Labor Supply and Directed Technical Change: Evidence from the Termination of the Bracero Program in 1964*

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Abstract

This paper studies the impact of labor supply on the creation of new technology, exploiting a large exogenous shock to the US agricultural labor supply caused by the termination of the Bracero agreements between the US and Mexico at the end of 1964. Using a text-search algorithm allocating patents to crops, I show a negative labor-supply shock induced a sharp increase in innovation in technologies related to more affected crops. The effect is stronger for technology related to labor-intensive production tasks. Farm-value dynamics indicate that, despite the positive technology reaction, the policy change was undesirable for farm owners.

Keywords— Directed Technical Change, Labor Supply, Induced Innovation, Automation, Immigration Restrictions, Bracero

JEL Classifications— J08, F22, O31, O33

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1 Introduction

Whether labor abundance/scarcity encourages or discourages technical advance is one of the oldest debates in economics (Malthus 1959; Ricardo 1951). Intuitively, when a factor such as labor becomes more expensive, it spurs invention directed to economizing the use of that factor (Hicks 1932; Zeira 1998). On the other hand, a low number of workers reduces the number of potential users of new technologies (Kremer 1993; Acemoglu 1998). Acemoglu (2010) theoretically shows that the direction of the effect depends on whether technical advance reduces or increases the marginal product of labor. Whether labor scarcity may induce technical advance in practice, however, is an open empirical question (Acemoglu 2010, p. 1071).

Technical advance includes the creation and adoption of new technologies. A few studies test the effect of labor supply on the adoption of technology (Lewis 2011; Hornbeck and Naidu 2014; Clemens et al. 2018). However, they do not address the creation of new technologies.

In this paper, I offer an empirical test for the effect of labor supply on the creation of new technologies. To do so, I utilize a large exogenous shock to the labor supply in the US agricultural sector caused by the termination of the Bracero agreements between the United States and Mexico in 1964. The Bracero agreements were a set of three bilateral agreements between the United States and Mexico to regulate bilateral flows of temporary low-skill labor, spanning 1942–1964 (Clemens et al. 2018). Varying substantially between crops, Bracero workers accounted for about 11% of the total seasonal farm workforce in 1964. The exclusion of those workers from the labor force generated a sharp decline in the labor supply in a very short period.

The first objective of this paper is to document the pattern of the creation of new technologies caused by this shock to the labor supply. Using a text-search algorithm to allocate patents to crops, I show that the Bracero exclusion induced a sharp increase in innovation in technologies related to crops with a higher share of Bracero workers relative to crops with a lower share. Innovators reacted fast, introducing new technologies right after the termination of the program. Innovation in technologies related to high-exposed crops remained high more than 15 years after the end of the program. Thus, the patent data reveal substantial directed technical change towards technologies related to crops with labor scarcity.

To further ensure the robustness of the results, I instrument the share of Bracero workers by the average distance from Mexico and the average historical Mexican population in the counties producing each crop. The IV strategy yields quantitatively similar results.

An alternative robustness check employs patent data to measure the technological similarity between crops. Utilizing the latter, I calculate the "technically-predicted" exposure of the crops to the Bracero program, predicted by the exposure of technologically similar crops. I show that the actual exposure to the Bracero program is not correlated with the technically-predicted exposure measure. Furthermore, I re-estimated the difference-in-differences regressions controlling for the technically-predicted exposure, isolating the part in the exposure to the labor-supply shock that is not predicted by the technical features of the crops. Once again, the estimated effects are similar.

The second objective of this paper is to study the heterogeneous effect of labor supply on different types of technology. Using detailed data on labor requirements by production task and crop, I compare the impact of a labor-supply shock on the creation of technologies related to more labor-intensive tasks relative to less labor-intensive tasks. Triple difference estimates confirm that the effect is stronger in technologies related to more labor-intensive production tasks. Assuming that such technologies tend to be more labor-saving, these results suggest that labor scarcity encourages the creation of labor-saving technology more than labor-augmenting technology.

In the last part of the paper, I study the impact of the termination of the Bracero program on the profitability of farm businesses. Using information from the US agricultural census, I show that more exposed counties experienced a greater decline in farm values after the shock relative to less-exposed counties. These results, however, are valid only for states that participated in the Bracero program. Taken together, these results show that a negative shock to the supply of low-skilled labor, implied by immigration restrictions, is harmful to farm owners even in the medium and long run, despite the positive technology reaction.

As mentioned earlier, the effect of labor scarcity on the invention of new technology is theoretically ambiguous. To illustrate the two opposite forces, section 2 summarizes the main results of two simple models, with different assumptions about the exact way technology is shaping production.[1] These models have contradicting predictions about the effect of labor supply on innovation activity. If technology increases the quantity of production for every level of labor, as the standard macroeconomics literature suggests, then an increase in labor supply encourages technological progress. On the other hand, if new technology replaces workers, an increase in labor supply discourages technological progress. Taking together, the sign of the effect is theoretically ambiguous and must be answered empirically. This theoretical framework also motivates the examination of the heterogeneous impact of labor scarcity on the creation of labor-saving technologies and labor-augmenting technologies.

In recent years, there has been an increasing interest in the joint dynamics of artificial intelligence (AI) technology and the labor market (Aghion et al. 2017; Acemoglu and Restrepo 2018). Whether an increase in the available labor supply encourages or discourages technological progress is crucial for the rate of development of AI. If greater labor supply discourages the development of automated technologies, as suggested by the results of this paper, an initial positive shock to AI technologies will increase the available supply of labor (or reduce wages) and hence discourages the development of further AI technology. In other words, the discouraging effect of labor abundance on the creation of labor-saving technologies limits the long-run growth rate of AI technology on the one hand, and unemployment due to automation on the other hand (Nakamura and Zeira 2018; Acemoglu and Restrepo 2018).

The effect of labor supply on technological progress is a fundamental question in economic history. The famous Habakkuk hypothesis claims that US labor scarcity in the 19th century induced

[1] The models themselves are presented in Appendix B.

rapid technological progress relative to Britain (Habakkuk 1962). Similarly, Allen (2009) claims that high wages in 18th century Britain were a preponderant reason for the Industrial Revolution occurring there as opposed to elsewhere.[2] This paper contributes to the economic history literature by providing causal evidence for the impact of labor supply on the creation of new technology.

The claim that the termination of the Bracero program increased the pace of labor-saving technological innovation is not new. For example, Runsten and LeVeen (1981) argued that

> "For many years, California agriculture has relied upon abundant supplies of cheap foreign labor, coming mainly from Mexico. As the rural labor market maintained segmented from the rest of the economy, this allowed the mechanization of these specialty crops to be postponed. In 1964, when the use of Mexican labor became constrained by the end of the Bracero Program, a strong inducement was given to introduce mechanical harvesting techniques."

This claim, however, has never been rigorously tested.

Clemens et al. (2018) exploit the termination of the Bracero program to study the effect of labor scarcity on the labor market. They use state-level variation in the exposure to the Bracero program to show that the program's termination did not affect local wages or employment. They also provide supporting evidence for the positive effect of labor scarcity on the adoption of already-existing technologies. The current paper complements their findings by offering an explicit mechanism for their results: the positive innovation response to labor scarcity can dampen the wage response.[3]

This article contributes to the literature on the effect of factor supplies on technological progress. Newell et al. (1999) and Popp (2002) demonstrated that increased energy prices re-direct innovation to more energy-efficient technology. Hanlon (2015) found that the scarcity of US cotton exported to England during the US Civil War induced the development of new technologies that augmented Indian cotton. Closer to the current topic, Lewis (2011) and Hornbeck and Naidu (2014) have shown that areas with a lower relative supply of low-skilled labor adopted more advanced technology.[4]

The results of this paper are also relevant for understanding the impact of immigration on technological change. Most of the literature has focused on high-skilled immigration, which affects the supply side of innovation (Hunt and Gauthier-Loiselle 2010; Kerr and Lincoln 2010; Borjas and Doran 2012; Moser et al. 2014; Moser and San 2020). In contrast, this paper studies the technological response to limits on low-skilled foreign labor.

Two recent working papers by Doran and Yoon (2019) and Andersson et al. (2019) study the effects of mass migration waves on technological innovation using geographical variation in receiving and sending communities, respectively. The current research complements those papers in two ways. First, my identification strategy takes advantage of an exogenous policy shock that affected only

[2] See also Hayami and Ruttan (1970) and Alesina et al. (2018) for similar arguments.

[3] Methodologically, unlike Clemens et al. (2018) that use state-level variation in the exposure to the Bracero program, I use crop-level variation that better captures changes in innovation.

[4] See also Lafortune et al. (2015), Lew and Cater (2018), and Abramitzky et al. (2019) for similar results.

low-skilled workers. Moreover, it does so in the context of a guest worker program that enables to isolate the impact of a pure labor-supply shock from other changes usually accompanied by conventional immigration, coming from the role of the immigrants as citizens, consumers, and potential inventors.[5] Second, I use patents issued in the United States, the technological leader of the time. Thus, these patents are more likely to reflect frontier inventions. This is aided by the fact that my variation is at the crop level, as opposed to spatial variation. Giving that technological invention is to a large extent globally applicable, the variation in this paper is better able to capture groundbreaking inventions, as opposed to local adjustments of already-existing technologies.

Finally, this paper also contributes to the literature on the impact of immigration on firms' outcomes. Several papers have found a positive impact of increasing high-skilled immigration on the productivity, size, and profits of firms (Kerr and Lincoln 2010; Ghosh et al. 2014; Doran et al. 2014; Peri et al. 2015; Beerli et al. 2021). Brunello et al. (2020) find that low-skilled immigration also has a small but positive effect on firms' profits. The current paper strengthens the latter results by suggesting that, despite the positive technology reaction to low-skilled immigration declining, the farmers' profits (embedded at the farmland values) go down.

2 Theoretical Framework

Theoretically, the impact of labor supply on technological progress depends on how one assumes technology is shaping production. In Appendix B, I build two simple models to illustrate this point. I show that if technology increases the quantity of output for every level of labor, as the standard macroeconomics literature suggests, then an increase in labor supply encourages technological progress. On the other hand, if new technology replaces workers, an increase in labor supply discourages technological progress. Taking together, the sign of the effect is theoretically ambiguous and must be answered empirically.

Importantly, how technology is introduced in each model offers a conceptual framework for distinguishing between different types of technological improvements. For each technological invention, one should consider whether it is more similar to one type of technology or the other. Consider, for example, the invention of the tomato harvester. For a given amount of workers (and land), it does not change the production quantity. However, it can economize the workers needed to produce the same amount of output; therefore, it better aligns with the labor-saving technology type. On the other hand, a new fertilizer, for instance, increases the production for a given amount of land and labor; hence, it better aligns with the labor-augmenting technology type. Using that classification of technologies, the theory suggests different effects for a change in labor supply on the two types of inventions. Section 6 further explores this.

[5] See Moser and San (2020) for the effect of the 1920s quota acts on high-skilled scientists and inventors.

3 Historical Background and Data

3.1 The Bracero Program

Existing from 1942 until 1964, the Bracero program allowed over four million Mexican agricultural workers to migrate legally, making it the most extensive guest worker program in the history of the United States (Kosack 2016).

The wartime Bracero program started on August 4, 1942, when the US government concluded with Mexico an agreement to use Mexican agricultural labor on US farms. From 1942 to 1947, more than 200,000 agricultural workers entered the United States from Mexico. The program's post-war era began in 1948 when Braceros contracted directly with US employers. Approximately 200,000 Mexican legal workers entered the United States between 1948 and 1950. In August 1951, Congress approved Public Law 78, which served as the statutory basis for Bracero contracting until it expired in December 1964. By June 1952, the Bracero system became a permanent component of US farm labor. During the period 1952-1959, on average, 335,000 Mexican workers were annually employed on US farms (Craig 1971).

Opposition to the Bracero program solidified in the early 1960s when more interest groups had joined the fight against imported Mexican labor. In March 1962, the US government required farmers to offer Braceros at least the statewide average wage that in some Bracero-using regions was considerably higher than the area wage. The program finally terminated at the end of 1964. The principal policy goal of excluding Braceros was to improve labor-market conditions for US farm-workers by reducing the size of the workforce (Craig 1971; Clemens et al. 2018).[6]

3.2 Data

The measure of the exposure to the shock in the primary analysis (section 5) is the share of foreign seasonal labor just before the termination of the Bracero program. The outcome variable is the innovation activity by year and crop, measured by the number of agricultural patents for each year and crop, possibly scaled by forward citations. In section 6, I utilize additional information on labor requirements by crop and technological type to examine the differential effects across different types of technology. Finally, in section 7, I use data on farm values from the census of agriculture to examine the impact of the program on the farmers. Below, I describe the exposure and outcome measures used in the primary analysis. Appendix C provides additional details on these data, as well as the other data sources that I use in the paper.

Exposure to the Bracero Program: Share of Foreign Seasonal Labor

Exact data on Bracero workers by the crop is unavailable. However, during the period 1948-1964, 94.5% of the foreign workers admitted for temporary employment in US agriculture were

[6] See the timeline of the main events in Table A1.

Mexican (Bureau of Employment Security 1966, Tables 1 and 3). Hence, in this paper, I use the share of foreign seasonal workers in the total seasonal employment for each crop in 1964 as a proxy for the share of Bracero workers (Bureau of Employment Security 1966, Table 5).[7] For most of the statistical analysis of this paper, I use the total number of person-hours worked annually by foreign and local seasonal workers.[8] The sample for the primary analysis consists of 16 crops that used 4,000 or more person-months of foreign labor in 1964. This measure has a significant variation in the data, ranging from 55% in lettuce to 2% in tobacco (Table 1). For a robustness check, I also use a binary version of the exposure measure, where crops above the median of foreign share are defined as exposed crops (Table A5).

[Table 1 about here]

Innovation Measure: Allocating Patents to Crops

My first measure of technology innovation is the number of USPTO patents by crop and year. To account for the quality of the innovation, I also use the number of patents weighted by the number of their forward citations. Because most of the Braceros were allocated to harvesting tasks, I focus on technological innovations related to harvesting and mowing (CPC class A01D) in the primary analysis in section 5. In section 6, I compared patenting in this class with patenting in other technological classes using information on the labor requirements by task and crop (see Table 5).

I allocated patents to crops by searching the text of patents for the crop names. I collected the full text of the patent from Google Patents and looked for the crop names in the title, abstract, claims, and description sections of the patent document. If more than one crop appears in the text of one patent, I allocate the patent to the crop which appears first.[9] I determined the invention's date by the application date of the patent.[10]

Between 1948 and 1985, US inventors were awarded 2,563 patents related to harvesting and mowing, which mentioned at least one of the 16 crops (Table 1). I also collected data from the Google Patents website on the number of citations for each patent.

A basic prediction of the endogenous growth literature is that innovation activity is increasing with scale; the larger is the value of a market, the higher are the incentives to invent new technologies

[7] This measure is highly correlated with another potential measure of the share of Bracero workers, which is the 1964 to 1965 change in the share of foreign workers (the Pearson correlation coefficient is 0.72).

[8] For robustness, I also use the share of foreign workers in the total seasonal employment at the date of peak foreign employment from (Bureau of Employment Security 1966, Table 21).

[9] I estimate robustness checks using other procedures, such as assigning the patents to all the crops or splitting its weight between the crops (see Table A6).

[10] The application date is missing for 34 patents in the sample, for which I estimated the application date by subtracting the median lag between the application date and issue date in the sample (2.6 years) from the issue date.

relevant to that market (Romer 1990; Aghion and Howitt 1992). I use this prediction to validate the text search algorithm that assigns inventions (measured by patents) to the different markets (here, crops). Indeed, the data show a strong positive correlation between the average number of patents by crop and the average value of production by a crop for the period 1948-1985 (Figure 1).[11]

[Figure 1 about here]

4 Agricultural Innovation and Patenting in the US

Before turning to the primary analysis, this section provides descriptive information on innovation and patenting in the US. I focus on patents in the primary sample, namely patents of harvesting and mowing technologies related to one of the 16 crops described above, and compare them to the entire set of USPTO patents in the same year.

I start by examining the identity of the inventors. In particular, I check whether the inventors are individual inventors that assign the patents to themselves or firms and other institutions that employ the inventors. Figure A1 shows a monotonic decline in the share of patents that belong to individual inventors for the patents in our sample over the years, from more than 60% in 1948 to less than 40% in 1985. A similar decline in the share of patents by individual inventors occurred to other US patents, from 40% in 1948 to less than 20% in 1985. However, the levels of patents by individuals are consistently higher for the sample of agricultural innovation than other innovations. Finally, the data show no differential pattern between patents issued before and after the end of the Bracero program for both patents inside and outside the sample.

Next, Figure A2 shows the average number of inventors per patent by year. In this case, the data show a monotonic *increase* for both patents in the sample and other patents. At the beginning of the analyzed period, the average number of inventors per patent was around 1.2 for both groups. At the end of the period, the number of inventors per patent is 1.6 for patents in the sample and 2.0 for other patents. Once again, there is no differential pattern between patents issued before or after 1964 in both groups.

Another interesting question is how patent applications in the sample are expected to be reviewed by the US Patent Office. In particular, I check the time between the application and publication of the successful patents. Figure A3 shows that patents in the sample are reviewed faster than other patents. Over 1948-1985, the average time between application and publication was 2.6 years for patents in the sample, compared to 3.0 for other patents. Over the years, the pattern of this variable seems to be similar for patents inside and outside the sample, and without any significant change in 1964.

[11] The value of each crop was collected from various publications of the US Department of Agriculture. See Appendix C for additional details and see Table A2 for additional descriptive statistics of the crops in the sample.

Finally, I check some institutional features of the market for agricultural innovation studied in this article compared to the overall market for innovation. To do so, I calculated the number of unique assignees, patents per assignees, as well as other concentration (or market power) measures separately for each group of patents (sample/other patents) and years (1948-1964/1965-1985). Table A3 reports the results.

The number of assignees for patents in the sample is 637 and 800 before and after 1964. The growth rate in the number of assignees for other patents is higher (from 210,531 to 317,974). The number of patents per assignee in the sample is 1.7 for both periods. This figure is much higher in the broader set of patents, with 3.7 and 4.4 patents per assignee in 1948-1964 and 1965-1985, respectively.

To further examine the concentration in the market for invention, I calculate the Herfindahl-Hirschman Index, which is the sum of squares of the share percentage of patents issued by each assignee (ranges between 0 and 10,000). This measure shows a decrease in the market concentration between the two periods for both patents inside and outside the sample. The share of patents owned by the top 1, 3, 5, 10, 30, and 50 assignees also decreased between the two periods for both groups of patents. However, the share of patents owned by top 1, 3, 5, 10, 30, and 50 *percent* of assignees slightly decreased between the periods for patents in the sample, but *increased* for patents outside the sample.

Overall, the information presented in this section suggests no apparent difference in the type of inventors or the way the US patent office reviewed the patents before and after the termination of the bracero program. The patterns of market concentration are less clear. Some of the measures suggest no change (patents assignee) or even a decrease (share of patents by top *percent* of assignees) in the concentration between the periods for patents in the sample, compared to an increase in those measures for other patents. However, other measures (Herfindahl-Hirschman Index and share of patents by top *number* of assignees) suggest a decrease in market concentration for both groups.

5 Effects of Labor Scarcity on Invention in the United States

My empirical strategy compares changes in invention across crops that were differentially affected by the termination of the Bracero program. Figure 2 illustrates the main results. The relative number of patents for crops with low exposure to the Bracero program reveals almost no change before and after 1965.[12] However, for crops in the medium and high exposure groups, there is a noticeable jump around the end of the Bracero program. The rest of this section explores this finding more rigorously.

[12] To account for the scale differences between crops, I calculated the annual number of patents by crop and year relative to the pre-period (1948-1964) average of that crop. See Figure A4 for a similar graph by crop.

[Figure 2 about here]

The dependent variables, citation-weighted or unweighted patent counts by crop and year, are skewed and nonnegative. For example, 26.6% of the crop/year observations in the data correspond to years of no patent output; the figure climbs to 76.1% if one focuses on crop/year observations with no more than five patents.

To address this count nature of the data, I estimate the model using the Poisson Quasi Maximum-likelihood Estimator, first suggested by Hausman et al. (1984). This estimator is fully robust to distributional misspecification, and it also maintains certain efficiency properties even when the distribution is not Poisson (Wooldridge 1999, 2010).[13] I compute QML "robust" standard errors, which are consistent even if the underlying data-generating process is not Poisson. These standard errors are robust to arbitrary patterns of serial correlation (Wooldridge 1997; Bertanha and Moser 2016).[14]

The years of analysis for most of the specifications are 1948-1985.[15] I chose 1948 for two main reasons. First, it is the first year that the Bracero workers were employed directly by the farmers and not by the US government. Second, choosing a year in the middle of the period avoids an additional (positive) shock to the labor supply at the program's beginning.[16]

5.1 Baseline Specification

My estimating equation relates crop i's output in year t to characteristics of i:

$$ln\left[\mathbb{E}(Innovation_{it}|X_{it})\right] = \beta \cdot ForeignShare_i \cdot post_t + \gamma_i + \delta_t \tag{1}$$

where $Innovation_{it}$ is a measure of innovation output at crop i at year t, $ForeignShare_i$ is the share of foreign workers in the total number of seasonal workers in crop i one year before the termination of the Bracero program, $post_t$ denotes an indicator variable that switches to one after 1965, the γ_i's correspond to crop fixed effects, the δ_t's stand for a full set of calendar year indicator variables, and X_{it} denotes all the independent variables on the right-hand side of the equation.

Table 2 presents the main results. Column (1) examines the determinants of the 16 crops' patent count. I find a significant increase in the yearly number of patents produced after 1965 in crops

[13] Except for the conditional mean, the distribution of the outcome variable given the dependent variables and the coefficients is entirely unrestricted. In particular, there can be overdispersion or underdispersion in the latent variable model (Wooldridge 1997).

[14] Due to the small number of crops (16 in most specifications), I did not cluster the standard errors in the crop-level regressions. However, results are robust for clustering the standard errors at the crop level (Table A4).

[15] The results are robust to the choice of the start and end years (Table A8).

[16] Unfortunately, I cannot estimate the effect of this positive shock due to the lack of data on the share of Mexican workers by crop in the first years of the Bracero program.

that were more exposed to the Bracero program. A one percentage point rise in the share of foreign workers before the policy change increases the innovation activity by 3.3 percent (significant at one percent). Compared with an average of 4.06 annual patents per crop in 1948-1964, an increase of one standard deviation in the labor-supply shock increases the number of patents by 70.7%, which amounts to 2.87 additional annual patents per crop at the average pre-period level.[17]

[Table 2 about here]

Column (2) provides the results for citation-weighted patents, a measure that takes into account the quality of the innovation. The effect is somewhat smaller: A one percentage point rise in the share of foreign workers increases the quality-adjusted innovation measure by 2.3 percent.

A potential challenge to the difference-in-differences estimation is that pre-treatment trends may drive the difference between the patenting of crops with different degrees of exposure. To address this concern and to check the persistence of the effect, I explored the dynamics of the effects uncovered in Table 2 by estimating a specification in which the treatment effect interacts with a set of indicator variables corresponding to a particular calendar year and then graphing the effects and the 95% confidence interval around them.[18]

Following the end of the Bracero program, the treatment effect rises monotonically, peaking three to four years after Bracero exclusion, and remaining at the same level (see Figure 3). Two aspects of this result are noteworthy. First, the fact that R&D responded so quickly to the negative labor-supply shock suggests that part of the new patented technologies were ready, or at least close to being ready, at that time. Potentially, the expected labor shortage provided only a "nudge" to the inventors of these technologies to make them operational or even just to issue a patent for them. However, the data show no evidence of recovery—the effect of Bracero exclusion persisted for at least 15-20 years. This result suggests that labor scarcity not only, or mainly, induced the patenting of (almost) existing technologies but mostly induced the invention of new technologies. Second, the event study coefficients fluctuate around zero and are not significantly different from zero for periods before 1965, showing no evidence for a pre-treatment trend.

[Figure 3 about here]

5.2 Robustness Checks

Appendix A provides additional evidence testing the robustness of the results. The first set of robustness checks evaluate the sensitivity of the results for the definition of the treatment. My

[17] The percentage change in innovation for an increase of a standard deviation σ in the share of foreign workers is $\exp(\beta \cdot \sigma) - 1$. For $\beta = 3.258$ and $\sigma = 0.164$, the percentage change is $\exp(3.258 \cdot 0.164) - 1 = 0.707$.

[18] The small size of the sample (16 crops) does not allow the estimation of many coefficients simultaneously with satisfactory precision. Therefore, I estimate biennial coefficients. A similar picture was obtained when estimating annual coefficients but with larger confidence intervals.

preferred exposure definition is a continuous variable measuring the exposure to the shock in 1964, one year before the end of the program. This measure carries more information than a binary treatment variable, which is more common in difference-in-differences studies. The results, however, are robust to the use of a dummy variable, where crops above the median of foreign share in 1964 get the value one. I estimate the model separately for the two versions of the outcome variable, the number of patents and citations-weighted patents. The Poisson estimate of the effect is an increase of 92.5 log points (significant at 1 percent). This estimate suggests that, after 1964, American inventors produced 152 percent additional patents in high exposed crops relative to low-exposed crops. The estimated effect using the quality-adjusted measure of invention is a 60.3 log points (or 83 percent) increase in invention (Table A5, columns 3-4).

The primary measure of exposure in this paper is the share of foreign seasonal workers in the total number of person-hours annually worked in 1964. However, the results are robust to using the share of foreign workers in the total seasonal employment at the date of peak foreign employment. The Poisson estimators using this measure of exposure to the Bracero program are somewhat smaller but still significant at one percent (Table A5, columns 5-6).

The process of Bracero exclusion began in 1962 when the US government raised the required wage rate for Bracero workers and was completed at the end of 1964 (Craig 1971). In the specifications above, I picked the post-year to be 1965. Defining the post-year to be 1962, however, the results are virtually unchanged (Table A5, columns 7-8).

In the baseline specification, I use the share of foreign seasonal workers in 1964 as a proxy for workers under the Bracero program. Another (probably tighter) measure of the share of Bracero workers is the 1964 to 1965 change in the share of foreign workers. Using this measure to define the exposure to the Bracero program, the estimates of the effects are somewhat smaller, but still statistically significant at least at five percent (Table A5, columns 9-10).

I also checked the sensitivity of the results to the algorithm assigning patents to crops. I compared five different alternatives. 1) The baseline algorithm assigns the patent to the first crop that appears in the text of the patent. The four alternative algorithms are: 2) assigning the patent to the crop that was mentioned more times than any other crop, 3) assigning a patent to each crop mentioned in the text, 4) assigning equal weight to each crop mentioned so that the sum of the weights is one, and 5) assigning weights proportional to the number of times each crop is mentioned. All algorithms yield similar results, both for the innovation measure based on patent counts and the innovation measure based on the number of citations (Table A6).

The next set of robustness checks alternate the crops included in the analysis. Restricted by the data availability, the baseline sample of this paper contains crops that used 4,000 or more person-months of foreign labor in 1964. This choice implies that these crops tend to be labor-intensive. Moreover, prominent crops (e.g., wheat, corn) are not part of the original sample. To examine the validity of the results for a broader range of crops, I extended the sample by the ten field crops with the largest acreage in the 1964 agricultural census.[19] Unfortunately, I did not find exact data on the share of foreign workers in crops with less than 4,000 person-months of foreign labor in 1964, including these field crops. However, the foreign share of the category "Hay and Grain" is 1.2 percent. In what follows, I assumed that each of the ten field crops has the common foreign share of 1.2 percent. Columns 3-4 of Table A7 show the results of the difference-in-difference specification for the aforementioned extended sample. The effect of labor scarcity on innovation is positive and significant for both innovation measures. The magnitude of the effect is comparable to the original sample of 16 crops, although a bit smaller. The effect of a one percentage point rise in the share of foreign workers is 2.8 percent for a simple patents-count innovation measure and 1.5 percent for the quality-adjusted measure.

I also extended the sample to include ten additional crops of which information on the share of foreign workers in 1962 in California is available.[20] Columns 5-6 of Table A7 report the results for a sample containing the 16 original crops and the ten "California crops". The results are virtually identical to the baseline results, with estimates of a 3.1 and 2.3 percent increase in the number of patents and citations, respectively. Finally, columns 7-8 of Table A7 show the results for all crops together. The estimated effects are 2.8 and 1.5 percent (significant at one percent).

The years of analysis in the baseline specification are 1948-1985. To check the sensitivity of the results for this choice, which is somewhat arbitrary, I estimated the baseline specification for different periods. Table A8 indicates that the results are not sensitive to that decision.

Although the preferred statistical model for count data is the Poisson model, I checked the sensitivity of the results for three alternative models. Columns 3-4 of Table A9 report the results of a Negative Binomial model. The estimators are positive with a similar magnitude (effect of 2.2 and 2.0 percent for patent and citation counts, respectively, significant at 1 percent). Next, I estimated a zero-inflated Poisson regression. This model assumes that two different processes generated the outcome variable. The first process is governed by a binary distribution that generates extra zeros. If the first process yields zero, the outcome is simply zero. However, if the binary process yields one, the outcome is sampled from a Poisson distribution. I assume that the excess zero counts (the first process) come from a logit model. Maximum likelihood estimates of this model yield results that are very similar to the baseline Poisson model (2.9 and 1.8 percent increase, and significant at one percent, Table A9, columns 5-6). Finally, I estimated an OLS model, where the outcome variable is the natural log of the count of patents and citations (observations with zero patents/citations are dropped from the regression). An estimate of the effect using the patents measure shows an effect of a 1.5 percent increase, smaller from the baseline Poisson estimate (significant at 1 percent). Using the quality-adjusted inventions measure, I find that the estimated effect is an increase of 2.0 percent, similar to the baseline estimate (significant at one percent, Table A9, columns 7-8).

As I discussed earlier, the data show no evidence for pre-treatment trends. To further address

[19] These crops are: barley, corn, flax-seed, oats, peanuts, rice, rye, sorghum, soybeans, and wheat.

[20] These crops are apricots, cherries, olives, peaches, pears, plums, prunes, lemons, almonds, and walnuts.

this concern, I estimated the baseline specification with crop-specific linear pre-trends. The estimates are greater (4.9 and 4.5 percent for patents and citations, respectively) and statistically significant at one percent (Table A10, columns 3-4).

5.3 The Decision about the Bracero Workers and Instrumental Variables estimation

What explains the variation in the share of Mexican workers between the crops? My identifying assumption is that controlling for crop and year fixed effects, changes in patenting would have been comparable for crops with a high and low share of Mexican workers if the US government had not terminated the Bracero program. This assumption is violated if the percentage of Mexican workers is correlated with factors that generate unparalleled innovation activity trends for unrelated reasons. For example, suppose the share of Mexican workers is higher in crops with higher labor requirements per acre, and there is convergence in the invention dynamics such that crops with higher labor requirements close the gap by having more labor-saving inventions in later years. In that case, the estimated effect is not the causal effect of the Bracero exclusion.

Using data on the value of production, seasonal labor, and acreage of the crops, Table A11 reports the correlation between the foreign share of seasonal labor in 1964 and various measures of labor productivity, yield, and market size. The data suggest no significant correlation between the foreign share and any of these measures (p-value is always greater than 10 percent). While the data show no correlation between the exposure measure and any of the observable characteristics of the crops, the rest of this section uses instrumental variables to address the possibility that other (unobservable) characteristics might violate the parallel trend assumption.

Two logical instruments are the distance from Mexico and the historical share of the population of Mexican origin. The data show that, other things equal, seasonal Mexican workers tended to work in places closer to the US-Mexico border and in places that attracted older waves of immigration. The exclusion restriction requires that those variables must not affect the technological progress differentially in the pre and post periods, except for its impact through the channel of the Bracero program termination. Indeed, it is unlikely that the proximity to Mexico or the historical share of Mexicans impacts the technological progress differentially before and after 1965 other than its effect through the Bracero program.[21]

To construct the instrument, I use county-level information on the distance from Mexico, and the share of the Mexican population in 1940, taken from the US census of population. As my innovation measures are at the crop level, I need to transform the instruments from the spatial dimension into the crop distention. To do so, I use the US agricultural census from 1964 for information on the

[21] The exclusion restriction does not require that the cross-sectional variation of the instruments would not affect the technological progress itself. The instruments remain valid even if the cross-sectional variation is related to these instruments. For instance, if the crops closer to Mexico tend to have faster technological progress, this would be picked up by the crop fixed effect, and the exclusion restriction would still hold.

crops produced in each county. More precisely, the average distance from Mexico of a crop i is measured by $d_i = \sum_c d_c w_{ic}$ where d_c is the minimal distance between the Mexican border and the center of the county c, and w_{ic} is the percent of the acreage of crop i in county c in the total acreage of crop i in 1964. The crop-average Mexican population is calculated similarly.

To implement the IV for count-data, I use a model first introduced by Mullahy (1997). It is widely used in the empirical literature and has better asymptotic properties than the additive errors models.[22] The model takes the form:

$$Innovation_{it} = exp\left[\beta \cdot ForeignShare_i \cdot post_t + \gamma_i + \delta_t\right] \cdot \epsilon_{it} \tag{2}$$

where ϵ_{it} is a unit-mean error term. The treatment variable $ForeignShare_i{\cdot}post_t$ is instrumented by $z_i \cdot post_t$, where z_i is either the average distance from Mexico, or the 1940 average percentage of Mexicans in the population of the counties growing the crops (or both). The GMM estimators of the model are presented in Table 3.[23] In the first and fourth columns, the instrument used is the average distance from Mexico. The estimates for a one percentage point rise in the share of foreign workers are 4.9 and 5.3 percent for the patents and citations measures, respectively (significant at one percent). In the second and fifth columns, I use the average share of the Mexican population similarly. The estimates of the effect are a 3.0 percent increase in patents (marginally significant, p-value = 0.067) and a 4.3 percent increase in citations (significant at five percent). Finally, the third and sixth columns report the estimates where both instruments are used. The estimates are 4.5 and 5.0 percent, respectively, both significant at 1 percent. Overall, the IV estimates of the effect are somewhat higher than the baseline estimates. This indicates that, if anything, the simple Poisson estimates of the effect are biased toward zero.

[Table 3 about here]

5.4 Building Predicted Exposure using a Technology-Based Similarity Matrix

An additional threat for the identification strategy comes from a potential technical similarity between groups of crops. If exposure to the Bracero program is not randomly distributed across the groups, differential technical progress between the groups might confound the results.

[22] See Cameron and Trivedi (2013) for a review on count-data instrumental variables estimation. Similar results were obtained using additive-errors and control-function models.

[23] See Table A12 for the corresponding "first-stage" estimates. The Poisson-GMM estimation method does not rely on an actual first stage but on the moment conditions implied by the exclusion restriction. Anyway, I report the OLS coefficients of a linear first stage. Those are the exact coefficients obtained in the first stage when using the control function method to estimate the IV-Poisson (instead of GMM), which provides very similar results.

To address this concern, I checked the correlation between the exposure to the Bracero program and the technical features of the crops. To do so, I build a "technically-predicted exposure" measure which is the leave-one-out predicted exposure according to the exposure of crops that are similar to the original crop regarding technical properties. The technically-predicted exposure enables me to check whether the technical features of a crop predict its actual exposure to the program.

I measured the technical similarity between crops by the number of patents that mention both crops. If many technological innovations are relevant for two crops simultaneously, those crops have a lot in common regarding technical properties. Specifically, I build a similarity matrix where the off-diagonal entry (i, i') is the number of patents in the sample that mention crops i and i' somewhere in the text, and the diagonal entries are set to zero. Then, each row in the matrix is normalized to sum to one. Table A13 shows the similarity matrix. The results indicate, for example, that citrus is most similar to apples and that asparagus is a combination of celery, lettuce, and tomatoes. Using this similarity matrix, I constructed the technically-predicted exposure as follows:

$$ForeignShare_i^{TP} = \sum_{i' \neq i} w_{i,i'} ForeignShare_{i'} \tag{3}$$

where $ForeignShare_{i'}$ is the foreign seasonal workers shares of crop i'. The data show no correlation between the actual foreign shares and the technically-predicted ones (Figure 4). This indicates that the crop's exposure to foreign labor is orthogonal to the technological features of the crops measured by the patent-based similarity measure described above.

[Figure 4 about here]

Furthermore, I re-estimated the Poisson regressions controlling for the technically-predicted exposure. By doing so, I isolated the part in the exposure to the labor-supply shock that is not predicted by the technical features of the crops. The difference-in-differences specification takes the form:

$$\begin{aligned} ln\left[\mathbb{E}(Innovation_{it}|X_{it})\right] = {} & \beta \cdot ForeignShare_i \cdot post_t \\ & + \alpha \cdot ForeignShare_i^{TP} \cdot post_t + \gamma_i + \delta_t \end{aligned} \tag{4}$$

The results for the two invention measures are reported in Table 4. The estimated effect is 3.6 and 2.5 percent for the patents and citations measures, respectively (significant at 1 percent). These estimates are close to the baseline results.

[Table 4 about here]

Overall, the results in this section provide additional support to the claim that the allocation of Mexican workers between crops was not systematically correlated with features of the crops that affect future technological innovation. Therefore, the labor-supply shocks can be treated as if they are randomly assigned to the crops.

6 Effects by Type of Technology

The main prediction of the theoretical model presented above is that a negative shock of the labor supply should increase labor-saving technological progress more than labor-augmenting technologies. An ideal way to check this prediction is to identify labor-savings and labor-augmenting technologies from the text of the patent. However, in practice, this task is not easy to perform, the more so through an automatic algorithm. For example, a patent for "Grape Harvester" was granted in 1973 (US patent number 3,766,724). This innovation improves the performance of a mechanical grape harvester that replaces manual laborers; therefore, it should be classified as a labor-saving technology. In the text of the patent, however, none of the words "labor", "work", "job", "employment", "task", "save", or "replace" appear.

To bypass this problem, I use information on the labor intensity of different tasks as a proxy for the probability of a technological innovation related to these tasks to be labor saving. The underlying assumption is, ceteris paribus, the incentive to develop new labor-saving technology for a particular task is higher the higher that task's labor intensity is. To conduct this, I used the technological classification of the patents together with data on labor requirements per task and crop.

In particular, I collected data on labor requirements from the State of California's "Report and Recommendations of the Agricultural Labor Commission" (State of California 1963). This data includes information on California's 25 most valuable crops in 1960. For each of these crops, the report lists in detail all the tasks needed to produce the crop, together with estimates on person-hours and labor cost required to produce an acre of that crop. Among the 25 crops included in this data set, 18 have information on the exposure to the Bracero program (either at the country level in 1964 or for the state of California in 1962).

To get a link between agricultural tasks and technology, I manually classified each task into one of the six agricultural patent subclasses.[24] To do so, I chose the technology subclass most similar to the task's description using the subclass's detailed definitions.[25] For example, the production of tomatoes in 1960 required 12.5 person–hours of "thinning" per acre, at the cost of 13.12 dollars. I classified this task into CPC subclass A01B ("Soil Working In Agriculture"), which contains the group "thinning machines" (A01B 41).[26]

For each class-crop pair, I calculated the share of labor requirements for this technological class

[24] See the definition of these subclasses in Table A14.

[25] The definitions of the CPC classification can be found at `https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html`.

[26] Table A15 reports the classification of all tasks.

over the total labor requirements of that crop. I used two versions of these labor-intensity measures, one using person-hours and the second using monetary cost. The second measure takes into account potential differences in skills or efficiency units of the labor inputs. Among the six subclasses, only three have a significant percentage of labor: Soil Working (A01B), Harvesting (A01D), and Cultivating (A01G). The average share of person-hours labor inputs for these crops is 15 percent, 50 percent, and 26 percent, respectively (Table A14).[27] As a robustness check, I also estimated a specification where the labor-intensity measure equals one for Harvesting, which is the most labor-intensive category on average, and zero for the other two categories. This specification does not require information on the actual labor intensity of each class-crop, thus allowing estimation with all crops which I have data on their exposure to the Bracero program.

Using those measures, I estimated the following continuous triple-difference specification:

$$ln\left[\mathbb{E}(Innovation_{ijt}|X_{ijt})\right] = \beta \cdot ForeignShare_i \cdot Intensity_{ij} \cdot post_t + \gamma_{ij} + \delta_{it} + \epsilon_{jt} \qquad (5)$$

where $Innovation_{ijt}$ is the number of US patents/citations in crop i, technological class j, and year t. $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i in 1964. $Intensity_{ij}$ is a measure of labor inputs required to perform task j in crop i. $post_t$ indicates years after 1964. γ_{ij}, δ_{it}, and ϵ_{jt} are crop-task, crop-year, and task-year fixed effects, respectively.

The Poisson quasi-maximum likelihood estimates of equation 5 imply a substantial higher effect of Bracero exclusion after 1964 in the more labor-intensive tasks relative to the less labor-intensive tasks. This result is true for the three different labor-intensity measures. The first measure is the percentage of person-hours required for tasks in class j over the total person-hours required for producing crop i. Using that measure, the effect of a one percentage point rise in the share of foreign workers on patents after 1965 is higher by 3.2 percent in technological classes required 100 percent of the labor compared with technological classes required no labor. (Table 5, column 1, significant at one percent). The effect is slightly smaller, 2.2 percent, when using the citations measure of innovation (Table 5, column 2, significant at five percent).

[Table 5 about here]

In the theoretical model described above, I assumed workers are homogeneous, and therefore there is only one wage level. In reality, however, some tasks can only be performed by higher-skilled workers and cost more per hour of work. The second measure of labor intensity takes this into account by weighting the hours required to perform a task with the wage rate paid for that task. The measure is the share of labor cost for a class of tasks in the total labor cost of a crop. Using this labor-intensity measure, I find the results are virtually the same as the results of the first measure. The estimates for β are now 3.1 and 2.1 percent, respectively (5, columns 3-4).

[27] Results are robust for including all six technology subclasses in the analysis.

The first two labor-intensity measures require exact information about the labor requirements of each task and crop. This data is available only for 18 out of 26 crops with information on the exposure to the Bracero program. The third measure of labor intensity equals one for harvesting tasks, the most labor-intensive class on average, and zero for the other two classes. Using this measure I can estimate equation 5 with all 26 crops.[28] The triple-difference estimates are now slightly smaller, 2.5 and 1.8 percent, respectively (Table 5, columns 5-6).

To further investigate the triple-difference results, I estimate difference-in-differences specifications for each technology subclass separately. The results in Figure 5 show that the point estimates are monotonically increasing with the labor intensity of the task. In the Soil Working subclass, which is the least labor-intensive subclass (accounts for 14 percent of the labor requirements per crop on average), a one percentage point rise in the share of foreign workers *decreases* the number of patents by 0.53 percent (the 95 percent confidence interval is [-1.96,0.90]). The estimated effect in the Cultivating subclass (26 percent of the labor requirements) is an increase of 0.87 percent, and the confidence interval is [-0.05,1.79]. Finally, the estimate for the Harvesting subclass (50 percent of the labor requirements) is 3.14, and the confidence interval is [2.26,4.01].

[Figure 5 about here]

Overall, the results presented in this section indicate that the effect of labor scarcity on technological progress is greater in more labor-intensive tasks. Under the assumption that labor-saving technologies are more likely to be developed for labor-intensive tasks, the results suggest that labor scarcity encourages the invention of labor-saving technologies more than other technologies, in accordance with the theory.

Without making this assumption, a more modest interpretation of the results of this section can be offered. One can think of the additional information about the task's labor intensity as a measure of the shock intensity. The extra dimension allows adding of fixed effects for year-crop, year-class, and crop-class pairs. These fixed effects address many potential threats to the baseline difference-in-differences specification, such as time-varying crop-specific demand shocks that, for some reason, are correlated with the Bracero shock. Thus, the results offer an additional robustness check for the effect of labor supply on technical innovation.

7 The Impact on Farm Owners

How the Bracero exclusion impacted the farm owners that employed the Bracero workers? In principle, the profits of farm owners should decline after the Bracero exclusion due to their loss of low-cost labor. Under standard assumptions (e.g., without externalities), this is true even if we

[28] These crops include the 16 crops in the main data set and additional ten crops with information on the exposure in the state of California. The results are similar when restricting the sample to the 16 original crops (estimates of 2.7 and 1.7 percent, respectively, significant at five percent).

consider the positive technological reaction, as revealed by the fact that farmers chose to hire the Bracero workers when possible and fought against the program's cancellation. However, if there are sufficiently large externalities such as knowledge spillovers, the policy change may cause a "big push" dynamic that makes farmers better off in the medium and long run by "being forced" to adopt the newly available labor-saving technology (Hornbeck and Naidu 2014).

To check whether farmers won or lost from the policy change, I used the land value to measure the profits of the farm owners. The value of a farm would increase if, following the end of the program, it became more profitable to be a farmer in farms that were more exposed to the program.

In particular, I use the US census of agriculture for the years 1950-1982 to build a panel data of land-value per acre by county and year. Additionally, using the same data sets and the exposure measures by crop, I construct a measure of the exposure of a county c to the Bracero program in the following way:

$$Exposure_c = \sum_i ForeignShare_i \cdot AcreageShare_{ic} \tag{6}$$

where $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i and $AcreageShare_{ic}$ is the share of crop i in the total acreage of county c in the 1964 census. The regression equation is:

$$ln(Value_{ct}) = \sum_{\tau=1950}^{1982} \beta_\tau \cdot \mathbb{I}(t=\tau) \cdot Exposure_c + \gamma_c + \delta_t + \epsilon_{ct} \tag{7}$$

where γ_c and δ_t are county and year fixed effects, respectively. I ran separate regressions for Bracero and non-Bracero states.[29] Figure 6 shows a permanent decrease in farm values of counties that are relatively more exposed to the shock. These results are valid only for states that participated in the Bracero program.

[Figure 6 about here]

The results of this section show that despite the positive technology reaction, farmers who employed Bracero workers were adversely affected by the termination of the program, even in the medium and long run. In other words, innovation was not enough to offset the lower labor supply for the affected farms.[30] This fact comports with historical documentation about farmers' opposition to the program's termination.

[29] Following Clemens et al. (2018), I defined Bracero states as having some Braceros in 1955 and non-Bracero states as having zero Braceros in 1955.

[30] Hornbeck and Naidu (2014) also find a negative impact on farmland values per acre after a negative shock to the supply of low-skilled workers. Similar results (although not always statistically significant) also obtained by Lafortune et al. (2015) and Abramitzky et al. (2019).

Moreover, in a recent study, Clemens et al. (2018) show that although the termination of the program aimed to increase the wages and employment rate of local US workers, both employment and wages were not affected. Taken together, one can conclude that Bracero exclusion made capital worse off while making labor no better off.[31]

Finally, the fact that the negative impact starts only after the termination of the Bracero program suggests that the policy change was also unexpected, justifying the identification strategy of this paper.

8 Conclusion

This study provides evidence that the supply reduction of seasonal Mexican workers in the United States after the termination of the Bracero program caused the invention of new harvesting machines. I demonstrated that US inventors focused their efforts on developing new technologies that supported the production of crops that were affected by the labor-supply shock. Moreover, I showed that more inventions related to production tasks that required intensive labor input were invented, probably because those technologies tended to be more labor-saving. Finally, I show that the immigration restrictions were harmful to farm businesses, despite the positive technological response.

The termination of the Bracero agreement caused a massive negative shock to agricultural labor supply with high variation between the different crops. This shock provides a rare opportunity to study the effect of labor supply on the creation of new technologies. The fact that this study focused on innovations in the United States, technological leaders of the time, and the use of between crop variation helped capture this type of technological progress.

I developed a new method to classify patents into crops, using the entire text of the patent. While the vast majority of studies use only the count of patents and citations of the patents to measure technology, the patent text provides a new rich world of information that needs to be explored. The current study takes a small step in this direction, but there is much more to be done. One concrete example is the identification of labor-saving innovations. This study attempts to indirectly measure it using the information on the labor-intensiveness of different tasks. However, a direct measure based on the terminology used in the patent could be more effective.

This study focused only on one industry, agriculture. Despite the importance of this industry in economic development and economic history, the direction and magnitude of the effect in different industries would also be of much interest. Moreover, there are reasons to believe that technological progress in agriculture tends to be more labor-saving than in other sectors (Acemoglu 2002, 2010).

[31] It is behind the scope of this paper to study the impact of the Bracero exclusion on aggregate welfare. The increased innovation could have had off-farm benefits such as higher productivity, lower output prices, or spillovers to other innovations that offset (or even reverse) the harm to the landowning farmers. Nevertheless, the results suggest that the Bracero exclusion caused a Pareto loss to both domestic workers and farmers collectively.

Thus, the finding that labor scarcity encourages innovation in this industry is consistent with the theory. Future research on the heterogeneity of the effect by industry and the factors that can explain this heterogeneity is needed.

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Table 1: Number of Harvesting and Mowing Patents between 1948-1985, the Number of Patents Before and After 1965, and the Share of Seasonal Foreign Workers in 1964 by Crop

Crop	Number of Patents 1948-1985	Before 1948-1964	After 1965-1985	Ratio After/Before	Foreign Share of Seasonal Work
Apples	74	27	47	1.7	3.8
Asparagus	51	12	39	3.3	19
Beans	277	127	150	1.2	2.4
Celery	20	8	12	1.5	32.4
Citrus	201	42	159	3.8	21.6
Cotton	772	494	278	.6	3.7
Cucumbers	39	11	28	2.5	27.4
Grapes	137	13	124	9.5	3.3
Lettuce	25	9	16	1.8	55.3
Melons	18	6	12	2	28.4
Potatoes	213	139	74	.5	3.6
Strawberries	37	12	25	2.1	13.8
Sugarbeets	117	63	54	.9	19.9
Sugarcane	155	38	117	3.1	46.9
Tobacco	206	76	130	1.7	1.9
Tomatoes	121	26	95	3.7	26.2
Sum/Median	2463	1103	1360	1.9	19.4

Notes: This table summarizes the outcome measure (number of patents) and the treatment variable (foreign share of seasonal workers) for each crop in the main sample. The last row presents the sum for the second, third, and fourth columns and the median for the last two columns.

Table 2: Effects of Bracero Exclusion on Invention: Baseline Estimates

	(1) Patents	(2) Citations
Foreign share × post	3.258***	2.271***
	(0.474)	(0.497)
Effect of SD increase in exposure	2.87	10.79
Mean patents/citations before 1965	4.06	23.90
Treatment mean	0.19	0.19
Treatment sd	0.16	0.16
Year FE	Yes	Yes
Crop FE	Yes	Yes
N (crops × years)	608	608

Notes: Difference-in-differences regressions with continuous treatment compare changes in patenting per year in more exposed crops with changes in less exposed crops: $ln\left[\mathbb{E}(Innovation_{it}|X_{it})\right] = \beta \cdot ForeignShare_i \cdot post_t + \gamma_i + \delta_t$ where $Innovation_{it}$ is the number of US patents/citations in crop i and year t, $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i in 1964, $post_t$ indicates years after 1964, and γ_i and δ_t are crop and year fixed effects, respectively. The table reports the Poisson quasi-maximum likelihood estimators of the percentage change in innovations resulting from an increase of one percentage point in the exposure to foreign labor. The average response is the estimated change in the number of patents/citations per year for a one standard deviation increase in the exposure at the average number of patents/citations per crop and year before 1965. All specifications include crop and year fixed effects. Robust standard errors are shown in parentheses.

Table 3: Effects of Bracero Exclusion on Invention: Instrumental Variables

	Patents			Citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign share × post	4.849***	2.968*	4.466***	5.272***	4.272**	4.968***
	(1.565)	(1.622)	(1.499)	(1.587)	(1.742)	(1.538)
Instruments	Distance	Population	Both	Distance	Population	Both
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
N (crops × years)	608	608	608	608	608	608

Notes: Difference-in-differences regressions with instrumental variables: $Innovation_{it} = exp[\beta \cdot ForeignShare_i \cdot post_t + \gamma_i + \delta_t] \cdot \epsilon_{it}$ where ϵ_{it} is a unit-mean error term. The treatment variable $ForeignShare_i \cdot post_t$ is instrumented by $z_i \cdot post_t$, where z_i is either the average distance from Mexico, or the average percentage of the Mexican population in 1940 of the counties growing the crops (or both). The dependent variable is the number of patents in columns 1-3 and the number of forward citations in columns 4-6. Estimators presented are based on Mullahy (1997) count-data IV model with multiplicative errors. The results reported in columns 1 and 4 use the average distance from Mexico as an instrument variable. Columns 2 and 5 show the results using the Mexican population IV, and in column 3 and 6 both instruments are used. The average distance from Mexico of a crop i is measured by $d_i = \sum_c d_c w_{ic}$ where d_c is the minimal distance between the Mexican border and the centroid of county c, and w_{ic} is the percent of acreage of crop i in county c out of the total acreage of crop i. The average Mexican population of a crop is calculated in a similar way using data from the 1940 US population census. All specifications include crop and year fixed effects. Robust standard errors are shown in parentheses.

Table 4: Effects of Bracero Exclusion on Invention: Continuous Difference in Differences Controlling for Technically-Predicted Exposure

	(1) Patents	(2) Citations
Foreign share × post	3.588***	2.474***
	(0.517)	(0.557)
Technically-predicted foreign share × post	2.392**	1.377
	(0.981)	(1.188)
Mean patents/citations before 1965	4.06	23.90
Year FE	Yes	Yes
Crop FE	Yes	Yes
N (crops × years)	608	608

Notes: Poisson quasi-maximum likelihood estimators of Difference-in-differences model with two continuous treatments: $ln\left[\mathbb{E}(Innovation_{it}|X_{it})\right] = \beta \cdot ForeignShare_i \cdot post_t + \alpha \cdot ForeignShare_i^{TP} \cdot post_t + \gamma_i + \delta_t$. $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i in 1964. $ForeignShare_i^{TP}$ is the "technically-predicted" foreign share of a crop i, which is the weighted average of foreign shares of all other crops, where the weights are a measure of the similarity between the crops, measured by the number of patents in the sample that mentions both crops. The weights are normalized to sum to one. All specifications include crop and year fixed effects. Robust standard errors are shown in parentheses.

Table 5: Effects of Bracero Exclusion on Invention in Labor Intensive Tasks: Triple-difference Estimates

	(1) Patents	(2) Citations	(3) Patents	(4) Citations	(5) Patents	(6) Citations
Foreign percentage × labor-class × post	3.224***	2.271**				
	(0.964)	(1.052)				
Foreign percentage × cost-class × post			3.133***	2.161**		
			(0.953)	(1.024)		
Foreign percentage × class × post					2.459***	1.775***
					(0.550)	(0.628)
Mean patents/citations before 1965	2.19	14.14	2.19	14.14	1.89	12.72
Crop-Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Class-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N (crops × classes × years)	1,447	1,447	1,447	1,447	2,096	2,096

Notes: Triple-difference regressions with continuous treatment comparing the effect of Bracero exclusion on patenting in labor-intensive tasks with the effect in less labor-intensive tasks: $ln\left[\mathbb{E}(Innovation_{ijt}|X_{ijt})\right] = \beta \cdot ForeignShare_i \cdot Intensity_{ij} \cdot post_t + \gamma_{ij} + \delta_{it} + \epsilon_{jt}$. $Innovation_{ijt}$ is the number of US patents/citations in crop i, technological class j, and year t. $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i in 1964. $Intensity_{ij}$ is a measure of labor inputs required to to perform task j in crop i. $post_t$ indicates years after 1964. γ_{ij}, δ_{it}, and $\epsilon_{jt}$are crop-task, crop-year, and task-year fixed effects, respectively. The table reports the Poisson quasi-maximum likelihood estimators of β. In the four first columns, I use information on the labor requirement by crop and task to measure the relative labor intensity of a crop-class pair. In columns (1) and (2), $Intensity_{ij}$ is the percentage of hours of labor required for tasks in class j for producing crop i, while in columns (3) and (4) it is the relative labor cost. In columns (5) and (6), $Intensity_{ij}$ equals one for harvesting and mowing tasks (the most labor intensive class on average) and zero for other classes. Robust standard errors are shown in parentheses.

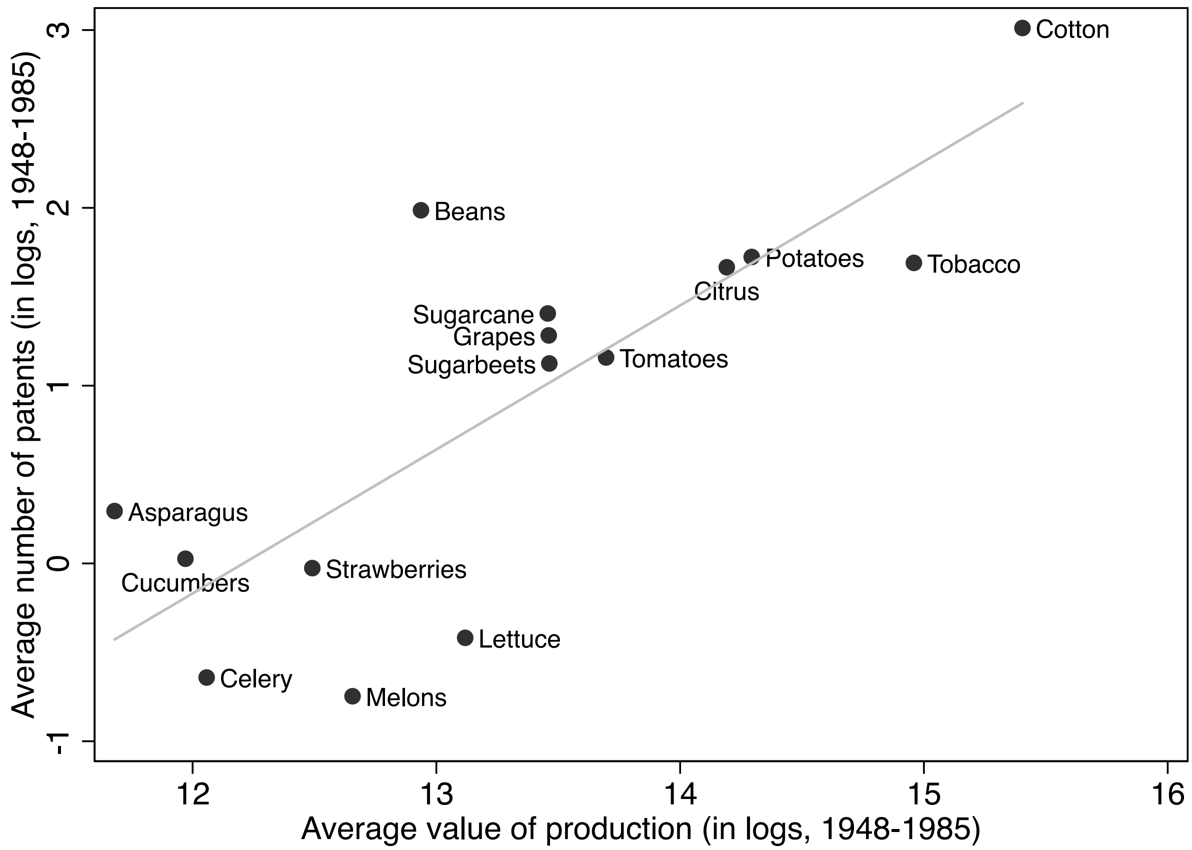

Figure 1: Correlation between Invention and Market Values

Notes: This figure shows the correlation between the innovation activity related to a crop and the crop's market value. Innovation is measured by the log of the average number of US patents related to harvesting technologies in 1948-1985. The text-search algorithm for allocating patents to crops is described in the text. Log average value of production in the years 1948-1985 in 1980 dollars. Data in market values exist for all crops in the sample except apples. The coefficients (and robust standard errors) of the fitted line are -9.89 (1.92) and 0.81 (0.14) for the intercept and slope, respectively. The Pearson correlation coefficient is 0.80

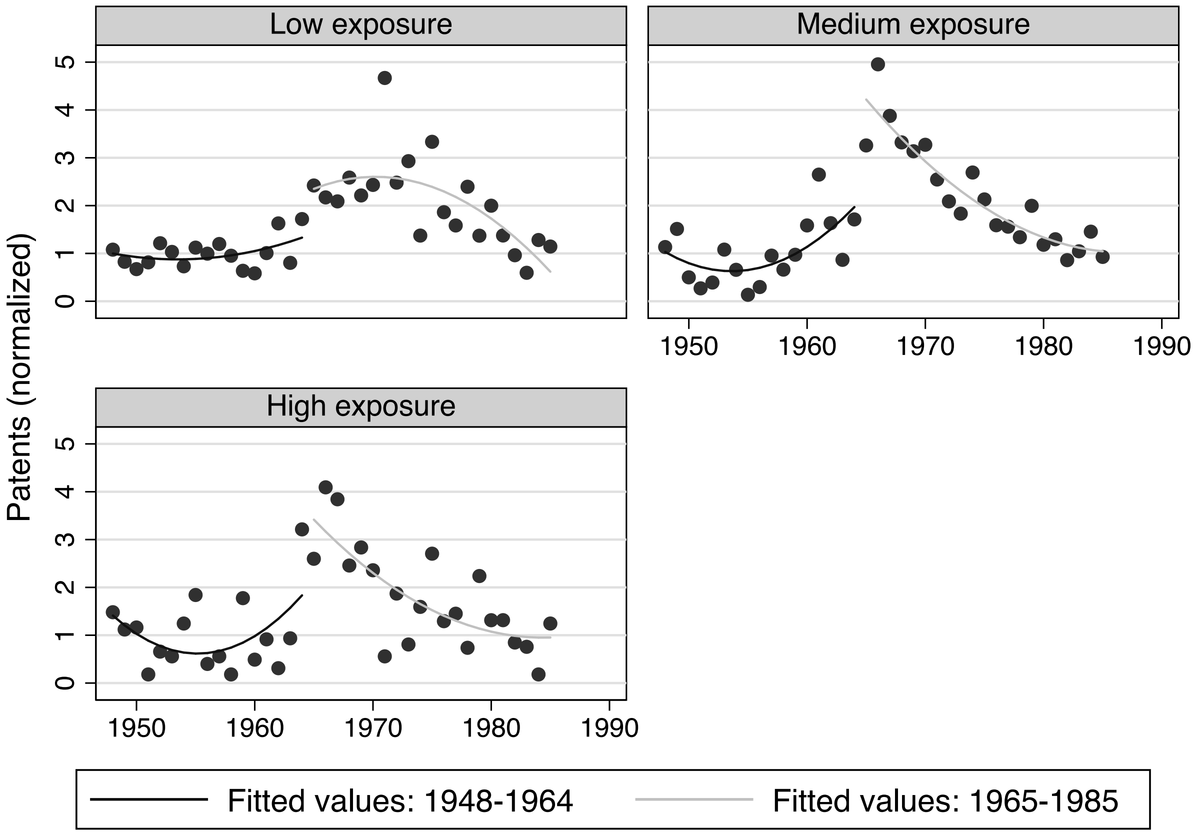

Figure 2: Invention over Time for Crops with Low, Medium and High Exposure to the Bracero Program

Notes: Low exposure: six crops with at most 3.8 percent of foreign workers. Medium exposure: five crops with between 3.8-26.2 percent foreigners. High exposure: five crops with at least 26.2 percent foreigners. The normalized patents measure is the average normalized number of patents for the crops in the exposure group. Each crop-year observation is divided by the crop's pre-period (1948-1964) average number of patents per year.

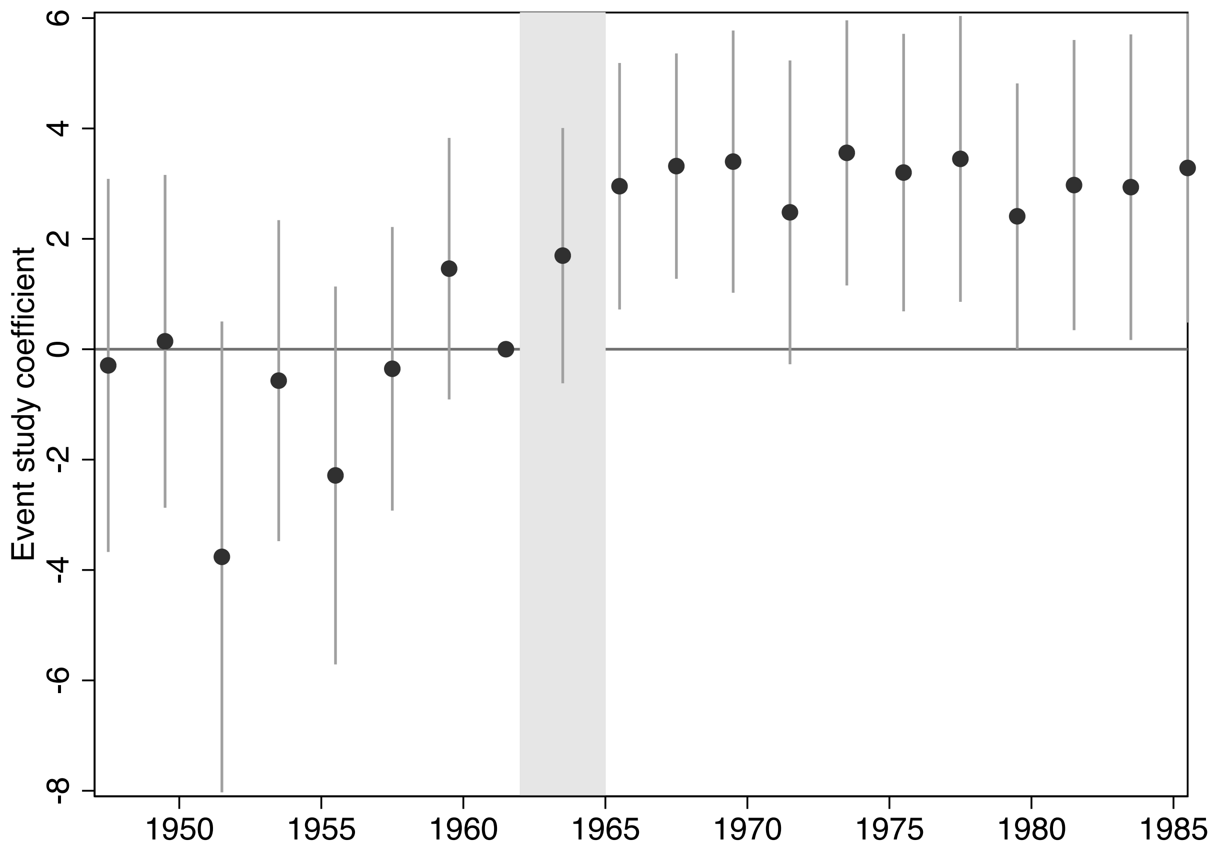

Figure 3: Effects of Bracero Exclusion on Invention: Event Study

Notes: Event study regression with continuous treatment comparing patenting per year in more exposed crops with patenting in less exposed crops: $ln\left[\mathbb{E}(Innovation_{it}|X_{it})\right] = \beta_t \cdot ForeignShare_i i + \gamma_i + \delta_t$ where $Innovation_{it}$ is the number of US patents in crop i and year t, $ForeignShare_i$ is the foreign percentage of seasonal workers in crop i in 1964 (in percentage points), β_t is the bi-annual indicator variable and γ_i and δ_t are crop and year fixed effects, respectively. The graph plots the Poisson quasi-maximum likelihood estimators of β_t and the 95 percent confidence interval (using robust standard errors) of these coefficients.

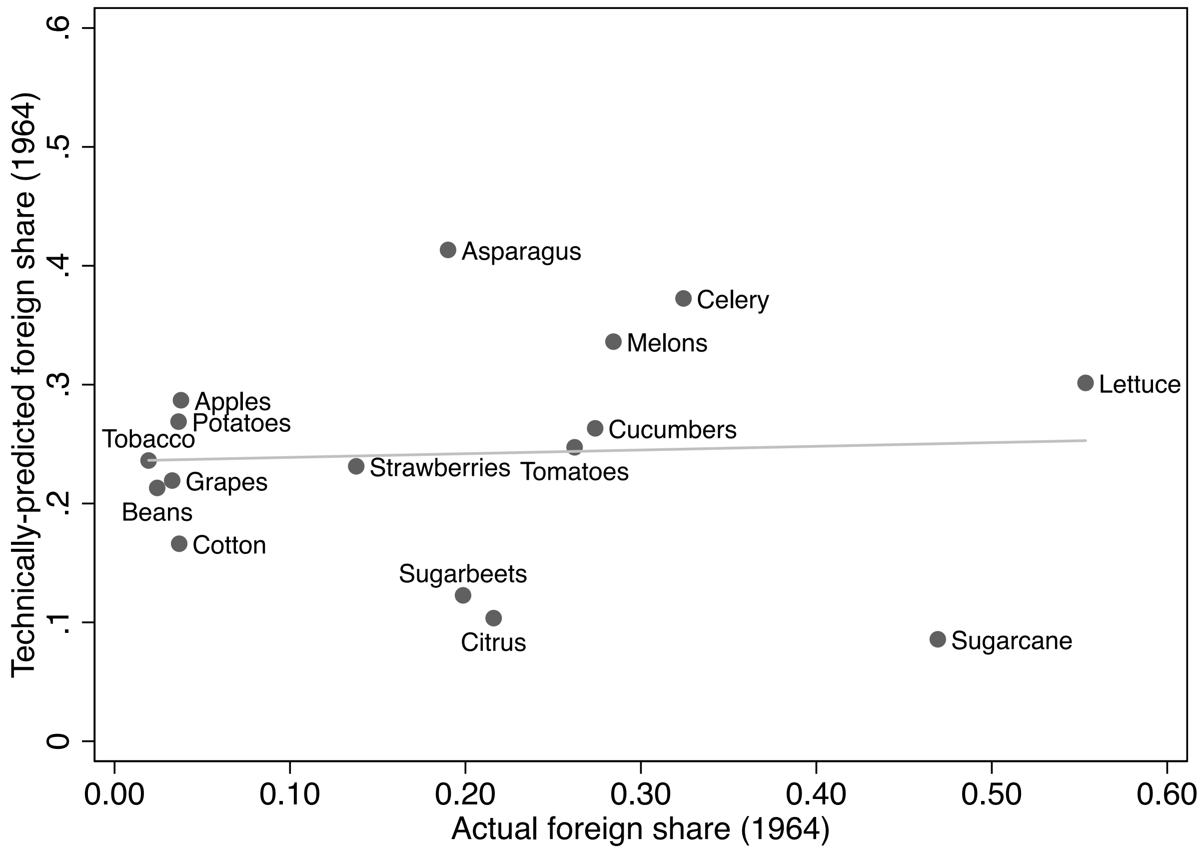

Figure 4: Correlation between Actual and Technically-Predicted Share of Foreign Seasonal Workers in 1964

Notes: This figure show the correlation between the share of foreign seasonal workers in 1964 and the technically-predicted share by crop. The technically-predicted foreign share of a crop i is the weighted average of foreign shares of all other crops, where the weights are a measure of the similarity between the crops, measured by the number of patents in the sample that mentions both crops. The weights are normalized to sum to one. The coefficients (and robust standard errors) of the fitted line are 0.17 (0.13) and 0.10 (0.47) for the intercept and slope, respectively. The Pearson correlation coefficient is 0.06

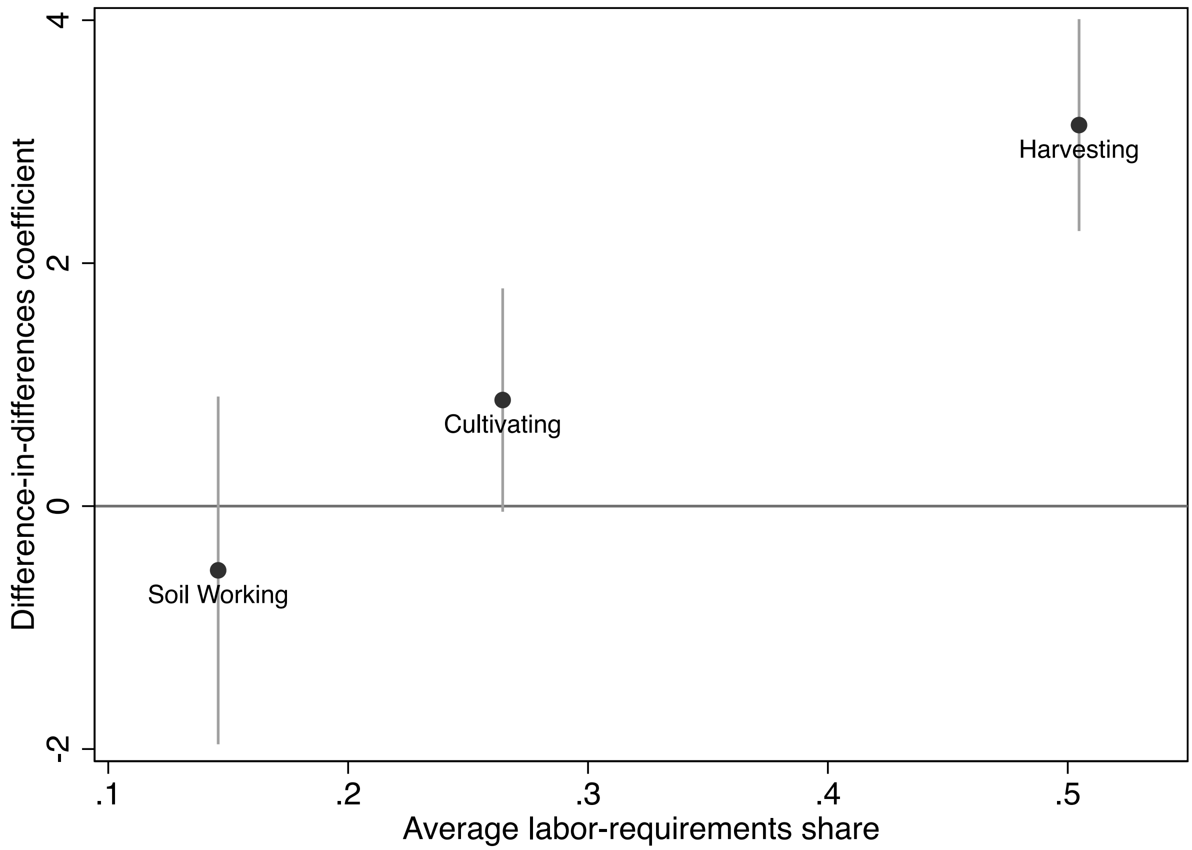

Figure 5: Difference-in-Differences coefficients by Technological Class

Notes: This graph shows the difference-in-differences estimates of the effect of exposure to the Bracero program on innovation (equation 1) for three agricultural CPC patent subclasses separately. The y-axis shows the Poisson quasi-maximum likelihood estimates and their 95 percent confidence interval (using robust standard errors). The x-axis shows the share of labor requirements for the corresponding technological subclass over the total labor requirements of a crop, averaged across the crops.

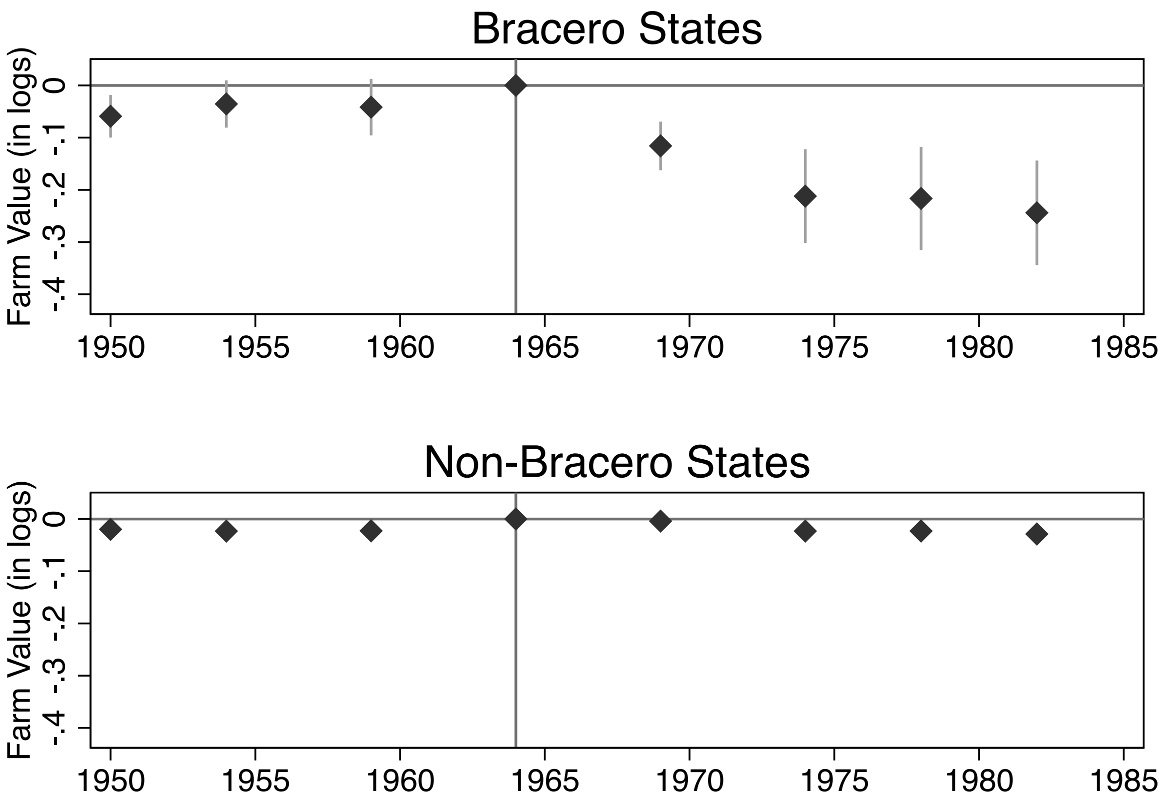

Figure 6: Effects of Bracero Exclusion on Farm Values

Notes: Event study regression with continuous treatment comparing farm values per agricultural-census year in more exposed counties with farm values in less exposed counties: $ln(Value_{ct}) = \sum_{\tau=1950}^{1987} \beta_\tau \cdot \mathbb{I}(t = \tau) \cdot Exposure_c + \gamma_c + \delta_t + \epsilon_{ct}$. $Value_{ct}$ is the value of an acre of agricultural land in county c in census year t. $Exposure_c$ is a measure of the exposure of county c to the Bracero program, calculated by $Exposure_c = \sum_i ForeignSharei \cdot AcreageShare_{ic}$ where $ForeignSharei$ is the foreign percentage of seasonal workers in crop i and $AcreageShare_{ic}$ is the share of crop i in the total acreage of county c in the 1964 census. The exposure is normalized to have a mean of zero and a unit standard deviation. β_t is a census specific indicator variable and γ_c and δ_t are county and year fixed effects, respectively. The graph plots the OLS estimators of β_t and the 95 percent confidence interval of these coefficients. Standard errors are clustered at the county level.