Abstract

Patent protection was introduced for novel crop varieties in 1985, and it affected crops differentially depending on their reproductive structures. Exploiting this variation across crops, I find that the introduction of patent protection increased new technology development, measured as the release of new plant varieties. It also increased private research investment and had positive spillover effects on innovation in complementary agricultural technologies other than varieties. Furthermore, the introduction of patent protection increased downstream productivity. First, I show that it led to an increase in crop yields. Second, I show that in U.S. counties that—due to differences in crop-specific suitability—were more exposed to the change in patent law, it increased agricultural land values. During the sample period, profits in more exposed counties increased despite the fact that, intuitively, expenditure on crop varieties also went up. Large farms benefited disproportionately and profits in areas with the smallest farms declined. Taken together, the results suggest that patent incentives had a major positive effect on technology development and played an important role in shaping the distribution of downstream productivity and profits.
1 Introduction

What is the impact of the availability of intellectual property protection on innovation and productivity? There is a widespread belief that intellectual property protection underpins technological progress and productivity growth. The ability to profit from new ideas is at the heart of models of endogenous growth, and intellectual property protection is often listed among a set of institutions that are important for long run development (e.g. Romer, 1990; Acemoglu and Robinson, 2012). Moreover, patent protection might shape not only the level but also the distribution of profits across sectors, producers, or occupations. Nevertheless, our understanding of the empirical relationship between the availability of intellectual property protection and innovation is limited and remains a topic of intense debate (Lerner, 2009; Moser, 2016; Williams, 2017). The impact of intellectual property protection on productivity is even less clear. Since patent protection is one of the primary policy levers used to encourage technological progress, understanding its impact on innovation and downstream production is of critical importance.

This paper provides empirical evidence of the relationship between the availability of patent protection, technological progress, and productivity by investigating the introduction of patent protection for novel crop varieties in the United States. While intellectual property protection for most innovations has existed since the U.S.’s founding, full patent protection for crop varieties (e.g. seeds) was not permitted. Certain crops, however—those for which it was feasible to produce hybrid varieties—had \textit{de facto} intellectual property protection prior to the introduction of formal intellectual property protection (e.g. Butler and Marion, 1985; Gupta, 1998; Fernandez-Cornejo, 2004; Fajardo-Vizcayno et al., 2014). Hybrid varieties can only be produced accurately by the developer and, because seeds generated by the first generation hybrid have often vastly different properties from the original hybrid, cannot be reproduced by farmers or competing inventors; this affords innovators with “the same commercial right that an inventor receives from a patented article” (Jones, 1920; Kloppenburg, 2005). Non-hybrid varieties, however, once sold, are easily reproducible; formal contracting is required to prevent them from being saved or sold.

In one fell swoop, the legal regime changed in 1985 and inventors could for the first time claim patent-level protection for non-hybrid varieties. In \textit{Ex Parte Hibberd}, the US Patent and Trademark Office ruled that seeds, plant tissue, and plants were patentable subject matter under the utility patent statute. The ruling was a shock; in the words of William Lesser (1987):

\[ \text{[V]irtually overnight, and to the great surprise of many, seeds became patentable.} \]

This narrative forms the basis of this paper’s empirical analysis and design: a difference-in-differences framework that compares crops that received formal patent protection in 1985 with

\footnote{See Kline et al. (2019) for a recent treatment.}

\footnote{Indeed, Boldrin and Levine (2013) argue that there is “no empirical evidence that [patents] serve to increase innovation and productivity, unless productivity is identified with the number of patents awarded” (p. 3).}

\footnote{Weaker forms of protection had existed for some crops prior to 1985, but these, anecdotally, had little impact and were of limited import to inventors. The history of IP protection for varieties is discussed in Section 2.1.}
a control group that had “built-in” (or, *de facto*) patent protection prior to the introduction of legal patent rights (Gupta, 1998).

In order to analyze the consequences of the introduction of intellectual property protection, I first determined the set of crops that are “hybrid-compatible” and therefore had *de facto* protection prior to 1985. The key determinant of whether hybrid varieties can be generated for a given crop is its flower structure (Fajardo-Vizcayno et al., 2014; Bradford, 2017). If a crop has “perfect flowers”—flowers that contain both the male and female reproductive parts—the plant self-pollinates and generating a hybrid is often technologically infeasible or prohibitively costly. When the male and female flowers are separate and on different parts of the plant, generating hybrid varieties is more straightforward (e.g. Wright, 1980; Whitford et al., 2013). Thus, I ascertained the flower structure of all crops grown in the United States in order to determine their “hybrid compatibility.”

Using this fixed characteristic of crops’ flower structure to measure hybrid-compatibility furthermore circumvents the empirical issue that the actual development of hybrid varieties is potentially endogenous to, for example, research effort. Indeed, I find that hybrid-compatible and hybrid-incompatible crops are balanced across a range of crop-specific characteristics that determine the location, structure, and demands of variety development. The details of plant reproduction and the relationship between hybridization, flower structure, and intellectual property protection, are discussed in much more detail in Section 2.

In order to compare technological progress in hybrid-compatible compared to hybrid-incompatible crops over time, I compile a data set of crop-specific innovation. A common measure of innovation is patenting activity; however, since this paper investigates the impact of introduction of patent rights, patents themselves are not a useful dependent variable. Therefore, a key empirical challenge was the construction of other measures of innovation that are observable both before and after the introduction of patent rights. I overcome this challenge using the United States Department of Agriculture’s (USDA) *Variety Name List*. The *List*, which has been compiled by the USDA since the late 19th century and which I obtained via a Freedom of Information Act (FOIA) request, is maintained in order to prevent fraud in the seed market and is designed to be a comprehensive list of all crop varieties released in each year. This data set makes it possible to track crop-level innovation in new plant varieties—precisely the innovations that became patentable in 1985—both before and after the introduction of patent rights.

I supplement the *Variety Name List* with three additional measures of crop-level technology development. First, I compile data on research investment by crop from the USDA Current Research Information System (CRIS). To calculate research investment allocated to each crop in each year, I aggregate the research project-level data reported by CRIS to the crop-by-year level using the commodity (i.e. crop) information associated with each project. The key benefit of the CRIS data

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4 Corn is an example of a crop without perfect flowers; nearly all corn production relies on hybrid varieties and corn hybrids have existed since the early 20th century. Other examples are buckwheat, spinach, squashes, and cucumbers. Wheat, on the other hand, has perfect flowers and hybrid varieties are not used.

5 In the words of the USDA, the *List* is compiled “from sources such as variety release notices, official journals, seed catalogs, and seed trade publications, as well as names cleared for use by seed companies.”
is that it contains both public research investment and all private research investment directed toward research projects that received any public funding; thus, while the measure of private investment is incomplete, I can use the CRIS data to (imperfectly) compare the response of private and public investment to the availability of patent protection. Second, I compile data on crop-specific patenting in technologies other than varieties; these technologies were patentable during the entire sample period. I assigned patents within relevant patent classes to individual crops if the crop name appears in the patent title, abstract, or keywords. The patent data make it possible to estimate spillover effects of patent availability for varieties on innovation in other crop-specific technologies. Third, I compile measures of crop yields in order to estimate the impact of patent rights on productivity directly. This makes it possible to test whether the innovative activity measured in the varieties data translated into measurable changes in physical productivity.

I find that the introduction of patent protection led to a dramatic and persistent increase in the development of new crop varieties. While variety development in hybrid-compatible and hybrid-incompatible crops were on similar trends prior to 1985, following the change in patent law they diverged sharply. Compared to hybrid-compatible crops, hybrid incompatible crops experienced a 0.123 standard deviation increase in new variety development during the ten years following the introduction of patenting and a 0.167 standard deviation increase in new variety development during the twenty years following the introduction of patenting. The effect is driven by non-perennial crops—crops that must be re-planted every one or two years—for which profit opportunities from recurrent variety sale was plausibly largest and patent protection was most profitable.

Turning to research investment, I find that the availability of patent protection increased private research investment and did not have a significant effect on public research investment. Thus, the shift in research investment toward new profit opportunities seems to have been driven predominately by the private sector. Next, I investigate how the introduction of patent protection for crop varieties affected crop-specific innovation in technologies other than varieties. The new profit incentives to develop new varieties for hybrid-incompatible crops might have also affected innovative output in other technologies if, for example, improved varieties were complementary inputs in production with other technologies, or if improved varieties became substitutes for functions that had been performed by other technologies (e.g. insect resistant seeds are substitutes for insecticides).

Using patent data to measure crop-specific innovation for non-variety technologies, I find some evidence that for certain technology classes, and those that anecdotally have complementarities in production with improved varieties, the introduction of patent protection for varieties led to a relative increase in innovative output for hybrid incompatible crops. Thus, there were positive spillover effects of the introduction of variety patents on innovation in technologies whose patent law did not change. These spillover effects plausibly amplified the productivity consequences of the introduction of patent protection, and demonstrate that in evaluating the impact of intellectual property protection is important to take into account the response of innovative activity in
technologies other than those that directly gained protection.

Did this documented increase in new variety development and private research investment increase downstream agricultural productivity? It could be the case that the marginal innovation induced by the patent law change was relatively insubstantial and did not translate into major changes in crop yields or input cost saving. This could be for purely technological reasons or because, for example, the ability to enforce intellectual property led to an increase in copycat and business stealing inventions that did not truly expand the technological frontier. An advantage to focusing on the agricultural sector is that it is possible to directly measure crop-specific productivity dynamics using data on crop yields. I document that the introduction of patent protection had a discernible positive effect on crop-level agricultural yields that persisted after 1985. Thus, the introduction of patent protection affected not only innovative output but also measurable components of agricultural productivity.

This first set of findings demonstrates that patent protection for plant varieties had a large positive impact on innovative activity and crop yields. There are at least three important components of the impact of the introduction of patent protection on production that the first set of results does not address. First, patent protection comes with potentially significant trade-offs; at least since Nordhaus (1969), models of patenting and innovation have emphasized the need to balance the potential benefits of patent protection with the costs to consumers in the form of higher prices for patented technologies. The first set of findings is not informative about whether the benefits from induced innovation outweighed the potential higher cost to consumers (i.e. farmers) of patented technologies.

Second, the use of new patented technologies could have led to input and land use adjustment, as well as general equilibrium price effects, that together could dampen or amplify the impact of the introduction of patent protection on downstream profitability. A decline in producer prices for farmers growing treatment crops due to increased national productivity, for example, might have eroded the impact of more productive varieties on profits. Third, and most mundanely, new varieties could do many things other than improve physical yields, including improve taste or texture, reduce the need for spending on complementary inputs, or confer other benefits that would not be captured by crop yields.

In order to fully capture the impact of intellectual protection on downstream production, I focus on fixed geographic units—U.S. counties—and estimate the impact of county-level exposure to the change in patent law based on county-level suitability for crops that are in the treatment and control groups. For each U.S. county, using models of maximum potential crop yield from the Food and Agriculture Organization’s (FAO) Global Agro-Ecological Zones (GAEZ) database,

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6 For example see Cohen et al. (2019) on patent trolls.
7 Indeed, there are myriad news stories of agricultural biotechnology companies threatening to sue or actively suing farmers for saving patented seed technologies and farmers, unable to compete on the market with old cultivars and unable to afford yearly re-purchase of modern seeds, losing their livelihoods. Monsanto, on the other hand, argues that its “continuous innovative cycle” is “fueled in part by patents” and that allowing farmers to save seeds would limit the ex ante incentives provided by patent protection, ultimately making farmers worse off (see here: https://monsanto.com/company/media/statements/food-inc-documentary/). On the negative impact of the high price of patented technologies on certain farmers, see: https://www.cbsnews.com/news/agricultural-giant-battles-small-farmers/.

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I predict the optimal crop mix and estimate the share of county land on which the model predicts hybrid incompatible crops—crops in the “treatment group”—are grown.\(^8\) I treat this share as a measure of each county’s exposure to the introduction of patent protection.\(^9\) If a county specializes in hybrid compatible crops that already had de facto intellectual property protection, then the county was relatively unexposed to the change in patent law. If, on the other hand, a county specializes in crops for which patents are required in order to prevent seeds from being saved, sold, or used by other inventors, the county was exposed to the change in patent law. I combine these county-level exposure measures with data on outcomes from the 1974–1997 rounds of the US Census of Agriculture in order to consistently estimate the impact of exposure to the patent law change on agricultural land values, capturing the net present value of agricultural profits.

Exposure to the introduction of patent protection had a large positive effect on agricultural land values; the patent law increased the long run (i.e. net present value) profitability of producers that were most directly affected. This result is robust to the inclusion of state specific trends as well as to controlling flexibly for trends in pre-period land devoted to agriculture and agricultural revenue, and is larger in magnitude after restricting the sample to counties with above median pre-period farmland. According to the most conservative estimates, a one standard deviation increase in a county’s exposure to the introduction of patenting—as measured by the share of its cropland devoted to hybrid incompatible crops—led to a 0.19 standard deviation increase in land values after 1985. Thus, the long run effect of the introduction of patenting on agricultural profits capitalized into land values was positive and significant.

What drove the documented positive impact of the patent law change on the profitability of producers? As might be predicted by a Nordhaus (1969)-style model, I find that more-exposed counties increased input spending on crop varieties. This is consistent with producers paying higher prices for patented inputs.\(^{10}\) However, farm profits, measured as agricultural revenues net of variable costs, also increased in more exposed counties during the sample period, suggesting that the productivity increase from patented technologies outweighed the higher input costs, even in the short run. Price effects were insufficient to erode the impact of productivity for farmers growing treatment crops. Land devoted to crop production also increased in more exposed counties, which may have amplified the long run impact of the patent law on land values as more land was put to productive use.

Did all counties benefit equally from the introduction of patent protection? Anecdotally, large

\(^8\)See, for example, Costinot and Donaldson (2012), who introduce this methodology.

\(^9\)I also validate the estimates of county-level exposure using the GAEZ data with actual data on the distribution of production across crops estimated using the 1982 Census of Agriculture.

\(^{10}\)The increase in spending on crop varieties could in theory be driven either by higher seed prices or a larger quantity of seed purchases—unfortunately, the Census of Agriculture does not collect data on input quantities. Nevertheless, some evidence suggests that finding is not driven only by an increase in the quantity of seed purchases. First, I find no evidence of a significant increase in spending on non-variety inputs, which would be expected if the results for variety expenditure were driven by an intensification of production or increase in cropland. Second, I control directly for the change in land devoted to crop agriculture and the impact of the patent law on spending on varieties does not change. Finally, while systematic data on seed prices during the sample period are limited, a case-study comparison of the average price of corn seeds (a large control crop) versus cotton seeds (a large treatment crops) shows that while prices were on similar trends prior to 1985, they diverge after 1985 as the relative price of cotton seeds increased (Figure A3).
farms benefitted disproportionately from the change in intellectual property regime (Willingham and Green, 2019). Small farms were less likely to adopt improved varieties, which often were complementary with scale and non-variety input investment; thus, small farmers of treatment crops may have benefitted less from the productivity potential of new varieties while at the same time receiving lower prices for their output because large farms producing the same crops became more productive. Indeed, there has been a range of qualitative and journalistic work arguing that the introduction of patent protection had major distributional consequences. I present two sets of results consistent with this narrative. First, I show that the positive effect of intellectual property protection on profits is limited to counties with large average farm revenue at the start of the period; counties in the bottom farm revenue quartile actually experience a decline in average profits as a result of the introduction of patent protection. I also show some evidence of the price mechanism: producer prices of treatment crops, compared to control crops, declined after 1985; however, data on producer prices during the sample period are limited so I am underpowered to detect a significant effect. Second, the introduction had a direct effect on the farm size distribution. In more exposed counties, the farm size distribution was shifted to the right, consistent with larger farms disproportionately thriving when patent protection was introduced.

This paper builds on multiple areas of existing research. Its first set of findings contribute to a better understanding of the impact of patent protection on research investment and output. Empirical estimates of the effect of patent protection on innovation are limited (Williams, 2017); the impact of the ability to protect intellectual property on equilibrium innovation is not obvious. Branstetter and Sakakibara (2002) use time-series data to analyze Japan’s 1998 patent law reform and argue that an expansion of patent scope had a limited impact on firms’ R&D. Budish et al. (2015) explore the impact of differences in effective patent length across cancer research investments, and find that longer patent length encourages private research investment. The relationship between patent enforcement and innovative output is further complicated by work documenting that intellectual property protection hinder follow-on research (e.g. Murray and Stern, 2007; Williams, 2013). Other studies have investigated country-level differences or changes in patent law (Lerner, 2002; Qian, 2007; Lerner, 2009), or looked to historical periods in order to

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11 There is also a range of more qualitative work on the impact of the introduction of variety patent protection on the farm sector. For example, see the 2005 report by the Center for Food Safety, “Monsanto vs. U.S. Farmers,” https://www.centerforfoodsafty.org/files/cfsmonsantovsfarmerreport1105.pdf. This subject has also been covered by many press outlets, including in several articles in the Washington Post (e.g. https://www.washingtonpost.com/lifestyle/food/unearthed-are-patents-the-problem/2014/09/28/9bd5ca90-4440-11e4-9a15-137aa0153527_story.html?utm_term=.4554eaffdb50) and in a series of articles in the New York Times (e.g. https://www.nytimes.com/2003/11/02/us/saving-seeds-subjects-farmers-to-suits-over-patent.html). A wide range of public interest stories, including the documentary Food, Inc., have at least implied that the introduction of intellectual property for plant varieties has hurt farmers and led to growth in profits for agrochemical and agricultural biotechnology companies.

12 See also Murray et al. (2016), which implies potentially large costs of intellectual property restrictions in biomedical research. Sampat and Williams (2019), however, find no evidence that patent protection reduces follow on research in an analysis of patents on human genes. The present study is also linked to a related literature that suggests that receiving patent protection is beneficial to firms and technology developers. For example, Gans et al. (2008) on technology licensing, or Gaule (2018) and Farre-Mensa et al. (2016) on the benefit to entrepreneurial firms and startups.
investigate the impact of patent protection (Moser, 2005, 2013, 2016).\textsuperscript{13}

This paper extends existing work in several ways. First, this study presents causal evidence of the impact of the introduction of intellectual property protection on research investment and technology development. Second, it shows that intellectual property protection had a discernible impact not only on technology but also on downstream productivity. Finally, it documents the impact of the introduction of intellectual property protection on the consumers of technology (i.e. farmers) and investigates directly whether the productivity benefits of more investment and innovation outweigh the potentially higher cost of patented technologies.

This paper also deepens our understanding of the impact of intellectual property for plant varieties in particular, which is at the core of several ongoing economic and policy debates. A handful of case studies have investigated the impact of historical changes in intellectual property protection in agriculture, focusing on individual crop case studies (Alston and Venner, 2002; Naseem et al., 2005; Moser and Rhode, 2011). Intellectual property protection for plant varieties in the U.S. and other countries has been proposed as an explanation of dramatic agricultural productivity growth during the second half of the 20th century, dubbed the "Green Revolution" (e.g. Evenson and Gollin, 2003). Since 1960, 74 countries have adopted intellectual property protection for plant varieties, and several countries are currently debating whether to introduce it; unsurprisingly, it has often been a politically contentious process. The introduction of patent protection in the US has also been blamed for declining farm profits, particularly for small farmers, as well as concentration of landholdings and agricultural research investment (Howard, 2015; Bonny, 2017). This paper, for the first time, estimates the impact of introducing patent protection for plant varieties on technology development and economic outcomes, including farm profits and the structure of production.

Finally, this paper builds on broad literature investigating the extent to which research investment is directed and re-directed in response to profit opportunities. Even in the agricultural context, there is a long history of studying how innovation responds to incentives and shapes agricultural productivity (e.g. Griliches, 1957; Hayami and Ruttan, 1971; Ruttan and Hayami, 1984; Olmstead and Rhode, 1993, 2008). I find that policy induced changes in profit opportunities had a large impact on the direction of new technology development; private research investment and novel variety development were narrowly targeted to the crops for which profit opportunities increased the most. Perhaps most related, Finkelstein (2004) finds that US policy designed to increase utilization of a set of preexisting vaccines led to a large increase in clinical trials for new vaccines. This study thus also builds the relatively small set of empirical studies that investigate the impact of changing profit incentives on the direction of technological change (e.g. Popp, 2002; Acemoglu and Linn, 2004; Hanlon, 2015).

The paper is organized as follows. The next section provides background information on the history of patent protection for plant varieties and a brief discussion of plant biology required

\textsuperscript{13}Also relevant is a recent and growing body of work on copyright protection. See Giorcelli and Moser (2019) on the impact of copyright protection on Italian operas, and also Biasi and Moser (2016) on the role of copyright protection in discouraging future innovation.
for the empirical analysis. Section 3 discusses the data. Section 4 presents the empirical strategy and results for the crop-level analysis while section 5 does the same for the county-level analysis. Section 6 discusses the results and concludes.

2 Background

2.1 Intellectual Property Protection for Plant Varieties

While most inventions have been considered patentable subject matter since the U.S.’s founding, this was not the case for inventions that are classified as living organisms. While agricultural inventions like new fertilizers, tractors, harvesters, etc. have been patentable since the 18th century, utility patent protection for new plant varieties—seeds, runners, etc.—was not available until 1985. While weaker forms of intellectual property protection for plant varieties were introduced by congress in 1930 and 1970, anecdotal evidence suggests that these policies were ultimately of limited import; innovators themselves claimed to put little weight on them and case studies provide little evidence that they affected innovation or production.\textsuperscript{14} The paramount limitation was that, prior to 1985, farmers were permitted to save seeds from one season to the next, effectively “re-making” the invention and preventing the inventor from profiting from its development and sale (\textit{Kloppenburg, 2005}, p. 265-6).\textsuperscript{15}

This changed in 1985 with the \textit{Ex Parte Hibberd} decision by the Patent and Trademark Office Board of Appeals. In 1980, the Supreme Court had ruled in \textit{Diamond v. Chakrabarty} (5-4 decision) that the distinction between life and non-life when it came to the patentability of inventions was not relevant. That case involved the patentability of a genetically modified bacterium that was useful for breaking down crude oil, and the Supreme Court wrote that “the patentee has produced a new bacterium with markedly different characteristics from any found in nature and one having the potential for significant utility. His discovery is not nature’s handiwork, but his own.” However, the USPTO was still not open to patent protection of plants or plant parts.\textsuperscript{16}

In 1985, a patent examiner rejected a patent application for a maize variety that the breeder argued was patentable subject matter following the \textit{Chakrabarty} decision. The developer appealed the decision, and the US Patent and Trademark Office (USPTO) Board of Appeals and Interfer-

\textsuperscript{14}Lesser (1987) notes that the 1970 protections from the Plant Variety Protection Act (PVPA) were considered by breeders to be far inferior to utility patent protection. Alston and Venner (2002), focusing on wheat, find no evidence that the PVPA affected wheat yields. Patenting following the 1930 Act that granted some protection to breeders of vegetatively-derived varieties (i.e. not seeds) was focused predominately on roses, and yet the Act did not increase innovation in rose varieties (see Moser and Rhode, 2011). Another indication of this is the fact that, while utility patents for plant varieties has been the subject of extensive litigation and owners of utility patents have taken major action to enforce their intellectual property, this was not the case for earlier forms of seed intellectual property; neither the 1930 nor the 1970 law was the subject of substantial infringement litigation (Kershen, 2003).

\textsuperscript{15}There are a range of other reasons that the introduction of utility patents was the form of intellectual property “that mattered.” Only after 1985 was the direct use of a protected variety in future research curtailed, as well as the ability of the USDA to curtail protection when it deemed important or necessary.

\textsuperscript{16}Indeed, the few applicants who sought protection for seeds or plant parts were soundly rejected (\textit{Kloppenburg, 2005}, p. 263)
ences reversed the rejection. Following the decision, the USPTO released a notice stating that “the Patent and Trademark Office is now examining applications including claims to plant life—e.g., plants per se, seeds, plant parts” (Hodgins, 1987, p. 88). The change in intellectual property regime was a shock, but was almost immediately taken advantage of by breeders and breeding companies (Lesser, 1987). Even by 1987 there were many patents granted as a result of the *Hibberd* decision, and these new patents were spread across multiple pre-existing patent classes (Hodgins, 1987).

### 2.2 Hybridization and *De Facto* Protection

It is common knowledge among farmers and agrochemical companies that hybrid plant varieties have *de facto* intellectual property protection (e.g. Butler and Marion, 1985; Fernandez-Cornejo, 2004; Fajardo-Vizcayno et al., 2014). In the words of Fernandez-Cornejo (2004), hybrid seeds “provided the private sector a natural method of protecting plant breeding investments” since saved hybrid seeds “produced substantially lower yields, encouraging farmers to repurchase seeds every year.”

The relationship between this feature of hybrids and intellectual property protection is explicit. Fernandez-Cornejo et al. (1999) note: “[A]ccording to the Patent Act of 1790, seeds were considered ‘products of nature’ and could not be patented. Hybrid seed technology, however, required farmers to repurchase seeds each year” (p. 19).

Gupta (1998) refers to this as “built-in” intellectual property protection that serves a very similar role to patent protection. He further argues, “In several self-pollinated crops like wheat, rice, barley, beans, etc., on the other hand, the commercially grown cultivars are actually ‘pure lines’ so that the yield does not decline and harvested seeds can be used for sowing the next crop” (p. 1320). Prior to the introduction of formal intellectual property, hybrid seed developers could reap the rewards of their innovation by making use of hybrids’ “built-in” patent protection. Developers of non-hybrid varieties, however, had little if any recourse.

Therefore, when formal patent protection was introduced, it predominately affected non-hybrid varieties and crops for which hybrid varieties were scarce or difficult to generate (Lesser, 1987). Agricultural firms and researchers are keenly aware of this distinction. Facing criticism for enforcing patent protection by suing farmers who saved its patented seeds under the new regime, Monsanto responded by asserting that farmers had not been saving hybrid seeds for decades and that patenting served a similar function for a different set of crops. That is, seed companies viewed hybrid varieties as effectively having intellectual property protection akin to patenting.

Why do hybrid varieties have *de facto* protection? When farmers use hybrid varieties, they very rarely save seeds to use the following year; the second generation (F2) seeds from hybrid

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17Importantly, this is still relevant for farming today. According to the University of Illinois Extension program, hybrid seeds are “often sterile or [do] not reproduce true to the parent plant.” Therefore, they warn: “never save the seed from hybrids.”

strains do not retain the beneficial characteristics of the first generation (F1) and are often of no use. Therefore, farmers are forced to return to the breeder every time they want a new seed, and cannot save, sell, or replicate the improved variety. Moreover, without access to the parent varieties used to generate the F1 hybrid, it is almost impossible for other breeders, seed marketing firms, or researchers to steal profits from the original developer. When farmers use non-hybrid varieties, on the other hand, they can save seeds for many seasons without sacrificing the beneficial characteristics of their original seeds and need not re-purchase the seed from the developer. Other developers can use non-hybrid varieties directly in the breeding process and build on their favorable characteristics.

The reason for this can be illustrated by a simple example. Suppose a breeder produces a hybrid variety by combining the male and female gametes of parent plants, Parent 1 and Parent 2. Further suppose that at a particular allele Parent 1 is homozygous dominant and Parent 2 is homozygous recessive. That is, Parent 1 has two copies of the dominant gene (AA) and Parent 2 has two copies of the recessive gene (aa). At that allele, the hybrid variety will be heterozygous (Aa) with probability 1. However, the offspring of the hybrid will be heterozygous at that allele with probability 0.5—with probability 0.25 it will be AA and with probability 0.25 it will be aa. The probability that offspring produced by the farmer match the improved variety at this allele is therefore 0.5.

In reality, the beneficial properties of a variety are not stored on a single allele; “hybrid vigor” results from the combination of many alleles and their interactions; indeed, the F2 hybrid can even have worse performance than either of the original parent varieties (e.g. Fajardo-Vizcayno et al., 2014). Even if there were only alleles A through Z, the probability that the farmer reproduces the improved variety with any given offspring would be: \((0.5)^{26} = 0.0000000149\). While quite stylized, this example illustrates that the probability that a farmer reproduces the desired characteristics of the hybrid variety are vanishingly small. If a farmer plants non-hybrid—or, “open pollinated”—varieties, those varieties can be reproduced exactly generation after generation and do not need to be re-purchased from the developer.

2.3 Hybrids and Flower Structure

A final question is what characteristics make breeders better able to generate hybrids from certain crops but not others. The key characteristic that matters during the sample period is the crop’s flower structure, and in particular, whether the crop has “perfect” or “imperfect” flowers (e.g. Wright, 1980; Butler and Marion, 1985; Fajardo-Vizcayno et al., 2014; Bradford, 2017). The distinction between perfect and imperfect flowers is displayed in the image in Figure 1. In words, perfect flowers have both the male and female parts of the plant in the center of the same flower; this is illustrated by the leftmost flower, in which the pistil (i.e. “female” reproductive organ) and stamen (i.e. “male” reproductive organ) are on the same part of the plant. Crops with imperfect flowers have the male and female reproductive material on different parts of the plant; this is illustrated by the remaining two flowers in Figure 1, both of which would be on the same plant but which
contain either only the male or only the female reproductive part.

When a crop has perfect flowers, it is often painstakingly difficult or impossible to generate new hybrids by combining genetic material from multiple plants (Whitford et al., 2013; Bradford, 2017).\textsuperscript{19} Separating and re-combining the male and female reproductive material (e.g. preventing self-pollination, separately isolating the genetic material, etc.) is often technologically infeasible or extremely costly in crops with perfect flowers. Hybridized wheat, for example—a major crop with perfect flowers—is very rare, and almost non-existent during the sample period despite being a hugely economically important plant. Other examples of crops with perfect flowers are barley, beans, carrots, and turnips.\textsuperscript{20} The opposite is true in the case of, for example, corn, as well as buckwheat, squashes, cucumber, and spinach.

Throughout the paper when I refer to a crop as “hybrid compatible,” this means that the crop has imperfect flowers, facilitating the hybridization process. Because vegetatively (i.e. asexually) reproducing crops can also be re-produced by the farmer, I also categorize all crops that can reproduce vegetatively in the treatment group, but show throughout that the results are robust to controlling for vegetative reproduction. The benefit of this measure compared to a measure that relied on actual rates of hybridization—aside from the fact that the actual share of hybrid varieties is not possible to measure for more than a small set of crops—is that actual hybrid development is endogenous to crop-specific research investment and demand. Crops’ flower structures, on the other hand, are fixed and do not change with human behavior.

\textsuperscript{19}See also Jones et al. (1947) for a discussion of flower structure and onion hybridization.

\textsuperscript{20}Indeed, the first hybrid variety for barley, despite being a globally important crop, did not occur until it was released, following years of research effort and investment, by Syngenta in 2003, which is after this paper’s sample period; even still, the penetration of hybrid varieties for barley remains limited. See the news release here: https://www.cabi.org/agbiotechnet/news/2886.
3 Data

3.1 Defining Treatment Status

In order to identify which crops were affected by the introduction of patent protection, I constructed a data set of the structure and reproductive process of all crops produced in the United States. The main independent variable is an indicator variable that equals one if a crop is not hybrid compatible. To measure this, for all crops grown in the United States I determined whether or not the plant has perfect flowers. This is used throughout the empirical analysis as a reduced form proxy for hybrid compatibility.\(^{21}\) In total, this information was compiled from 339 separate sources. This information is used to construct the key independent variables in the analysis.

In order to investigate whether “hybrid compatibility” is correlated with other crop-level characteristics that affect crop breeding and variety-development, I merge together my data set and the ECOCROP Database, which contains information about plant-specific growing conditions for over 2,500 species. The database, discussed at greater length in Moscona and Sastry (2020), was compiled from a sweeping set of agronomist and expert surveys conducted during the early 1990s and contains a range of plant characteristics, in addition to upper and lower “cut-off” values for a range of environmental characteristics (e.g. temperature, rainfall) beyond which crop productivity declines. This makes it possible to check whether treatment and control crops in the analysis are balanced on conditions that determine the location, structure, and demands of crop breeding.

3.2 Crop-Level Innovation

I combine multiple sources of data to compile a consistent data set of crop-specific measures of R&D and productivity that are possible to track over time. First, to estimate the number of new varieties developed in each year for each crop, I rely on the USDA Variety Name List. The Variety Name List, obtained through a Freedom of Information Act request, is a list of all released crop varieties known to the USDA. The USDA began collecting data on all released varieties during the 19th century in order to prevent fraud in the seed market; it is designed to be comprehensive and uses a broad range of sources in order to identify crop varieties. While the list is unlikely to cover every variety released in the US, it is intended to be as comprehensive as possible; according to the USDA, the List is compiled “from sources such as variety release notices, official journals, seed catalogs, and seed trade publications, as well as names cleared for use by seed companies.” Breeders have an incentive to report new varieties to the USDA for inclusion in the list because farmers frequently check the List to make sure that varieties they purchase were cleared. The List is structured as a series of PDF files with separate columns for the crop name (e.g. alfalfa, sorghum), variety name (e.g. 13R Supreme, Robinson H-400 B), and the year when the variety

\(^{21}\)I also compiled a range of additional information about each crop—including the way it reproduces (i.e. sexually vs. vegetatively) and whether or not the crop is a tuber—that might affect the style and process of innovation in varieties for that crop.
was released. I digitized the full list and use it to compute the number of varieties released for each crop in each year.

Second, to measure crop-specific R&D investment, I rely on data on project-level R&D spending since 1970 from the USDA Current Research Information System (CRIS). CRIS’s reporting and data complication protocol was established in 1966 by the Secretary of Agriculture in order to better document research funding in agriculture and how it changes over time; however, 1970 was the first year when the full information collection process took place and the data were compiled. Crucially, the CRIS data also report the commodity or commodities that are the focus of each research project. For each project focusing on plants or crops (as opposed to livestock, machinery, etc.), funding is broken down by crop; if the project covers multiple crops, then the share of funding devoted to each crop is also reported. I aggregate the project level data to compute a crop-level measure of R&D investment for each crop over time. When a single project covers multiple crops, I assign each crop its corresponding share of the project’s total funding. The CRIS compiles project-level data on R&D expenditure for all research projects that received any public support, including funding from the USDA and its research agencies, the National Institute of Food and Agriculture (NIFA), state agricultural experiment stations, land grant universities, and other state and local institutions. For all projects that received funding from any public source, the CRIS data also asks researchers to report private funding received for the project. Therefore, for the set of projects in the data set, it is possible to compare the impact of patent protection availability on private and public investment. However, an important caveat is that the data set does not contain all private R&D, only private R&D for projects that received any public funding; I am not aware of a more comprehensive measure of crop-level private R&D investment.

Third, to measure crop-level innovative output for all technologies other than agricultural varieties, I use patent data. Using the patent database PatSnap, I computed the number of patents in Cooperative Patent Classification (CPC) classes A01B, A01C, A01D, A01F, A01G, A01H, and A01N (i.e. CPC classes that relate to non-livestock agriculture) that were associated with each crop. To match patents to crops, I searched for the name of each crop in the Variety Name List in all patent titles, abstracts, and keywords lists. Thus, for each crop, CPC class, and year in the sample period, I estimate the number of patented technologies. Finally, measures of output, area harvested, and yield for each crop are from the Food and Agriculture Organization (FAO) and the USDA.

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22 While sometimes a the day and month are listed, in most cases during the sample period, only the year is included. While in later years, the List often reports the company or breeder name for each variety, unfortunately this did not began until after the period under investigation.

23 For a description, see here: https://cris.nifa.usda.gov/aboutus.html

24 For crops with multiple possible names, I searched for both and combined them. For example, sometimes corn is referred to as maize; sometimes sorghum is referred to as jowar; etc.
### 3.3 County-Level Data

I construct a county-level panel from the 1974-1997 rounds of the US Census of Agriculture. The Census of Agriculture contains a range of information about the U.S. agricultural sector and agricultural production.\(^{25}\) This includes information about land value, agricultural revenue, expenditures on a series of inputs, farm size, and the area under cultivation for a broad set of crops. It also reports the number of farms in each county within a series of size and revenue bins.\(^{26}\)

In order to construct the county-level treatment variable, I used data on the predicted maximum potential yield for all crops available from the Food and Agriculture Organization (FAO) Global Agro-Ecological Zones (GAEZ) database. These data are reported by the FAO as a (roughly) 9.25km \(\times\) 9.25km raster grid, with each grid cell containing the maximum attainable yield for a given crop in that grid cell based on ecological and topographical characteristics of the cell and characteristics of the crop in question.\(^{27}\) The FAO potential yield model is constructed using parameters derived from controlled experiments, and not from data on actual agricultural inputs and output (see Costinot et al., 2016, p. 18). Combining the FAO data with crop-specific producer prices from 1985, I determine which crop would maximize output at the grid-cell level. I then determine the share of grid-cells in each county on which this model would predict that one of the hybrid-incompatible crops should be cultivated. I use measure of the predicted share of county land devoted to treatment crops as the county-level treatment variable. I also compute an analogous measure using the actual composition of crop-cultivation in each county using the 1982 Census of Agriculture. Reassuringly, the actual measure and the GAEZ-derived measure are strongly correlated; I present a version of the county-level results in which the GAEZ-derived measure is used as an instrument for the actual county-level share of hybrid-incompatible crops.

### 4 Patenting and Innovation: Crop-Level Analysis

#### 4.1 Empirical Strategy

My empirical approach compares hybrid compatible to hybrid incompatible crops before and after the introduction of intellectual property protection in 1985 using a difference-in-differences design. The main estimating equation is:

\[
\text{Innovation}_{ct} = \alpha_c + \delta_t + \beta \cdot \text{Not Hybrid}_c \cdot \text{Post}^{1985} + X'\Gamma + \epsilon_{ct} \tag{1}\]

---


\(^{26}\)To my knowledge, farm-level data with information on the crop-composition of production do not exist for this period so I am restricted to estimating the impact of county-level exposure to new patent protection.

\(^{27}\)The FAO maximum potential yield data “...reflect yield potentials with regard to temperature, radiation and moisture regimes prevailing in the respective grid-cells. The model requires the following crop characteristics: Length of growth cycle (days from emergence to full maturity); length of yield formation period; maximum rate of photosynthesis at prevailing temperatures; leaf area index at maximum growth rate; harvest index; crop adaptability group; sensitivity of crop growth cycle length to heat provision; development stage specific crop water requirements, and coefficients of crop yield response to water stress” (FAO GAEZ)
For each outcome, the regression is estimated on a balanced panel of crops for the years 1975-1995. Throughout the analysis, \( c \) indexes crops and \( t \) indexes years. \( \alpha_c \) and \( \delta_t \) are crop and year fixed effects respectively. \( I_{\text{Post 1985}} \) is an indicator that equals one in all years after 1985 and NotHybrid \( c \) is crop-specific indicator that equals one if a crop is not hybrid compatible (i.e. has perfect flowers). These are the “treatment” crops in the analysis. The coefficient of interest is \( \beta \), the impact of the introduction of patent protection crop-specific innovation in treatment relative to control crops. Standard errors are double clustered by crop and year.

In order to ensure that treatment and control crops were on similar trends prior to the introduction of patent protection, I also present estimates of the following equation:

\[
\text{Innovation}_{ct} = \alpha_c + \delta_t + \sum_{\tau \in T_{\text{pre}}} \beta_{\tau} \cdot \text{Not Hybrid}_c \cdot \delta_{\tau} + \sum_{\tau \in T_{\text{post}}} \beta_{\tau} \cdot \text{Not Hybrid}_c \cdot \delta_{\tau} + X'\Gamma + \epsilon_{ct} \tag{2}
\]

Here, the coefficients of interest are the \( \beta_{\tau} \). The identification assumption is that prior to the introduction of patent protection, hybrid compatible and incompatible crops are on similar trends; that is, when \( \tau \in T_{\text{pre}} \), \( \beta_{\tau} \) should not be statistically distinguishable from zero. When \( \tau \in T_{\text{post}} \), the \( \beta_{\tau} \) identify the effect of patent protection crop-specific innovation.

### 4.1.1 Balance: Characteristics that Affect Breeding

The empirical analysis relies on the assumption that crops with imperfect flowers are an appropriate control group for crops with perfect flowers. While throughout the results section below, I will document that there are no “pre-trends”—that is, that for each outcome variable both sets of crops are on similar trends prior to 1985—in order to build confidence, I first investigate differences between treatment and control crops across a range of crop-level characteristics that affect variety development. To collect these characteristics, I merged my crop-level data set with the ECOCROP Database, described above, which reports information about a broad set of crop characteristics and growing constraints.

Table 1 reports estimates of the following specification:

\[
x_i^c = \xi^i \cdot \text{Not Hybrid}_c + \epsilon_i^c
\]

where \( x_i^c \) are crop-level characteristics listed in columns 1, 4, and 7; the sample mean of each characteristic is displayed in columns 2, 5, and 8. These characteristics include an indicator if a plant has a single stem, an indicator if a plant is perennial, minimum and maximum crop cycle length (days of the year), optimal soil depth and salinity, as well as a range of “cut-off” values for temperature, rainfall, and soil pH at which crop productivity changes. For each crop and environmental characteristic, ECOCROP reports two ranges: (i) a range within which crop performance is “optimal” (i.e. an inner range) and (ii) a range within which crop cultivation is possible (i.e. an outer range). Thus, for each crop and environmental characteristic, ECOCROP

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28The sample included is all crops in the ECOCROP database which also appear in the Varieties Names List analysis. This changes slightly across variables in Table 1 due to missing data in ECOCROP.
Table 1: Balance Across Characteristics that Affect Breeding

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>(1) Sample Mean</th>
<th>(2) Not Hybrid vs. Hybrid</th>
<th>(3) Variable Name</th>
<th>(4) Sample Mean</th>
<th>(5) Not Hybrid vs. Hybrid</th>
<th>(6) Variable Name</th>
<th>(7) Sample Mean</th>
<th>(8) Not Hybrid vs. Hybrid</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Stem Plant (0/1)</td>
<td>0.315</td>
<td>-0.0190 (0.282)</td>
<td>Perennial Plant (0/1)</td>
<td>0.350</td>
<td>0.0685 (0.179)</td>
<td>Min. Crop Cycle (Days)</td>
<td>83.29</td>
<td>8.092 (16.59)</td>
<td></td>
</tr>
<tr>
<td>Max. Crop Cycle (Days)</td>
<td>182.9</td>
<td>-22.12 (42.03)</td>
<td>Opt. Soil Depth (cm)</td>
<td>2.039</td>
<td>0.0417 (0.296)</td>
<td>Opt. Soil Salinity (dS/m)</td>
<td>1.020</td>
<td>0.0213 (0.0150)</td>
<td></td>
</tr>
<tr>
<td>Temp. Opt. Range, Max. (°C)</td>
<td>26.31</td>
<td>-0.893 (1.951)</td>
<td>Temp. Opt. Range, Min.</td>
<td>15.95</td>
<td>-0.205 (1.717)</td>
<td>Temp. Feasible Range, Max.</td>
<td>33.73</td>
<td>-2.591 (2.542)</td>
<td></td>
</tr>
<tr>
<td>Temp. Feasible Range, Min.</td>
<td>6.408</td>
<td>-3.329 (1.042)</td>
<td>Rain Opt. Range, Max. (mm)</td>
<td>1.176</td>
<td>-10.19 (123.9)</td>
<td>Rain Opt. Range, Min.</td>
<td>668.4</td>
<td>-110.5 (81.72)</td>
<td></td>
</tr>
<tr>
<td>Rain Feasible Range, Max.</td>
<td>2.297</td>
<td>58.50 (414.9)</td>
<td>pH Opt. Range, Min.</td>
<td>397.1</td>
<td>50.52* (29.24)</td>
<td>pH Opt. Range, Max. (0-14)</td>
<td>7.066</td>
<td>-0.0518 (0.150)</td>
<td></td>
</tr>
<tr>
<td>pH Opt. Range, Min.</td>
<td>5.868</td>
<td>0.242 (0.176)</td>
<td>pH Feasible Range, Max.</td>
<td>8.146</td>
<td>-0.0430 (0.180)</td>
<td>pH Feasible Range, Min.</td>
<td>4.936</td>
<td>0.00789 (0.173)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a crop. Columns 1, 4, and 7 list a series of crop-level characteristics, and columns 2, 5, and 8 report the sample mean of each corresponding characteristic. Columns 3, 6, and 9 report estimates of the relationship between each characteristic and the "not hybrid compatible" indicator variable. Each coefficient was estimated from a separate regression. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.2 Results

4.2.1 New Crop Varieties

Baseline Estimates. This section examines the impact of the introduction of patent protection on the development and release of crop varieties; this is the key outcome variable because varieties were exactly the technology for which patent protection became available in 1985. Estimates of Equation (1) are reported in Table 2. Since the number of variety releases is a count variable, and since there zeroes on the left hand side of the regression, I report a Poisson pseudo-maximum likelihood estimate (columns 1-2) in addition to OLS specifications computing the inverse hyperbolic sine of the dependent variable (columns 3-4). In columns 2 and 4, I control flexibly for vege-

29Whenever Poisson estimates are reported, I use pseudo-maximum likelihood estimators in order to ensure appropriate standard error coverage; see Wooldridge (1999).
Table 2: Patent Protection and Novel Plant Varieties

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Specification:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New Varieties (count)</td>
<td>Poisson</td>
<td>OLS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Hybrid Compatible, $\times 1_{t}^{Post1985}$</td>
<td>0.748***</td>
<td>0.737***</td>
<td>0.109***</td>
<td>0.164***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.234)</td>
<td>(0.256)</td>
<td>(0.0334)</td>
<td>(0.0413)</td>
<td></td>
</tr>
<tr>
<td>Crop Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Reproduction Type Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,260</td>
<td>2,260</td>
<td>2,280</td>
<td>2,280</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.815</td>
<td>0.817</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** The unit of observation is a crop-year. All specifications include crop and year fixed effects. In columns 1-2, the outcome variable is the number of new varieties and in columns 3-4, it is the inverse hyperbolic sine transformation of the number of new varieties. The regression model is noted at the top of each column. Reproduction type controls include a full set of year indicators interacted with an indicator if a crop reproduces vegetatively. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

The main identifying assumption is that, absent the change in patent law, innovation in hybrid-compatible and hybrid-incompatible crops would have been on similar trends. Figure 2 displays coefficient estimates from the event study analysis (Equation 2); reassuringly, I find no evidence of pre-trends. Innovation in the treatment and control group are on very similar trends prior to 1985. They diverge markedly after 1985; the first significant difference between treatment and control crops emerges in 1986 and the difference grows and persists in the years that follow. Thus, the baseline results document that the availability of patent protection drastically increased technology development and release. When new varieties for specific crops became protectable intellectual property, the development of new varieties for those crops increased.

**Sensitivity and Robustness.** Table 6 investigates the robustness of the baseline results; in order to incorporate an increasing number of control covariates, all columns report OLS estimates. For reference, column 1 reproduces column 4 from Table 2. While Figure 2 does not indicate that there were pre-existing trend differences in variety development between treatment and control crops, it is nevertheless possible that pre-existing trends are affecting the result despite not being statistically detectable in the event study analysis (see Freyaldenhoven et al., 2019). To rule out this
possibility, I control for pre-period innovation explicitly. I document that the results are similar and, if anything, more precise after controlling flexibly for trends in crop-level innovation prior to 1985 (column 2). I also reproduce the baseline results after controlling separately for year indicators interacted with variety release in 1975, 1980, and 1984; the inclusion of these additional 57 controls flexibly captures trends in pre-period variety development. These results, following the same structure as Table 2, are reported in Table A1 and are very similar to the baseline results albeit less precise in the case of the OLS estimates.

While the results in Table 1 showed no systematic evidence of physiological differences between treatment and control crops, there was weak evidence that treatment crop productivity is somewhat more sensitive to low levels of rainfall (column 6, row 5). In order to document this feature of the data is not affecting the results, in column 6 of Table 6 I control for all four crop-specific rainfall sensitivity measures from the ECOCROP database interacted with a full set of year indicators. If anything, the coefficient of interest becomes larger in magnitude.

A potential concern is that the baseline result is driven by a small number of influential observations and not a persistent shift in innovative activity. To investigate this possibility, I re-estimate the baseline OLS specification after excluding the most influential observations as measured by their Cook’s Distance. These estimates, both with and without the full set of control covariates, are presented in columns 4-5 and document that the results are similar and, if anything, larger in magnitude after omitting the most influential observations.

Next, I investigate whether the results are sensitive to extending the post-treatment period. In columns 6-7 of Table 6, I reproduce the baseline results after extending the post-treatment period to 2000, both without (column 6) and with (column 7) the full set of controls. The results are again similar and, if anything, larger in magnitude, consistent with the persistent and accumulating impact of the availability of patents on innovation.

Finally, I investigate the robustness of the results to alternative standard error clusters. In the baseline results, standard errors are double-clustered by crop and year. The definition of a “crop” in this context was taken from the Varieties Names List; however, it could be possible that regression errors are correlated across crops that are biologically similar. For example, broccoli, cauliflower, and turnips are in the data as separate crops; however, all three crops are genetically similar and indeed part of the Brassica genus. To address this issue, I rely on the taxonomic classification of each crop in the ECOCROP database and I reproduce the baseline estimates double-clustering standard errors by genus and year (results are very similar if standard errors are just clustered by genus). In the example above, this would mean broccoli, cauliflower, and turnips would all be part of the same cluster. The precision of the estimates, reported in Table A2, are very similar using this alternative clustering strategy.

**Heterogeneity: Variety Purchase Frequency.** Patent protection provided *ex ante* incentives to invest in research because it allowed innovators to sell new non-hybrid varieties to farmers at a

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30Following Bollen and Jackman (1985), I drop observations with Cook’s Distance greater than $4/n$ where $n$ is the number of observations in the regression sample.
price that exceeded marginal cost. A key difference brought about by the change in patent law was that farmers could no longer save non-hybrid varieties and as a result, farmers were forced to purchase seeds from the developer rather than “re-produce” them free of cost. This made the potential profits from developing a new variety much higher. However, other features of patent protection—for example, the disclosure requirement and the fact that patent holders had to provide information about the details of their invention—might have also contributed to the growth in variety development after 1985.

I investigate the direct importance of variety sale profit opportunities by testing for heterogeneity based on crop lifespan. Certain crops in the sample are perennial, meaning they live for more than two years; if the ability to sell varieties to farmers each planting season were driving the increase in variety development, we would expect the effect to be muted for perennial crops since the opportunities to re-sell a variety to a given farmer are more limited. Table A3 examines heterogeneity in the baseline estimates based on whether a crop is perennial or not. Using both Poisson and OLS regression models, I estimate the impact of patent protection separately for non-perennial and perennial crops (columns 1-2, 5-4), and also estimate the heterogeneous impact of the introduction of patent protection from a single regression model (columns 3-4, 7-8). Across specifications, I find that the effect of the introduction of patent protection for perennial crops is smaller in magnitude and not distinguishable from zero; the effect is driven entirely by crops for which varieties must be used more frequently by farmers and hence for which profit opportunities
Table 3: Patent Protection and Novel Plant Varieties: Robustness

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline Sample</td>
<td>Excluding Influential Observations</td>
<td>Post-Treatment Period Extended to 2000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent Variable is New Varieties (asinh)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Hybrid Compatible \times g^{\text{Post 1985}}</td>
<td>0.164***</td>
<td>0.191***</td>
<td>0.219**</td>
<td>0.175**</td>
<td>0.243**</td>
<td>0.240**</td>
<td>0.260**</td>
</tr>
<tr>
<td></td>
<td>(0.0413)</td>
<td>(0.0656)</td>
<td>(0.102)</td>
<td>(0.0633)</td>
<td>(0.109)</td>
<td>(0.103)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Crop Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Reproduction Type Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-Period Innovation Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Rainfall Sensitivity Controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,280</td>
<td>2,280</td>
<td>2,060</td>
<td>2,126</td>
<td>1,921</td>
<td>2,964</td>
<td>2,964</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.817</td>
<td>0.826</td>
<td>0.835</td>
<td>0.908</td>
<td>0.919</td>
<td>0.787</td>
<td>0.805</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects and the outcome variable is the inverse hyperbolic sine transformation of the number of new variety releases. Reproduction type controls include a full set of indicators interacted with an indicator if a crop reproduces vegetatively. Pre-period innovation controls include the log of the number of new varieties released for each crop prior to 1985 interacted with a full set of year indicators. Rainfall sensitivity controls include all four rainfall exposure crop-specific cut-off measures from the ECOCROP database interacted with a full set of year indicators. In columns 4-5, I exclude observations with Cook’s Distance greater than 4/n where n is the number of observations in the regression. In columns 1-5, the post-treatment period is 1985-1995 while in columns 6-7 it is 1985-2000. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

from patented varieties were potentially largest for the breeder. This is consistent with the ability to profit from the development of new varieties by selling them to farmers before each use as an important driving mechanism.

Discussion of Magnitudes. The estimated magnitudes are quantitatively significant. In the specification with all included controls, the coefficient estimates imply that, compared to the pre-period, hybrid-incompatible crops experienced a 0.139 standard deviation relative increase in variety development after the introduction of patent protection. Estimates of the longer run effect (columns 6-7 of Table 6) are larger and imply that hybrid incompatible crops experienced a 0.166 standard deviation relative increase in variety development. While these estimates are large, it is also worth noting that in many models of technology development, including standard endogenous growth models, there would be zero incentives to invest in research and development were it not for the possibility of patent protection.

It is also worth discussing the fact that, in order to make progress on econometric identification, this study relied on differences-in-differences comparisons across crop groups; as a result, as is the case in virtually all difference-in-differences estimates, is that the treatment effect is the differential change in variety development between the treatment and control groups. It is thus not possible to causally estimate the direct effect of the introduction of patenting on the treatment
Table 4: Patent Protection and Patterns of R&D Investment

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) Public Research Investment</th>
<th>(2) Private Research Investment</th>
<th>(3) Share Private Research Investment</th>
<th>(4) Total Scientist-Years Funded, Public + Private</th>
<th>(5) Total Investment per Scientist-Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not Hybrid Compatible, $1_t \times \text{Post 1985}$</td>
<td>-0.294 (0.771)</td>
<td>0.479** (0.207)</td>
<td>0.0224** (0.00832)</td>
<td>-0.160 (0.267)</td>
<td>0.160** (0.0727)</td>
</tr>
<tr>
<td>Crop Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,220</td>
<td>1,220</td>
<td>1,151</td>
<td>1,220</td>
<td>1,148</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.842</td>
<td>0.927</td>
<td>0.576</td>
<td>0.932</td>
<td>0.877</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is listed at the top of each column; in columns 1-2 and 4-5, the inverse hyperbolic sine transformation of the dependent variable is used. All columns report OLS estimates. Standard errors, double-clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

and control groups separately. For example, the estimates could be driven by a shift in variety development across hybrid compatible and incompatible crops rather than an absolute increase in variety development in the treatment group.

A range of evidence, however, lends support to the interpretation that the results are driven by an absolute increase in treated technologies and not a commensurate decline in untreated technologies. First, I find no evidence of an absolute decline in variety development or research investment (below) in the control group. Second, discussed in greater detail below, I do not find evidence of a relative decline in investment or technology development for treatment crops in technologies other than varieties, suggesting that the results are not driven by shifting research investment across technology types. Finally, there is no reason to think that breeders and agricultural biotechnology firms—particularly large firms, which made up a growing share of total research investment after 1985—were financially constrained in terms of their ability to expand total research investment. With all this said, this study cannot causally identify the counterfactual trajectory of technology development for the control group and estimated magnitudes should be interpreted with this in mind.

4.2.2 Research Investment

While the previous section documented that varietal innovation was directed toward crops for which intellectual property protection for varieties became available, examining changes in crop-specific research investment and its sources makes it possible to probe the mechanisms and characteristics of the innovative shift. First, I investigate whether the re-direction of innovative activity was driven by the public sector, the private sector, or both. Intuitively, the private sector may be
more motivated by profit and hence more responsive to incentives provided by patent protection; however, there is some evidence suggesting that the public sector may respond as well, albeit less dramatically (e.g. Budish et al., 2015). Table 4 reports estimates of the impact of patent availability on research investment from various sources. I find a negative but statistically insignificant relationship between the availability of patent protection and public investment (column 1), which is further attenuated and very close to zero after controlling for trends in pre-period public investment (Table A4, columns 1-2).

At the same time, I estimate a positive and significant relationship between the availability of patent protection and private investment (column 2). Consistent with this, the share of total investment from the private sector also significantly increases for crops exposed to the change in patent regime (column 3). The positive effect on innovative output documented in the previous sections thus seems to have been driven by an increase in private sector investment.

Figure 3 investigates the impact of patent availability on research investment over time. I find no evidence of a difference in trend in public or private research investment between treatment and control crops prior to 1985. After 1985, the parallel trends continue for public sector investment (Figure 3a); however, the trends in private research investment sharply diverge following the change in patent law (Figure 3b). The baseline results are also robust to controlling directly and flexibly for the pre-period level and trend in the relevant dependent variable (see Table A4, columns 2, 4, and 6); these findings suggest that the baseline estimates are not driven by pre-existing trends in investment.

One question is why the effect on private investment appears to return to its pre-treatment level by 1995; I hypothesize that this pattern is due to the main limitation of the research investment data, which is that it only includes private research investment in research projects that

Figure 3: **Research Investment.** Coefficient estimates from Equation (2). The dependent variables are the inverse hyperbolic sine of private research investment (a) or public research investment (b) in the crop-year pair. Standard errors are double-clustered by crop and year; 95% confidence intervals are reported.
received public funding as well. Thus, it is possible that a substantial share of research projects in treatment crops shifted over time to entirely private funding and hence exited the data. Since the impact on new varieties persists after 1995, it seems unlikely that private research investment actually returned to pre-treatment levels.\footnote{To my knowledge it is not possible to track private research investment by crop outside of the CRIS data, so this limitation is not possible to surmount.} This logic implies that the estimated impact on private research investment from Table 4 is likely an underestimate, especially in later years, and should be considered a lower bound.

An additional piece of evidence lends support to the hypothesis that private investment increased permanently in response to the availability of patent protection. While I am unaware of data on crop-level private sector research investment over time outside of the CRIS data, I compiled data on total private sector research investment in both (i) breeding activity and in (ii) agricultural chemicals from Klotz et al. (1995) and Fernandez-Cornejo (2004). Total private sector investment over time in both breeding and chemicals, relative to investment in 1984, is displayed in Figure 4. While private sector investment in breeding and chemicals are on similar trends prior to 1985, they diverge in 1986 and investment in breeding accelerates. Moreover, unlike Figure 3 and consistent with a long-run shift in private sector investment, the relative increase in private sector breeding research is persistent in Figure 4. While this result is admittedly suggestive, it is consistent with a long-run increase in private sector breeding research following the introduction of variety patents.

Finally, the availability of patent protection seems to have concentrated research investment in a smaller set of researchers. Columns 5-6 of Table 4 document that while patent protection has no
effect on the total number of crop-specific scientist-years, it has a positive and significant impact on investment per scientist-year. Unfortunately, in the CRIS data it is not possible to distinguish between scientist-years funded by public versus private sources. However, this result suggests that the crop-level changes in research investment are driven by greater investment per scientist and not by shifting of scientist labor across crops.

4.2.3 Spillover Effects: Crop Technologies Other Than Varieties

The availability of patent protection for plant varieties might have had substantial spillover effects to other crop-specific technologies other than varieties. There are major complementarities between different agricultural inputs, and new seed technologies might give rise to the development of complementary non-variety inputs. A famous example is the development of the tomato harvester by two scientists—engineer Coby Lorenzen and crop breeder Gordie Hanna—at the University of California in 1959. It was widely viewed that tomato production could be made more productive with more efficient harvesting mechanisms; however, existing tomato varieties would not have been tough enough to survive being handled by most modern harvesters. Thus, the development and use of mechanical harvesting technology required the development and use of a novel tomato variety that was sufficiently hardy and would not be destroyed in the harvester. Varietal innovation facilitated innovation in harvester technology.32

Spillover effects, however, need not be positive. While it is intuitive there maybe positive spillover effects from variety innovation to harvester development, the same is not necessarily true for agricultural chemicals and biocides. Robinson and Cowling (1996), for example, explain how modern crop breeding has and can continue to reduce pesticide dependence (see also e.g. Leppik, 1970; Ratnadass et al., 2012); thus, we might expect a limited or even negative impact of additional variety innovation on improvements in agricultural chemicals.33 Is the increase in variety development driven in part by a shift in innovative resources away from biocides and toward varieties? Understanding the sign and magnitude of these spillovers is important for understanding the aggregate impact of intellectual property protection on innovation.

Unlike crop varieties, other agricultural technologies were patentable through the sample period. Therefore, I use patent grant data to measure the impact of the extension of patents for varieties on crop-specific technologies other than varieties. I use the CPC class information to determine the “type” of technology. Table 5 reports estimates of Equation (1) in which the outcome variables are crop-specific patent grants in a series of mutually exclusive technology classes; all columns report Poisson pseudo maximum likelihood estimates.34 Column 1 suggests that there

---

32 Another example of this phenomenon is the widespread increase in development and adoption of corn harvesting technologies following the development of hybrid corn. The genetic uniformity of hybrid varieties, in addition to physiological characteristics of the plant stalk and structure, made it possible to develop mechanical harvesters that drastically increased productivity; see Kloppenburg (2005, p. 117) for a discussion.

33 Indeed, Monsanto itself was founded as a chemical company and shifted research investment toward agricultural biotechnology and variety development during the 1980s and 1990s.

34 The sample in each specification was determined by searching the patent data for patents in each CPC class related to all crops in the Variety Name List. Thus, in some cases the sample size is slightly reduced when there was not a patent
were positive and significant spillover effects to harvester technology development, consistent with the intuition provided by the tomato harvester anecdote. Innovation in crop-specific harvester and mower technology increased disproportionately for hybrid-incompatible crops following the change in patent regime.

Columns 2-3 tell a similar story for planting technologies. In column 2, the outcome variable is patent grants related to planting, sowing, and fertilizing, while in column 3 it is patents related to soil working machinery. In both cases the coefficient estimate is positive and similar in magnitude; in column 3, it is statistically significant. This suggests there were also complementarities between novel varieties and planting technology. I find no evidence of spillover effects on crop-specific biocides; this result is presented in column 4. While the point estimate is negative, the coefficient estimate is small and statistically insignificant. The increase in variety development was not met with an observable and corresponding decline in development of chemical technologies.

All outcome variables thus far were pre-harvest or harvest technologies. Using the patent data it is also possible to measure crop-specific post-harvest technologies (these correspond to CPC class A01F). I estimate a negative but small and statistically insignificant relationship between variety patent availability and post-harvest technology development. While this is not a true placebo test, the null result in this column suggests that the positive effects in columns 1-3 were not driven by, for example, an overall increase in crop-level demand or innovative effort, which would have likely been accompanied with a corresponding increase in post-harvest innovation.

Event study estimates (Equation 2) for the statistically significant outcome variables in Table 5 during the sample period within the given CPC class explicitly linked to each crop in the Variety Name List.
are presented in Figure A1. It does not appear that patenting of the relevant technologies for treatment and control crops were on different trends prior to 1985. However, patenting activity in both harvesting and mowing as well as soil working technologies differ in many years after 1985, consistent with a causal effect of the introduction of variety patents on innovation in complementary technologies.

### 4.2.4 Productivity

Did the innovative output that resulted from the change in patent law have a discernible impact on crop productivity? As a first strategy to answer this question, I estimate the crop-level relationship between exposure to the patent law and national agricultural yields. If the availability of patent protection increased downstream agricultural productivity, we would expect the yield—output per area—of more exposed crops to increase. In Table 6, I report estimates of the relationship between the availability of patents and national crop yield, measured as total national output divided by the land area devoted to the crop. I find a positive and significant relationship between the availability of patent protection and crop-specific productivity. This relationship is similar after controlling flexibly for the reproduction type of each crop (column 2). The estimated effect is also similar after controlling flexibly for crop-specific pre-period yields (column 3) or, in the spirit of Freyaldenhoven et al. (2019), for the crop-specific pre-period yield trend (column 4). Finally, the estimate is qualitatively very similar if yields are measured in levels rather than logs (column 5).
Figure A2 investigates the relationship between patent protection and crop yields over time, using the control set from the specifications in columns 4 and 5. In Figure A2a, the dependent variable is log of output per area and in Figure A2b it is output per area. Reassuringly, and as in the previous set of results, I find no evidence of pre-existing yield trends. The trends diverge only after the change in patent regime and in the first year that variety development was significantly different between treatment and control crops (see Figure 2). Finally, columns 5-6 of Table 6 investigate the impact on output and area harvested separately. I find that patent protection had a positive but small impact on area harvested and a large (albeit imprecise) impact on crop-level output.

Thus, these results document that the introduction of patent protection affected not only crop-level innovative output but also measurable components of crop productivity. The remainder of the paper is devoted to investigating these “downstream consequences” of patent protection in greater depth.

5 Downstream Effects: County-Level Analysis

To this point, the results have documented that following the introduction of patent protection for plant varieties, technology development increased substantially for hybrid-incompatible (i.e. treatment) compared to hybrid-compatible (i.e. control) crops. This translated into a discernible impact on crop yields. However, there are at least three reasons why crop yields do not fully capture the impact of patent protection on production and on the “consumers” of patented technologies (i.e. farmers). First, the introduction of patent protection might have increased the cost of varieties, thereby muting or reversing the impact of higher productivity on farm profits. Second, input and land use adjustments, as well as general equilibrium price effects, could amplify or dampen the impact of new technology on downstream productivity. Finally, new varieties could have increased the value of output without affecting physical productivity by, for example, changing the taste, texture, or other crop characteristics.

To fully capture the impact of patent protection on agricultural production, I turn to an analysis in which the units of observation are fixed geographic units: US counties. I then measure the extent to which each county was “exposed” to the introduction of patent protection by estimating the share of its crop composition that consisted of hybrid-incompatible (i.e. treatment) crops, and estimate the impact of county-level “exposure” on agricultural land values and profits directly.

5.1 Empirical Strategy

I assign each county a treatment value based on the share of county land on which, in 1985, it was optimal to cultivate crops that are not hybrid compatible (that is, crops that form the treatment group in the crop-level analysis). To estimate this share, I use FAO GAEZ models of crop-specific maximum potential yield, along with 1985 producer prices from the USDA. For each grid cell g in
the GAEZ data, I determine the optimal crop \( c(g) \) as

\[
c(g) = \arg\max_c \{ A_{cg} \cdot \text{Price}_{c}^{1985} \}
\]

where \( A_{cg} \) is the maximum potential yield of crop \( c \) in cell \( g \) and \( \text{Price}_{c}^{1985} \) is the producer price of crop \( c \) in 1985 according to the USDA.\(^{35}\)

For each county \( i \), I compute the share of county land on which hybrid incompatible crops are predicted to grow as:

\[
\text{Share Not Hybrid}_i = \frac{\sum_{g \in i} \mathbb{I}^{c(g) \in \text{Not Hybrid}}}{\sum_{g \in i} \mathbb{I}^{c(g) \in \text{Not Hybrid}}} + \frac{\sum_{g \in i} \mathbb{I}^{c(g) \in \text{Hybrid}}}{\sum_{g \in i} \mathbb{I}^{c(g) \in \text{Hybrid}}}
\]

where \( \mathbb{I}^{c(g) \in \text{Not Hybrid}} \) is a grid-cell-level indicator that equals one if \( c(g) \) is not hybrid compatible. The GAEZ-derived predicted share is strongly correlated with the actual share of hybrid-incompatible crops planted in each county in 1982, displayed in the map in Figure 5. The map is intuitive; for example, the white-shaded region in the upper Midwest and Plains region is the “corn belt” and corn is a large, hybrid-compatible crop in the data. The correlation between the actual share of land devoted to hybrid incompatible crops and the GAEZ-derived prediction is documented in Figure 6. However, the GAEZ-derived measure is unaffected by potentially endogenous production choices that could be correlated with trends in county-level characteristics. Thus, it is a geographically and ecologically fixed measure of the county-level exposure to the

\(^{35}\)It is possible and indeed likely that different farmers faced different prices for their output; however, I abstract from this possibility since I am unaware of data on producer prices by detailed geography or farm type.
change in patent law.

I estimate the county-level impact of exposure to the introduction of intellectual property protection using the estimating equation:

$$y_{it} = \alpha_i + \delta_{st} + \phi \cdot \text{Share Not Hybrid}_i \cdot \mathbb{I}^{Post1985} + X'\Gamma + \epsilon_{it}$$ (3)

where $i$ indexes counties and $t$ indexes time. $\alpha_i$ and $\delta_{st}$ denote county and state-by-year year fixed effects respectively, and the coefficient of interest is $\phi$. $\phi$ captures the impact of the introduction of patent protection in 1985 on outcomes $y_{it}$. In the baseline specification, standard errors are double clustered by county and state-census-round pair. In order to make sure that more- and less-exposed counties are on similar trends prior to the introduction of intellectual property protection, I also report estimates from a second regression equation:

$$y_{it} = \alpha_i + \delta_{t} + \sum_{\tau \in T^{pre}} \phi_{\tau} \cdot \text{Share Not Hybrid}_i \cdot \delta_{\tau} + \sum_{\tau \in T^{post}} \phi_{\tau} \cdot \text{Share Not Hybrid}_i \cdot \delta_{\tau} + X'\Gamma + \epsilon_{it}$$ (4)

Analogous to Equation (2), the coefficients of interest are the $\phi_{\tau}$. When $\tau \in T^{pre}$, $\phi_{\tau}$ should not be statistically distinguishable from zero. When $\tau \in T^{post}$, the $\phi_{\tau}$ identify the county-level effect of the introduction of patent protection over time.

Figure 6: GAEZ-Derived Prediction vs. Actual Share Hybrid Incompatible Cropland. The unit of observation is a county. The graph displays a partial correlation plot between county-level GAEZ-derived prediction of the hybrid incompatible share and the hybrid incompatible share computed from the 1982 US Census of Agriculture. State fixed effects are included on the right hand side. The coefficient as well as the standard error and t-statistic are reported at the bottom of the graph.
Table 7: Value of Agricultural Land

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exposure, x 1_{Post 1985}</td>
<td>0.166***</td>
<td>0.136***</td>
<td>0.0740***</td>
<td>0.0921**</td>
</tr>
<tr>
<td></td>
<td>(0.0325)</td>
<td>(0.0273)</td>
<td>(0.0281)</td>
<td>(0.0363)</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Census Round Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Additional Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Census Round x State Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>18,192</td>
<td>18,115</td>
<td>18,115</td>
<td>9,102</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.872</td>
<td>0.898</td>
<td>0.922</td>
<td>0.934</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a county-year. All specifications include county and year fixed effects. The additional controls include pre-period log of farmland area interacted with a full set of year fixed effects and pre-period log of total farm revenue interacted with a full set of year fixed effects. Standard errors, double clustered by state-year and county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

5.2 Results

5.2.1 Land Values

I first investigate the impact of exposure to the availability of patent protection on county-level agricultural land values. The value of land captures the net present value of agricultural profits and hence, is a useful measure of the impact of patenting on farm wealth. This strategy follows a range of prior work that uses agricultural land values as the preferred measure of the impact of policy changes or shocks on farm wealth (e.g. Mendelsohn et al., 1994; Hornbeck, 2012; Donaldson and Hornbeck, 2016).36 Estimates of Equation (3) are reported in Table 7, in which (log of) the value of land and buildings per acre is the outcome variable.

In column 1, only county and census round fixed effects are included on the right hand side, along with the independent variable of interest. The coefficient of interest is positive and significantly different from zero, suggesting that county-level exposure to the introduction of variety patenting increased agricultural land values. The introduction of patent protection indeed increased the net present value of farm profits; any general equilibrium effects, including the potentially lower prices received for crops whose cultivation was made more productive by new technology, were at least insufficient to fully erode the positive effect on productivity and profits.

The remaining columns explore the robustness of the result. In column 2, I control flexibly

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36Other work using a related framework focuses instead on farm profits (e.g. Deschénes and Greenstone, 2007). While there are issues with this approach (see Fisher et al., 2012), I also explore the impact on profits in the next section.
Figure 7: County-Level Agricultural Land Value Estimates Over Time. Coefficient estimates from Equation (2). The dependent variable is the log of agricultural land value. In 7b, year fixed effects interacted with log of agricultural land value in 1974 and 1982 are included as additional controls. Standard errors are clustered by county state-year pair; 95% confidence intervals are displayed.

for counties’ pre-period involvement in agricultural production by including pre-treatment land devoted to agriculture and total agricultural revenue, interacted with a full set of census round indicators, on the right hand side of the regression; the results are similar. In column 3, I also include state-by-census round fixed effects to absorb any time trends at the state level. Finally, in column 4 I restrict the sample to counties that had above median land devoted to agriculture in 1974, the start of the sample period. This is in order to make sure that the result is not driven by non-agricultural counties. The coefficient estimate is larger using the restricted sample and, despite reducing the sample size by half, the estimate remains precise.

Importantly, these estimates do not appear to be driven by pre-existing trends in land values. Figure 7a displays coefficient estimates from Equation (4), the impact of patent law exposure on land values over time. More- and less-exposed counties were on similar trends prior to 1985; however, their trends diverge following the law change and level off by 1997. In Table A5, I reproduce all baseline estimates after controlling directly for pre-trends in land values; that is, I include on the right hand side of all regressions both the (log of) land value in 1974 and (log of) land value in 1982 interacted with a full set of year indicators. The results remain positive and statistically significant, consistent with the baseline estimates not capturing pre-existing land value dynamics. In Figure 7b, I present the event study graph after including the pre-period trend controls; the result is very similar.

The estimated effects are quantitatively large. IV-2SLS estimates of the impact of the actual share of cropland devoted to hybrid-incompatible crops—whose magnitudes are easier to interpret than the reduced form presented in Table 7—are reported in Table A6. These estimate imply that a one standard deviation increase in the share of cropland devoted to hybrid-incompatible
crops—i.e. a one standard deviation increase in exposure to the patent law change—was associated with a 0.19 standard deviation increase in (log of) agricultural land values. This is a quantitatively large effect; however, perhaps this is not so surprising considering the fact that advances in breeding and agricultural biotechnology are a primary—if not the primary—force behind recent improvements in agricultural productivity in recent decades (e.g. Kloppenburg, 2005).

5.2.2 Short Run Impacts: Input Spending, Profits, and Land Adjustments

The impact of introduction of variety patenting on land values suggests that, in the long run, the benefit of variety patents to the agricultural sector were expected to outweigh the costs. What short-run impacts and adjustments drove this effect? To investigate this question, I turn to direct measures of input spending and profits during the sample period in the Census of Agriculture. Conveniently, the Census distinguishes between spending on different input types. In column 1 of Table 8, I find a positive and significant relationship between exposure to the patent law change and spending on crop varieties. I do not find pre-existing trends in variety spending across counties; more exposed counties increase spending on variety inputs only after the introduction of patent protection, and the result is robust to controlling directly for pre-period trends in variety expenditure (Figure A5a). Moreover, I find no evidence of a significant impact on county-level spending on other variable inputs, including chemicals, fertilizers, or petroleum (columns 2-3). This is consistent with the availability of patent protection increasing downstream variety costs, as would be predicted by the standard model of patent protection.37

Next, I turn to the impact of variety patents on farm profits (i.e. total revenue − total cost). In column 5 of Table 8, the outcome variable is total county-level profits. The coefficient of interest is positive and significant, suggesting that even in the short run (i.e. by 1997), exposure to the change in patent law increased farm profits and the benefits of new technologies outweighed the increase in variety spending documented in column 1. The event study estimates are displayed in Figure A4a and show no evidence of pre-existing trends in county-level profits. According to the IV estimates, a one standard deviation increase in the share of a county’s cropland devoted

37In theory, the impact of patent availability on variety spending could be driven by the fact that patented seed inputs are more expensive or by changes in total cropland increased in more exposed counties. First, the fact that I find much smaller effects for spending on inputs other than varieties suggests that the result in column 1 is not driven by an across-the-board expansion of crop production and input use. Second, I control for total land devoted to crops on the right hand side; while this is a “bad control,” it is useful for testing whether county-level crop land mediates the relationship between patent law exposure and seed spending; I find that the coefficient of interest in this version of the specification from column 1 remains positive and significant (φ = 0.0842, p = 0.022), suggesting that the increase in land devoted to crops is not driving the result. Finally, while one might ideally compare seed prices for treatment and control crops over time, actual data on seed prices are scarce, particularly for years prior to 1985 and for crops in the control group. However, consistent data on seed prices for corn (a major control crop) and cotton (a major treatment crop) have been collected systematically. Figure A3 presents corn and cotton seed prices over time, relative to the price in 1984. The two trends are similar prior to 1985 but diverge by 1990; in relative terms, cotton seed prices increase by markedly more than corn seed prices following the introduction of patenting. Since this figure is just a case study and simply compares time series patterns for two crops, it should be interpreted with caution. Nevertheless, this cluster of evidence suggests that the introduction of patent protection did indeed lead to higher prices faced by consumers of newly patentable technology.
to hybrid-incompatible crops was associated with a 0.155 standard deviation increase in county profits. In column 6, the outcome variable is agricultural profits per farm; again, the coefficient of interest is positive and statistically significant. Even in the short run, the average benefit of the introduction of patent protection to the agricultural sector outweighed its costs.

The direct effect of the change in patent regime on profits via its impact on crop productivity could be amplified by land use adjustments. Columns 7-8 of Table 8 document some evidence that land devoted to crop production was expanded in counties more exposed to the introduction of patent protection. In column 7, the outcome variable is log of land area devoted to crops, and the coefficient estimate is positive and sizeable, but statistically insignificant ($p = 0.108$). In column 8, when the dependent variable is the share of farmland devoted to crop production, the coefficient estimate is positive and significant. Intuitively, farmers more exposed to the introduction of variety patents, and hence the beneficiaries of more crop-specific innovation, also seem to have shifted land toward crop production. These adjustments may have amplified the short run impact of the introduction of patent protection under a fixed land allocation, and contributed to the large positive impact on land values documented in Table 7.

### 5.2.3 Winners and Losers?

There are potentially large complementarities between the use of improved farm varieties and farm scale. Several qualitative accounts have argued that large farms benefitted disproportionately from the growth in improved seed varieties, and that small farms have been hurt by increased seed prices (e.g. Willingham and Green, 2019). This has been explained by production...
Table 9: Interactions with Farm Size

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) Downstream Patent Benefits: Heterogeneity by Farm Size</th>
<th>(2) Farm Size Distribution: Direct Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Value of Land and Buildings Per Acre</td>
<td>Total County Profits</td>
</tr>
<tr>
<td>Share Not Hybrid Compatible, x Post 1985</td>
<td>0.0261</td>
<td>-1.725**</td>
</tr>
<tr>
<td>(0.0389)</td>
<td>(771.3)</td>
<td>(1.135)</td>
</tr>
<tr>
<td>2nd Size Quartile</td>
<td>0.0571</td>
<td>2.547**</td>
</tr>
<tr>
<td>(0.0713)</td>
<td>(1.107)</td>
<td>(1.545)</td>
</tr>
<tr>
<td>3rd Size Quartile</td>
<td>0.0516</td>
<td>3.917***</td>
</tr>
<tr>
<td>(0.0462)</td>
<td>(1.030)</td>
<td>(1.332)</td>
</tr>
<tr>
<td>4th Size Quartile</td>
<td>0.0379</td>
<td>4.340***</td>
</tr>
<tr>
<td>(0.0457)</td>
<td>(1.435)</td>
<td>(1.850)</td>
</tr>
</tbody>
</table>

County Fixed Effects: Yes  Yes  Yes  Yes  Yes
Census Round x State Fixed Effects: Yes  Yes  Yes  Yes  Yes
Additional Controls: Yes  Yes  Yes  Yes  Yes
Observations: 18,115 18,122 18,122 18,142 18,142
R-squared: 0.923 0.849 0.754 0.949 0.964

Notes: The unit of observation is a county-year. All specifications include county and state-by-year fixed effects. The additional controls include pre-period log of farmland area interacted with a full set of year fixed effects and pre-period log of total farm revenue interacted with a full set of year fixed effects. The outcome variable is listed at the top of each column. Size quartiles refer to the county-level position in the farm size distribution, where farm size is measured as county-level agricultural revenue per farm. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

38This second point has been disputed, however, and it is often argued that farmers growing hybrid crops were never able to save seeds, so the ability to save seeds could not be important. See, for example: https://geneticliteracyproject.org/2016/08/17/why-activists-but-few-farmers-complain-they-cant-save-patented-seeds/. This does not necessarily imply, however, that the switch from a regime in which it is possible to save seeds to a regime in which it is not possible to save seeds did not have distributional consequences.

39Farm size is defined as total agricultural revenue per farm.
Figure 8: **Farm Profits, High vs. Low Pre-Period Farm Size.** The unit of observation is a county-year. Each point is a coefficient estimate from Equation (4); the outcome variable is total county profits. Standard errors are clustered by county state-year pair; 95% confidence intervals are displayed.

size bins (column 1), the coefficient estimates are small in magnitude and statistically indistinguishable from zero. As noted above, however, land values capture long run change in expected profits and not necessarily the direct effect on farmers during the sample period; indeed, in the long run the farm size distribution can endogenously adjust. The next set of estimates turn to the heterogeneous impact on farm profits directly, measured either as total profits (column 2) or profits per farm (column 3). In both cases, I estimate large and significant differences across farm size bins. According to the estimates in columns 2-3, for example, a county in the smallest farm size quartile that cultivated only hybrid-incompatible crops experienced a $1.7 million decline in profits as a result of the patent law (or, $1,368 per farm), while a county in the largest farm size bin that cultivated only hybrid-incompatible crops experienced a $4.3 million increase in profits (or, $6,816 per farm). The estimates over time for farms above and below median pre-period farm size are displayed in Figures 8a and 8b. Thus, in the short run, the introduction of patent protection had major distributional consequences downstream.

Why do the heterogeneous impacts on land value differ from the heterogeneous impacts on farm profits? I already suggested that this may have to do with endogenous changes to the farm size distribution. In particular, exposure to the change in patent law might shift the farm size distribution rightward since large farms are disproportionately productive in the new patent regime. This would dampen the impact of the initial county farm size on long-run profits. Columns 4-5 of Table 9 document this pattern. Thus, the farm size distribution was itself directly affected by the introduction of patenting. Table A7 documents this pattern using a series of more disaggregated farm size bins. The number of farms in the largest size bin significantly increases, while the number of farms in smaller size bins either are unaffected or decline. Therefore, heterogeneous
impact on profits but not land values could be driven by the fact that land prices also incorporate longer-run changes in the structure of production, including the growth of large farms in regions affected by the introduction of patent protection.

Although about the introduction of patenting could cause profits for counties with small farms on average to decline? Intuitively, farmers for whom new seeds were a bad investment might have been able to continue to farm as they were before 1985 and see no change in profits. There are several reasons, however, why this might not be the case. First, anecdotally many farmers were caught off guard by the fact that they were unable to save patented inputs. Homan McFarling for example, in 1998 purchased soybean seeds and he claimed not to know that they were patented by Monsanto—Monsanto sued him for saving his seeds and was awarded $780,000 in damages. Moreover, McFarling had lost his stock of saved seeds.40 Second, and perhaps more plausibly, the results could be driven by a decline in producer prices following the introduction of more productive inputs. While on average, general equilibrium price effects did not erase farm profits following the introduction of patent protection, this may not have been the case for small farmers. If small farmers experience more muted productivity increases from improved inputs or choose not to adopt new seeds, but large farms become more productive after the change in patent regime, price effects could lead to an absolute decline in small farm profits.

While during the sample period, producer price data were collected systematically only for a small set of crops (22-25 depending on the year), comparing the evolution of hybrid compatible and hybrid incompatible crops over time yields a striking pattern; this is displayed in Figure 9. While producer prices for the hybrid-compatible and hybrid-incompatible crops in the USDA producer price data are on similar trends prior to 1985, they diverge around 1988 and remain on

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different trends thereafter. This is consistent with a decline in producer prices as a result of the introduction of variety patenting; this plausibly led to a decline in profits for small farms, if they experienced a smaller productivity increase than large farms and were paid a lower price for their output. However, these results should be taken as suggestive since, due to the small sample size, statistical precision is low; the differences-in-differences estimate with (log of) producer prices as the outcome is $-0.26$ with a standard error of 0.31.

6 Discussion and Extensions

This paper documents that the ability to protect intellectual property increased technology development and productivity in US agriculture. While patent protection could in theory come with significant costs to consumers, US farmers were on average made better off by the introduction of patent protection: agricultural land values and profits increased. In this context, the costs of patent protection were outweighed on average by large productivity benefits.

In order to identify the causal effect of the availability of patent protection, this paper focused on a particular industry and context. What lessons might there be for other settings? I would hypothesize that the estimated impact of the introduction of patent protection on innovative output is close to an upper bound. Absent intellectual property protection, new non-hybrid seeds can be easily used, replicated, and re-sold. Once a breeder sells a seed, without formal patent protection there is no way to stop others from producing and selling that same seed, using it as an input in future research, and stealing the original innovator’s rents. Therefore, the impact of patent protection on ex ante research incentives in this context is likely large. In other industries, innovators may be able to recoup some of their profits by maintaining trade secrets; indeed, in many sectors the ability to protect trade secrets has a meaningful impact on R&D (Png, 2017). Thus, in some sense non-hybrid plant varieties are the context where patents are most useful and where one would expect the most dramatic impact of the introduction of patenting on innovation.

A related question about the external relevance of this paper’s findings is whether one would expect similar results in other countries. Whether countries—particularly low-income countries—should adopt intellectual property protection for plant varieties has been and remains the subject of intense debate (e.g. Cullet, 2001; Srinivasan, 2005; Jördens, 2005; Correa et al., 2015). Since 1960, 74 countries have adopted intellectual property protection for plant varieties, and several countries are currently debating whether to introduce it; unsurprisingly, it has often been a politically contentious process.\footnote{See here, for example, on potatoes in India: https://finance.yahoo.com/news/potato-pepsi-obsessing-over-india-080435284.html.} Here too, it seems likely that this paper’s estimates offer an upper bound; pre-existing infrastructure for both private and public R&D in agriculture was larger than all other countries, and the United States has a large and comparatively wealthy farm sector making potential profits from novel varieties large.\footnote{For example, US inventors own three times as many agricultural patents as the second highest patenting country (Japan) and two times as many agriculture-related publications as the second highest publishing country (China).} The heterogeneous impacts of intellectual property
protection across countries is the subject of ongoing work.

A final question about the interpretation of the paper’s estimates, briefly mentioned above, is whether the differential impact of patent protection on hybrid compatible and hybrid incompatible crops was driven by an absolute increase in research activity and investment in hybrid incompatible crops or, in part, a shift in research activity across crops or technologies. While foolproof evidence on this point is not possible, a range of evidence lends support to the interpretation that the results are driven (at least in part) by an absolute increase in treated technologies and not a commensurate decline in untreated technologies. First, I do not find systematic evidence that the introduction of patent protection for varieties shifted research activity away from non-variety agricultural technologies. I find no evidence of a decline in patenting activity for non-variety technologies following the introduction of patent protection for varieties; if anything, likely because of technological complementarities, the introduction of variety patents led to an increase in innovation in certain non-variety technologies (e.g. harvesters; see Table 5). Second, I do not find evidence that the introduction of patent protection led to an absolute decline in research investment in hybrid compatible crops, which might indicate that the results of the paper are driven by shifting research investment across crops rather than an absolute increase in research investment in treated crops. The trends in private research investment from the CRIS data for hybrid compatible and hybrid incompatible crops separately are shown in Figure A6. There is no evidence of an absolute decline in private investment in hybrid compatible crops after 1985; in fact, research investment appears to increase in both the treatment and control group, but increases by a larger magnitude for treatment compared to control crops. Finally, total private research investment in breeding increased dramatically during the sample period, making it unlikely that biotechnology firms were always forced to reduce investment in control crops in order to increase investment in treatment crops (see e.g. the dashed line in Figure 4). In all of these cases, however, it is of course not possible to know the counterfactual trends in the absence of the change in patent law; thus, this evidence is only suggestive.

While, on average, I find that the introduction of patent protection had a positive effect on the consumers of newly patentable technologies—i.e. farmers—the last part of the paper shows that its impacts were highly heterogeneous. Patent law made counties with smaller farms on average worse off in the short run. This raises a set of questions about the impact of patenting and research incentives on the structure of downstream production that, to my knowledge, have not been explored in prior empirical work. Patent law might disproportionately benefit downstream producers who, for whatever reason, are better positioned to make use of improved technologies. As a result, those producers may increase their market share, as indeed seems to have been the case for large farms following the introduction of patent protection for seeds (Tables 9 and A7). These changes in the structure of production changes might then amplify or dampen the overall effect of intellectual property protection on downstream productivity. Moreover, if producers that

Both statistics are more extreme when patents and articles are citation weighted. For more information, see here: https://www.ers.usda.gov/amber-waves/2016/november/us-agricultural-rd-in-an-era-of-falling-public-funding/
benefit from patent protection produce different products from producers that do not, this logic implies that that patent protection might affect not only the direction of innovation (e.g. Moser, 2005) but also the “direction” of production. The absence of farm-level data or more detailed output information makes it difficult to investigate these questions in the context of the present study; however, this seems like an exciting area for future work.

Changes in the patent regime may affect not only the market structure of downstream production but also the market structure of the innovative activity itself. These changes in the market structure of the innovative sector may also shape the long run consequences of the introduction of patent protection. Qualitative work suggests that patent protection played a major role in the recent drastic consolidation of the seed industry (e.g. Bonny, 2017); the five firm concentration ratio in the global seed sector increased from 10% in 1985 to nearly 55% in 2016. There is substantial theoretical justification for the hypothesis that the introduction of patenting contributed to this significant increase in concentration (Gilbert and Newbery, 1982; Fudenberg et al., 1983). While this paper was able to study the impact of the introduction of patenting on the concentration of production by linking crops to counties using counties’ crop composition, measuring the concentration of crop-level innovation over time is more challenging. However, using data compiled by Fernandez-Cornejo (2004) from a range of sources, it is possible to track the four firm concentration ratio (CR4) of seed sales for corn—a control crop—and cotton—a treatment crop—over time. These trends are presented in Figure 10 and the time series pattern is striking. The CR4 for corn and cotton seeds were on similar trends prior to 1985; after 1985, they diverge and the CR4 for cotton seeds increases substantially relative to the CR4 for corn seeds. This is merely a case study; however, it suggests that changes in the market structure of the innovative sector might be an

Figure 10: Four Firm Concentration Ratio, Corn and Cotton Seeds. This figure plots the four firm concentration ratio (CR4) for seed sales for corn and cotton. The data were compiled from Fernandez-Cornejo (2004).
important factor mediating the long run impact of the introduction of patenting. This too seems like an interesting area for future exploration.

7 Conclusion

This paper investigates the impact of the introduction of patent protection on technology development and downstream productivity and profits. I identify the causal effect of the introduction of patent protection for novel plant varieties and tissue by comparing innovative activity between crops with perfect and imperfect flowers, before and after the introduction of patent protection in 1985. Imperfect flowers facilitate the development of hybrid crop varieties, which have *de facto* intellectual property protection even in the absence of formal patents; hence, crops with imperfect flowers serve as a control group to estimate the impact of the introduction of patent protection. In order to measure innovation both before and after the introduction of patenting at the crop-level, I construct a new and comprehensive data set of crop-specific variety releases—the exact technology that became patentable in 1985—research investment, patenting in non-variety technologies, and crop yields.

I find that the introduction of patent protection led to a substantial increase in technology development. This was driven predominately by an increase in private research investment, and had a discernible positive impact on crop yields. To more completely investigate the impact of the availability of patent protection on downstream production and the “consumers” of patented technology, I measure county-level exposure to the introduction of patenting using counties’ crop composition. Counties that were more exposed to the change in patent law experienced an increase in land values and profits; in this context, even though patent protection implies a trade off between ex ante incentives and deadweight loss, I find that the productivity benefits of patent incentives outweighed the additional costs paid by consumers. Not all rents from innovation were accrued by the inventors; substantial profits flow downstream.

The idea that the ability to patent new technologies could lead to an increase in productivity has been challenged in recent writing. For example, Boldrin and Levine (2013) argue that there is “no empirical evidence that [patents] serve to increase innovation and productivity, unless productivity is identified with the number of patents awarded” (p. 3). The present study stands in sharp contrast to these claims by documenting that the introduction of patent protection was of great consequence in US agriculture. The ability to patent new technologies led to a dramatic increase in technology development and shaped patterns of agricultural productivity and profits across the US.

References


Bonny, Sylvie, “Corporate concentration and technological change in the global seed industry,” *Sustainability*, 2017, 9 (9), 1632.


Correa, Carlos M et al., “Plant variety protection in developing countries: A tool for designing a sui generis plant variety protection system: An alternative to UPOV 1991,” By: Association for Plant Breeding for the benefit of society (APBREBES) and its member organizations: Berne declaration, the development fund, SEARICE and third world network, 2015.


Kloppenburg, Jack Ralph, First the seed: The political economy of plant biotechnology, Univ of Wisconsin Press, 2005.


Figure A1: **Patent Protection and Complementary Technologies Over Time.** Coefficient estimates from Equation (2). The dependent variables are noted at the bottom of each sub-figure. Standard errors are clustered by crop and 95% confidence intervals are reported.
Figure A2: **Patent Protection and Crop Yields Over Time.** Coefficient estimates from Equation (2). The dependent variables are noted at the bottom of each sub-figure. Standard errors are clustered by crop and 95% confidence intervals are reported.

Figure A3: **Corn vs. Cotton Seed Prices.** This figure plots the average price of corn seeds and cotton seeds in the US, relative to the price in 1984.
Figure A4: **County-Level Farm Profit Estimates Over Time.** Coefficient estimates from Equation (2). The dependent variable is total county profits. In A5b, year fixed effects interacted with log of agricultural land value in 1974 and 1982 are included as additional controls. Standard errors are clustered by county state-year pair; 95% confidence intervals are displayed.

Figure A5: **County-Level Variety Expenditure Estimates Over Time.** Coefficient estimates from Equation (2). The dependent variable is (log of) total spending on crop varieties. In A5b, year fixed effects interacted with log of agricultural land value in 1974 and 1982 are included as additional controls. Standard errors are clustered by county state-year pair; 95% confidence intervals are displayed.
Figure A6: Private R&D Investment. This figure private R&D investment from the CRIS data for hybrid compatible and hybrid incompatible crops separately. The data are normalized so that each line reports research investment relative to investment in 1984.

Table A1: Patent Protection and Novel Plant Varieties: Controlling Directly for Pre-Trends

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td>New Varieties (count)</td>
<td>New Varieties (asinh)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specification:</td>
<td>Poisson</td>
<td>OLS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Hybrid Compatible, x (1_{t}^{Post1985})</td>
<td>0.509**</td>
<td>0.511**</td>
<td>0.148*</td>
<td>0.182**</td>
</tr>
<tr>
<td>(0.236)</td>
<td>(0.242)</td>
<td>(0.0852)</td>
<td>(0.0836)</td>
<td></td>
</tr>
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<td>Crop Fixed Effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Reproduction Type Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Total Pre-Period Varieties x Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>1975, 1980, 1984 Varieties x Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,260</td>
<td>2,260</td>
<td>2,280</td>
<td>2,280</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.844</td>
<td>0.846</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. In columns 1-2, the outcome variable is the number of new varieties and in columns 3-4, it is the inverse hyperbolic sine transformation of the number of new varieties. The regression model is noted at the top of each column. Reproduction type controls include a full set of year indicators interacted with an indicator if a crop reproduces vegetatively. Standard errors, double clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A2: Patent Protection and Novel Plant Varieties: Clustering by Genus

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<th>Specification:</th>
<th>Poisson</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Not Hybrid Compatible ( \times 1_\text{Post1985} )</td>
<td>0.748***</td>
<td>0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
<td>(0.0147)</td>
<td></td>
</tr>
<tr>
<td>Crop Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Reproduction Type Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>2,260</td>
<td>2,260</td>
<td>2,280</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.815</td>
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<td>0.817</td>
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</tbody>
</table>

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. In columns 1-2, the outcome variable is the number of new varieties and in columns 3-4, it is the inverse hyperbolic sine transformation of the number of new varieties. The regression model is noted at the top of each column. Reproduction type controls include a full set of year indicators interacted with an indicator if a crop reproduces vegetatively. Standard errors, double clustered by crop genus and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A3: Patent Protection and Novel Plant Varieties: Heterogeneity by Crop Lifespan

<table>
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<tr>
<th>Dependent Variable:</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>New Varieties (count)</td>
<td>Non-Perennial Crops</td>
<td>Perennial Crops</td>
<td>Full Sample</td>
<td>Non-Perennial Crops</td>
<td>Perennial Crops</td>
<td>Full Sample</td>
<td></td>
</tr>
<tr>
<td>Specification:</td>
<td>Poisson</td>
<td>OLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not Hybrid Compatible ( \times 1_\text{Post1985} )</td>
<td>0.780***</td>
<td>0.162</td>
<td>0.780***</td>
<td>0.757***</td>
<td>0.241**</td>
<td>-0.00709</td>
<td>0.241**</td>
<td>0.234**</td>
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<tr>
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<td>(0.250)</td>
<td>(0.167)</td>
<td>(0.266)</td>
<td>(0.284)</td>
<td>(0.0965)</td>
<td>(0.0664)</td>
<td>(0.0983)</td>
<td>(0.0879)</td>
</tr>
<tr>
<td>Perennial x Not Hybrid Compatible, ( \times 1_\text{Post1985} )</td>
<td>-0.618</td>
<td>-0.597</td>
<td>-0.597</td>
<td>(0.493)</td>
<td>(0.479)</td>
<td>-0.249**</td>
<td>-0.261*</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Crop Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
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<tr>
<td>Perennial Crop x Year Fixed Effects</td>
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<td>No</td>
<td>Yes</td>
<td>Yes</td>
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<td>No</td>
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<td>Yes</td>
</tr>
<tr>
<td>Reproduction Type Controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
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<tr>
<td>Observations</td>
<td>1,340</td>
<td>720</td>
<td>2,060</td>
<td>2,060</td>
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<td>720</td>
<td>2,060</td>
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<tr>
<td>R-squared</td>
<td>0.831</td>
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<td>0.830</td>
<td>0.834</td>
<td></td>
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Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. In columns 1-4, the outcome variable is the number of new varieties and in columns 5-8, it is the inverse hyperbolic sine transformation of the number of new varieties. The regression model and sample are noted at the top of each column. Reproduction type controls include a full set of year indicators interacted with an indicator if a crop reproduces vegetatively. Perennial is an indicator that equals one if a crop is coded as perennial in the ECOCROP database. Standard errors, double clustered by crop genus and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A4: Patent Protection and R&D Investment: Controlling for Pre-Period Innovation and Trends

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Public Research Investment</th>
<th>Private Research Investment</th>
<th>Share Private Research Investment</th>
</tr>
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<tbody>
<tr>
<td>Not Hybrid Compatible $i \times \text{Post}_{1985}$</td>
<td>0.0644 (0.731)</td>
<td>-0.0669 (0.276)</td>
<td>0.635* (0.349)</td>
</tr>
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Crop Fixed Effects: Yes, Yes, Yes, Yes, Yes, Yes
Year Fixed Effects: Yes, Yes, Yes, Yes, Yes, Yes
Pre-period Public Investment x Year FE: No, Yes, No, No, Yes, Yes
Pre-period Private Investment x Year FE: No, No, No, Yes, Yes, Yes
Observations: 1,220, 1,220, 1,220, 1,220, 1,151, 1,151
R-squared: 0.892, 0.984, 0.942, 0.956, 0.593, 0.728

Notes: The unit of observation is a crop-year. All specifications include crop and year fixed effects. The outcome variable is listed at the top of each column; in columns 1-2 and 4-5, the inverse hyperbolic sine transformation of the dependent variable is used. All columns report OLS estimates and the controls included in each specification are noted at the bottom of each column. Standard errors, double-clustered by crop and year, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A5: Value of Agricultural Land: Controlling for Pre-Trends

<table>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log Value of Land and Buildings Per Acre</td>
<td>Full Sample</td>
<td>Above Median Initial Farmland</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exposure $i \times \text{Post}_{1985}$</td>
<td>0.181*** (0.0300)</td>
<td>0.132*** (0.0263)</td>
<td>0.0643** (0.0257)</td>
<td>0.0569** (0.0280)</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Census Round Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Additional Controls</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Census Round x State Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>1974 and 1982 log Value of Land x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>18,192</td>
<td>18,115</td>
<td>18,115</td>
<td>9,102</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.872</td>
<td>0.898</td>
<td>0.922</td>
<td>0.934</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a county-year. All specifications include county and year fixed effects. The additional controls include pre-period log of farmland area interacted with a full set of year fixed effects and pre-period log of total farm revenue interacted with a full set of year fixed effects. All columns also include the county-level log value of land in 1974 and 1982 interacted with the full set of year fixed effects. Standard errors, double clustered by state-year and county are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.
Table A6: County-Level Results: IV Estimates Using Actual Crop Shares

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log Value of Land and Buildings per Acre</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>log Land Area in Crop Production</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Share Farmland in Crop Production</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>log Spending on Crop Varieties</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Share Spending on Crop Varieties</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Total County Profits</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>County Profits Per Farm</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
</tbody>
</table>

Share Not Hybrid Compatible x $\frac{\text{Post 1985}}{t}$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | 0.982*** | 0.498 | 0.127** | 1.812*** | 0.0549*** | 20,105** | 26.19** |
| | (0.345) | (0.330) | (0.0606) | (0.632) | (0.0196) | (9,873) | (10.43) |

County Fixed Effects: Yes
Census Round x State Fixed Effects: Yes
Additional Controls: Yes
K-P F-Statistic: 77.277
Observations: 17,806

Notes: The unit of observation is a county-year. All specifications include county and year fixed effects. The additional controls include pre-period log of farmland area interacted with a full set of year fixed effects and pre-period log of total farm revenue interacted with a full set of year fixed effects. The outcome variable is listed at the top of each column and all columns report IV-2SLS estimated where the GAEZ-derived predicted non hybrid compatible share is used as an instrument for the actual share of non-hybrid compatible crop production computed from the US Census of Agriculture. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table A7: Patents and the Farm Size Distribution

| Dependent Variable is the Number of Farms with Total Revenue: |
|---------------------|-----|-----|-----|-----|-----|-----|-----|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| <2500 | 2500-5000 | 5000-9999 | 10000-24999 | 25000-49999 | 50000-99999 | 100000+ |

Share Not Hybrid Compatible x $\frac{\text{Post 1985}}{t}$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | -0.0411* | -0.0167 | -0.0354 | -0.0171 | -0.0307 | 0.00923 | 0.0952*** |
| | (0.0212) | (0.0225) | (0.0226) | (0.0229) | (0.0234) | (0.0243) | (0.0293) |

County Fixed Effects: Yes
Census Round x State Fixed Effects: Yes
Additional Controls: Yes
Observations: 18,285
R-squared: 0.949

Notes: The unit of observation is a county-year. All specifications include county and state-by-year fixed effects. The additional controls include pre-period log of farmland area interacted with a full set of year fixed effects and pre-period log of total farm revenue interacted with a full set of year fixed effects. The outcome variables are the number of farms in a series of size bins, listed at the top of each column. Standard errors, clustered by county, are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.