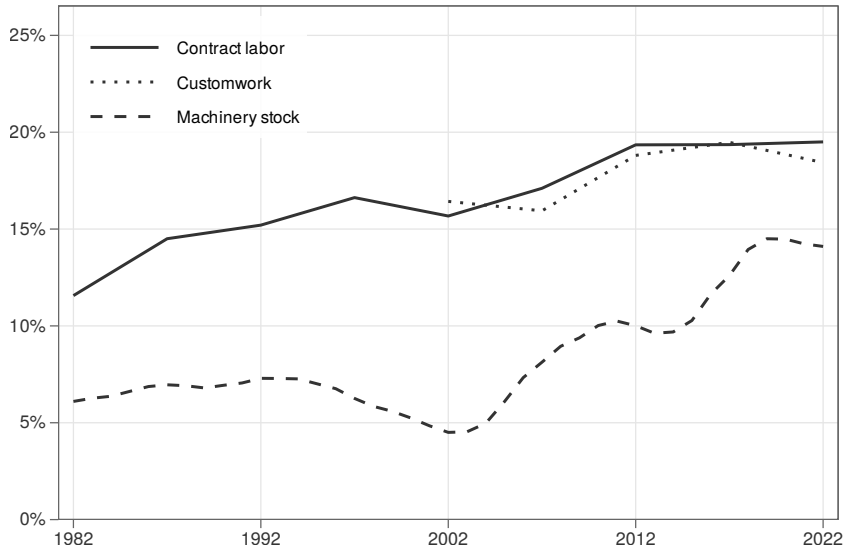


Figure 1. Share of labor and machinery managed by service providers. The solid line shows contract labor expenditures as a share of total labor expenses. The dotted line shows custom work and custom hauling expenditures as a share of total capital expenses. The dashed line shows the share of agricultural machinery capital stock owned by service providers.

billion in 2022 (a 5 percent decrease), while the value held by support service providers increased from $16.4 billion to $39.3 billion (140 percent growth).[3] As a result, the share of the agricultural machinery capital stock owned by farms fell from 93.9 percent to 85.9 percent, while the share held by service providers rose from 6.1 percent to 14.1 percent (dashed line in Figure 1).

2.2. Agricultural Productivity

The vertical disintegration of farm production reflected in the growing dependence on agricultural services coincides with significant growth in agricultural productivity. Between 1948 and 2021, farm output nearly tripled while use of quality-adjusted farm inputs remained essentially flat, implying an annualized total factor productivity growth rate of 1.49 percent (USDA Economic Research Service 2025). Agriculture is a productivity growth

[3] In the BEA Fixed Asset Accounts, the support services industry is reported in combination with forestry, fishing and related activities. This is not a concern, as we only focus on assets—tractors and other agricultural machinery—predominately used for agricultural production.

outlier: integrated industry-level growth accounts assembled by the Bureau of Economic Analysis and the Bureau of Labor Statistics allow for productivity comparisons across industries and reveal that annualized TFP growth from 1962–2016 in Farming (1.61 percent) was surpassed only by Computer and electronic products (4.85 percent) and Warehousing and storage (1.87 percent) among 36 industries (Eldridge et al. 2020). Farm productivity growth has remained robust in recent years, averaging 1.3 percent annually over 2002–2021.

National agricultural productivity in the U.S. is calculated using the TFP growth accounting framework (Wang et al. 2024), a methodology pioneered by Solow (1957) and further refined by Jorgenson and Griliches (1967). Drawing on this framework, Chambers and Pieralli (2020) decompose measured U.S. agricultural TFP growth into contributions from technical change, weather, scale and input effects, and adaptation to the production frontier. Such decompositions, however, treat the boundary of the farm business as fixed and therefore assign productivity gains arising from vertical disintegration to one of these existing components, most plausibly technical change. Under this approach, TFP growth is measured as the difference, or residual, between the growth rates of output and input, adjusted for quality changes. The Solow residual, referred to by Abramovitz (1956) as "a measure of our ignorance," captures all factors affecting output that are not accounted for in productivity calculations. Quality adjustment plays a significant role in growth accounting for many industries and prevents misattributing improvements in the quality of inputs to improvements in production technology. Agricultural services enter USDA productivity measurement through quality-adjusted expenditures on contract labor and intermediate inputs, but improvements in service quality are difficult to fully capture.[4] Because directly

[4]Quality mismeasurement arises when observed prices fail to fully reflect changes in the effective efficiency units embodied in inputs. In the context of agricultural services, quality improvements may take the form of precision technologies, enhanced managerial expertise, or improved coordination across tasks, dimensions that are difficult to observe directly and are not captured by standard deflators applied to custom work or contract labor expenditures. When such quality improvements are omitted, growth in real intermediate inputs is understated and measured TFP growth is correspondingly overstated.

measuring these multidimensional quality attributes in agricultural services is impractical with available data, relating services payroll to crop yields provides an indirect but tractable approach to capturing the net effect of service provider quality improvements on farm productivity. As a result, empirical estimates presented here have implications for potential over- or under-estimation of farm TFP growth, a question we return to in the Discussion.

The existing literature has attributed agricultural TFP growth primarily to technological improvement arising from public and private sector R&D investments, enhanced by public infrastructure, agricultural extension, and technology spillovers (Alston et al. 2010; Huffman and Evenson 2006; Fuglie and Heisey 2007; Plastina and Fulginiti 2012; Wang et al. 2013). In relating TFP growth directly to R&D expenditures, there is little interrogation in this literature of intermediate steps between scientific discovery and commercial application of new technologies. As a consequence, the contribution of vertical disintegration to productivity growth in U.S. agriculture remains undocumented. The relationship between technological change and vertical disintegration is likely complementary rather than competing. Technical change such as larger equipment, simplified pest management through herbicide-tolerant varieties, or precision agriculture technologies, may increase the returns to specialization by expanding the efficient scale of specific production activities beyond what individual farms can justify. In this sense, R&D investments may contribute to agricultural productivity not only through direct improvements in biological or mechanical efficiency, but also indirectly by enabling the emergence of specialized service markets. The existing literature, by attributing all productivity gains correlated with R&D to "technical change," may conflate these distinct channels. Our analysis captures the specialization channel but cannot fully separate it from technology-induced scale effects that enabled market thickening in the first place.

3. Outsourcing and Productivity

In the previous section, we documented the growth of agricultural support services and the increasing availability of support services in crop production. To our knowledge, no prior work has examined how vertical disintegration—the emergence and growth of entire industries supplying production services—affects productivity. Holmes (1999) provides empirical evidence that vertical disintegration is greater in localized industries, consistent with the Stiglerian prediction that market thickness enables specialization, but his analysis focuses on the conditions under which disintegration occurs rather than its productivity effects. There is, however, a substantial literature outside of agriculture examining the relationship between firm-level outsourcing decisions and productivity.[5] We briefly review this work here, placing it in the context of agricultural production.

It is first useful to distinguish among three related, but nevertheless distinct, concepts. First, *technology adoption* refers to what inputs or practices a farm uses. A large literature examines technology adoption and farm performance (e.g., Khanna 2001; Bullock and Lowenberg-DeBoer 2007; Shi, Chavas, and Lauer 2013). Second, *outsourcing* concerns organizational boundaries, that is, whether the farm performs an activity itself or procures it externally. The literature reviewed below investigates the role of outsourcing on business performance. Finally, *vertical disintegration*, as used in this article, refers to market structure: the emergence and growth of entire industries that supply production services, making outsourcing possible at scale. This third phenomenon is the focus of our subsequent empirical analysis.

[5] Our use of the term outsourcing follows the transaction-cost and property-rights tradition in the theory of the firm, which treats make-or-buy decisions as arising from tradeoffs between market exchange and internal organization once contracting, monitoring, and asset-specificity costs are taken into account (Coase 1937; Williamson 1985). In this framework, outsourcing may increase or decrease productivity depending on how ownership and control over productive assets affect incentives (Grossman and Hart 1986; Hart and Moore 1990). Our analysis departs from this firm-level literature by focusing on vertical disintegration as a market-level phenomenon, rather than on individual farms' organizational choices.

Theoretical work indicates that the decision by profit-maximizing firms to outsource production activities can either increase or decrease productivity (Heshmati 2003; Görg and Hanley 2004; Lahiri 2016). Gains to specialization and the economies of scale available to service providers would tend to improve productivity by increasing output and/or lowering costs. For example, a harvesting company can spread the overhead cost of capital purchases over multiple customers while enjoying preferential financing terms, increasing the rate at which newer, more efficient combines are adopted. Some of these efficiency gains flow to farm businesses through larger harvests (higher revenue) or reduced production costs, so that outsourcing is both productivity- and profit-enhancing. On the other hand, the absence of firm-specific knowledge and inefficiencies arising from moral hazard in the principal-agent relationship between firms buying and selling production services would tend to lower productivity.

Agricultural operations introduce an added complexity that is generally ignored in existing theoretical models of outsourcing, namely that the overwhelming majority of farms in the United States are family businesses. Households are utility-maximizers, not profit-maximizers, and the farm business is often only one of several income sources for farm families. The decision to outsource production activities may allow for a greater allocation of time to off-farm labor opportunities or simply more leisure, increasing the incentive to accept lower on-farm productivity from service providers. Alternatively, allocating some production activities to a third party may allow farm operators to more effectively plan and manage other aspects of the farm business, thereby increasing overall farm productivity. The complex and potentially countervailing effects of time simultaneously entering the utility function, income constraint, and agricultural production function of farm households only increases the potential ambiguity between outsourcing and productivity in agricultural production.

The theoretical ambiguity between outsourcing and productivity is reflected in the conflicting set of empirical results that examine manufacturing and service industries, with

findings that alternatively show that outsourcing can have positive (Bardhan, Whitaker, and Mithas 2006; Thouin, Hoffman, and Ford 2009), mixed or insignificant (Bengtsson and Dabhilkar 2009; Kotabe and Mol 2009), or even negative (Broedner, Kinkel, and Lay 2009; Cho, Ozment, and Sink 2008) effects on firm performance. The empirical literature that considers the relationship between productivity and outsourcing specifically in agriculture is largely absent with one notable exception. Lu, Du, and Qiu (2022) examine the effect of agricultural mechanization services in China. Using a 2018 survey of rural households, they find positive effects in plowing, transplanting, and harvesting services, and a negative effect in pesticide spraying. To the best of our knowledge, however, no studies exist on this topic for agriculture in the United States.

Studies of the agricultural services sector also offer mixed findings on the potential relationship between outsourcing and agricultural productivity in the United States. Using the National Agricultural Workers Survey (NAWS), Wang and Loduca (2025) find that farm workers employed by contract labor providers receive lower wages than workers hired directly by farms. This would suggest that labor productivity is lower for contract labor. Yet, Babkin et al. (2022) find that the real annual mean wage to nonagricultural workers employed by establishments providing support services to crop production increased nearly $10,000 between 1992 and 2016, indicating potentially significant growth in the productivity of the workers managing and directing farm workers.

Given both the theoretical ambiguity and the lack of consistent empirical findings within a relatively thin literature, the productivity effects of outsourcing production activities in crop farming remains an open question. As discussed above, we do not observe farm-level outsourcing decisions directly. Instead, we measure vertical disintegration by tracking the expansion of industries that provide production services to crop farmers. Evidence that this growth contributes to crop yields provides indirect evidence that farmers benefit from outsourcing to service providers. In the next section, we present our data and methodology

for examining the relationship between the availability of agricultural support services and county-level crop yields.

4. Data and Methodology

There are significant data and methodological challenges to estimating the relationship between crop services and farm productivity. In this section, we describe these issues and the feasible strategies we adopt to best overcome them. Broadly, the challenges facing researchers are twofold: first, the lack of granular, unsuppressed data that links the specific services purchased from specialist providers to the output produced on farms; and second, the potential endogeneity that arises when local agricultural productivity determines demand for, and thus the equilibrium supply of service providers. We tackle both these issues by utilizing restricted administrative microdata and a dual-track econometric strategy that moves from cross-sectional stylized facts to longitudinal robustness checks.

4.1. Data

4.1.1. Calculating crop yields

Information on agricultural production is taken from county-level data on crop production from the publicly available tables published as part of the Census of Agriculture by the USDA National Agricultural Statistical Service from 2002 to 2022. We use variables on the dollar value of crop sales, total and average harvested land acreage, production of selected crops (soybeans, corn, and wheat) in bushels and distribution of land. For the relatively small share of counties with a crop services establishment but any of sales, production, or land acreage suppressed in the Census of Agriculture, these values are imputed by allocating the state value unaccounted for by counties with reported values in proportion to the share of operations in data-suppressed counties.[6] We use the Herfindahl–Hirschman

[6]State production values are available from the Census of Agriculture. We then sum over the reported sales and output values for the subset of counties where these data are not suppressed. The difference between

Index (HHI) as the measure of farmland concentration, approximating it from binned land size data using the rule of thumb described in Cowell and Mehta (1982), which provides a reliable estimate for farmland concentration when exact operation sizes are masked.

While these data provide a comprehensive view of crop production at the county-level, they do not allow for the calculation of TFP and such estimates are not published elsewhere. Instead, we turn to the simpler but still widely used (single-factor) measure of land productivity, measured in units of output per acre of harvested cropland. Output can be measured either in dollars of sales or in physical units such as bushels. Although crop sales per acre has the advantage of collapsing all crop production into a single productivity number, it also comes with two notable disadvantages. First, vegetables, fruits, and horticulture tend to return higher sales per acre than grains while also being more labor intensive, so that counties with sales dominated by these crops are more likely to have service providers with high payrolls regardless of farm productivity. Second, even within a single crop, price variation based on the variety grown or time of harvest can generate variation in yield when measured by sales per acre. Therefore, in addition to total crop sales per acre, we also consider physical yields of three major grain crops—corn, soybeans, and wheat—measured in bushels per acre, restricting each sample to counties with positive production of the respective crop.

Similarly to TFP, the former measure allows for aggregation over all crops, but doing so also captures potentially confounding crop composition effects. Figure 2 shows county mean of sales per acre and yields of the three crops—corn, soybeans and wheat—used in

state totals and the aggregate for unsuppressed counties is then allocated across the counties with suppressed values in proportion to the share of farms located in each suppressed county, e.g., if a suppressed county reported n farms and there are N farms over all data-suppressed in that state, the county received n/N of the value calculated for the set of data-suppressed counties. Depending on the year and crop-type, 5-15% of county yields for counties with a 1151 establishment are so imputed, generally from low production counties. For example, based on the QCEW sample of counties with at least one 1151 establishment, corn yield in 2002 would not be imputed for a single county in Illinois, Indiana, Iowa, or Ohio. Estimation results are robust to the omission of counties with imputed yield.

this paper in the sample of counties with active presence of agricultural service providers. Mean land productivity is increasing for all crop categories in almost all 5-year intervals.

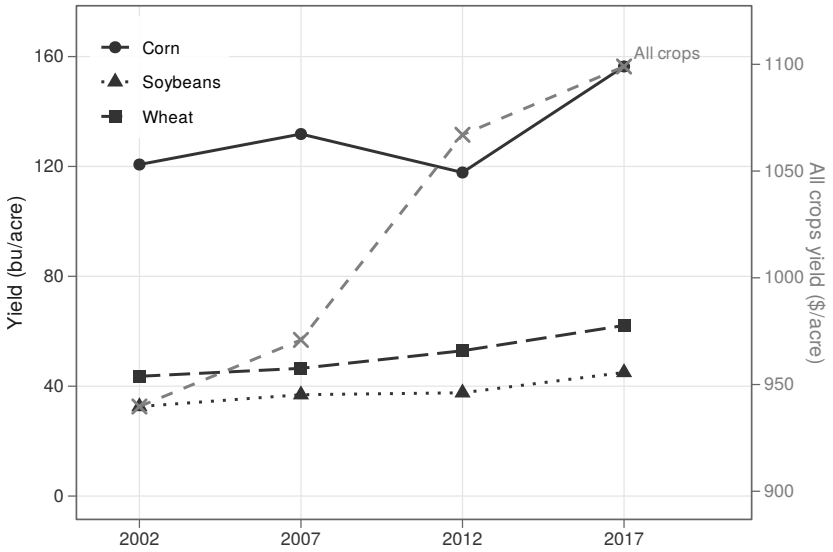


Figure 2. County mean land productivity in sales (all crops) or bushels (corn, soybeans and wheat) per acre

4.1.2. Measuring Support Service Activity

All publicly available data currently published by Federal statistical agencies on activity in support services for agricultural production present severe limitations.[7] From the demand (use) side, service expenditures from the Census of Agriculture are spread across multiple non-exclusive categories that cannot be separately attributed to crop or livestock farming without access to the underlying microdata. From the supply side, although the U.S. Census Bureau included agricultural services in the 2022 Economic Census, industry-level sales are not published below the national level.

In the absence of sales information, expenditure on payroll to workers employed by businesses providing crop services can serve as a reasonable proxy for economic activity. Although industry-level payroll is independently reported by the Census Bureau in the

[7] We focus on Federal data sources because proprietary establishment databases, such as NETS or InfoGroup, suffer from inadequate data quality and impute sales from the reported number of employees (Barnatchez, Crane, and Decker 2017).

County Business Patterns (CBP) and by the Bureau of Labor Statistics in the Quarterly Census of Employment and Wages (QCEW) at the state- and county-level, states are too large an aggregation to be informative, while county-level data are subject to substantial confidentiality-preserving suppression. Moreover, in the case of CBP, approximately half the crop services sector is excluded from coverage (Dunn and Hueth 2017).

The extent of data suppression is highlighted in Table 1, which reports aggregated data from QCEW and the Census of Agriculture into three categories defined by the data availability for NAICS 1151 establishments in QCEW: counties without crop service providers, counties with service providers and unsuppressed employment and payroll, and counties with service providers where employment and payroll are suppressed to protect business data confidentiality. Out of 1,889 counties with crop service providers, employment and payroll are suppressed for 74.5% (1,408 counties), accounting for 36% of all crop services establishments. Although county-level values for payroll and employment are not available for the suppressed counties, it is possible to calculate the aggregate values by differencing the unsuppressed values from the national totals. While the establishments in suppressed counties constitute only 15% of total employment and 17% of total payroll, they operate in counties where about a half of all crop production is taking place. Therefore, relying on publicly available data would omit an unacceptably large share of domestic crop production, likely biasing any subsequent econometric estimates.

We overcome the limitations of public data by using the payroll information included in the 2022 revision of the Longitudinal Business Database (LBD), a Federal restricted-access dataset compiled from IRS administrative records accessed through the Federal Statistical Research Data Center (FSRDC) network. The LBD provides information on establishment location, primary NAICS industry and payroll, reported separately for agricultural and non-agricultural workers as recorded on IRS Forms 943 and 941, respectively. Although employment is also reported in the LBD, it is restricted to the number of employees during the pay-period including March 12. This value is clearly uninformative about the

Table 1. Data suppression in 2017 QCEW

Measure	Total	No services	Unsuppressed	Suppressed	% suppr.
Counties	3,074	1,185	481	1,408	45.8%
Establishments	11,300	0	7,245	4,055	35.9%
Employment	334,480	0	283,204	51,276	15.3%
Payroll, $mln	10,507	0	8,708	1,799	17.1%
Farms	1,017,021	269,628	249,286	498,107	49.0%
Land, 1000 acres	317,975	55,112	88,042	174,821	55.0%
Sales, $mln	232,192	24,952	104,041	103,198	44.4%

Establishments, employment, and payroll for crop services from the Quarterly Census of Employment and Wages (QCEW). The "Suppressed" category includes counties for which number of establishments, but either employment or payroll are not reported at the county-level. Aggregate totals for the suppressed category are calculated by differencing the aggregate for unsuppressed counties from reported national totals. Farms, acreage, and sales aggregated to category totals from county-level data from the Census of Agriculture.

use of agricultural labor given the high seasonality of farm hiring. Babkin et al. (2022) provide a detailed discussion of strengths and weaknesses of the LBD dataset for the study of the agricultural services industry.

Given that yield is calculated from acreage and output, which are reported at the county level, we aggregate LBD establishment data to the same resolution, effectively treating each county as a local service market. We acknowledge that county boundaries imperfectly delineate local service markets. However, absent establishment-level data on the geographic scope of service provision, the county represents the finest resolution at which service activity and farm productivity can be systematically matched.

Table 2 reports the evolution of the number of establishments, payroll and market concentration in the NAICS 1151 sector at the county level from 2002 to 2017 in the LBD. In line with the national aggregate trends reported in Section 2, the average number of establishments has been slowly declining while the average real payroll has nearly doubled from $2.4 to $4.0 million.[8] Notably, there is no evidence of an increasing local market con-

[8] A careful reader may notice minor differences in the values reported in Table 2 from the LBD compared to Table 1 using QCEW. Although both are built from administrative data, the LBD is constructed from Federal payroll tax filings, while the QCEW uses state unemployment insurance filings. The set of businesses legally

centration, as the mean and median payroll shares of the largest establishment in a county remained fairly stable around 73% and 78% respectively. This finding is in sharp contrast to the trends of increasing market concentration in agricultural production on farms and in adjacent markets along the production chain beyond the farm gate.

Table 2. County distribution of service providers

Variable	Year	N	Mean	S.D.	25%	50%	75%
Establishments	2002	2,100	5.75	15.7	1	3	5
	2007	2,000	5.46	14.1	1	3	5
	2012	2,000	5.25	13.6	1	2	5
	2017	2,000	5.19	13.9	1	3	5
Payroll	2002	2,100	2.36M	16.9M	50.7K	198K	799K
	2007	2,000	2.82M	22.8M	50.5K	231K	899K
	2012	2,000	3.12M	26.1M	65.1K	278K	1.05M
	2017	2,000	4M	36.4M	73.5K	353K	1.21M
Largest payroll share	2002	2,100	73.02%	26.15%	52.25%	77.50%	100%
	2007	2,000	73.51%	25.94%	51.91%	78.70%	100%
	2012	2,000	73.98%	25.80%	52.84%	80.57%	100%
	2017	2,000	73.93%	25.45%	52.49%	77.53%	100%

Values from the Longitudinal Business Database (LBD) applying rounding to meet nondisclosure standards (including the sample size rounded to the nearest 100). Quantiles are quasi-quantiles calculated as the mean of values in the neighborhood around the true quantile observation.

4.2. Empirical Strategy

Identifying the relationship between agricultural support services and farm productivity faces a fundamental identification challenge: the observed level of service activity is likely endogenous to local productivity. Higher productivity areas tend to be more profitable and thus better able to afford the premium of specialized providers, potentially leading to positive selection that biases estimates upward. Conversely, the marginal benefit of

obligated to submit income and payroll tax withholding differs slightly from those required to contribute to unemployment insurance, the former determined nationally and the latter varying state-to-state. In addition, the sample frame for the LBD used by the Census Bureau is a different sample frame than the one used for the QCEW by the Bureau of Labor Statistics and there is no systematic attempt to reconcile industry assignments between the two. Despite these differences, the estimated size of the industry is similar across datasets as are industry-level trends.

outsourcing production activities to specialist providers may be greater in low-productivity areas, leading to negative selection and downward bias. As both mechanisms are plausible, it is impossible to sign the potential direction of bias *a priori*.

Because this is the first systematic investigation of vertical disintegration in this context, we adopt a dual-track empirical strategy. First, we use cross-sectional variation to establish stylized facts about the equilibrium relationship between crop services and crop yields. Second, we leverage the longitudinal dimension of the data to estimate changes in yield conditional on baseline values, mitigating the confounding effects of selection into the market on local agricultural productivity.

4.2.1. Cross-sectional Analysis

The first track of our approach treats each Census year between 2002 and 2017 as an independent cross-section. This allows the estimated relationship to vary across crop types and over time. We include controls for total harvested land, mean farm acreage, and the HHI of farm acreage to account for structural differences in county-level farm activity.

$$(1) \quad Productivity = \beta_0 + \beta_1 Payroll + \beta_2 Land + \beta_3 AvgLand + \beta_4 LandHHI + \varepsilon$$

Productivity is measured either in bushels per acre for corn, soybeans and wheat or dollars per acre for all crops, i.e., yield. Productivity, payroll, land, and average land are log-transformed to adjust the skewness of variable distributions and to allow interpretation of coefficients as elasticities. In a second set of specifications, we test whether the relationship between payroll and productivity varies by the total size (total acreage) or size distribution (mean farm acreage) in the county.

$$(2) \quad \begin{aligned} Productivity = {} & \beta_0 + \beta_1 Payroll + \beta_2 Land + \beta_3 Payroll \times Land \\ & + \beta_4 AvgLand + \beta_5 Payroll \times AvgLand + \beta_6 LandHHI + \varepsilon \end{aligned}$$

The sign on β_3 acts as a test of market thickness. A positive β_3 suggests that the effect of vertical disintegration is stronger in "thicker" agricultural markets where service providers can achieve better economies of scale. Similarly, a positive value for β_5 indicates that the productivity benefits of crop services tend to be larger in areas where providers serve fewer, but larger farms (higher average land for a given level of total land).

4.2.2. Longitudinal Analysis

The preceding cross-sectional analysis generates a large collection of new empirical findings that are an important contribution to the scant literature investigating outsourcing and vertical disintegration in agricultural production. Nevertheless, an obvious limitation to purely descriptive estimates is that the size of the agricultural services sector is not determined by random assignment across county, but is rather a market outcome. Although controls for land area, average farm size, and acreage concentration mitigate concerns about structural differences across counties that may correlate with the provision of crop support services, the models cannot account for any remaining unobserved county characteristics that jointly influence both the scale of agricultural service provision and farm productivity. Further, it is difficult to know *a priori* the direction in which this confounding relationship will bias estimates.

We attempt to mitigate this concern and thereby increase the potential utility of our study findings to researchers and policy-makers by leveraging the longitudinal nature of our data to directly control for observed differences in lagged productivity across counties. Specifically, we use the productivity growth rate, measured as log difference $\Delta Productivity_{t+5} = Productivity_{t+5} - Productivity_t$, as the outcome in repeated cross-sectional regressions while controlling for base year productivity.

$$\begin{aligned}\Delta Productivity_{t+5} &= \beta_0 + \beta_1 Productivity_t + \beta_2 Payroll_t \\ &+ \beta_3 Land_t + \beta_4 AvgLand_t + \beta_5 LandHHI_t + \varepsilon_t\end{aligned} \tag{3}$$

The inclusion of base-year productivity serves two vital functions. First, it addresses the possibility that the scale of crop service provision is determined by local agricultural productivity. Second, productivity tends to exhibit mean reversion, with above-average years tending to follow below-average years and vice versa; controlling for base-year productivity accounts for this tendency. We can see this intuition in the algebra of OLS coefficient estimates. Letting Y_1 and Y_0 denote end-year and base-year productivity, while A_1 and A_0 denote end-year and base-year access to crop services, the estimate of β_1 (after partialing out the other independent variables) is[9]:

$$(4) \quad \hat{\beta}_1 = \frac{Var(Y_0)Cov(A_0,Y_1) - Cov(A_0,Y_0)Cov(Y_0,Y_1)}{Var(A_0)Var(Y_0) - [Cov(A_0,Y_0)]^2}$$

The denominator is the variation in base-year access to crop services that is uncorrelated with base-year productivity. The first term in the numerator is the raw relationship between crop services and productivity, while the second term subtracts off the selection bias that arises because access and productivity are correlated in the baseline. If service providers select into high-productivity areas ($Cov(A_0,Y_0) > 0$) and high-productivity areas tend to stay productive ($Cov(Y_0,Y_1) > 0$), a simple correlation would overestimate β_1. On the other hand, if reversion to the mean is the dominant dynamic feature of productivity series such that $Cov(Y_0,Y_1) < 0$, a simple correlation would underestimate β_1.

5. Results

5.1. Stylized Facts from Cross-sectional Analysis

Table 3 reports the estimated elasticities of farm productivity with respect to service provider payroll from estimation of Equation 1 (complete regression results are presented in Appendix Table A.1). Across all years and specifications, we find a persistent,

[9]Notice, the estimate of β_1 is the same in the regression using end-period productivity (Y_1) as the dependent variable as in the regression using the change in productivity (Y_1-Y_0) as the dependent variable.

statistically significant relationship between the intensity of support service activity and agricultural yields.

Table 3. Payroll coefficient estimates

Year	Crop	Corn	Soybeans	Wheat
2002	0.228^{***}	0.035^{***}	0.008^{*}	0.043^{***}
	(0.010)	(0.006)	(0.004)	(0.005)
2007	0.196^{***}	0.027^{***}	0.009^{+}	0.048^{***}
	(0.010)	(0.005)	(0.005)	(0.005)
2012	0.194^{***}	0.063^{***}	0.028^{***}	0.033^{***}
	(0.009)	(0.007)	(0.005)	(0.005)
2017	0.193^{***}	0.020^{***}	0.007^{+}	0.024^{***}
	(0.010)	(0.004)	(0.004)	(0.006)

Notes: Each entry is a coefficient estimate from a separate regression of log of yield on the log of payroll of crop services providers controlling for log total acreage in crops, the log of mean farm size, and the HHI of land in farms. Robust standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the crop sales specification (Column 1), a 10% increase in crop service payroll is associated with a 1.9% to 2.3% increase in sales per acre. While these estimates are the largest in magnitude, they likely capture the higher labor intensity of high-value specialty crops. To isolate physical efficiency, we turn to grain-specific yields (Columns 2–4). Even after removing price effects and specialty-crop bias, the associations remain positive and significant: a 10% increase in payroll is associated with yield increases of 0.2–0.6% for corn, 0.1–0.3% for soybeans, and 0.2–0.5% for wheat.[10]

[10] As noted earlier, for 5-15% of counties in the regression sample, yields are imputed based on state residuals because of data suppression in the Census of Agriculture. This approach would tend to reduce variation in the dependent variable, and thereby increase the estimated standard errors of regression coefficients. In this exercise, this concern is wholly theoretical: the standard errors reported in Table 3 are all quite small and no economically meaningful coefficient estimates are statistically insignificant.

5.2. The Role of Farm Scale and Concentration

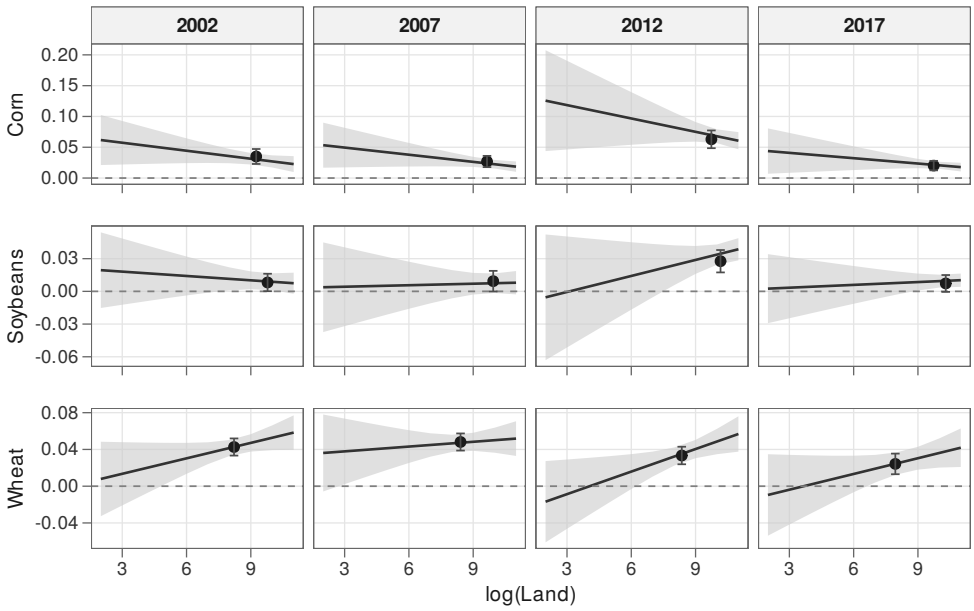
Estimation of Equation 2 reveals that the relationship between service providers and yields is not uniform, but rather is moderated both by the scale of local crop production (total acres harvested of a given crop) and the distribution of that land across producers (mean crop acres harvested per grower). For easier interpretation, the results for each of the three grain crops are plotted as marginal effects evaluated at different levels of crop acreage (top panel) and mean of harvested crop acreage (bottom panel) in Figure 3 (complete regression results are reported in Appendix Tables A.2-A.4). For reference, the point estimates from the non-interacted model displayed at the 50th percentile of the corresponding land variable is also plotted.

For wheat, the association between crop services payroll and yield increases with total harvested farmland which would support the hypothesis that substitution toward support services has the greatest benefit in thick markets where the benefits of scale can be most exploited. In contrast, however, the interaction effects for corn point in the opposite direction, while soybean yields show little sensitivity to county-level land distribution. Identifying the reasons for this heterogeneity presents an interesting and important avenue for future research.

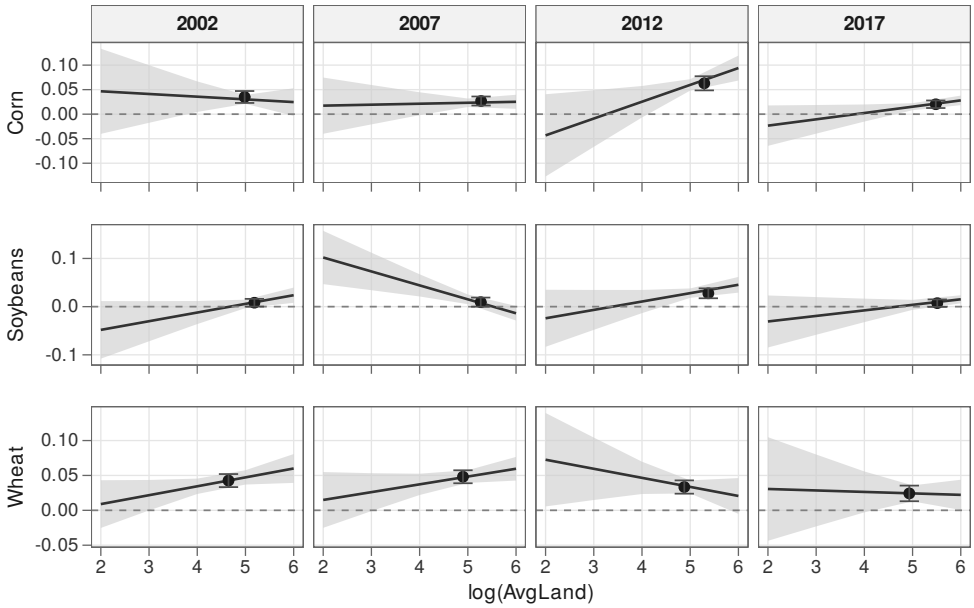
The moderating effect of average farm size is more consistent across commodities. The yield-payroll elasticity generally increases with average farm acreage, suggesting that service providers deliver higher marginal productivity gains in markets characterized by larger individual operations. Nevertheless, the sporadic reversal in the moderating relationship for each crop (interestingly never in the same year) also suggests it is sensitive to temporal shocks or shifting crop conditions.

Figure 3. Marginal effect of crop services payroll on crop yields

A. At different levels of total harvested farmland



B. At different levels of average harvested farmland



5.3. Longitudinal Analysis: Conditional Productivity Growth

The longitudinal specification (Equation 3) evaluates whether service intensity at the start of a period predicts yield growth over the subsequent five years. By controlling for base-year productivity, we isolate the relationship between services and improvements in performance, mitigating the selection biases inherent in cross-sectional levels. Estimates for the payroll coefficients are reported in Table 4, with the final interval (2017–2022) capturing the disruptive effects of the COVID-19 pandemic on agricultural supply chains (complete regression estimates are reported in Appendix Table A.5).

Table 4. Payroll coefficient estimates in the dynamic model

Years	Crop	Corn	Soybeans	Wheat
2002–2007	0.006	0.009^{*}	0.006	0.020^{***}
	(0.005)	(0.004)	(0.004)	(0.004)
2007–2012	0.030^{***}	0.049^{***}	0.028^{***}	0.007^{*}
	(0.006)	(0.006)	(0.005)	(0.004)
2012–2017	0.035^{***}	-0.004	-0.003	0.000
	(0.007)	(0.005)	(0.004)	(0.006)
2017–2022	-0.001	0.017^{***}	0.005	0.001
	(0.008)	(0.004)	(0.004)	(0.004)

Notes: Each entry is a coefficient estimate from a separate regression of change in log of yield on the log of payroll of crop services providers controlling for log total acreage in crops, the log of mean farm size, and the HHI of land in farms in the base year. Robust standard errors in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All statistically significant coefficients are positive, providing robust support that the positive relationship between crop service activity and crop productivity is not merely a statistical artefact arising from selection, (i.e., providers choosing to locate in already-productive areas), but rather reflects a substantive link whereby an increased presence of service providers contributes to subsequent productivity gains. Moreover, while the estimated magnitude of the relationship varies across crop and over time, where statistically

significant, the elasticity estimates from the longitudinal specification imply economically meaningful effects.

For example, counties with 10% higher crop services payroll in the base year would tend to exhibit growth in crop sales per acre that was 0.3% greater between 2007 to 2012 and 0.35% greater between 2012 to 2017. A similar pattern exists when looking at individual crops. A 10% increase in crop services payroll would tend to increase corn yields by 0.09% in 2002–2007 and 0.49% in 2007–2012, becoming small and statistically insignificant in 2012–2017 before increasing to 0.17% from 2017 to 2022.

To gain further intuition about the economic significance of these elasticity estimates, Table 5 translates the statistically significant estimated elasticities from Table 4 into the expected change in growth rates for a county moving from the 50th to the 75th percentile of the service payroll distribution. Doing so would increase the expected productivity growth rate between 2007 and 2012 for all crop sales by 4.0 percentage points. For corn, productivity growth would have been 1.2 percentage points larger between 2002 and 2007, 6.6 percentage points larger between 2007 and 2012, and 2.0 percentage points larger between 2017 and 2022.

Table 5. Implied change in productivity growth rate moving from 50th to 75th percentile of payroll distribution

Years	Crop	Corn	Soybeans	Wheat
2002–2007	–	1.2	–	2.7
2007–2012	4.0	6.6	3.5	1.0
2012–2017	4.6	–	–	–
2017–2022	–	2.0	–	–

Each entry reports differences in productivity growth rate in percentage points calculated over statistically significant coefficients from Table 4 and percentiles from Table 2.

A pattern that stands out in these results across all yield measures is the weakening of the relationship between crop services activity and productivity over time. It is possible this reflects the disruption of the agricultural supply chain during and immediately after

the COVID-19 crisis. Alternatively, it also mirrors the observed decline in new business formation in the crop services sector and would be consistent with an exhaustion of the scale benefits previously arising from the outsourcing of production activities to specialist providers.

6. Discussion

This article provides the first systematic evidence that the vertical disintegration of U.S. agriculture—the outsourcing at scale of production activities from farms to specialized service providers—contributes to farm productivity. While the emergence of this upstream service sector has been a defining structural change in the organization of agricultural production over the past half-century, its impact has remained largely ignored in the empirical literature. By leveraging restricted-access administrative microdata from the Longitudinal Business Database (LBD), we overcome data quality issues in publicly available resources to document a robust relationship between service intensity and agricultural performance that persists across two decades and multiple commodity types. Key to establishing robustness, we show that the positive relationship between local crop services activity and productivity survives the inclusion of baseline productivity. This suggests that the association reflects a substantive link rather than a statistical artefact from the selection of service providers into high productivity counties.

As the first systematic attempt to document these empirical patterns, this study establishes a benchmark that should motivate future effort identifying the causal mechanisms that link support services and productivity. For example, the innovative use here of establishment microdata to measure activity in support services could be complemented with information on support service purchases contained in farm microdata. Currently, however, these data are not available in the same data environment and there is no data product that directly links the services purchased by farms to the businesses hired to perform those services at the establishment level. Further, although our longitudinal estimates purge static

selection effects, future research using instrumental variables or natural experiments (e.g., localized labor shocks or specific regulatory shifts) would be valuable to bolster and refine the causal evidence, recognizing that identification in these specifications is local to the potentially narrow crop, year, or location affected by the shock. Nevertheless, by offering strong evidence that the relationship between support services and farm productivity is both substantive and economically meaningful, we provide the empirical justification for additional studies on the organizational boundaries of the farm, as well as careful consideration of the implications for those studying productivity growth in agriculture.[11]

First, the services industry is becoming less dynamic in a sense that the rates of exit and entry have been in steady decline over the last three decades. It is possible that the biggest productivity impact of disintegration happens when forces of creative destruction are pushing new entrepreneurs to innovate with new forms of agricultural business organization. This can be studied by looking at a longer time frame and examining the cross-sectional variation in establishment entry and exit.

Second, like many other industries, farming is characterized by long-term consolidation. The number of service providers, on the other hand, has generally remained flat, even increasing slightly in recent years, while local market concentration has not changed since 2002. This implies that service providers are on average working with fewer farms in their local markets, potentially shifting the balance of market power towards farm businesses. Does consolidation of the farm sector prevent or encourage consolidation of services?

Third, the secular increase in farm total factor productivity (TFP) is one of the most robust stylized facts about agricultural production in the United States. Much of the research on TFP growth focuses on research and development (R&D) by input providers

[11] The crop support services sector examined in this article is only one among many industries that supply inputs directly to farmers, including seed, fertilizer, agricultural chemicals, and equipment manufacturing. These upstream industries are themselves supplied by additional sectors further up the supply chain. Future work can examine growth and productivity dynamics across this broader set of input industries, though significant challenges remain in identifying which components of multi-purpose industries are dedicated to agricultural markets. See Hueth et al. (2026) for a forthcoming research report in this direction.

and technology adoption by farms. The positive relationship between support services and crop productivity presented here suggests better incorporating support services into this research area would be valuable. There may be direct productivity gains from the reorganization of agricultural production activities that will capture some of the unexplained residual that continues to exist after quality adjustment for technological improvement. In addition, support service providers, because they are able to operate at a larger scale than most farms, may play a vital role in the diffusion of new and better technologies.

For example, while the modern practice of agricultural TFP growth accounting incorporates a broad array of quality adjustments (USDA Economic Research Service 2025; Wang et al. 2024), treatment of service provider expenditures is still limited. The effects of service providers on farm productivity documented in this paper have important implications for the productivity accounting literature. Purchased machine services are considered a substitute for own-capital input, and the same price index is applied for quality adjustment of both expenditure types. However, the positive relationship between support service activity and productivity presented in this paper suggests a "Specialist Efficiency Premium": machinery managed by providers may achieve higher utilization rates and embody more recent vintage technology than in-house farm capital. Failing to account for these differences in machinery input quality leads to an underestimation in the growth rate of quality-adjusted service input and a corresponding overestimation of farm total factor productivity (TFP) growth. Essentially, a portion of what is currently measured as residual "farm productivity" may actually be the efficiency gains generated by the vertical disintegration of the production process itself.

Our findings on the heterogeneity of the yield-provider relationship across crop types and land acreages suggest an avenue for a more accurate quality adjustment of service expenditures. Similarly to how labor expenditures are broken down into demographic groups by worker characteristics (gender, age, education and employment class), each with its own productivity and growth rates, service expenditures can be also broken down based on the

characteristics of the farms that employ them with quality price adjustments specific to the types of crops grown. Service expenditures by producers of crops that do not exhibit strong productivity effects can be adjusted using the same price index as for owned machinery, while expenditures by producers of crops whose productivity is enhanced by hiring service providers are adjusted with a lower price index (i.e., higher constant efficiency quantity).

Agricultural service providers can be thought of as intermediaries between farms and agricultural inputs, a perspective that clarifies the potential implications of market power for TFP growth accounting. For example, if farms hire labor directly, the market power of an individual farm is likely low, and in equilibrium, workers are paid their marginal product. In this case, the labor share of farm revenue approximates the output elasticity of labor. But, if the emergence of service providers as intermediaries in the agricultural labor market creates a degree of local monopsony power, workers are paid less than their marginal product so that quality-adjusting contract labor relative to hired labor causes overestimation of TFP. Moreover, the resulting overestimation of farm TFP growth becomes more important as the share of contract labor in farm labor expenditures is increasing. Given the often very high levels of local market concentration in the agricultural service sector, and previous findings that contract workers are paid less than hired workers of same qualifications (Wang and Loduca 2025), this may be occurring.

Recent work on manufacturing productivity illustrates both the broader significance of quality mismeasurement and a potential connection to our findings. Atalay et al. (2025) demonstrate that producer price indices insufficiently capture quality improvements in durable goods, leading to systematic understatement of manufacturing TFP growth. To the extent that manufacturers supply agricultural service providers with precision equipment, GPS-guided machinery, and other advanced technologies, or supply farmers directly, these quality mismeasurements may be capturing the same phenomenon from opposite ends of the supply chain: understated quality improvement in manufacturing output prices corresponds to understated quality improvement in farm input prices. The bias directions differ

with manufacturing, but the underlying cause is the same unmeasured quality differential flowing through intermediate goods markets. This connection suggests that comprehensive productivity accounting requires coordinated attention to quality adjustment across linked industries. While resolving these measurement challenges is beyond the scope of the present analysis, the positive yield-services relationship we document provides the first direct evidence that vertical disintegration represents a distinct channel of productivity growth that warrants explicit treatment in agricultural TFP accounting frameworks.

Finally, while our analysis focuses on U.S. agriculture, the underlying mechanism may have wider relevance. A substantial literature examines how agricultural development in low- and middle-income countries depends on the emergence and thickening of downstream value chains connecting farmers to processors and consumers (e.g., Reardon 2015; Barrett et al. 2022; Bellemare 2022). A similarly large literature examines the determinants and impacts of technology adoption by farmers in developing countries (e.g., Feder, Just, and Zilberman 1985; Foster and Rosenzweig 2010; Suri 2011). Our findings highlight a complementary but understudied dimension of agricultural development: the thickening of upstream markets for specialized input services. Technology adoption may depend not only on farmer characteristics and access to information, but also on the existence of well functioning markets supplying the relevant technologies and services. The productivity growth and farm consolidation that have characterized U.S. agriculture over the past half century have occurred alongside the expansion of a sector supplying labor, machinery, and management services to farmers. This upstream development represents another form of value chain deepening that warrants greater attention from researchers studying the organizational foundations of agricultural productivity growth.

In conclusion, by documenting a robust relationship between vertical disintegration and agricultural yields, this study identifies a distinct, but previously overlooked channel of productivity growth. As agricultural economists continue to refine TFP measurement frameworks, accounting for the shifting boundary between farm and non-farm production will

be essential for understanding the sources of past gains and anticipating the trajectory of future agricultural innovation.

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A. Appendix

Coefficients of lesser interest have been suppressed for confidentiality disclosure avoidance, showing only sign and statistical significance. Standard errors are in parenthesis with superscript indicators for statistical significance as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All variables except LandHHI are expressed in natural logarithms.

Table A.1. Full static model regression results

(a) Crop sample

	2002	2007	2012	2017
Payroll	0.2276***	0.1963***	0.1939***	0.1933***
	(0.010)	(0.010)	(0.009)	(0.010)
Land	[−]**	[−]*	[+]	[+]
AvgLand	[−]***	[−]***	[−]***	[−]***
LandHHI	[+]***	[+]***	[+]***	[+]***
Num.Obs.	2100	2000	2000	2000
R2	0.404	0.332	0.353	0.381

(b) Corn sample

	2002	2007	2012	2017
Payroll	0.03501***	0.02685***	0.06289***	0.02021***
	(0.006)	(0.005)	(0.007)	(0.004)
Land	[+]***	[+]***	[+]	[+]***
AvgLand	[+]	[+]*	[+]	[−]**
LandHHI	[+]***	[+]***	[+]	[+]
Num.Obs.	1800	1800	1800	1800
R2	0.131	0.185	0.088	0.154

Table A.1. Full static model regression results (continued)

(c) Soy sample

	2002	2007	2012	2017
Payroll	0.008158*	0.009365^{+}	0.02766***	0.007249^{+}
	(0.004)	(0.005)	(0.005)	(0.004)
Land	[+]***	[+]***	[+]***	[+]***
AvgLand	[−]***	[−]***	[−]***	[−]***
LandHHI	[+]***	[+]***	[+]	[+]**
Num.Obs.	1500	1400	1500	1500
R2	0.183	0.153	0.075	0.187

(d) Wheat sample

	2002	2007	2012	2017
Payroll	0.04264***	0.04811***	0.03339***	0.02424***
	(0.005)	(0.005)	(0.005)	(0.006)
Land	[+]*	[+]$^{+}$	[+]	[+]
AvgLand	[−]***	[−]***	[−]***	[−]***
LandHHI	[−]	[+]$^{+}$	[−]***	[−]**
Num.Obs.	1800	1800	1800	1700
R2	0.197	0.101	0.122	0.130

Table A.2. Regression of corn yields on service provider payroll (with interactions)

	2002	2007	2012	2017
Payroll	0.09777	0.05072	-0.04154	-0.02101
	(0.065)	(0.042)	(0.043)	(0.029)
Payroll$\times$Land	-0.004337	-0.003867^{+}	-0.007226	-0.002893
	(0.003)	(0.002)	(0.005)	(0.002)
Payroll$\times$AvgLand	-0.0055	0.001963	0.03432^{*}	0.01288^{*}
	(0.014)	(0.009)	(0.014)	(0.006)
Land	$[+]^{***}$	$[+]^{***}$	$[+]^{+}$	$[+]^{***}$
AvgLand	[+]	[+]	$[-]^{+}$	$[-]^{**}$
LandHHI	$[+]^{***}$	$[+]^{***}$	[+]	[+]
Num.Obs.	1800	1800	1800	1800
R2	0.135	0.186	0.103	0.158

Table A.3. Regression of soybean yields on service provider payroll (with interactions)

	2002	2007	2012	2017
Payroll	-0.07118^{+}	0.1553^{***}	-0.1087^{**}	-0.06268
	(0.040)	(0.038)	(0.038)	(0.042)
Payroll$\times$Land	-0.00133	0.0004612	0.004899	0.0008629
	(0.002)	(0.003)	(0.003)	(0.002)
Payroll$\times$AvgLand	0.01799^{+}	-0.02894^{***}	0.01738^{+}	0.01151
	(0.009)	(0.009)	(0.009)	(0.008)
Land	$[+]^{***}$	$[+]^{***}$	[+]	$[+]^{***}$
AvgLand	$[-]^{***}$	[$-$]	$[-]^{**}$	$[-]^{***}$
LandHHI	$[+]^{***}$	$[+]^{***}$	[+]	$[+]^{*}$
Num.Obs.	1500	1400	1500	1500
R2	0.186	0.161	0.086	0.192

Table A.4. Regression of wheat yields on service provider payroll (with interactions)

	2002	2007	2012	2017
Payroll	-0.06265^{**}	-0.0221	0.03012	-0.01058
	(0.022)	(0.023)	(0.046)	(0.058)
Payroll×Land	0.005607^{+}	0.001738	0.008186^{*}	0.005713^{+}
	(0.003)	(0.003)	(0.003)	(0.003)
Payroll×AvgLand	0.01276^{+}	0.01118	-0.01299	-0.002107
	(0.007)	(0.007)	(0.012)	(0.012)
Land	[−]	[+]	$[-]^{+}$	[−]
AvgLand	$[-]^{***}$	$[-]^{***}$	[−]	$[-]^{*}$
LandHHI	[−]	$[+]^{+}$	$[-]^{***}$	$[-]^{**}$
Num.Obs.	1800	1800	1800	1700
R2	0.210	0.106	0.126	0.133

Table A.5. Full dynamic model regression results

(a) Crop sample

	2002	2007	2012	2017
Payroll	0.005679	0.02956^{***}	0.03453^{***}	-0.001143
	(0.005)	(0.006)	(0.007)	(0.008)
Yield	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$
Land	[+]	[−]	[+]	[−]
AvgLand	[+]	$[+]^{+}$	$[-]^{*}$	[+]
LandHHI	$[+]^{+}$	[−]	[+]	[−]
Num.Obs.	2100	2000	2000	2000
R2	0.201	0.248	0.081	0.053

(b) Corn sample

	2002	2007	2012	2017
Payroll	0.009286^{*}	0.04946^{***}	-0.004179	0.01684^{***}
	(0.004)	(0.006)	(0.005)	(0.004)
Yield	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$
Land	$[+]^{***}$	[−]	$[+]^{***}$	$[+]^{***}$
AvgLand	$[+]^{**}$	[+]	$[-]^{**}$	$[-]^{***}$
LandHHI	$[+]^{***}$	[−]	$[+]^{**}$	[+]
Num.Obs.	1800	1800	1800	1800
R2	0.438	0.246	0.559	0.164

Table A.5. Full dynamic model regression results (continued)

(c) Soy sample

	2002	2007	2012	2017
Payroll	0.006437	0.02769^{***}	-0.002755	0.005432
	(0.004)	(0.005)	(0.004)	(0.004)
Yield	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$	$[-]^{**}$
Land	$[+]^{***}$	$[+]^{***}$	$[+]^{***}$	$[+]^{***}$
AvgLand	$[-]^{***}$	$[-]^{*}$	$[-]^{**}$	$[-]^{***}$
LandHHI	$[+]^{***}$	$[+]^{*}$	[+]	$[+]^{***}$
Num.Obs.	1500	1400	1500	1500
R2	0.183	0.427	0.530	0.059

(d) Wheat sample

	2002	2007	2012	2017
Payroll	0.01967^{***}	0.007459^{*}	0.0004892	0.001189
	(0.004)	(0.004)	(0.006)	(0.004)
Yield	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$	$[-]^{***}$
Land	[+]	[−]	$[+]^{*}$	[−]
AvgLand	[−]	$[-]^{*}$	$[-]^{***}$	$[-]^{**}$
LandHHI	$[+]^{+}$	$[-]^{***}$	[−]	[−]
Num.Obs.	1800	1800	1800	1700
R2	0.225	0.338	0.141	0.135