Comments on "The Roots of Agricultural Innovation: Patent Evidence of Knowledge Spillovers"

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Economists use the terms "knowledge spillovers" and "research spillovers" to indicate the positive effects that the R&D investments of one firm may have on other firms. The idea that research investments generate positive externalities, and thus increase productivity growth and subsequent innovation of other firms, is one the primary justifications for government R&D support policies.

Measurement and identification of research spillovers is one of the classic research questions in the field of economics of innovation. For many decades, researchers struggled to find a way to measure empirically these spillovers. Krugman (1991) wrote that knowledge spillovers "*are invisible; they leave no paper trail by which they may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes*."

Empirical scholars responded to Krugman documenting and leveraging a variety of paper trails, in the forms of citations in patents and scientific publications. This generated a vibrant, large and growing literature.[1] Clancy, Heisey, Ji and Moschini contribute to this stream of research providing a thoughtful examination of knowledge spillovers from non-agricultural technologies into agricultural innovation.

The chapter employs three different empirical measures of knowledge spillovers. The first measure exploits citations made by patent documents. Consider a patent protecting an agricultural technology that cites many prior patents that are not classified by the patent office as agricultural technologies. In this case the citation pattern suggests that knowledge spillovers from outside agriculture were important for the development of the innovation. The chapter builds on this idea, and also leverages the richness of the patent data to measure the specialization of the firm owning the cited patent. The more agricultural patents cite firms that are not specialized in agriculture, the stronger is the support to the idea that there are important knowledge spillovers from other industries.

The second measure of spillovers presented in the paper relies on patent citations to scientific publications. The intuition behind this measure is that citations from agricultural patents to non-agricultural academic journals reveal that academic research in other scientific domains has significant knowledge spillovers into agriculture.

[1] See Bloom et al. (2013) for a recent contribution and a description of the various empirical approaches developed in the literature.

The final measure is based on a textual analysis algorithm that identifies the appearance of new 'textual concepts' (i.e. text strings) on agricultural patents. With this approach, the presence of knowledge spillovers is revealed by textual concepts which are new in agricultural patents but are not not novel in other technology fields.

The empirical analysis in the paper suggests that knowledge spillovers from outside agriculture are a statistically significant and economically important driver of agricultural innovation. A large fraction of these spillovers appears to be derived from biology and chemistry, two research fields that are technologically close to agriculture.

The large spillovers documented by Clancy, Heisey, Ji and Moschini have important implications for our understanding of how shocks propagate in the economy through industry linkages. There is a growing literature examining how supply and demand shocks that originate in one industry may percolate through vertical chains or disseminate to other industries (Barrot and Sauvagnat, 2016; Galasso and Luo, 2018). The results described in the chapter show strong research linkages between agriculture and other technology areas, which suggest that agricultural innovation may be exposed to shocks in these research domains.

To develop some policy implications, it is important to understand the channels through which knowledge is transmitted to (and from) agricultural research. Numerous studies in the economics of innovation literature implicitly assume that knowledge flows are not tradable, and that the empirically measured research spillovers only capture unintended external effects. While this may be an appropriate assumption in some contexts, it may not be valid in many technology sectors. In the presence of well-functioning markets for technology knowledge may be transmitted across firms through patent licensing contracts. Moreover, firms may leverage their intellectual property assets to facilitate knowledge exchanges with some fields but not others. As explained in a recent study by Arque-Castells and Spulber (2019), to understand the role played by the market for technology is essential to assess the wedge between the social and private rates of return of R&D. Combining data on out-of-field citations with data on patent licensing, reassignment and litigation may help understanding the extent to which knowledge flows are internalized.

The innovation literature has stressed the importance of general purpose technologies (GPTs). These are inventions that have potential applications across a wide number of sectors (Bresnahan and Trajtenberg, 1995). Examples of GPTs include the steam engine, the electric motor, microprocessors and, more recently, artificial intelligence. GPTs have been shown to be powerful source of growth in sectors that can develop complementary technologies. The literature has documented substantial heterogeneity across sectors in the development of technologies that incorporate and complement GPTs. These differences are typically linked to market structures and appropriability conditions. In light of these findings, an interpretation of the results described

by Clancy, Heisey, Ji and Moschini is that the agricultural sector has been very effective at exploiting GPTs originating in other sectors. In principle, the high rate of GPT adoption by agricultural innovators may have enhanced the innovation incentives in the GPT itself (Cockburn et al., 2020).

The estimates in the chapter show that the percentage of prior-art citations that accrue to patents not classified as agricultural patents is very large in some agricultural subsectors. For example, about 90 percent of patents cited by "animal health" patents are not classified by the United States Patent and Trademark Office (USPTO) as agricultural patents. This is a striking result. One important thing to notice, though, is that interpreting the magnitude of citation-based measures of spillovers is challenging. This is because it is not clear what the appropriate benchmark should be. As a reasonable first step, Clancy, Heisey, Ji and Moschini examine whether the fraction of citations made to non-agricultural patents is above or below 50 percent. Technology areas in which more than half of the cited references belong to other fields are highlighted as fields receiving large external knowledge spillovers. A more general analysis of this issue may require benchmarking the propensity of agricultural patents to cite out-of-the-field patents with similar propensity measures in other technological areas.

From a conceptual perspective, one also has to consider the possibility that the magnitude of spillover effects may be determined by the relative size of a technology field. This may be particularly important when two research areas are technologically very close but differ in size. Consider the following example. There are two technology fields: field A and field B. In field A there are 10 patents and in field B there are 90 patents. Now assume that each of these 100 patents randomly cites one of the other 99 patent. In this case, if citations are i.i.d., one would observe many more patents in field A citing patents in field B than patents in field B citing patents in field A. At the same time, the high propensity of field A patents to cite out of the field patents is not really revealing that each invention in field A builds disproportionally from field B. It is simply reflecting the fact that A is a small field, with less knowledge inputs to draw from, and heavily connected to the larger field B.

In conclusion, Clancy, Heisey, Ji and Moschini make a convincing case that ideas that originate outside of agriculture have important effects on agricultural research, perhaps a role as important as R&D investments within agriculture. They also provide a variety of different and powerful empirical measures to capture knowledge flows into agriculture. Future research should focus on further understanding the drivers and implications of these important findings.

References

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