# An Empirical Investigation of Productivity Spillovers along the Agricultural Supply Chain

Sergio H. Lence and Alejandro Plastina

Total factor productivity (TFP) has long been recognized as a major engine of growth for U.S. agriculture in the post-war period, despite the methodological differences in the approaches used to calculate it.[1] Furthermore, TFP growth in the farm sector compares very favorably to similar measures of productivity growth in other sectors of the U.S. economy (Kendrick and Grossman 1980; Jorgenson, Gollop, and Fraumeni 1987; Jorgenson and Schreyer 2013; Jorgenson, Ho, and Samuels 2014; Garner and others 2019). In particular, Jorgenson, Ho, and Samuels (2014) find that although the farm sector ranked 15th out of 65 industries in its contribution to national value-added from 1947 to 2010, it ranked fifth in its contribution to national productivity growth, accounting for 7.5 percent of total U.S. TFP growth over the same period. Using a different data set, Garner and others (2019) find that the farm sector ranked fourth in TFP growth across 63 industries in the United States from 1987 to 2016.[2]

Prior agricultural economics research has contributed to policy discussions on how to increase food, fiber, and, more recently, biofuel output using fewer inputs mostly by identifying endogenous drivers of agricultural productivity—and, to a lesser extent, by decomposing TFP changes into more meaningful economic terms that can be addressed

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through alternative policy instruments.[3] Agricultural economics researchers have extensively evaluated the effects of knowledge spillovers from other sciences into agriculture as well as the effects of knowledge spill-ins from agricultural research and development (R&D) conducted in other jurisdictions on agricultural productivity (Coe and Helpman 1995; Schimmelpfennig and Thirtle 1999; Huffman and others 2002; Alston and others 2010; Plastina and Fulginiti 2011).[4] However, none have yet analyzed productivity spillovers between the agricultural sector and other economic sectors. This issue is important because knowing the ways in which agricultural productivity affects, and is affected by, productivity in other sectors of the economy seems critical in designing better policies aimed at enhancing growth.

In this article, we identify productivity linkages between the agricultural sector and 62 other sectors of the U.S. economy and measure short- and long-run productivity spillovers from and to the agricultural sector. Our results highlight how positive spillovers (synergies) across sectors can be exploited to optimize the cost efficiency of policy interventions to foster economic growth. Our results also highlight the need to abate negative intersectoral spillovers to avoid promoting productivity growth in one sector at the expense of others. These results are particularly relevant given the challenging decisions that U.S. policymakers face in reactivating the domestic economy in the aftermath of the coronavirus pandemic.

## I. Estimation Methods

We investigate productivity spillovers along the agricultural supply chain by analyzing the historical pairwise association between a productivity measure in the agricultural sector and the same productivity measure for each of $N$ non-agricultural sectors of the economy. The specific productivity measures employed in the present study are the logarithms of the historical time series for TFP and the partial productivities of labor (LPP) and capital (KPP). That is, using subscripts $a$ to designate the agricultural sector, $n$ to represent the non-agricultural sector, and $t$ to denote time, our focus of attention are the productivity pairs $\{TFP_{a,t}, TFP_{n,t}\}$, $\{LPP_{a,t}, LPP_{n,t}\}$, and $\{KPP_{a,t}, KPP_{n,t}\}$ for each of the $N$ non-agricultural sectors.

The appropriate way to model the pairwise association between productivity in the agricultural sector and productivity in the *n*th non-agricultural sector (for example, $\{TFP_{a,t}, TFP_{n,t}\}$) depends on whether the productivity series are characterized by unit roots. Therefore, the first step of the proposed approach is testing the null hypothesis of a unit root for each of the series. We use the method advocated by Elliott, Rothenberg, and Stock (1996), which they show to be more powerful than the standard Augmented Dickey-Fuller unit-root test (Dickey and Fuller 1979, 1981). To impose as few restrictions as possible, we allow for both a constant and a trend in the deterministic model used for detrending (which is required by the test). As explained in the "Results and Discussion" section, the null of a unit root cannot be rejected at standard levels of significance for the vast majority of the productivity series. In contrast, the unit-root null is strongly rejected for most series when tested using their first differences. Hence, we proceed under the assumption that all productivity series have a unit root but are stationary when first-differenced.

Given the aforementioned assumption about the time-series properties of the productivity data, in the second step, we estimate a vector autoregression (VAR) in levels (as opposed to first differences) for each pair of productivities (for example, $\{TFP_{a,t}, TFP_{n,t}\}$) to determine the appropriate number of lagged terms to include in the pairwise analysis (Pfaff 2008b). The estimated VARs include both a constant and a trend as deterministic regressors. The optimal number of lags is determined according to the Akaike information criterion (AIC) (Akaike 1974).

In the third step, we estimate a vector error-correction model (VECM) for each agricultural/non-agricultural productivity pair (for example, $\{TFP_{a,t}, TFP_{n,t}\}$), setting the number of lagged terms equal to the corresponding number of lags identified in the second step. The purpose of fitting this VECM is to test whether the productivity series in each pair are cointegrated. More specifically, for each productivity pair, we perform the Johansen cointegration trace test (Johansen 1995). Following the recommendations by Franses (2001), we allow for both a constant term and a trend in the cointegration relationship. For example, TFP in the agricultural sector and TFP in the *n*th non-agricultural sector are cointegrated if a coefficient $\beta$ exists such that the series $e_{an,t}$, defined as:

$$e_{an,t} \equiv TFP_{a,t} - \beta TFP_{n,t} - \alpha_0 - \alpha_1 t \qquad (1)$$

is stationary. In the above expression, $\alpha_0$ and $\alpha_1$ are coefficients, and $t$ denotes time. Thus defined, cointegration between $TFP_{a,t}$ and $TFP_{n,t}$ means that TFP in agriculture and the $n$th non-agricultural sectors tend to move together toward the equilibrium value of ($\alpha_0$ + $\alpha_1 t$), where the equilibrium value may be different from zero $(if\, \alpha_0 \neq 0 \text{ or } \alpha_1 \neq 0)$ and may have a deterministic trend $(if\, \alpha_1 \neq 0)$. The relevance of the cointegration analysis is that the existence of cointegration indicates a long-term relationship between the two series involved. That is, finding that productivity in agriculture and the non-agricultural sector are cointegrated allows us to conclude that they tend to move together in the long run.

Failure to find evidence of cointegration between two series characterized by unit roots suggests that they do not tend to move together in the long run. However, they may nevertheless exhibit joint short-term dynamics. If the null hypothesis of no cointegration is not rejected for a particular productivity pair, we investigate the existence of joint short-term dynamics by setting up a VAR in first differences and testing for Granger causality and instantaneous causality (Granger 1969; Lütkepohl 2006). For example, the first-difference VAR corresponding to the TFPs in agriculture and in the $n$th sector is:

$$\begin{aligned}\Delta TFP_{a,t} &= \sum_{k=1}^{K} \phi_{a,k} \Delta TFP_{a,t-k} + \sum_{k=1}^{K} \phi_{n,k} \Delta TFP_{n,t-k} + \phi_{a,0} + \phi_{a,trend} t + u_{a,t}, \\ \Delta TFP_{n,t} &= \sum_{k=1}^{K} \theta_{n,k} \Delta TFP_{n,t-k} + \sum_{k=1}^{K} \theta_{a,k} \Delta TFP_{a,t-k} + \theta_{n,0} + \theta_{n,trend} t + u_{n,t},\end{aligned} \qquad (2)$$

where $\Delta TFP_t \equiv TFP_t - TFP_{t-1}$, $\phi$s and $\theta$s are coefficients, and the residuals $u_{a,t}$ and $u_{n,t}$ have variances of $\sigma_a^2$ and $\sigma_n^2$ and covariance of $\sigma_{a,n}$. In this instance, TFP in the $n$th sector does not Granger cause TFP in agriculture if and only if $\phi_{n,1} = \ldots = \phi_{n,K} = 0$. Analogously, TFP in agriculture does not Granger cause TFP in the $n$th sector if and only if $\theta_{a,1} = \ldots = \theta_{a,K} = 0$. Instantaneous causality exists if $\sigma_{a,n} \neq 0$. The optimal number of lags $K$ in the first-difference VAR (2) is based on the AIC (Akaike 1974).

The cointegration test alone does not allow us to tell whether productivity shocks in each of the two sectors have permanent effects on both sectors, or whether a productivity shock in one sector affects the other sector's productivity permanently without the reverse being true. Furthermore, productivities in agriculture and in the *n*th non-agricultural sector may exhibit joint short-term relationships even if they are not cointegrated. In this instance, a productivity shock in one sector will have a short-term effect on the other sector's productivity that fades away over time. To analyze the nature of the short- and long-term relationships between each pair of productivities (for example, $\{TFP_{a,t}, TFP_{n,t}\}$), in the fourth and final step, we compute the impulse response function (IRF) for each productivity pair. IRFs are constructed based on the productivity pair's best-fitting VECM if the two series are cointegrated at the 5 percent significance level and on the best-fitting first-difference VAR (2) otherwise.

Estimation is performed in the R version 3.6.1 programming language and software environment. We use the package urca version 1.3-0 to test for unit roots and cointegration, and the package vars version 1.5-3 to select the optimum number of lags in the VARs, test for causality, and compute the IRFs (Pfaff 2008a, 2008b).

## II. Data

Our main data set is the analytical KLEMS-type data used by Jorgenson, Ho, and Samuels (2017), henceforth "the JHS data."[5] Succinctly, the data contain the annual amounts of output, capital, labor, and materials in both nominal and real terms for each of the 65 industries in the U.S. National Income and Product Accounts from 1947 through 2014. This long time span is desirable, as it allows us to apply the proposed time series methods, many of which rely on asymptotic results for a large number of time series observations. Another desirable property of the data is that, being KLEMS-type, they are computed using harmonized definitions and aggregation procedures across industries—that is, individual series are comparable across industries because they are based on the same or similar definitions.

The JHS data set defines the agricultural sector as the "farms" industry. To allow for the possibility of stronger spillovers between agriculture and closely related sectors, we classify non-agricultural sectors into "ag-related" and "non-ag-related" sectors. Ag-related sectors comprise the following 10 industries: forestry, fishing and related activities;

wood products; furniture and related products; food and beverage and tobacco products; textile mills and textile product mills; apparel and leather and allied products; paper products; rail transportation; truck transportation; and food services and drinking places. Non-ag-related sectors comprise the 52 other industries excluding farms, federal general government, and state and local general government.[6]

The JHS data set does not report productivity measures per se. However, it allows us to construct TFP, LPP, and KPP indexes in a straightforward manner. We calculate the TFP index as the ratio of real output to real input, where real input is the Törnqvist input index obtained from the capital, labor, and intermediate input series in the database. We calculate the LPP index as the ratio of real output to real labor; similarly, we construct the KPP index as the ratio of real output to real capital. For all three indexes, we set the base year to 2010.

Although the JHS data set has several desirable properties for our analysis, the most widely used productivity series for agriculture are constructed by the U.S. Department of Agriculture (USDA 2020). The USDA series are available from 1948 to 2017, which overlaps almost entirely with the period for the JHS series. Hence, as a robustness check, we also analyze the pairwise association between productivities in agriculture and the 62 non-agricultural sectors using the USDA agricultural series, instead of the "farm" series from the JHS data set.

## III. Results and Discussion

Table 1 summarizes the results from the unit root tests. Panel A shows that all of the agricultural productivity series fail to reject the null hypothesis of a unit root except for the TFP series from the JHS data. In contrast, all of the first-differenced agricultural productivity series strongly reject the unit root null, regardless of the productivity measure or the data set under consideration. Similarly, Panel B shows that the vast majority of non-agricultural productivity series cannot reject the unit root null, but do reject the null when first-differenced.[7] Overall, the results in Table 1 provide strong support for the assumption that productivity series are characterized by a unit root, and that the first-differenced series are stationary. Thus, we adopt this assumption for the remainder of the analysis.[8]

### *Table 1*

### Results of Unit-Root Tests Using the Elliott, Rothenberg, and Stock (1996) Method

Panel A: Results for Agricultural Productivities

| Productivity | Series | Test statistics | | Critical values at 10, 5, and 1 percent significance levels | | |
|---|---|---|---|---|---|---|
| | | JHS | USDA | 10 percent | 5 percent | 1 percent |
| TFP | Level | –3.77 | –2.33 | –2.74 | –3.03 | –3.58 |
| LPP | Level | –0.18 | –0.96 | –2.74 | –3.03 | –3.58 |
| KPP | Level | –1.56 | –1.09 | –2.74 | –3.03 | –3.58 |
| TFP | First-differenced | –4.86 | –5.03 | –2.74 | –3.03 | –3.58 |
| LPP | First-differenced | –5.42 | –5.44 | –2.74 | –3.03 | –3.58 |
| KPP | First-differenced | –4.69 | –3.77 | –2.74 | –3.03 | –3.58 |

Panel B: Results for Non-Agricultural JHS Productivities

| Productivity | Series | Percentage of sectors (count/total) for which unit-root null is rejected at 10, 5, and 1 percent significance levels | | | | | |
|---|---|---|---|---|---|---|---|
| | | Ag-related | | | Non-ag-related | | |
| | | 10 percent | 5 percent | 1 percent | 10 percent | 5 percent | 1 percent |
| TFP | Level | 0.0 (0/10) | 0.0 (0/10) | 0.0 (0/10) | 1.9 (1/52) | 0.0 (0/52) | 0.0 (0/52) |
| LPP | Level | 10.0 (1/10) | 10.0 (1/10) | 10.0 (1/10) | 5.8 (3/52) | 3.8 (2/52) | 0.0 (0/52) |
| KPP | Level | 10.0 (1/10) | 10.0 (1/10) | 0.0 (0/10) | 5.8 (3/52) | 0.0 (0/52) | 0.0 (0/52) |
| TFP | First-differenced | 90.0 (9/10) | 90.0 (9/10) | 60.0 (6/10) | 86.5 (45/52) | 78.8 (41/52) | 63.5 (33/52) |
| LPP | First-differenced | 60.0 (6/10) | 30.0 (3/10) | 30.0 (3/10) | 82.7 (43/52) | 71.2 (37/52) | 44.2 (23/52) |
| KPP | First-differenced | 70.0 (7/10) | 50.0 (5/10) | 50.0 (5/10) | 82.7 (43/52) | 73.1 (38/52) | 51.9 (27/52) |

Notes: The deterministic model to detrend the series includes a constant and a trend. The estimated models include two lagged differences for the series in levels, and one lagged difference for the first-differenced series.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

Given the large number of pairwise productivity relationships we estimate, it is not practical to provide a detailed report or analysis by individual sectors. Thus, in the following subsections, we focus on the results that tend to apply to most sectors.

### *Total factor productivity*

Table 2 reports the results of the cointegration tests. The first row reveals that agricultural TFP (measured using the JHS data set) is cointegrated with TFP in each of the 10 ag-related sectors at the 5 percent significance level over the 1947–2014 period. This result would seem to suggest strong long-term TFP spillovers between agriculture and ag-related sectors. However, the table also shows that agricultural TFP is cointegrated with TFP in all but one of the non-ag-related sectors at the 5 percent significance level over the same period. Together, these findings suggest that agricultural TFP tends to co-move with the TFPs of all sectors in the long run whether they are related to agriculture or not. In other words, the cointegration tests suggest that a sector's proximity to agriculture makes no difference to its TFP spillovers.

Charts 1 and 2 provide a graphic summary of the IRFs for the pairwise TFP relationships between agriculture and the other sectors. The pairwise relationships involving ag-related sectors are grouped on the left side of the solid vertical line, whereas those corresponding to the non-ag-related sectors are grouped on the right side. Within each group, a vertical dashed line separates sectors cointegrated with agriculture (left side) from sectors not cointegrated with agriculture (right side).[9] Sectors are listed in alphabetical order within subgroups.

The top two thirds of Chart 1 depict the 95 percent confidence intervals (CIs) for the one- and 10-year responses of non-agricultural TFPs to a shock to agricultural TFP. In contrast, the top two thirds of Chart 2 show the 95 percent CIs for the one- and 10-year responses of agricultural TFP to shocks in non-agricultural TFPs. The bottom third of Charts 1 and 2 show the number of years it takes to achieve 90 percent of the respective 10-year response. Below both charts are three rows of circles: the first row shows filled circles for sectors cointegrated with agriculture and empty circles otherwise. Filled and empty circles in the second and third rows denote whether the respective VECMs

*Table 2*
**Sectors Exhibiting Pairwise Cointegrating Relationships with Agriculture**

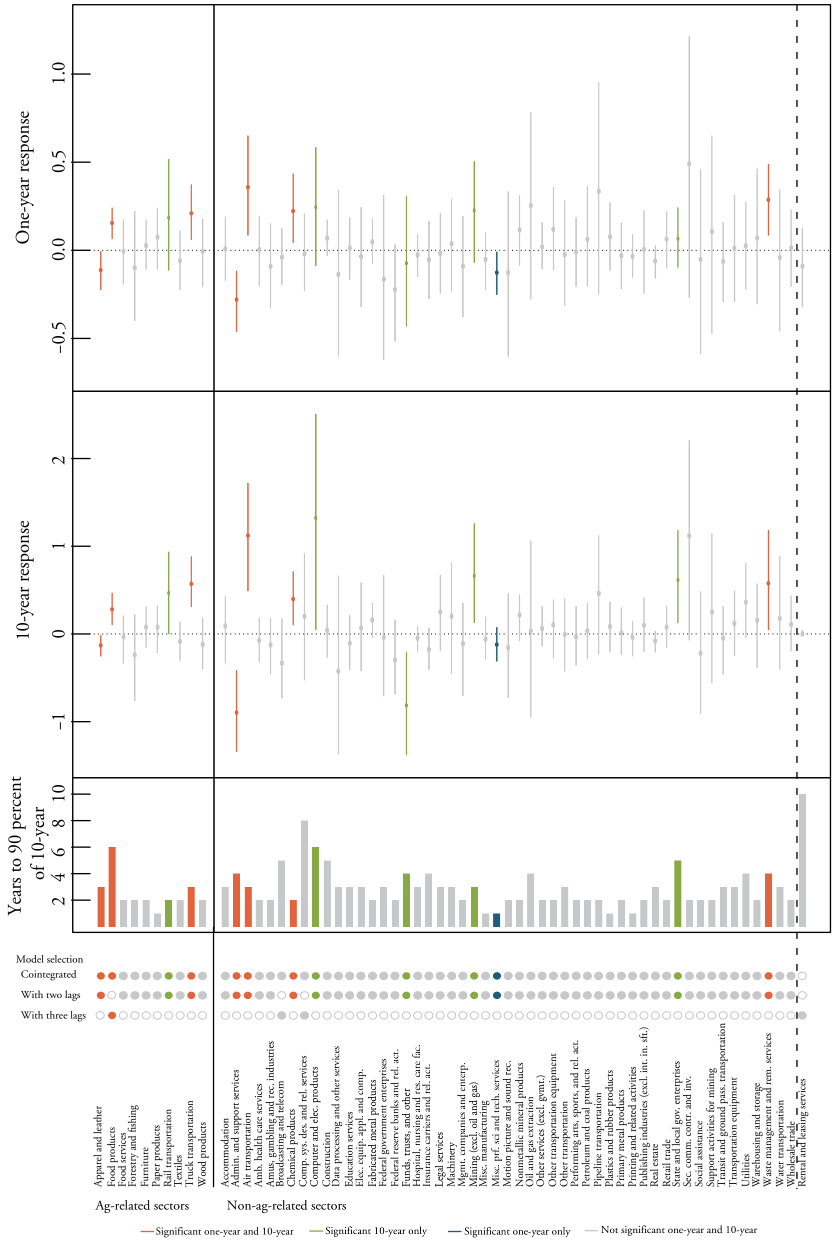
| | | Percentage of sectors (count/total) exhibiting pairwise cointegrating relationships with agriculture at 5 percent significance level | | | | | |
|---|---|---|---|---|---|---|---|
| | | Ag-related | | | Non-ag-related | | |
| Productivity | Database | Entire period | First half | Second half | Entire period | First half | Second half |
| TFP | JHS | 100.0 (10/10) | 40.0 (4/10) | 50.0 (5/10) | 98.2 (51/52) | 48.1 (25/52) | 46.2 (24/52) |
| LPP | JHS | 80.0 (8/10) | 10.0 (1/10) | 20.0 (2/10) | 28.8 (15/52) | 15.4 (8/52) | 11.5 (6/52) |
| KPP | JHS | 40.0 (4/10) | 60.0 (6/10) | 60.0 (6/10) | 15.4 (8/52) | 48.1 (25/52) | 67.3 (35/52) |
| TFP | USDA | 90.0 (9/10) | 40.0 (4/10) | 40.0 (4/10) | 88.5 (46/52) | 36.5 (19/52) | 48.1 (25/52) |
| LPP | USDA | 50.0 (5/10) | 0.0 (0/10) | 50.0 (5/10) | 21.2 (11/52) | 28.8 (15/52) | 73.1 (38/52) |
| KPP | USDA | 30.0 (3/10) | 90.0 (9/10) | 40.0 (4/10) | 17.3 (9/52) | 63.5 (33/52) | 40.4 (21/52) |

Note: "Entire period" is 1947–2014 for JHS and 1948–2014 for USDA; "first half" is 1947–80 for JHS and 1948–80 for USDA; and "second half" is 1981–2014 for both JHS and USDA.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

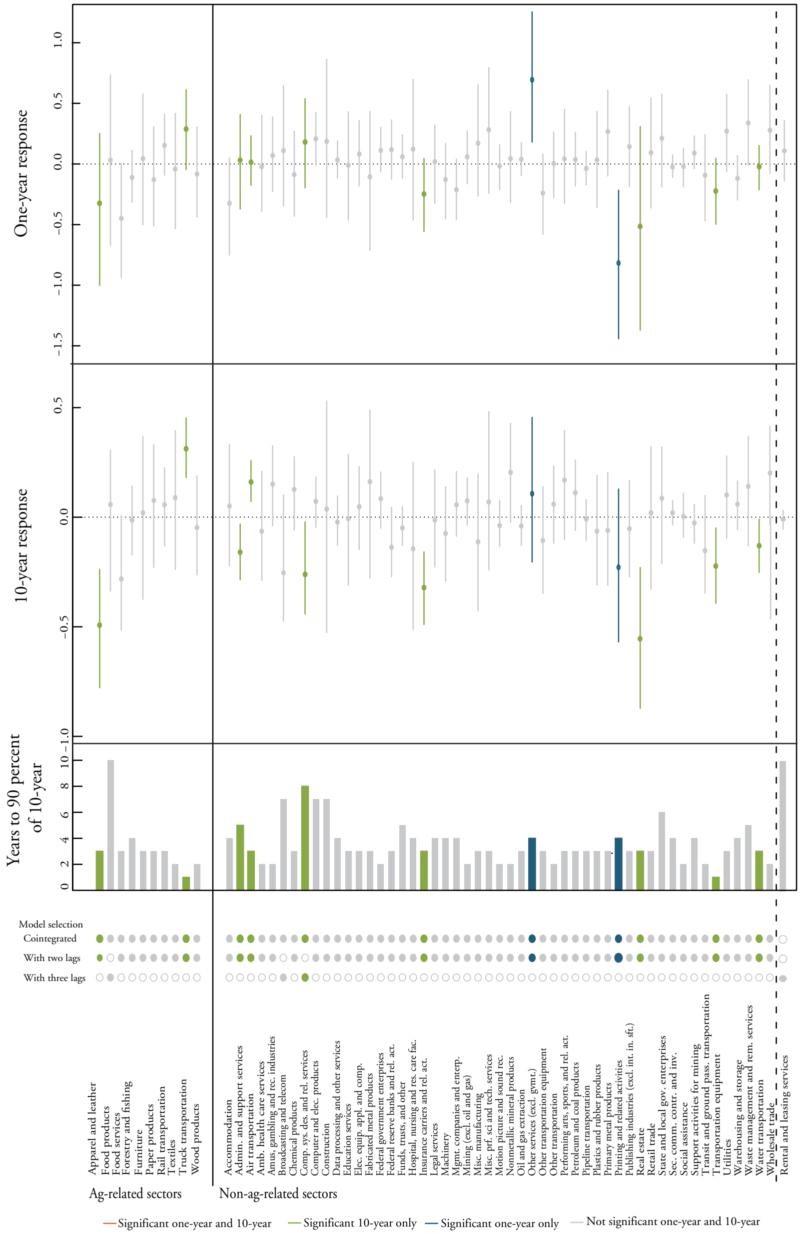
(if cointegrated) or first-difference VARs (if not cointegrated) contain two or three lags.

Comparing the top two thirds of Chart 1 shows that the significant one-year responses are fewer and smaller in magnitude than their 10-year counterparts. According to the bottom third, typically no more than five years elapse to achieve 90 percent of the 10-year response. However, given the large percentage of sectors cointegrated with agriculture, the most striking finding from this chart is the small number of sectors that exhibit significant 10-year TFP responses to an agricultural TFP shock. Only four of the 10 ag-related sectors, or 40 percent, show a significant response to an agricultural TFP shock after 10 years. The share of non-ag-related sectors with a significant 10-year response is even lower (eight out of 52 sectors, or 15.4 percent). Among the significant 10-year responses, nine out of the 12 are positive, which suggests a tendency for significant 10-year responses to be positive.

## *Chart 1*
## Response of Non-agricultural Sectors' TFP to Shocks in Agricultural TFP



## *Chart 2*
### Response of Agricultural TFP to Shocks in Non-agricultural Sectors' TFP



Similar to Chart 1, the top two thirds of Chart 2 show that the significant one-year responses of agricultural TFP to non-agricultural TFP shocks are fewer and smaller in magnitude than the significant 10-year responses. As in Chart 1, Chart 2 reveals a major difference between the percentage of sectors cointegrated with agriculture (almost 100 percent) and the percentage of sectors whose shocks have a significant effect on agriculture after 10 years (less than 20 percent). Unlike Chart 1, however, Chart 2 shows a tendency for the significant 10-year responses to be negative, as seven out of nine bear a negative sign.

The first row of Table 3 shows that the only TFP pair with no evidence of cointegration does not exhibit Granger causality in either direction. Furthermore, the non-cointegrated TFP pair does not appear to be characterized by instantaneous causality, either. Both of these results are consistent with the shock responses depicted in Charts 1 and 2.

Overall, despite the strong evidence of pairwise TFP cointegration between agriculture and essentially all sectors reported in Table 2, Charts 1 and 2 demonstrate that TFP shocks in agriculture have a significant long-term effect on a relatively small number of sectors, and that in the long-term, agricultural TFP responds significantly to TFP shocks in only a handful of sectors. The significant long-term responses to agricultural TFP shocks have a slight tendency to be positive, whereas the opposite is true of the significant long-term responses of agriculture to TFP shocks in other sectors.

### *Partial productivity of labor*

The second row of Table 2 shows that for LPP, 80 percent of ag-related sectors are cointegrated with agriculture at the 5 percent significance level over the 1947–2014 period compared with only 28.8 percent of non-ag-related sectors. The difference in the frequency of cointegration across the two groups is statistically significant, suggesting stronger LPP spillovers between agriculture and ag-related sectors than between agriculture and non-ag-related sectors.[10]

Remarkably, even though eight of the 10 ag-related sectors are cointegrated with agriculture, none of their LPPs have significant one- or 10-year responses to an agricultural LPP shock (Chart 3). Chart 4 shows an almost identical result for ag-related sectors' LPP

*Table 3*
**Non-cointegrated Sectors Exhibiting Causal Relationships with Agriculture**

| | | Percentage of non-cointegrated sectors (count/total) exhibiting causal relationships with agriculture at 5 percent significance level | | | | | |
|---|---|---|---|---|---|---|---|
| | | Ag-related sectors | | | Non-ag-related sectors | | |
| | | Granger causality | | Instantan. causality | Granger causality | | Instantan. causality |
| Productivity | Database | Ag to non-ag | Non-ag to ag | | Ag to non-ag | Non-ag to ag | |
| TFP | JHS | n/a | n/a | n/a | 0.0 (0/1) | 0.0 (0/1) | 0.0 (0/1) |
| LPP | JHS | 0.0 (0/2) | 0.0 (0/2) | 0.0 (0/2) | 5.4 (2/37) | 5.4 (2/37) | 5.4 (2/37) |
| KPP | JHS | 0.0 (0/6) | 0.0 (0/6) | 0.0 (0/6) | 4.5 (2/44) | 0.0 (0/44) | 4.5 (2/44) |
| TFP | USDA | 0.0 (0/1) | 0.0 (0/1) | 0.0 (0/1) | 33.3 (2/6) | 0.0 (0/6) | 33.3 (2/6) |
| LPP | USDA | 0.0 (0/5) | 0.0 (0/5) | 0.0 (0/5) | 12.2 (5/41) | 0.0 (0/41) | 9.8 (4/41) |
| KPP | USDA | 14.3 (1/7) | 0.0 (0/7) | 0.0 (0/7) | 0.0 (0/43) | 0.0 (0/43) | 4.6 (2/43) |

Note: Cells marked "n/a" denote that all pairs are cointegrated.
Sources: Jorgenson, Ho, and Samuels (2017) and USDA (2020).

shocks: agricultural LPP has no significant one-year responses to these sectors' shocks, and only one significant 10-year response.

Charts 3 and 4 demonstrate a noticeable, albeit less stark, contrast between the 28.8 percent of non-ag-related sectors cointegrated with agriculture and the much smaller percentages with significant one- and 10-year effects (see Table 2). An agricultural LPP shock yields a significant response at the one- and 10-year marks in only one of the 15 cointegrated non-ag-related sectors (see Chart 3). Similarly, LPP shocks in just three of the 15 cointegrated non-ag-related sectors have a significant effect on agricultural LPP after 10 years, and none have a significant effect at the one-year mark (see Chart 4).

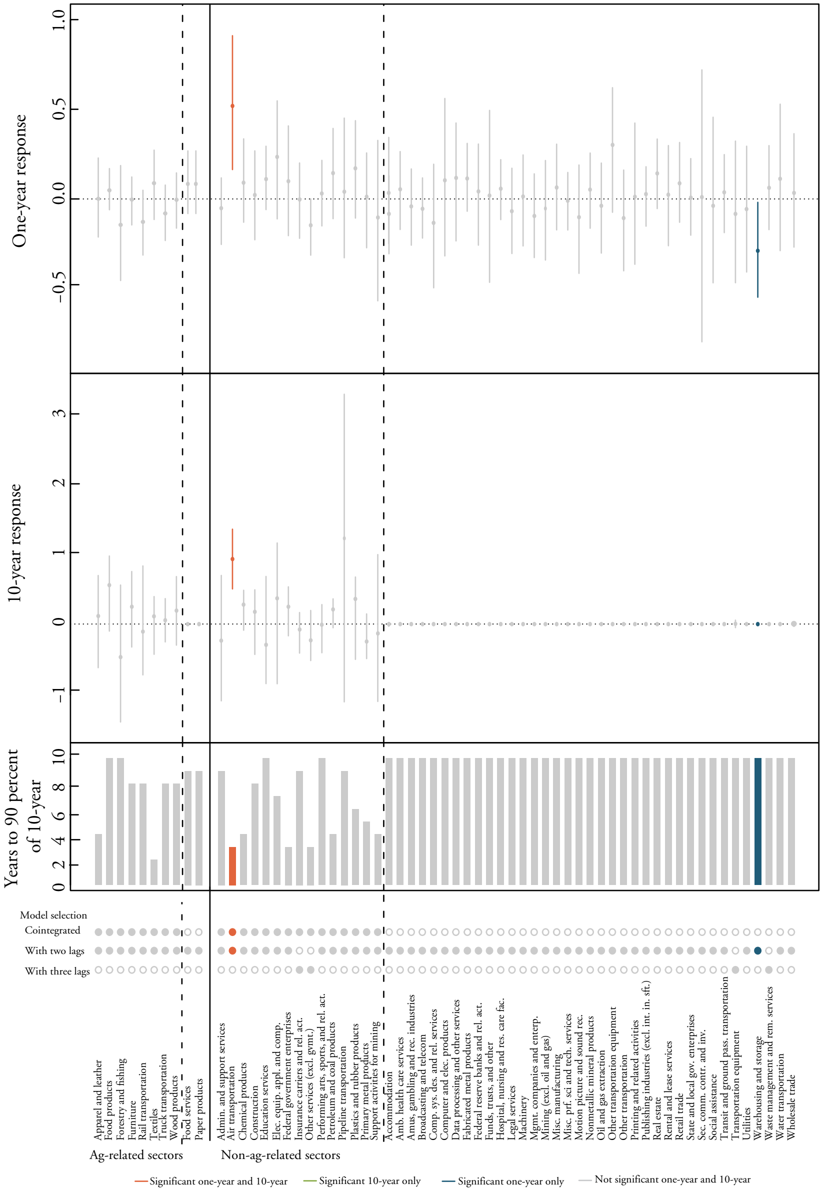
The LPPs of non-cointegrated sectors—two of which are ag-related and 37 of which are non-ag-related—appear to be unrelated to agricultural LPP in the short term.[11] According to Chart 3, shocks to agricultural LPP yield a significant one-year response to LPP in only one non-cointegrated sector. Likewise, Chart 4 shows that shocks to LPP in only two non-cointegrated sectors yield a significant one-year response to agriculture LPP. The second row of Table 3 confirms these results, reporting a negligible percentage of pairs characterized by Granger causality or instantaneous causality.

Overall, few sectors have significant LPP responses to agricultural LPP shocks. The same can be said about the number of sectors whose LPP shocks significantly affect agricultural LPP. In fact, the small frequency of significant responses is consistent with what could be expected by pure chance. Thus, the significant responses we find may be an artifact of chance rather than meaningful economic relationships.

### *Partial productivity of capital*

Out of the three productivities under examination, KPP has the fewest pairwise cointegrations from 1947 to 2014. According to the third row of Table 2, 40 percent of ag-related sectors and 15.4 percent of non-ag-related sectors exhibit KPP cointegration with agriculture, about half the shares observed for LPP. Although our results for KPP suggest that ag-related sectors are more likely to be cointegrated with agriculture than non-ag-related sectors, the difference is not significant at the 5 percent level.[12]

## *Chart 3*
### Response of Non-agricultural Sectors' LPP to Shocks in Agricultural LPP



## *Chart 4*
## Response of Agricultural LPP to Shocks in Non-agricultural Sectors' LPP

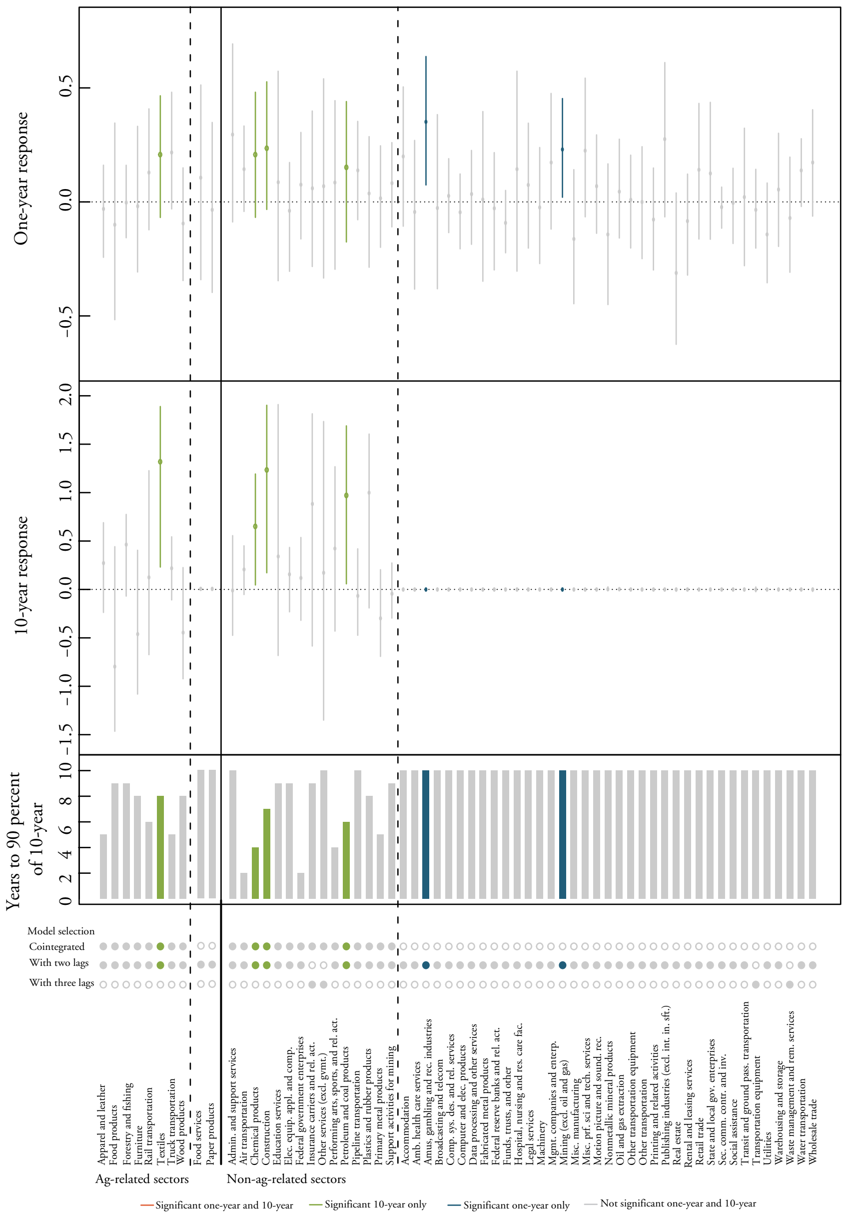


Chart 5 depicts the responses of ag-related and non-ag-related sectors' KPP to KPP shocks in agriculture. Only two ag-related sectors and one non-ag-related sector respond significantly after 10 years. Furthermore, only one sector, in the ag-related group, has a significant one-year response.

Chart 6 presents similar results for the responses of agriculture's KPP to KPP shocks in ag- and non-ag-related sectors. KPP shocks in only one ag-related sector exert a significant 10-year effect on agricultural KPP, and none exert a significant one-year effect. Likewise, KPP shocks in only one non-ag-related sector have a significant effect on agricultural KPP after both one and 10 years.

Strikingly, Charts 5 and 6 reveal that none of the non-cointegrated sectors (six ag-related and 44 non-ag-related) have statistically significant KPP relationships with agriculture after one year. The third row in Table 3 provides additional evidence regarding the lack of short-term pairwise KPP relationships between agriculture and other sectors. The number of non-cointegrated pairs characterized by Granger causality or instantaneous causality is zero for the ag-related group and negligible for the non-ag-related group.

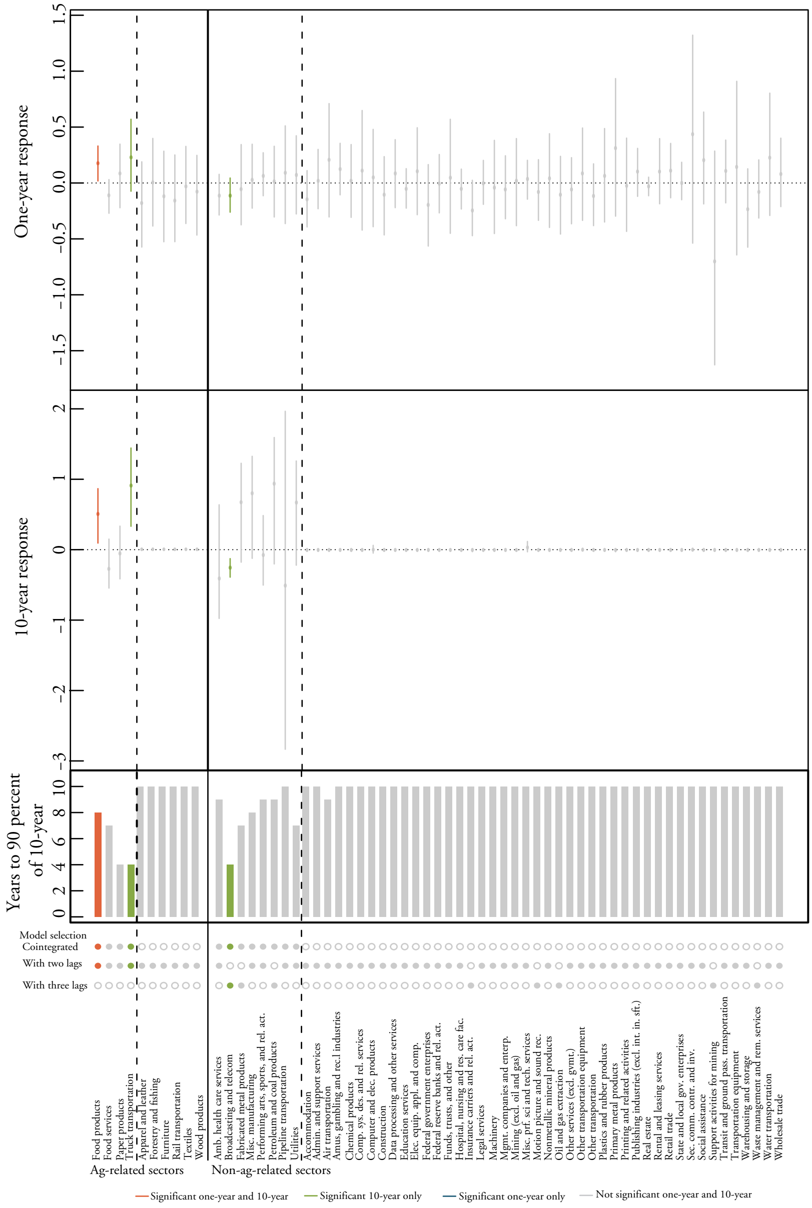
In summary, the evidence for KPP suggests very few, if any, significant short- or long-term spillovers from agriculture to other sectors, or vice-versa.

## IV. Have Agricultural Productivity Spillovers Changed over Time?

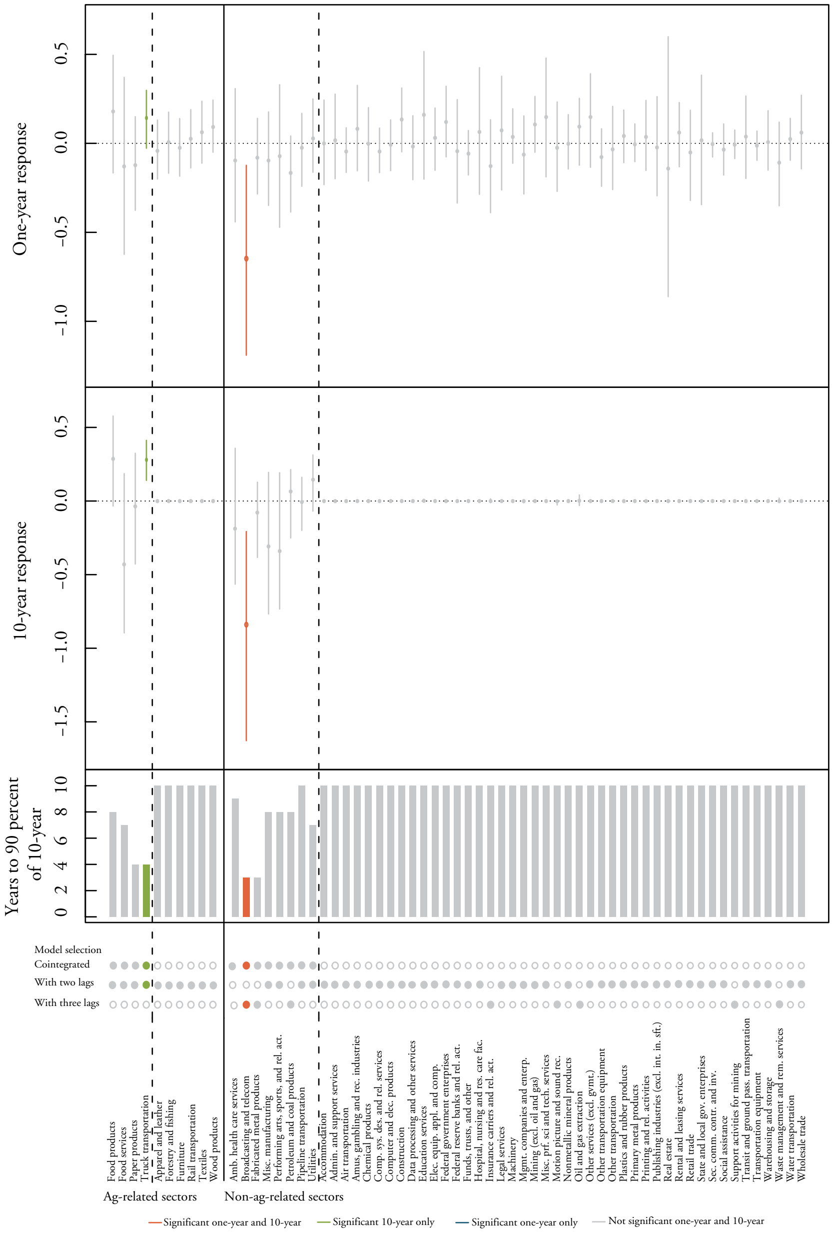
Thus far, our empirical analysis has assumed that the pairwise productivity relationships between agriculture and other sectors remained constant over the 1947 to 2014 period covered by the JHS data. However, this period was characterized by substantial changes in technology, demography, regulations, and policies that all likely influenced the economic structure of the sectors under analysis. Thus, it is reasonable to hypothesize that the pairwise productivity relationship between agriculture and a particular sector may have shifted over time, rendering our previous analysis too restrictive. For this reason, we also conduct separate empirical analyses for two subperiods: 1947–80 and 1981–2014.

Table 2 reveals that for both TFP and LPP, estimations over subperiods yield fewer significantly cointegrated pairs. In the case of TFP, only about half of the cointegration relationships that are significant over the entire period are also significant in the individual subperiods

## *Chart 5*
## Response of Non-agricultural Sectors' KPP to Shocks in Agricultural KPP



## *Chart 6*
## Response of Agricultural KPP to Shocks in Non-agricultural Sectors' KPP



1947–80 or 1981–2020. The number of significant LPP relationships between agriculture and non-ag-related sectors also drops by about half after breaking down the sample into two subperiods, and the drop is even more pronounced for LPP relationships between agriculture and ag-related sectors. These results for TFP and LPP are consistent with relatively stable but not particularly strong cointegrating relationships over the entire 1947–2014 period: cutting the number of observations in half for the subperiod analysis reduces the precision of the estimates, thereby weakening the evidence against the null hypothesis of no cointegration to the point where it may no longer be rejected.

In contrast, many more pairwise KPP relationships are significantly cointegrated over the 1947–1980 or 1981–2014 subperiods than over the full 1947–2014 sample (see Table 2). The greater number of cointegrated KPP relationships in the subperiods than the full sample implies that KPP relationships changed substantially over time. Relationships over the subperiods must have been relatively strong to reject the null of no cointegration, because subperiod estimates rely on fewer observations and are, all else equal, less precise than the full-period estimates. If such strong relationships had been sustained over time, they would have led to even stronger rejections of the no-cointegration null when using the entire sample; instead, the full-sample estimates weakened the evidence of cointegration.

In the interest of space, the subperiod equivalents of Charts 1 through 6 and Table 3 are omitted, as they do not provide valuable additional insights. To summarize, the productivity data suggest that the relationship between agriculture and other sectors was not particularly strong and remained relatively stable over the full period analyzed for TFP and LPP. For KPP, however, evidence suggests that the relationship between agriculture and other sectors experienced major shifts between 1947 and 2014.

## V. Robustness Check: Pairwise Relationships Using USDA Agricultural Productivity Data

Shumway and others (2017) compare agricultural TFP measures from an earlier version of the JHS database with the 2014 version of the official TFP series published by the USDA. They find that, despite the methodological differences, the series are remarkably similar in terms of the average growth rates of agricultural TFP over 1948–2010 and the four selected subperiods (1948–73; 1973–95; 1995–2005; 2005–10). In this section, we extend the comparison period and assess TFP, KPP, and LPP spillovers between agriculture and the other sectors of the economy from 1948 to 2014.

Johansen cointegration tests over the entire 1948–2014 period show that the USDA and JHS data are similar for agricultural TFP but different for KPP. For the TFP series, the tests reject the null of no cointegration at the 1 percent significance level. For the LPP series, the evidence of cointegration is somewhat weaker: the tests reject the null of no cointegration at the 5 percent (but not 1 percent) significance level. In contrast, the KPP series shows no evidence of cointegration between the JHS and USDA data over the 1948–2014 period: the tests do not reject the no-cointegration null even at the 10 percent significance level. Overall, these cointegration results suggest that inferences drawn from the USDA data will be most similar to those drawn from the JHS data for TFP and most different for KPP.

The results from the pairwise cointegration tests in Table 2 indicate that the USDA database yields similar cointegration patterns for 1948–2014 to those in the JHS agricultural productivity data. That is, regardless of whether one relies on the JHS or the USDA data, TFP has the largest number of cointegrated pairs, while KPP has the fewest. However, for the non-ag-related group, the USDA data yield fewer cointegrated pairs than the JHS data in all instances other than KPP.

In the interest of space, graphs analogous to Charts 1 through 6 are included in the Appendix, as they exhibit similar patterns. Table 3 demonstrates that the non-cointegrated pairs for the USDA data show short-term causal relationships similar to those already described for the baseline data set. Overall, the USDA agricultural productivity data reinforce the results obtained using the JHS agricultural productivity data over the entire overlapping period.

Breaking down the sample period into halves suggests that the JHS and USDA series for TFP and LPP maintain a stable but not particularly strong relationship from 1948 to 2014. In both cases, tests reject the null of no cointegration for the entire overlapping period, but cannot reject the null even at the 10 percent significance level for one of the subperiods. Contrastingly, the relationship between the JHS and USDA series for KPP appears to have changed significantly over time. Although tests do not reject the null hypothesis of no cointegration over the entire 1948–2014 period at standard levels of significance, they do reject the null for each of the subperiods.

According to Table 2, the subperiod estimation using the USDA agricultural productivity data yields similar results to the subperiod estimation using JHS data for TFP and KPP. Specifically, when compared with the full period estimation, both subperiod estimations yield fewer significantly cointegrated pairs for TFP and more significantly cointegrated pairs for KPP. For LPP in non-ag-related sectors, however, the results differ. Specifically, the subperiod estimation using the USDA series yields more significantly cointegrated pairs than the estimation using the JHS data. In short, the subperiod analysis based on the USDA data provides additional support for two conclusions drawn earlier from the JHS data: first, that TFP was characterized by relatively stable but not strong cointegrating relationships over the full sample period; and second, that KPP relationships underwent substantial changes over time. However, the subperiod analysis using USDA data yields a finding for LPP that conflicts with the analysis using JHS data: the USDA data suggest major shifts in LPP relationships between 1948 and 2014, but the JHS data suggest steady but not strong relationships over time.

## VI. Conclusion

The present study is the first to explore the linkages between the agricultural sector and 62 other sectors of the U.S. economy from a productivity perspective from 1947 to 2014. Applying widely adopted time series methods to productivity measures derived from JHS, our analysis suggests that increasing (reducing) TFP in agriculture above (below) trend would negatively (positively) affect the TFP of three sectors and positively (negatively) affect the TFP of five sectors after one year, but generate long-lasting increases (reductions) in the TFP of nine sectors and lasting reductions (increases) in the TFP of three sectors. Shocks in the TFP of two sectors would spill over into the agricultural sector after one year (one with same sign, and the other with the opposite sign), and shocks in the TFP of nine sectors would have significant spillover effects into the agricultural sector after 10 years (two with the same sign, and seven with the opposite sign). Our results also suggest that the few significant LPP and KPP spillovers across sectors may be an artifact of chance, and that labor and capital productivity in the agricultural sector are unrelated to their counterparts in the rest of the U.S. economy.

Comparing the results obtained over the entire sample period against those from the 1947–80 and 1981–2014 subperiods reveals that the relationship between agriculture and other sectors was stable but not particularly strong for TFP and LPP. For KPP, however, the relationship between agriculture and other sectors changed substantially between 1947 and 2014. In any case, it is important to note that partial productivity measures like LPP and KPP might be highly sensitive to shifts in input mixes over time and therefore provide less reliable information on productivity change than TFP.

Our findings can help policymakers exploit intersectoral synergies and mitigate negative intersectoral spillovers to revive economic growth in the U.S. agricultural sector over the next decade. Furthermore, our approach can be applied to estimate the economy-wide effects of a specific policy designed to foster productivity growth in one sector of the economy. For example, our approach allows for the incorporation of spillover effects beyond the agricultural sector into the calculation of the social rate of return to public investments in agricultural R&D (and other productivity-enhancing public goods). Following Coe and Helpman (1995), our estimates can be used as weights in the calculation of an aggregate economic return in the rest of the economy stemming from the initial investment in the agricultural sector.

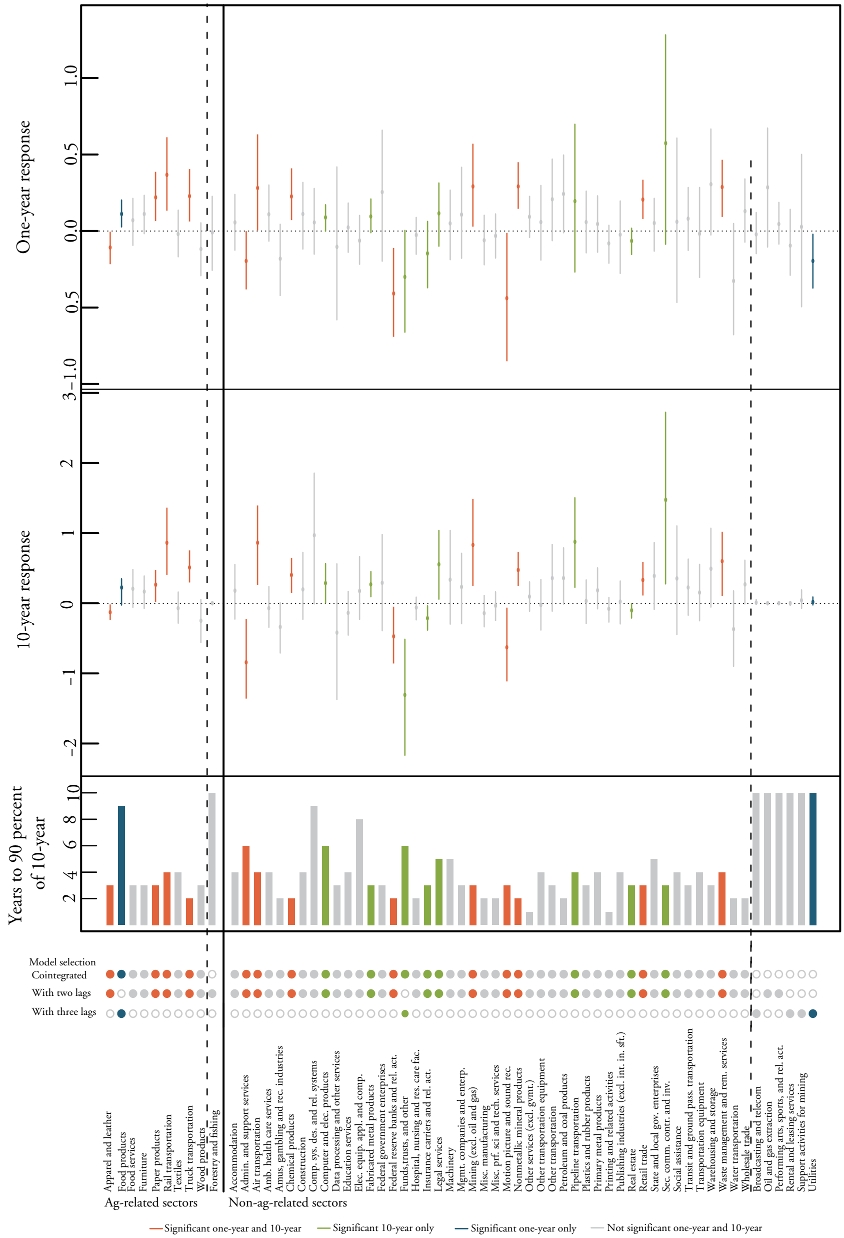
Our qualitative results are robust to the use of the USDA TFP series instead of the JHS TFP series for the agricultural sector, reinforcing the conclusion from Shumway and others (2017) that, despite methodological differences, TFP growth estimates from the two databases are remarkably similar. Qualitative results for LPP and KPP are also similar when using the USDA data instead of the JHS series. However, in the case of LPP, the analysis based on the USDA series suggests that the relationships changed over time, contradicting the stable but not strong relationships implied by the JHS data.

Although our analysis was not designed to measure the degree of convergence in productivity changes across sectors, our results tangentially inform such discussion by evaluating the cointegration in productivity series across sectors. In particular, we find no significant cointegrating vectors across agriculture and 50 other sectors in KPP, 39 other sectors in LPP, and one other sector in TFP, suggesting that those pairs of productivity series do not converge in time series (Bernard and Durlauf 1995). However, further analysis is required to evaluate whether two cointegrated productivity measures imply convergence in time series (depending on the significance of the coefficient $\alpha_1$ in equation (1)).

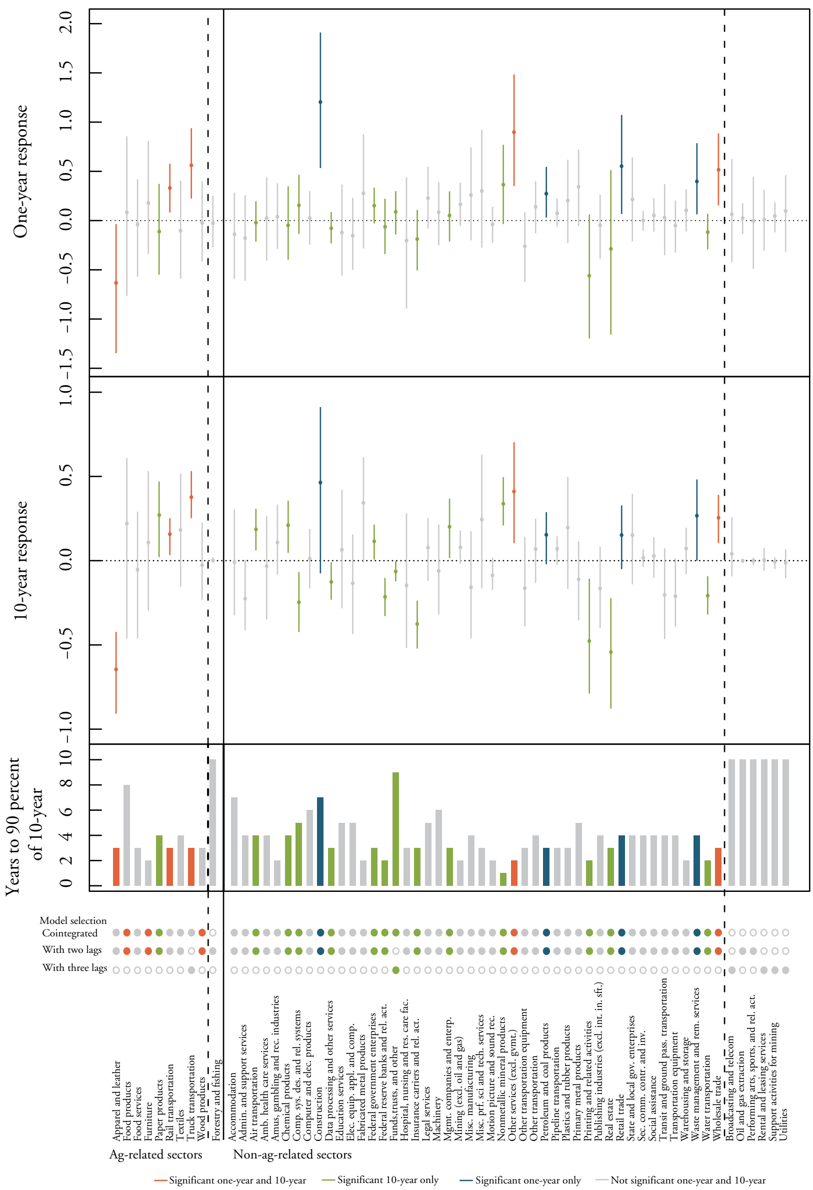
A major limitation of our empirical investigation resides in the top-down approach of the sectoral productivity comparisons. A future bottom-up study on the micro fundamentals for the sectors displaying significant productivity spillovers from and to agriculture is warranted to provide insights on the microeconomic foundation of the observed sectoral relationships. Another major limitation is the level of aggregation of the JHS data at the national level, which prevents richer state- or region-specific analyses.

# Appendix
# Supplementary Charts

## *Chart A-1*
## Response of JHS Non-agricultural Sectors' TFP to Shocks in USDA's Agricultural TFP

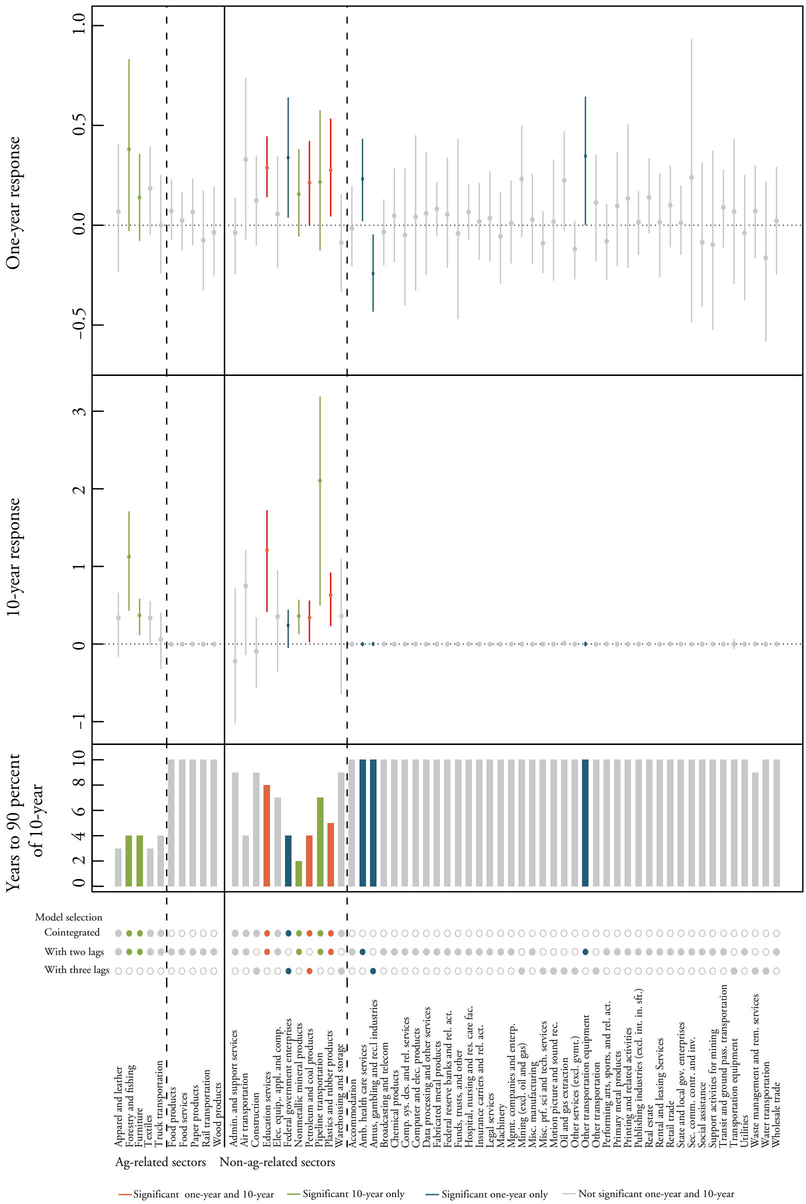


## *Chart A-2*
## Response of USDA's Agricultural TFP to Shocks in JHS Non-agricultural Sectors' TFP

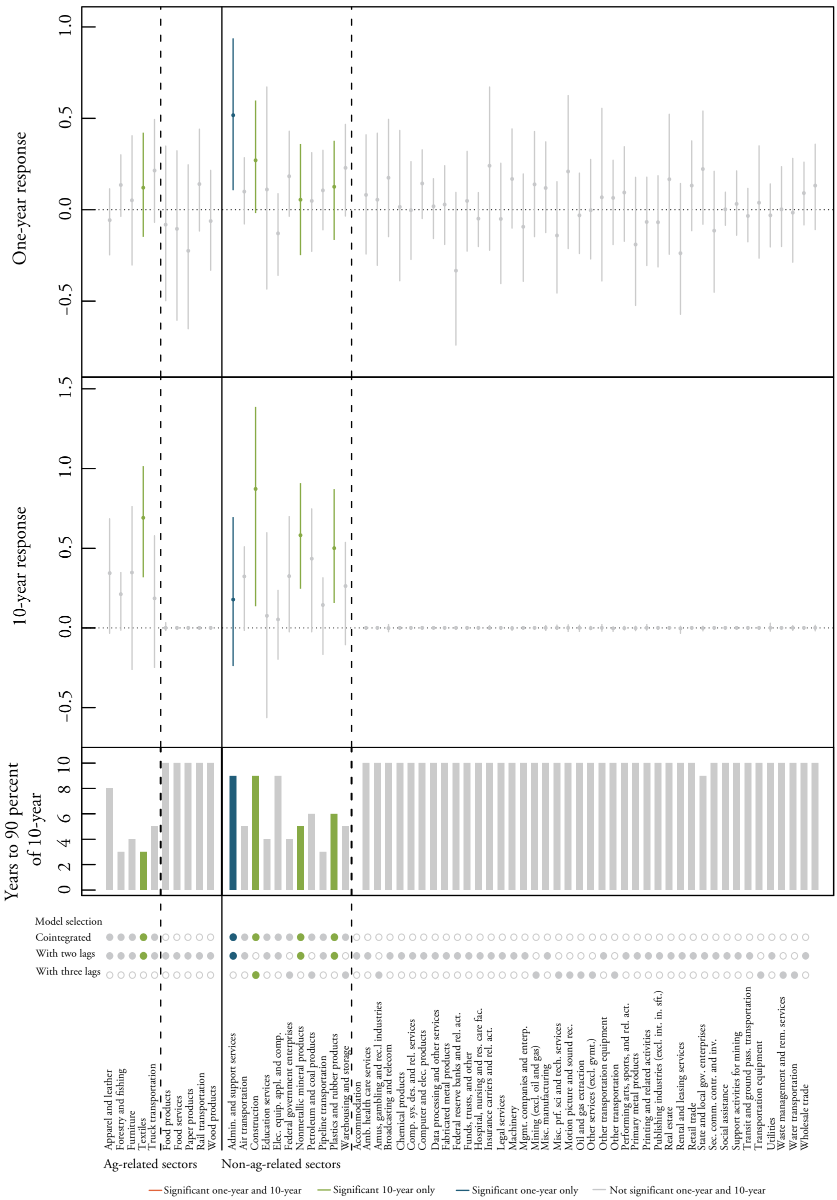


## *Chart A-3*

## Response of JHS Non-agricultural Sectors' LPP to Shocks in USDA's Agricultural LPP

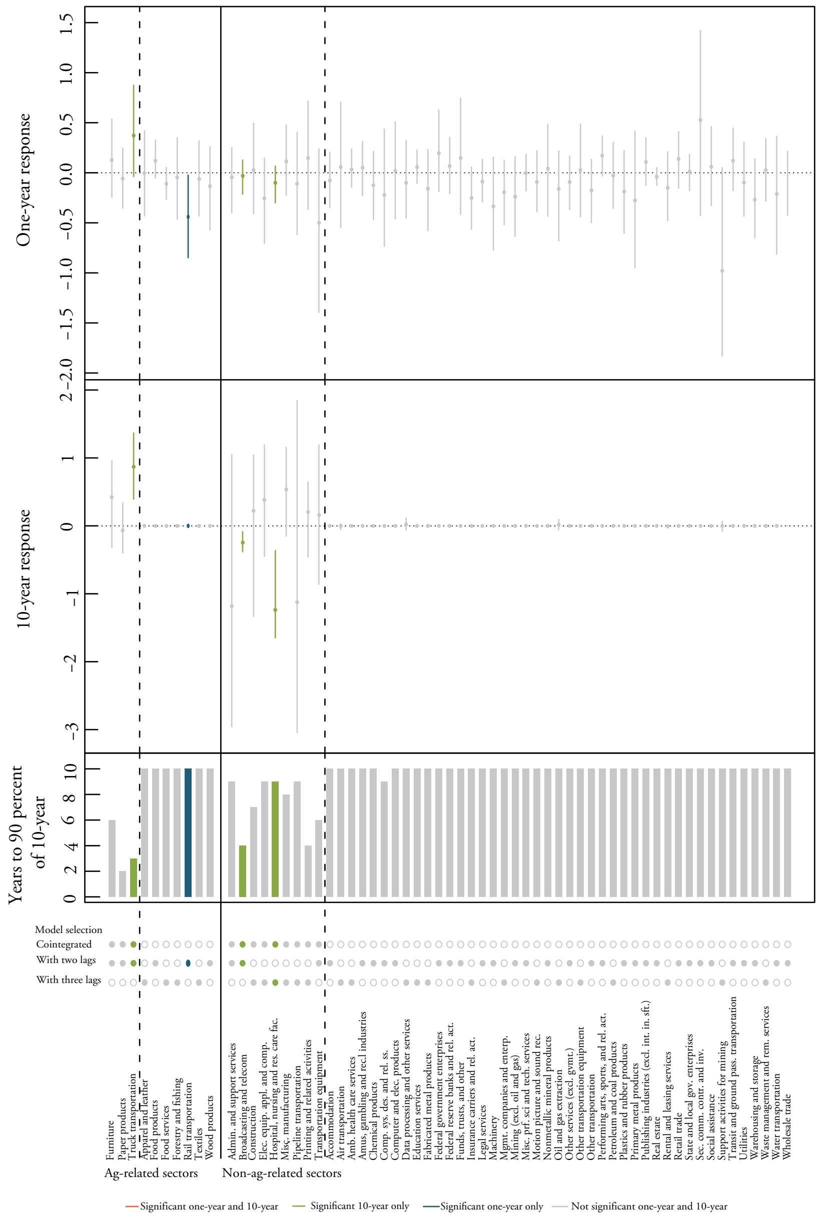


## *Chart A-4*
## Response of USDA's Agricultural LPP to Shocks in JHS Non-agricultural Sectors' LPP

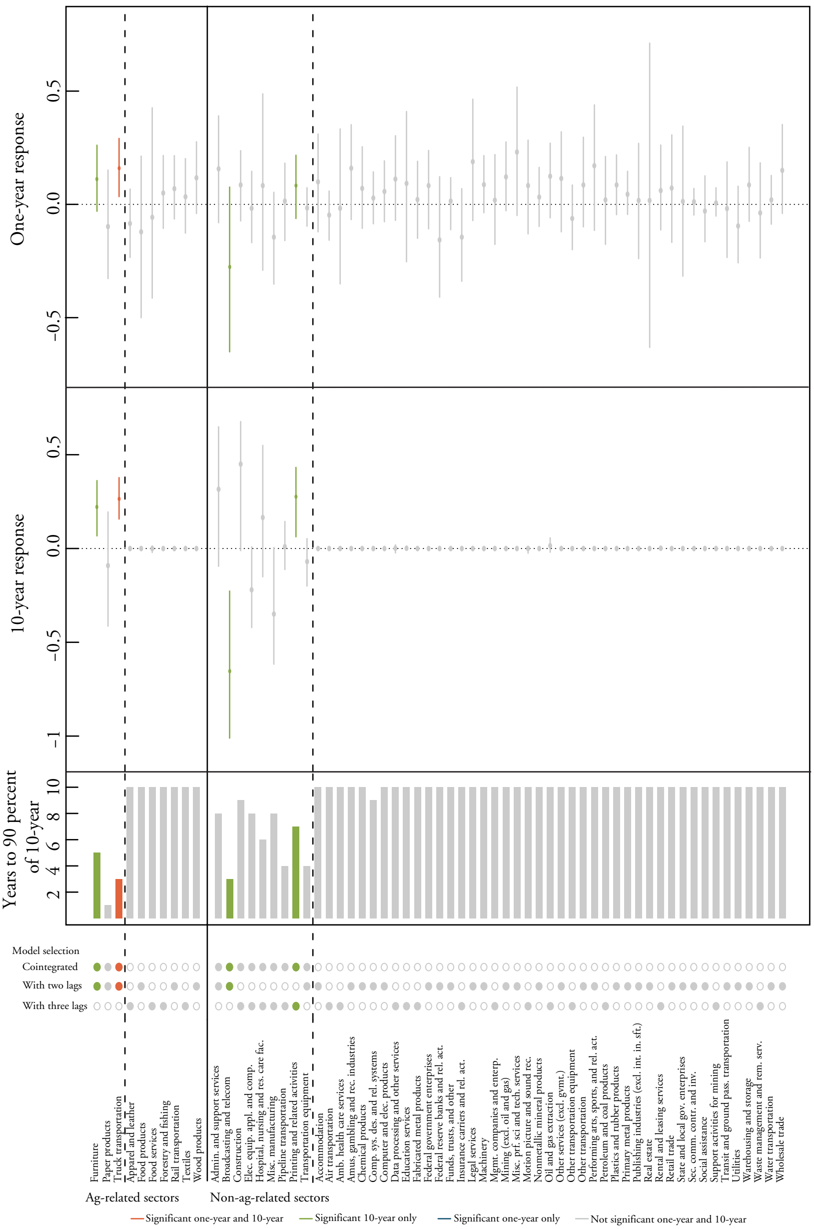


## *Chart A-5*

### Response of JHS Non-agricultural Sectors' KPP to Shocks in USDA's Agricultural KPP



## *Chart A-6*
## Response of USDA's Agricultural KPP to Shocks in JHS Non-agricultural Sectors' KPP



## Endnotes

[1]TFP has been shown to be a major source of agriculture growth in both state and national level data sets. On the state level, for example, see Craig and Pardey (1990a, 1990b); Huffman and Evenson (1989, 1993); Alston and Pardey (1996); Ball and others (1999); Acquaye, Alston, and Pardey (2003); O'Donnell (2012); Njuki, Bravo-Ureta, and O'Donnell (2018); Plastina and Lence (2018); Chambers and Pieralli (2020). On the national level, see USDA (1981); Ball (1985); Hauver (1989); Jorgenson and Gollop (1992); Ball and others (1997); Wang and others (2015).

[2]Garner and others (2019) use the concept of multifactor productivity instead of TFP in their analysis.

[3]The studies that disaggregate TFP in U.S. agriculture into technological changes; productive, allocative, and scale efficiencies; as well as price effects include Capalbo (1988); Morrison Paul and Nehring (2005); Andersen, Alston, and Pardey (2012); O'Donnell (2012, 2014); Plastina and Lence (2018); Njuki, Bravo-Ureta, and O'Donnell (2018); and Chambers and Pieralli (2020). Wang and others (2015), Fuglie and others (2017), Alston (2018), and Baldos and others (2019) provide recent reviews of the literature on research and development, extension services, knowledge spillovers, and communication and transportation infrastructure as major drivers of agricultural productivity. Earlier comprehensive literature reviews on the returns to productivity-enhancing investments in U.S. agriculture include Alston and others (2000); Huffman and Evenson (2006); Fuglie and Heisey (2007); Alston and others (2010); and Hurley, Rao, and Pardey (2014).

[4]Studies on knowledge spillovers from other sciences into agriculture include Huffman and Evenson (2006); Shoemaker and others (2001); and Wang, Xia, and Buccola (2009). Studies on knowledge spill-ins to agricultural productivity from agricultural R&D conducted in other jurisdictions include Coe and Helpman (1995); Schimmelpfennig and Thirtle (1999); Huffman and others (2002); Alston and others (2010); and Plastina and Fulginiti (2011).

[5] The acronym KLEMS stands for capital (K), labor (L), energy (E), materials (M), and services (S). Analytical KLEMS-type data are constructed by researchers in the WORLD KLEMS consortium; they have harmonized definitions and aggregation procedures so as to obtain industry-level productivity measures that are comparable across countries. The data are available online at http://www.worldklems.net/data.htm

[6]We exclude the federal general government and state and local general government industries from the analysis because their TFPs are constant for the entire period, yielding nonsensical regression estimates.

[7]Although the Elliott, Rothenberg, and Stock (1996) test is more powerful than the standard augmented Dickey-Fuller unit-root test, unit-root tests have

low power in general (that is, they have a low probability of correctly rejecting the null hypothesis of a unit root when in fact the series is stationary) (Enders 2014).

[8]Cointegration between two series requires that each of them be characterized by a unit root. Hence, if JHS's agriculture TFP series is assumed to be stationary, one should immediately conclude that it is not cointegrated with any of the non-agricultural sectors' TFPs.

[9]There is no dashed line within the ag-related group in Charts 1 and 2 because all ag-related sectors are cointegrated with agriculture in the case of TFP. In contrast, Charts 3 through 6 depict dashed lines within the ag-related group because not all of its sectors have partial productivities cointegrated with agriculture's.

[10]We use the exact test from Fisher (1954) to assess whether the probability of cointegration is the same for ag-related as for non-ag-related groups. For the test, we use the 2 x 2 contingency table consisting of eight cointegrated pairs and two non-cointegrated pairs for the ag-related group, and 15 cointegrated pairs and 37 non-cointegrated pairs for the non-ag-related group. The test rejects the null hypothesis of equal probabilities at the 0.4 percent significance level.

[11]These sectors cannot have long-term relationships with agricultural LPP because they are not cointegrated.

[12]Given the 2 x 2 contingency table consisting of four cointegrated pairs and six non-cointegrated pairs for the ag-related group and eight cointegrated pairs and 44 non-cointegrated pairs for the non-ag-related group, the exact test from Fisher (1954) rejects the null hypothesis of equal probabilities at the 9.1 percent significance level.

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