# LABOR SUPPLY AND DIRECTED TECHNICAL CHANGE: EVIDENCE FROM THE ABROGATION OF THE BRACERO PROGRAM IN 1964 *

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**Abstract**

This paper provides causal evidence for the impact of a shift in labor supply on the creation of new technology. To do so, it exploits a large exogenous shock to the labor supply in the US agricultural sector caused by the abrogation of the *bracero* agreements between the United States 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 the policy change was unexpected and undesirable for the 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). Kremer (1993) theorizes how labor abundance could cause the creation of new technologies that would raise the marginal product of labor (MPL), breaking the Malthusian trap. Acemoglu (2010) models how labor abundance could cause different forms of technical advance, with the effect on MPL depending on the type of technology. The applicability of these models 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, Lewis, and Postel 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 abrogation of the *bracero* agreements between the United States and Mexico in 1964. Varying substantially between crops, *bracero* workers accounted for around 11% of the seasonal labor force before the termination of the program. 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 fifteen 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 synthetic exposure of the crops to the *bracero* program, predicted by the exposure of technologically similar crops, and show that the actual exposure to the *bracero* program is not correlated with the synthetic exposure measure. Furthermore, I re-estimated the difference-in-differences regressions controlling for the synthetic 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 complete the analysis of the *bracero* shock by checking whether farm owners gained or lost from it. Using information from the US agricultural census, I show that counties that were more exposed to the shock 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, the results of this section show that the policy change was unexpected and undesirable for farm owners.

As mentioned earlier, the effect of labor scarcity on the invention of new technology is theoretically ambiguous. On the one hand, when a factor such as labor becomes more expensive, the demand for it decreases, and some of the adjustments would take place by technology substituting for that factor (Hicks 1963; Zeira 1998; Acemoglu 2010). On the other hand, a low number of workers of one type reduces the potential market size for new technologies for those workers (Acemoglu 1998, 2010).

To illustrate the two opposite forces, section 2 presents two simple models, with different assumptions about the exact way technology is shaping production. I show that 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, then an increase in labor supply discourages technological progress. Taking together, the sign of the effect is an open theoretical question which 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, Jones, and Jones 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 my 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 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.[1] 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 technology 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 abrogation 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 abrogation 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. My paper complements their findings by offering an explicit mechanism for their results: as the theoretical model in section 2 shows, the positive innovation response to labor scarcity can dampen the wage response.

This article contributes to the literature on the effect of factor supplies on technological progress. Newell, Jaffe, and Stavins (1999) and Popp (2002) demonstrated that increased energy prices redirect 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.

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 (Kerr and Lincoln 2010; Borjas and Doran 2012; Moser, Voena, and Waldinger 2014; Moser and San 2020). In contrast, my paper studies the technological response to limits on low-skilled foreign labor.

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

[1] See also Hayami and Ruttan (1970) and Alesina and Zeira (2006) for similar arguments.

affected only low-skilled workers.[2] Second, I use patents issued in the United States, the technological leader of the time. Thus, these patents should 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.

The remainder of this paper is structured as follows. The next section provides a theoretical framework to motivate this study. Section 3 introduces the historical background of the *bracero* program and its termination, while section 4 describes and summarizes the data. Section 5 presents the main empirical analysis — the effects of the termination of the program on innovation. Section 6 adds another dimension to the analysis — the technology type. Section 7 examines the impact on farm values. Section 8 concludes the paper.

# 2 Theoretical Framework

This section constructs a theoretical framework to capture the opposing effects of labor supply on technological change. I explicitly introduce two types of technologies. The first is labor-augmenting machines that increase the production for every level of labor (Acemoglu 1998). The second type is labor-saving technologies in the spirit of Zeira (1998). I show that an increase in the labor supply encourages the creation of new labor-augmenting technologies, but discourages the creation of new labor-saving technologies. Summing up the effects on the two different types of technology, the overall effect of labor supply on technological progress is theoretically unclear.

## 2.1 Labor-Augmenting Improvements

Following Acemoglu (1998, 2002), the production function of a representative competitive firm is:

$$Y = AL^{\beta} \tag{1}$$

where:

$$A = \int_0^1 q_A(a) x_A(a)^{\alpha} da \quad , \quad q_A(a) \in \{0, 1\} \quad , \quad \alpha, \beta > 0 \quad , \quad \alpha + \beta < 1 \tag{2}$$

The output produced from labor input $L$, assumed to be supplied inelastically, and labor-augmenting machines $\{x_A(a)\}$. The technology level is determined by the set of technologies available, $\{q_A(a)\}$.

Technology products are supplied by technology monopolists. Each monopolist sets a rental price $p_A(a)$ for the technology it supplies to the market. Following Alesina, Battisti, and Zeira

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

(2018), I assume that the invention cost of technology $a$ increases with $a$:

$$K_A(a) = g_A(a) \quad , \quad g'_A(a) > 0 \tag{3}$$

For simplicity, I also assume that the cost function is continuous and satisfies the Inada conditions $g_A(0) \to 0$ and $g_A(1) \to \infty$. After the invention of the machine, the inventor has full rights on that technology. The marginal cost of producing one machine unit is $\psi_A$.

The competitive producer chooses the quantity of machines of each type $\{x_A(a)\}$, and the quantity of the labor input $L$ in order to maximize profits:

$$\max_{\{x_A(a)\},L} \left( \int_0^1 q_A(a) x_A(a)^\alpha da \right) L^\beta - wL - \int_0^1 q_A(a) p_A(a) x_A(a) da \tag{4}$$

where the wage rate $w$, the prices of the machines $\{p_A(a)\}$, and the set of machines available $\{q_A(a)\}$, are given. The price of the final good is normalized to 1. From the first order conditions, the demand for machines is:

$$x_A(a) = \left( \frac{p_A(a)}{\alpha} \right)^{-\frac{1}{1-\alpha}} L^{\frac{\beta}{1-\alpha}} \tag{5}$$

and the demand for labor is:

$$L = w^{-\frac{1}{1-\beta}} (\beta A)^{\frac{1}{1-\beta}} \tag{6}$$

The inventor is confronted by a two-stage problem: (1) whether to enter the market and pay the fixed cost required to develop the new technology; and (2) to choose the optimal monopolistic price. Starting with the second problem, given that the new technology is available, the inventor maximizes gross profits (not including the entry cost):

$$\max_{p_A(a)} \Pi_A(a) = (p_A(a) - \psi_A) \, x_A(a) \tag{7}$$

where the demand function is given in (5). The optimal monopolistic price is:

$$p_A(a) = \frac{\psi_A}{\alpha} \tag{8}$$

and the corresponding gross profits are:

$$\Pi_A = \psi_A \left( \frac{1-\alpha}{\alpha} \right) \left( \frac{\psi_A}{\alpha^2} \right)^{\frac{-1}{1-\alpha}} L^{\frac{\beta}{1-\alpha}} \tag{9}$$

Returning to the inventor's first stage problem: the optimal gross profits are equal across all machine types but the fixed cost is an increasing function of $a$. Appendix B shows that the assumptions above about the entry cost function $g_A(a)$ guarantee the existence of a unique internal threshold $\bar{a} \in (0,1)$, such that the inventor has zero net profits:

$$g_A(\bar{a}) = \Pi_A(L) \tag{10}$$

Notice that an increase in the labor supply, $L$, increases the profits of each technology monopolist, and therefore the technology level, $\bar{a}$:

$$\frac{\partial \bar{a}}{\partial L} > 0 \tag{11}$$

This is a pure Acemoglu (1998)'s market size effect: a larger market for the technology, namely more workers who use it, leads to more innovation.

## 2.2 Labor-Saving Improvements

What happens when technology, rather than augmenting the production of each unit of labor, replaces human labor? In this section, I present a simple model with labor-saving technology progress in the spirit of Zeira (1998). The producer's technology is now:

$$Y = A \int_0^1 \left(e(l) + q_L(l) x_L(l)\right)^{\beta} dl \tag{12}$$

where $\beta \in (0,1)$ and $q_L(l) \in \{0,1\}$.[3] Each task, $l$, can be done by manual labor $e(l)$. If a machine of this type exists, i.e., $q_L(l) = 1$, the task can also be done by labor-replacing machine $x_L(l)$. Manual labor, $L$, is again assumed to be supplied inelastically. The cost of inventing technology $l$ is:

$$K_L(l) = g_L(l) \quad , \quad g_L'(l) > 0, \tag{13}$$

where $g_L(l)$ is continuous and satisfies the Inada conditions $g_L(0) \to 0$ and $g_L(1) \to \infty$. The marginal cost of producing one machine unit is $\psi_L$. The producer chooses the quantity of machines of each type $\{x_L(l)\}$, and the quantity labor for each task $\{e(l)\}$ to maximize profits:

$$\begin{aligned} \max_{\{x_L(l)\},\{e(l)\}} & A\left[\int_0^1 q_L(l) x_L(l)^{\beta} dl + \int_0^1 e(l)^{\beta} dl\right] \\ & - \int_0^1 p_L(l) x_L(l) dl - w \int_0^1 e(l) dl \end{aligned} \tag{14}$$

where the uniform wage rate $w$, the prices of the machines $\{p_L(l)\}$, and the set of machines available $\{q_L(l)\}$, are given. Because of the perfect substitution between manual labor and machines, if a

[3] Qualitative similar results obtained when $A = \int_0^1 q_A(a) x_A(a)^{\alpha} da, \alpha + \beta < 1$, and $q_A(a) \in \{0,1\}$ is given exogenously. For simplicity, I show the results of a model with a fixed $A$.

machine of type $l$ is available, the producer will use only the cheaper factor. Moreover, if in equilibrium no one buys the machine, the machine will not be invented as it is costly to invent it. For simplicity, I assume that if the producer is indifferent between hiring manual labor or machines, she will choose to employ only machines. Taking together, there is a threshold $\bar{l}$ such that tasks $l \leq \bar{l}$ are produced by machines, and tasks $l > \bar{l}$ are produced by labor. From the first order conditions, the demand for machines is:

$$x_L(l) = p_L(l)^{-\frac{1}{1-\beta}} (\beta A)^{\frac{1}{1-\beta}}, \tag{15}$$

and the demand for labor is:

$$e(l) = w^{-\frac{1}{1-\beta}} (\beta A)^{\frac{1}{1-\beta}}. \tag{16}$$

Given that a machine $l$ exists, the monopolist inventor sets the price to maximize gross profits:

$$\max_{p_L(l)} (p_L(l) - \psi_L)\, x_L(l). \tag{17}$$

Without further restrictions, the price that maximizes gross profits is $\frac{\psi_L}{\beta}$. However, because machines and labor are perfect substitutes, the inventor cannot charge a price higher than the wage rate. Therefore, the monopolistic price is:

$$p_L(l) = min(\frac{\psi_L}{\beta}, w). \tag{18}$$

In what follows, I focus on the case where $\psi_L \leq w \leq \frac{\psi_L}{\beta}$ and $p_L(l) = w$.[4] The technological level $\bar{l}$ is determined such that the marginal inventor has zero net profits:

$$g_L(\bar{l}) = \Pi_L = (w - \psi_L) \cdot (\beta A)^{\frac{1}{1-\beta}} w^{-\frac{1}{1-\beta}}. \tag{19}$$

An increase in the wage rate increases the maximal price the inventors can charge for the machines, and because this price is bellow the optimal unrestricted price, $w < \frac{\psi_L}{\beta}$, this increases the profits of all inventors, hence the technology level.

To establish a link between the wage rate and the labor supply, note that as wages are uniform across the different tasks, it is optimal to have the same amount of workers in each non-automated

[4] See Appendix B for the exact parametric conditions for this solution. When labor supply is very high, wages are low, so the marginal cost of producing each machine is higher than its potential price, which is bound above by the wage rate; therefore, no technology is invented. On the other hand, when labor supply is very low, the optimal monopolistic price of the machines is lower than the wage rate. In this range, the gross profits of the inventors, hence the technological level, are constant and do not react to shifts in the labor supply. My focus in the text is on the range where shifts in labor supply impact the technology.

task. Therefore, the labor in each non-automated task is $\frac{L}{1-\bar{l}}$ and the wage rate is:

$$w = \beta A \left( \frac{L}{1-\bar{l}} \right)^{\beta - 1}. \tag{20}$$

In Appendix B, I formally show that an exogenous increase in the labor supply decreases the wage rate and therefore decreases the technology level, $\bar{l}$:

$$\frac{\partial \bar{l}}{\partial L} < 0. \tag{21}$$

This is the Hicks (1963)'s substitution effect. When the labor supply is higher, wages are lower; therefore the potential saving from each new machine is lower. In this case, fewer labor-saving technologies will be developed.

## 2.3 Comparing the two models

Comparing the two models presented above, the theoretical prediction for the impact of labor supply on technological progress depends on the exact way we assume technology is shaping production. 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, then an increase in labor supply discourages technological progress. Taking together, the sign of the effect is an open theoretical question which 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 and classify it accordingly. 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 class. On the other hand, a new fertilizer, that increases the production for a given amount of land and labor, aligns with the labor-augmenting technology class.[5] Using that classification of technologies, the theory suggests different effects for a change in labor supply on the two classes of inventions. Section 6 will further explore this.

[5] In a recent paper, Acemoglu and Restrepo (2018) models the invention of new tasks, beside Zeira (1998)'s style labor-saving inventions. Note, however, that new task inventions in their model are similar to labor-augmenting inventions, as they effectively increase the productivity of manual labor. More precisely, the invention of a new task is equivalent to a positive labor-augmenting shock and a negative labor-saving shock, as the share of automated tasks decreases. One can think about the invention of new tasks as an example of labor-augmenting technology improvements.

# 3 Historical Background

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 (Craig 1971).

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 (Craig 1971; Clemens et al. 2018).[6]

The principal policy goal of excluding *braceros* was to improve labor-market conditions for US farm-workers by reducing the size of the workforce (Clemens et al. 2018).

# 4 Data

In this section, I describe the construction of each main data set. 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 information on labor intensity by crop and technological type to examine the differential effects across different types of technology. Finally, I use data on farm values from the census of agriculture to examine the impact of the program on the farmers (section 7).

## 4.1 Data on the Treatment: Share of Foreign Seasonal Labor

Exact data on Mexican seasonal 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

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

were Mexican (Secretary of Labor 1966, Tables 1 and 3). Hence, in this paper, I use the number of seasonal foreign workers in each crop as a proxy for the number of Mexican workers.

The primary measure of exposure is the share of foreign seasonal workers in the total seasonal employment for each crop in 1964 (Secretary of Labor 1966, Table 5). 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.[7] The sample for the primary analysis consists of sixteen 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 A3).

[Table 1 about here]

## 4.2 Data on the Outcome: US Patents 1948-1985

My first measure of technology innovation is the number of 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.[8] I determined the invention's date by the application date of the patent.[9]

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

[7] For robustness, I also use the share of foreign workers in the total seasonal employment at the date of peak foreign employment from (Secretary of Labor 1966, Table 21).

[8] 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 A4).

[9] 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.

### 4.3 Additional Data: US acreage, production and value

I collected data on the acreage harvested, production, and crop value for the period 1948-1985 (see Appendix C for details). Price is the ratio between value and production, and yield is the ratio between production and acreage (Table A1).

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 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).

[Figure 1 about here]

## 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 my main results. The relative number of patents for crops with low exposure to the *bracero* program reveals no change before and after 1965.[10] 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 initial finding more rigorously.

[Figure 2 about here]

The dependent variables, citations-weighted or unweighted patents counts by crop and year, are skewed and nonnegative. For example, 26% of the crop/year observations in the data correspond to years of no patent output; the figure climbs to 73.7% 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, Hall, and Griliches (1984). This estimator is fully robust to distributional misspecification, and it also maintains certain efficiency properties even when the distribution is not Poisson (Wooldridge 2010). 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

[10] To account for the scale differences between crops, I calculated the annual number of patents by crop and year relative to the 1948-1985 average of that crop.

2016), and hence immune to the issues highlighted by Bertrand, Duflo, and Mullainathan (2004) concerning inference in difference-in-differences estimation (Azoulay, Graff Zivin, and Wang 2010).

The years of analysis for most of the specifications are 1948-1985.[11] 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[12]

## 5.1 Baseline Specification

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

$$ln\left[\mathbb{E}(y_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \gamma_i + \delta_t \quad (22)$$

where $y_{it}$ is a measure of innovation output at crop $i$ at year $t$, $\%Foreign_i$ 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 $\gamma_i$'s correspond to crop fixed effects, the $\delta_t$'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 sixteen crops' patent count. I find a significant increase in the yearly number of patents produced after 1965 in crops that were more exposed to the *bracero* program. An increase of one percentage point 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 4.2 annual patents in the average crop in 1948-1985, an increase of one standard deviation in the labor-supply shock adds about seven patents per year.

[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: An increase of one percentage point in the exposure to the shock 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

[11] The results are robust to the choice of the start and end years (Table A6.

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

set of indicator variables corresponding to a particular calendar year, and then graphing the effects and the 95% confidence interval around them.[13]

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, I find 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 off-the-shelf 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 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. After 1964, American inventors produced 92 percent additional technological patents in high exposed crops relative to low-exposed crops. Using the quality-adjusted measure of invention, the estimated effect is a 60 percent increase in invention (Table A3, 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 the use of a 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 A3, 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 A3, columns 7-8).

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

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 A4).

The next set of robustness checks alternate the crops included in the analysis. Restricted by the availability of the data, 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 amount of acreage in the 1964 agricultural census.[14] 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, there is information on the foreign share of the category "Hay and Grain." For this analysis, I assumed that each of the ten field crops has the common foreign share of 1.2 percent. Columns 3-4 of Table A5 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 sixteen crops, although a bit smaller. The effect of an increase in one percentage point in the exposure to the *bracero* exclusion is 2.8 percent for a simple patents-count invention measure and 1.5 percent for the quality-adjusted measure.

I also extended the sample using data from the California agricultural sector. Data on the share of foreign workers in 1962 in Californian is available for ten additional crops.[15] columns 5-6 of Table A5 report the results for a sample containing the sixteen 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 A5 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 A6 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 report the results of a Negative

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

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

Binomial model. The estimators are positive with similar magnitude (effect of 2.2 and 2.0 percent for patents and citations counts, respectively). The estimator is marginally significant for the patents measure (p-value of 0.050) and significant at five percent for the citations measure. Next, I estimated a zero-inflated Poisson regression. This model assumes that the outcome variable was generated by two different processes. 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). 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 (not statistically significant). Using the quality-adjusted inventions measure, the estimated effect is an increase of 2.0 percent, similar to the baseline estimate (significant at five percent).

As I discussed earlier the data show no evidence for pre-treatment trends. To further address 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 (Table A8, columns 3-4, at five percent).

## 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 share of Mexican workers is correlated with factors that for unrelated reasons generate unparalleled trends in innovation activity. For example, if 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, then 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 A9 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 of a crop 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.[16]

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 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 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.[17] The model takes the form:

$$y_{it} = exp\left[\beta \cdot \%Foreign_i \cdot post_t + \gamma_i + \delta_t\right] \cdot \epsilon_{it} \tag{23}$$

where $\epsilon_{it}$ is a unit-mean error term. The treatment variable $\%Foreign_i \cdot post_t$ 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. In the first and fourth columns, the instrument used is the average distance from Mexico. The estimates for the effect of a one percentage point increase in the exposure 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

[16] The exclusion restriction does not require that the cross-sectional variation of the instruments do 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.

[17] 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.

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 Synthetic Exposure using a Technology-Based Similarity Matrix

An additional problem 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.

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 synthetic-exposure measure which is the predicted exposure according to the exposure of crops that are similar to the original crop regarding technical properties. The synthetic 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, it means that 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 A10 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 synthetic exposure as follows:

$$\%Foreign_i^{syn} = \sum_{i' \neq i} w_{i,i'} \%Foreign_{i'} \tag{24}$$

where $\%Foreign_{i'}$ is the foreign seasonal workers shares of crop $i'$. The data show no correlation between the actual foreign shares and the synthetic 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 synthetic 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:

$$ln\left[\mathbb{E}(patents_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \alpha \cdot \%Foreign_i^{syn} \cdot post_t + \gamma_i + \delta_t \quad (25)$$

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. In practice, however, this task is not easy to perform, the more so through an automatic algorithm. Consider for example a patent for "Grape Harvester" 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 greater that task's labor intensity. To conduct this, I used the technological classification of the patents together with data on task labor-requirements.

To construct the labor-intensity measures, I collected data on labor-requirements by task and crop in California in 1960 from the State of California's "Report and Recommendations of the Agricultural Labor Commission" (State of California 1963). This data includes information on person-hours and labor cost per acre for the various tasks of the production process for California's twenty-five most valuable crops in 1960. Then I manually classified each task into one of the seven agricultural CPC sub-classes (Table A11). For example, the production of tomatoes in 1960 required 12.5 person–hours of "thinning" per acre, at a cost of 13.12 dollars. I classified this task into CPC sub-class A01B ("Soil Working In Agriculture") which contains the group "thinning machines" (A01B 41). Among the 25 crops included in this data set, 18 have information on the exposure to the *bracero* program.

For each class-crop pair, I calculated the share of labor requirements for this technological class 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 seven sub-classes, 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 14 percent, 50 percent, and 27 percent, respectively (Table A11). 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 regression:

$$ln\left[\mathbb{E}(patents_{ijt}|X_{ijt})\right] = \beta \cdot \%Foreign_i \cdot Intensity_{ij} \cdot post_t + \gamma_{ij} + \delta_{it} + \epsilon_{jt} \tag{26}$$

where $y_{ijt}$ is the number of US patents/citations in crop $i$, technological class $j$, and year $t$. $\%Foreign_i$ 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. $\gamma_{ij}$, $\delta_{it}$, and $\epsilon_{jt}$ are crop-task, crop-year, and task-year fixed effects, respectively.

The Poisson quasi-maximum likelihood estimates of equation 26 imply a substantial higher effect of bracero exclusion after 1964 in the more labor-intensive tasks relative to the less labor-intensive tasks. I used three different measures for the labor intensity of technological classes. The first measure is the percentage of person-hours required for tasks in class $j$ over the total person-hours required for producing crop $i$. Triple-difference estimates indicate that the effect of one percentage point in the exposure to the *bracero* program on patents after 1965 is 3.2 percent higher in labor-intensive technological classes compared with technological classes without any labor requirements (Table 5, column 1, significant at one percent). The effect is slightly smaller, 2.2 percent, when using the citations measure of invention (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 be only performed by higher-skilled workers, and therefore 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, the results are virtually the same as the results of the first measure. The estimates for $\beta$ are now 3.1 and 2.1 percent, respectively (5, columns 3-4).

The first two labor-intensity measures require exact information about the labor requirements of each task and crop. This data is available only for eighteen out of twenty-six 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 26 with all twenty-six crops.[18] The results of the triple-difference effect are now slightly smaller, 2.5 and 1.8 percent, respectively (Table 5, columns 5-6).

Overall, these results indicate that the effect of labor scarcity on technological progress is greater in 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 for the intensity of the shock. The additional dimension allows adding of fixed effects for year-crop and year-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, we can interpret the results as an additional robustness check for the effect of labor supply on technical innovation.

# 7 The Winners and the Losers: The Impact on Farm Value

This section investigates the winners and losers from the abrogation of the *bracero* program. In a recent study, Clemens et al. (2018) show that US workers did not gain from the exclusion of the *bracero* workers. Although the abrogation aimed to increase the wages and the employment rate of local US workers, both employment and wages were not affected.

An unanswered question is whether the farmers won or lost from the policy change. To investigate this, I used the land value as a measure of the welfare of the farmers. 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.

I used 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

[18] These crops include the sixteen 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 sixteen original crops (estimates of 2.7 and 1.7 percent, respectively, significant at five percent).

crop, I constructed a measure of the exposure of a county $c$ to the *bracero* program in the following way:

$$Exposure_c = \sum_i \%Foreign_i \cdot \%Acreage_{ic} \tag{27}$$

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

$$ln(Value_{ct}) = \sum_{\tau=1950}^{1982} \beta_\tau \cdot \mathbb{I}(t = \tau) \cdot Exposure_c + \gamma_c + \delta_t + \epsilon_{ct} \tag{28}$$

where $\gamma_c$ and $\delta_t$ are county and year fixed effects, respectively. I ran separate regressions for *bracero* and non-*bracero* states.[19] Figure 5 shows a permanent decrease in farm values of counties that are relatively more exposed to the shock. These results are true only for states that participated in the *bracero* program.

[Figure 5 about here]

Two aspects of this result are noteworthy. First, the results support the assumption that the shock was unexpected. If the termination of the *bracero* program was expected before 1964, one should not see this decline in the farm values. Second, farmers who employed *bracero* workers were adversely affected by the termination of the program. This fact comports with historical documentation about farmers' opposition to the program's abrogation.

# 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 the development of new technologies that supported the production of crops that were affected by the labor-supply shock. Moreover, I showed that there were more inventions related to tasks that required intensive labor-input, probably because those innovations tend to be more labor-saving.

The abrogation 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, help to capture this type of technological progress.

[19] 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.

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 text of the patent 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. Needless to say, the importance of this industry in economic development and economic history. However, 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). Thus, the findings 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 |
|---|---|---|---|---|---|
| Lettuce | 25 | 9 | 16 | 1.8 | 55.3 |
| Sugarcane | 155 | 38 | 117 | 3.1 | 46.9 |
| Celery | 20 | 8 | 12 | 1.5 | 32.4 |
| Melons | 19 | 6 | 13 | 2.2 | 28.4 |
| Cucumbers | 39 | 11 | 28 | 2.5 | 27.4 |
| Tomatoes | 120 | 26 | 94 | 3.6 | 26.2 |
| Citrus | 134 | 23 | 111 | 4.8 | 21.6 |
| Sugarbeets | 117 | 63 | 54 | 0.9 | 19.9 |
| Asparagus | 51 | 12 | 39 | 3.3 | 19.0 |
| Strawberries | 37 | 12 | 25 | 2.1 | 13.8 |
| Apples | 140 | 65 | 75 | 1.2 | 3.8 |
| Cotton | 777 | 498 | 279 | 0.6 | 3.7 |
| Potatoes | 213 | 139 | 74 | 0.5 | 3.6 |
| Grapes | 152 | 16 | 136 | 8.5 | 3.3 |
| Beans | 358 | 147 | 211 | 1.4 | 2.4 |
| Tobacco | 206 | 76 | 130 | 1.7 | 1.9 |
| Sum/Median | 2563 | 1149 | 1414 | 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 first four columns and the median for the last column.

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

| | (1)<br>patents | (2)<br>citations |
|---|---|---|
| Foreign percentage × post | 0.033***<br>(0.013) | 0.023***<br>(0.008) |
| Average response | 2.17 | 8.91 |
| N (crops × years) | 608 | 608 |
| 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 |

*Notes:* Difference-in-differences regressions with continuous treatment compare changes in patenting per year in more exposed crops with changes in less exposed crops: $ln\left[\mathbb{E}(patents_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \gamma_i + \delta_t$ where $y_{it}$ is the number of US patents/citations in crop $i$ and year $t$, $\%Foreign_i$ is the foreign percentage of seasonal workers in crop $i$ in 1964, $post_t$ indicates years after 1964, and $\gamma_i$ and $\delta_t$ 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. Standard errors are clustered at the crop level.

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

| | Patents | | | Citations | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Foreign percentage × post | 0.049*** | 0.030* | 0.045*** | 0.053*** | 0.043** | 0.050*** |
| | (0.016) | (0.016) | (0.015) | (0.016) | (0.017) | (0.015) |
| Instruments | Distance | Population | Both | Distance | Population | Both |
| N (crops × years) | 608 | 608 | 608 | 608 | 608 | 608 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Difference-in-differences regressions with instrumental variables: $y_{it} = exp[\beta \cdot \%Foreign_i \cdot post_t + \gamma_i + \delta_t] \cdot \epsilon_{it}$ where $\epsilon_{it}$ is a unit-mean error term. The treatment variable $\%Foreign_i \cdot post_t$ 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 parenthesis.

**Table 4:** Effects of *Bracero* Exclusion on Invention: Continuous Difference in Differences with Synthetic Treatment

| | (1)<br>Patents | (2)<br>Citations |
|---|---|---|
| Foreign percentage × post | 0.036*** | 0.025*** |
| | (0.012) | (0.009) |
| Synthetic Foreign percentage × post | 0.024 | 0.014 |
| | (0.026) | (0.018) |
| N (crops × years) | 608 | 608 |
| Mean patents/citations before 1965 | 4.06 | 23.90 |
| Year FE | Yes | Yes |
| Crop FE | Yes | Yes |

*Notes:* Poisson quasi-maximum likelihood estimators of Difference-in-differences model with continuous treatment and "synthetic" continuous treatment: $ln\left[\mathbb{E}(patents_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \alpha \cdot \%Foreign_i^{syn} \cdot post_t + \gamma_i + \delta_t$. A "synthetic" 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. All specifications include crop and year fixed effects. Standard errors are clustered at the crop level.

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

| | (1) Patents | (2) Citations | (3) Patents | (4) Citations | (5) Patents | (6) Citations |
|---|---|---|---|---|---|---|
| Foreign percentage × labor-class × post | 0.032*** | 0.022** | | | | |
| | (0.012) | (0.010) | | | | |
| Foreign percentage × cost-class × post | | | 0.031*** | 0.021** | | |
| | | | (0.011) | (0.009) | | |
| Foreign percentage × class × post | | | | | 0.025** | 0.018** |
| | | | | | (0.010) | (0.007) |
| N (crops × classes × years) | 1,447 | 1,447 | 1,447 | 1,447 | 2,096 | 2,096 |
| 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 |

*Notes:* Triple-differences regressions with continuous treatment comparing the effect of *bracero* exclusion on patenting in labor-intensive tasks with the effect in less labor-intensive tasks: $ln\left[\mathbb{E}(patents_{ijt}|X_{ijt})\right] = \beta \cdot \%Foreign_i \cdot Intensity_{ij} \cdot post_t + \gamma_{ij} + \delta_{it} + \epsilon_{jt}$. $y_{ijt}$ is the number of US patents/citations in crop $i$, technological class $j$, and year $t$. $\%Foreign_i$ 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. $\gamma_{ij}$, $\delta_{it}$, and $\epsilon_{jt}$are crop-task, crop-year, and task-year fixed effects, respectively. The table reports the Poisson quasi-maximum likelihood estimators of $\beta$. 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. Standard errors are clustered at the crop-class level.

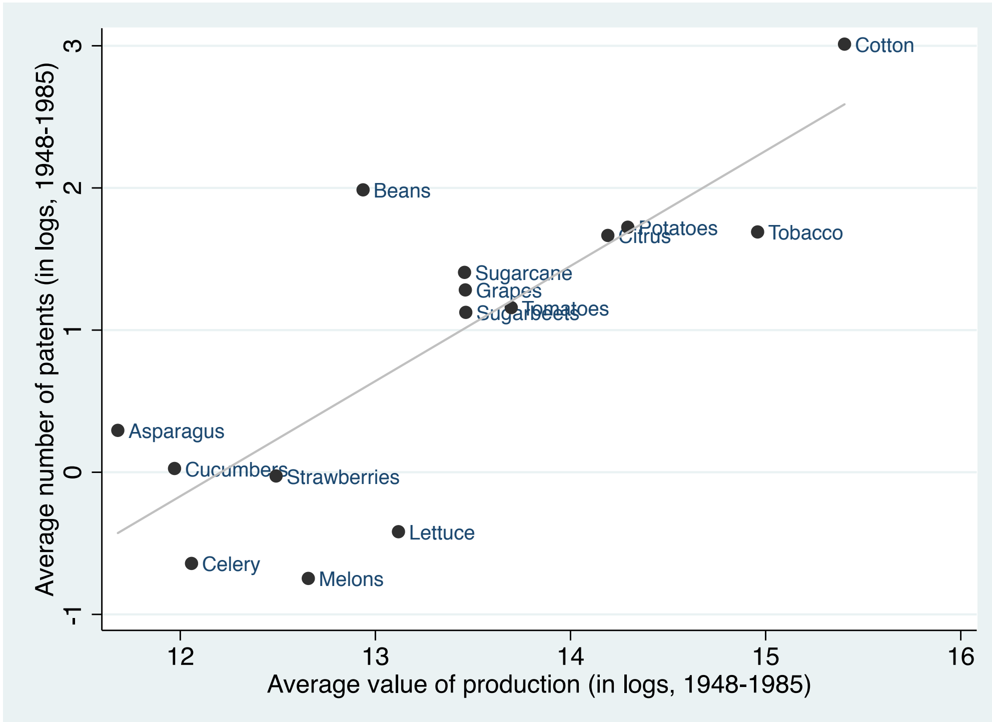


**Figure 1:** Correlation between Invention and Market Values

*Notes:* This figure shows the correlation between the number of patents related to a crop and the crop's market value. Number of US patents related to harvesting technologies. The text-search algorithm for allocating patents to crops is described in the text. Average value of production in 1980 dollars. Data in market values exist for all crops in the sample except apples.

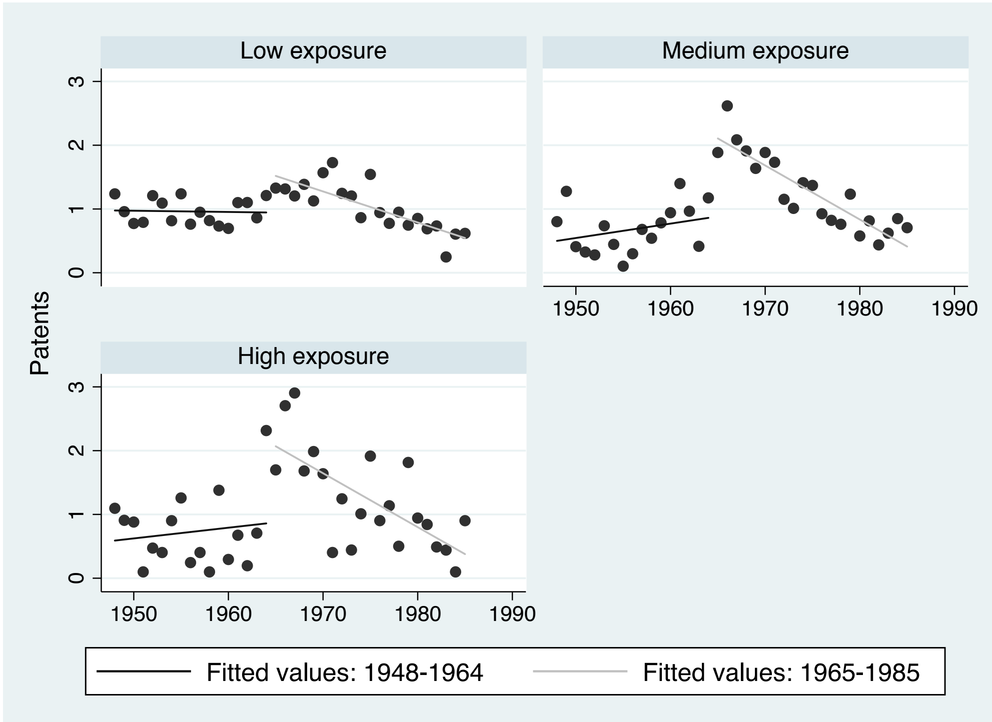


**Figure 2:** Invention over Time for Crops with Low, Medium and High Exposure to the *Bracero* Program

*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 patents measure is the average normalized number of patents for the crops in the exposure group, where each crop-year observation is normalized by the crop's 1948-1985 average.

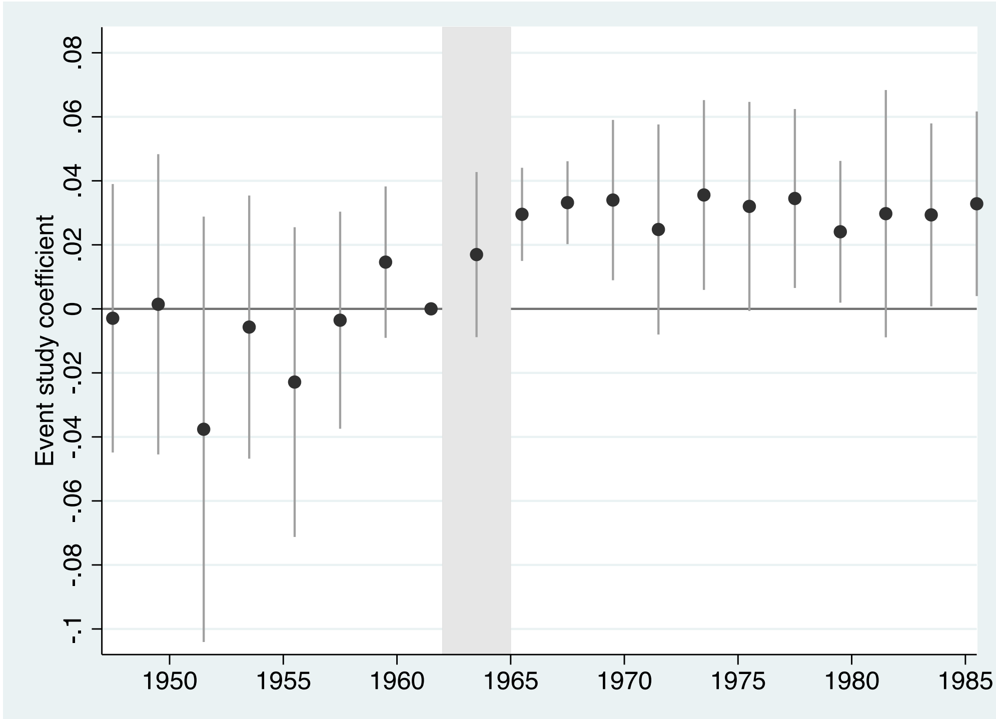


**Figure 3:** Effects of *Bracero* Exclusion on Invention: Event Study

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

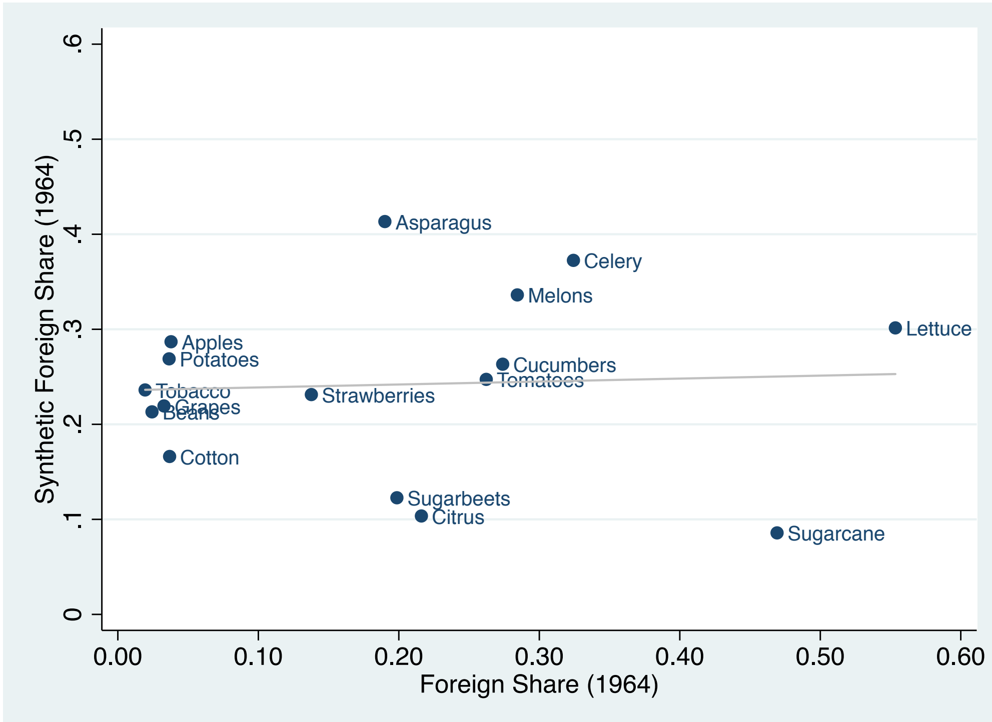


**Figure 4:** Correlation between Actual and Synthetic Share of Foreign Seasonal Workers in 1964

*Notes:* This figure show the correlation between the share of foreign seasonal workers in 1964 and the synthetic share by crop. A "synthetic" 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.

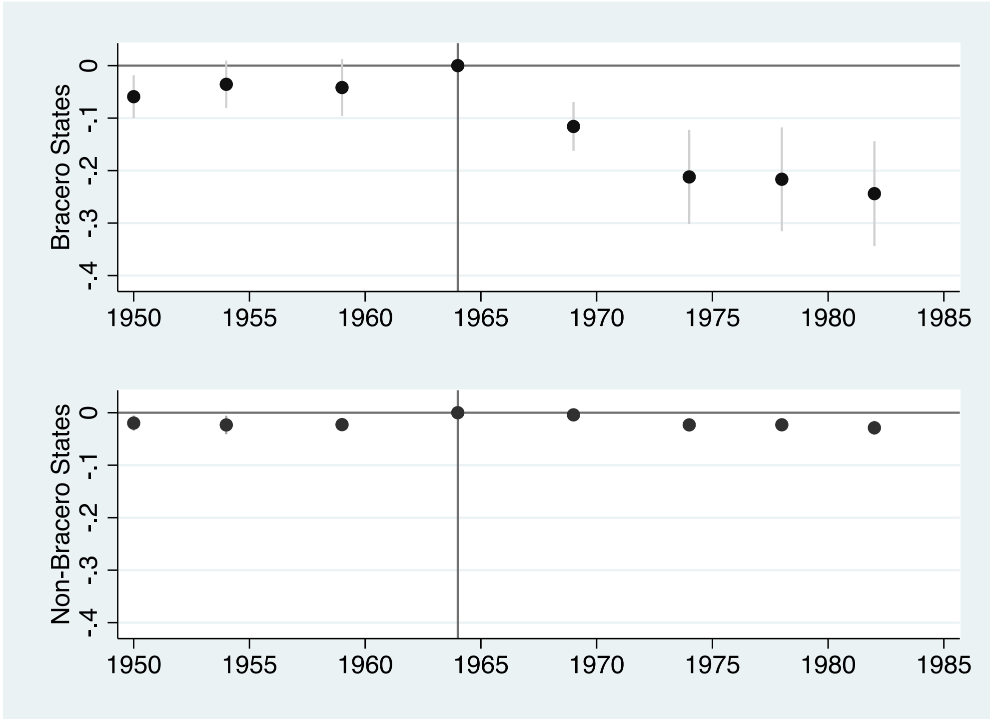


**Figure 5:** Effects of *Bracero* Exclusion on Farm Values

*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 $Exposure_c = \sum_i \%Foreign_i \cdot \%Acreage_{ic}$ where $\%Foreign_i$ is the foreign percentage of seasonal workers in crop $i$ and $\%Acreage_{ic}$ 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. $\beta_t$ is a census specific indicator variable and $\gamma_c$ and $\delta_t$ are county and year fixed effects, respectively. The graph plots the OLS estimators of $\beta_t$ and the 95 percent confidence interval of these coefficients. Standard errors are clustered at the county level.

# Appendices (for online publication)

## A Appendix Tables and Figures

**Table A1:** Timeline of Events

| Date | Event |
|---|---|
| August 1942 | Wartime program started |
| January 1948 | Postwar era: braceros contracted directly with US employers |
| August 1951 | Congress approved Public Law 78, which served as the statutory basis for the program until its end |
| March 1962 | US government required farmers to offer braceros at least the statewide average wage |
| December 1964 | Termination of the program |

*Notes:* The table is based on Craig (1971).

**Table A1:** Summary Statistics for Crops in the Sample, United States, 1948-1985.

| Crop | total labor | domestic labor | foreign labor | foreign percentage | acreage | production | value |
|---|---|---|---|---|---|---|---|
| Lettuce | 122,500 | 54,600 | 67,800 | 55.3 | 220,351 | 44,483 | 498,007 |
| Sugarcane | 105,700 | 56,100 | 49,600 | 46.9 | 588,511 | 491,619 | 698,747 |
| Celery | 44,400 | 30,000 | 14,400 | 32.4 | 34,434 | 15,389 | 172,452 |
| Melons | 64,700 | 46,300 | 18,400 | 28.4 | 426,346 | 41,421 | 313,727 |
| Cucumbers | 105,500 | 76,600 | 28,900 | 27.4 | 178,723 | 14,914 | 158,070 |
| Tomatoes | 345,100 | 254,600 | 90,500 | 26.2 | 474,035 | 131,244 | 887,708 |
| Citrus | 319,800 | 250,800 | 69,100 | 21.6 | . | 225,213 | 1,456,449 |
| Sugarbeets | 160,600 | 128,700 | 31,900 | 19.9 | 1,093,495 | 442,956 | 703,143 |
| Asparagus | 60,500 | 49,000 | 11,500 | 19.0 | 122,811 | 2,936 | 118,202 |
| Strawberries | 308,500 | 266,100 | 42,500 | 13.8 | 72,702 | 5,551 | 265,991 |
| Apples | 132,000 | 127,000 | 5,000 | 3.8 | . | . | . |
| Cotton | 1,769,400 | 1,704,200 | 65,200 | 3.7 | 14,420,034 | 61,122 | 4,898,662 |
| Potatoes | 246,600 | 237,700 | 9,000 | 3.6 | 1,422,176 | 292,770 | 1,613,069 |
| Grapes | 179,600 | 173,700 | 5,900 | 3.3 | 592,258 | 82,798 | 701,520 |
| Beans | 263,100 | 256,700 | 6,400 | 2.4 | 1,481,324 | 18,670 | 415,374 |
| Tobacco | 767,200 | 752,300 | 14,900 | 1.9 | 1,124,646 | 19,458 | 3,137,989 |

**Notes:** Seasonal hired labor, by crop and origin of worker, United States, 1964 and average acreage, production and value by crop, United States, 1948-1985. Data from Farm Labor Developments and USDA annual statistical bulletins (see Appendix C for details). Seasonal labor in person-months, acreage in acres, production in 1000 Cwt (100,000 pounds), and value of production in 1980 dollars. Crops listed in descending order of foreign seasonal hired labor relative to the total.

**Table A3:** Effects of *Bracero* Exclusion on Agricultural Invention, Robustness to the text-search algorithm

| | Baseline | | Binary | | Peak season | | Post=1962 | |
|---|---|---|---|---|---|---|---|---|
| | (1) patents | (2) citations | (3) patents | (4) citations | (5) patents | (6) citations | (7) patents | (8) citations |
| Foreign percentage × post65 | 0.033*** | 0.023*** | | | | | | |
| | (0.013) | (0.008) | | | | | | |
| Binary exposure × post65 | | | 0.925** | 0.603** | | | | |
| | | | (0.388) | (0.293) | | | | |
| Peak season × post65 | | | | | 0.027*** | 0.018*** | | |
| | | | | | (0.009) | (0.006) | | |
| Foreign percentage × post62 | | | | | | | 0.033** | 0.025*** |
| | | | | | | | (0.013) | (0.008) |
| N (crops × years) | 608 | 608 | 608 | 608 | 608 | 608 | 608 | 608 |
| Mean patents/citations before 1965 | 4.06 | 23.90 | 4.06 | 23.90 | 4.06 | 23.90 | 4.06 | 23.90 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table checks the sensitivity of the results to the definition of the treatment. The first two columns repeat the baseline specification, where the continuous treatment is the percentage of foreign workers out of the total seasonal employment and the "post" year is 1965, the first year after the abrogation of the *bracero* program. The next two columns use a binary treatment: crop is in the treatment group if the foreign percentage is above the median. In columns (5) and (6) the treatment is defined according to the foreign percentage at the date of peak foreign employment of each crop. The last two columns use the baseline continuous measure of the crop' exposure to the *bracero* exclusion, but change the "post" year to be 1962, when the US administration started to restrict the program. All specifications include crop and year fixed effects. Standard errors are clustered at the level of crops.

**Table A4:** Effects of *Bracero* Exclusion on Agricultural Invention, Robustness to the Text-search Algorithm

| | First crop | | Maximal crop | | All crops | | Equal weights | | Proportional weights | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) patents | (2) citations | (3) patents | (4) citations | (5) patents | (6) citations | (7) patents | (8) citations | (9) patents | (10) citations |
| Foreign percentage × post | 0.033*** | 0.023*** | 0.032*** | 0.022** | 0.030** | 0.022** | 0.030** | 0.021** | 0.032*** | 0.022** |
| | (0.013) | (0.008) | (0.012) | (0.009) | (0.012) | (0.009) | (0.012) | (0.009) | (0.012) | (0.009) |
| N (crops × years) | 608 | 608 | 608 | 608 | 608 | 608 | 608 | 608 | 608 | 608 |
| Mean patents/citations before 1965 | 4.06 | 23.90 | 4.06 | 23.90 | 4.37 | 26.74 | 4.06 | 23.90 | 4.06 | 23.90 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table checks the sensitivity of the results to how the text-search algorithm allocates patents to crops. The first two columns repeat the baseline algorithm, where the patent is allocated to the first crop mentioned in the text of the patent. The next two columns allocate the patent to the crop with the maximum mentions in the text. Columns (5) and (6) assign one patent to each one of the crops mentioned in the text. Columns (7) and (8) assign equal weights to each one of the crops mentioned such that the sum of the weights is one. Finally, the last two columns assign weights proportional to the number of times each crop is mentioned. All specifications include crop and year fixed effects. Standard errors are clustered at the level of the crop.

**Table A5:** Effects of *Bracero* Exclusion on Agricultural Invention, Robustness to the Sample of Crops

| | Baseline crops | | Baseline + Field | | Baseline + California | | All crops | |
|---|---|---|---|---|---|---|---|---|
| | (1) patents | (2) citations | (3) patents | (4) citations | (5) patents | (6) citations | (7) patents | (8) citations |
| Foreign percentage × post | 0.033*** | 0.023*** | 0.028*** | 0.015** | 0.031*** | 0.023*** | 0.028*** | 0.015*** |
| | (0.013) | (0.008) | (0.009) | (0.006) | (0.011) | (0.007) | (0.009) | (0.006) |
| N (crops × years) | 608 | 608 | 988 | 988 | 988 | 988 | 1,368 | 1,368 |
| Mean patents/citations before 1965 | 4.06 | 23.90 | 3.59 | 21.53 | 2.65 | 16.17 | 2.70 | 16.50 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table checks the sensitivity of the results to the crops comprising the sample. The first two columns repeat the baseline results, where the sample includes the sixteen crops for which there exist data on the foreign percentage of the total US seasonal labor. Crops are included in the data if they employed 4,000 or more person-months of foreign labor in 1964. In the next two columns, the sample is extended to include the ten greatest field crops (in terms of acreage, according to the 1964 agricultural census), and the foreign exposure of those crops is assumed to be equal to the foreign percentage of the group "Hay and Grain". The sample in columns (5) and (6) includes the baseline sixteen crops and additional ten crops for which data on the percentage of foreign workers in 1962 in California is available. The last two columns include all thirty-six crops together. All specifications include crop and year fixed effects. Standard errors are clustered at the level of crops.

**Table A6:** Effects of *Bracero* Exclusion on Agricultural Invention, Changing the Period of the Sample

| | Total Patents | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Last Year: | 1980 | 1981 | 1982 | 1983 | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 |
| First Year: | | | | | | | | | | | |
| 1943 | 0.029** | 0.029** | 0.029** | 0.029** | 0.029** | 0.029** | 0.028** | 0.028** | 0.027** | 0.027** | 0.027** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1944 | 0.030** | 0.029** | 0.029** | 0.030** | 0.029** | 0.029** | 0.028** | 0.028** | 0.027** | 0.027** | 0.027** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1945 | 0.031** | 0.031** | 0.031** | 0.031** | 0.031** | 0.031** | 0.030** | 0.030** | 0.029** | 0.029** | 0.029** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1946 | 0.031** | 0.031** | 0.031** | 0.031** | 0.031** | 0.031** | 0.030** | 0.030** | 0.029** | 0.029** | 0.029** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1947 | 0.033** | 0.033** | 0.032** | 0.033** | 0.032** | 0.032** | 0.032** | 0.031** | 0.030** | 0.030** | 0.030** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1948 | 0.033** | 0.033** | 0.033** | 0.033*** | 0.033** | 0.033*** | 0.032** | 0.031** | 0.031** | 0.031*** | 0.031*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1949 | 0.033** | 0.033** | 0.033** | 0.033** | 0.032** | 0.032** | 0.032** | 0.031** | 0.031** | 0.031** | 0.031** |
| | (0.014) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) |
| 1950 | 0.033** | 0.033** | 0.033** | 0.033** | 0.032** | 0.032** | 0.032** | 0.031** | 0.031** | 0.031** | 0.031** |
| | (0.014) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) |
| 1951 | 0.034** | 0.034*** | 0.033*** | 0.034*** | 0.033*** | 0.033*** | 0.033*** | 0.032*** | 0.031*** | 0.031*** | 0.031*** |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| 1952 | 0.033*** | 0.032*** | 0.032*** | 0.032*** | 0.032*** | 0.032*** | 0.031*** | 0.031*** | 0.030*** | 0.030*** | 0.030*** |
| | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) |
| 1953 | 0.030** | 0.030*** | 0.029*** | 0.030*** | 0.029*** | 0.029*** | 0.029*** | 0.028*** | 0.028** | 0.027*** | 0.028*** |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.010) | (0.010) |

*Notes:* This table checks the sensitivity of the results to the period of the analysis. Every cell in the table reports the Poisson quasi-maximum likelihood estimator of $\beta$ in the equation $ln\left[\mathbb{E}(patents_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \gamma_i + \delta_t$ where the analysis sample begins at one of the years 1943-1953 and end in one of the years 1980-1990. $y_{it}$ is the number of US patents in crop $i$ and year $t$, and the other variables are as explained above. Standard errors are clustered at the level of crops.

**Table A7:** Effects of *Bracero* Exclusion on Agricultural Invention, Robustness to the Econometric Model

| | Poisson | | Negative binomial | | Zero-inflated Poisson | | OLS | |
|---|---|---|---|---|---|---|---|---|
| | (1) Patents | (2) Citations | (3) Patents | (4) Citations | (5) Patents | (6) Citations | (7) ln(patents) | (8) ln(citations) |
| Foreign percentage × post | 0.033*** | 0.023*** | 0.022* | 0.020** | 0.029*** | 0.018*** | 0.015 | 0.020** |
| | (0.013) | (0.008) | (0.011) | (0.009) | (0.009) | (0.006) | (0.009) | (0.008) |
| N (crops × years) | 608 | 608 | 608 | 608 | 608 | 608 | 446 | 446 |
| Mean patents/citations before 1965 | 4.06 | 23.90 | 4.06 | 23.90 | 4.06 | 23.90 | 6.20 | 36.52 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table checks the sensitivity of the results to the econometric model in use. The dependent variable is the number of patents in odd columns and the number of citations in even columns. The first two columns repeat the baseline results of the Poisson quasi-maximum likelihood model. Columns (3) and (4) report the results of the negative binomial model. The next two columns show the estimates of a zero-inflated Poisson model where the equation that determines the observed count is zero is logit with the same covariates as the main estimation equation. The last two columns are the results of an OLS model, where the dependent variable is the natural log of patents or citations, and crop-year pairs with zero patents/citations are not included in the regression. All specifications include crop and year fixed effects. Standard errors are clustered at the level of the crop.

**Table A8:** Effects of Bracero Exclusion on Invention: Controlling for Linear Pretrends

| | Baseline | | Linear pretrends | |
|---|---|---|---|---|
| | (1) patents | (2) citations | (3) patents | (4) citations |
| treatment | 0.033*** | 0.023*** | 0.049** | 0.045** |
| | (0.013) | (0.008) | (0.023) | (0.018) |
| N (crops × years) | 608 | 608 | 608 | 608 |
| Mean patents/citations before 1965 | 4.06 | 23.90 | 4.06 | 23.90 |
| Year FE | Yes | Yes | Yes | Yes |
| Crop FE | Yes | Yes | Yes | Yes |
| Crop-specific linear pre-trends | No | No | Yes | Yes |

*Notes:* Poisson quasi-maximum likelihood estimators of the Difference-in-differences model with continuous treatment. The regressions reported in columns 3-4 include crop-specific pre-trends: $ln\left[\mathbb{E}(y_{it}|X_{it})\right] = \beta \cdot \%Foreign_i \cdot post_t + \eta_i \cdot t \cdot (1 - post_t) + \gamma_i + \delta_t$. All specifications include crop and year fixed effects. Standard errors are clustered at the level of crops.

**Table A9:** Correlation Matrix

| | %Foreign | Value/ labor | Acreage/ labor | Value/ acreage | Value | Labor | Acreage |
|---|---|---|---|---|---|---|---|
| %Foreign | 1.000 | | | | | | |
| | | | | | | | |
| Value/ labor | -0.102 | 1.000 | | | | | |
| | (0.729) | | | | | | |
| Acreage/ labor | -0.304 | 0.459 | 1.000 | | | | |
| | (0.291) | (0.115) | | | | | |
| Value/ acreage | 0.303 | 0.087 | -0.628 | 1.000 | | | |
| | (0.314) | (0.777) | (0.022) | | | | |
| Value | -0.450 | 0.378 | 0.573 | -0.149 | 1.000 | | |
| | (0.106) | (0.182) | (0.041) | (0.626) | | | |
| Labor | -0.415 | 0.193 | 0.526 | -0.176 | 0.976 | 1.000 | |
| | (0.110) | (0.509) | (0.053) | (0.566) | (0.000) | | |
| Acreage | -0.344 | 0.199 | 0.688 | -0.286 | 0.908 | 0.934 | 1.000 |
| | (0.228) | (0.516) | (0.007) | (0.343) | (0.000) | (0.000) | |

*Notes:* Pairwise correlation between the variables. Observations are crops ($N = 16$). %Foreign is the share of foreign seasonal workers in the total seasonal labor in 1964. Seasonal labor in 1964 in person-months units. Average acreage in 1948-1964 in acres. Average value of production in 1948-1964 in 1980 dollars. P-values in parentheses.

**Table A10:** Similarity Matrix

| Crop | Apples | Aspara | Beans | Celery | Citrus | Cotton | Cucumb | Grapes | Lettuc | Melons | Potato | Strawb | Sugarb | Sugarc | Tobacc | Tomato |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Apples | 0 | 1 | 2 | 0 | 58 | 3 | 1 | 11 | 1 | 1 | 7 | 3 | 2 | 0 | 2 | 8 |
| Asparagus | 8 | 0 | 0 | 17 | 0 | 0 | 0 | 8 | 25 | 0 | 8 | 0 | 8 | 0 | 0 | 25 |
| Beans | 3 | 0 | 0 | 3 | 3 | 25 | 7 | 14 | 3 | 2 | 7 | 3 | 3 | 2 | 7 | 17 |
| Celery | 0 | 10 | 10 | 0 | 0 | 0 | 10 | 0 | 25 | 0 | 10 | 0 | 0 | 0 | 10 | 25 |
| Citrus | 63 | 0 | 2 | 0 | 0 | 5 | 4 | 9 | 1 | 1 | 7 | 2 | 1 | 0 | 0 | 6 |
| Cotton | 7 | 0 | 25 | 0 | 8 | 0 | 3 | 3 | 2 | 5 | 10 | 8 | 7 | 2 | 12 | 7 |
| Cucumbers | 1 | 0 | 6 | 3 | 6 | 3 | 0 | 6 | 6 | 7 | 15 | 8 | 1 | 0 | 7 | 31 |
| Grapes | 24 | 2 | 15 | 0 | 19 | 4 | 7 | 0 | 4 | 2 | 7 | 4 | 0 | 0 | 2 | 11 |
| Lettuce | 3 | 9 | 6 | 14 | 3 | 3 | 11 | 6 | 0 | 6 | 9 | 6 | 0 | 0 | 0 | 26 |
| Melons | 4 | 0 | 4 | 0 | 4 | 12 | 19 | 4 | 8 | 0 | 4 | 0 | 0 | 0 | 4 | 38 |
| Potatoes | 7 | 1 | 3 | 2 | 6 | 5 | 9 | 3 | 2 | 1 | 0 | 7 | 24 | 1 | 5 | 26 |
| Strawberries | 10 | 0 | 5 | 0 | 5 | 13 | 15 | 5 | 5 | 0 | 20 | 0 | 3 | 0 | 5 | 15 |
| Sugarbeets | 4 | 2 | 4 | 0 | 2 | 9 | 2 | 0 | 0 | 0 | 64 | 2 | 0 | 4 | 2 | 2 |
| Sugarcane | 0 | 0 | 14 | 0 | 0 | 14 | 0 | 0 | 0 | 0 | 14 | 0 | 29 | 0 | 29 | 0 |
| Tobacco | 5 | 0 | 10 | 5 | 0 | 17 | 12 | 2 | 0 | 2 | 15 | 5 | 2 | 5 | 0 | 20 |
| Tomatoes | 7 | 2 | 8 | 4 | 5 | 3 | 17 | 5 | 7 | 8 | 24 | 5 | 1 | 0 | 6 | 0 |

*Notes:* The similarity between two crops is measured by the number of patents in the sample that mention both crops. The weights are normalized such that each row sums to one hundred.

**Table A11:** Plant-Agricultural Sub-Classes in the CPC Classification System: Definition of the Subclass, Number of Crop-Specific Patents and Labor Requirements

| Subclass | Definition | Patents | | | Labor share | |
|---|---|---|---|---|---|---|
| | | 1948-64 | 1965-85 | Total | mean | sd |
| A01B | Soil Working In Agriculture Or Forestry; Parts, Details, Or Accessories Of Agricultural Machines Or Implements, In General | 204 | 195 | 399 | 0.14 | 0.14 |
| A01C | Planting; Sowing; Fertilising | 192 | 288 | 480 | 0.04 | 0.07 |
| A01D | Harvesting; Mowing | 981 | 936 | 1,917 | 0.50 | 0.25 |
| A01F | Processing Of Harvested Produce; Hay Or Straw Presses; Devices For Storing Agricultural Or Horticultural Produce | 50 | 77 | 127 | 0.03 | 0.06 |
| A01G | Horticulture; Cultivation Of Vegetables, Flowers, Rice, Fruit, Vines, Hops Or Seaweed; Forestry; Watering | 198 | 581 | 779 | 0.27 | 0.15 |
| A01H | New Plants Or Processes For Obtaining Them; Plant Reproduction By Tissue Culture Techniques | 8 | 61 | 69 | 0.00 | 0.00 |
| A01N | Preservation Of Bodies Of Humans Or Animals Or Plants Or Parts Thereof; Biocides, E.G. As Disinfectants, As Pesticides, As Herbicides Pest Repellants Or Attractants; Plant Growth Attractants; Plant Growth Regulators | 3 | 38 | 41 | 0.02 | 0.01 |

*Notes:* Subclasses related to plants of the A01 class (agriculture) in the Cooperative Patent Classification (CPC). Sum of US patents belonging to each subclass, and mean and standard deviation of the share of labor requirements in California in 1960 for eighteen crops for which there is information on both labor requirements and seasonal foreign labor percentage.

# B Additional Details on the Model

## B.1 Labor-Augmenting Improvements:

***Definition of equilibrium:*** Given labor supply, $L$, marginal cost of machines production $\psi_A$, entry cost function $g_A(a)$, and the Cobb-Douglas parameters $\alpha$ and $\beta$, an equilibrium is defined by the wage rate $w$, machine prices $\{p_A(a)\}$, machine quantities $\{x_A(a)\}$, and the set of technologies available $\{q_A(a)\}$, such that:

1. Given the prices and the set of technologies available, $\{x_A(a)\}$ and $L$ maximize the producer's profits.
2. For each task $a \in [0,1]$ such that $q_A(a) = 1$, the machine price $p_A(a)$ maximizes the monopolist's gross profits.
3. Free entry condition: for each task $a \in [0,1]$, the monopolist chooses $q_A(a) = 1$ if and only if her net profits are positive.

***Existences and uniqueness of an equilibrium:*** The gross profits of the inventor are:

$$\Pi_A(a) = (p_A(a) - \psi_A)\left(\frac{p_A(a)}{\alpha}\right)^{-\frac{1}{1-\alpha}} L^{\frac{\beta}{1-\alpha}}. \tag{B1}$$

Taking the first order condition with respect to price, we obtain the optimal price $p_A(a) = p_A = \frac{\psi_A}{1-\beta}$ which is not a function of $a$. Therefore, the optimal gross profits are independent of $a$: $\Pi_A(a) = \Pi_A$.

Next I demonstrate the existence of a unique internal solution $\bar{a} \in (0,1)$. First, note that because $\beta \in (0,1)$, the gross profits $\Pi_A$ are positive for each combination of the parameters $\psi_A$, $\beta$, and $L$. Second, because $g_A(0) \to 0$, there exist $\epsilon > 0$ small enough such that $g_A(\epsilon) < \Pi_A$. Similarly, because $g_A(1) \to \infty$, there exist $\epsilon < \delta < 1$ close enough to 1 such that $g_A(\delta) > \Pi_A$. Finally, the monotonicity and continuity of $g_A(a)$ guarantee the existences of a unique $\bar{a} \in (0,1)$ such that $g_A(\bar{a}) = \Pi_A$.

***Comparative statics:*** This section examines what happens to the technology level ($\bar{a}$), the number of machines ($x_A$), the TFP ($A$), the output($Y$), and the wage rate ($w$), when the labor supply is increasing. From equation 9, we have $\Pi_A = C_1 L$ where $C_1$ is a constant term that depends only on the parameters $\psi_A$ and $\beta$. Because, $g_A(a)$ is monotonically increasing in $a$, we obtain: $\frac{\partial \bar{a}}{\partial L} > 0$.

From equation 5, the amount of machines is

$$x_A(a) = \left(\frac{\psi_A}{\alpha^2}\right)^{-\frac{1}{1-\alpha}} L^{\frac{\beta}{1-\alpha}} \equiv C_2 L^{\frac{\beta}{1-\alpha}} \tag{B2}$$

which increases with $L$. Substituting into equation 2, the TFP is

$$A = C_2 \bar{a} L^{\frac{\alpha\beta}{1-\alpha}} \tag{B3}$$

which is also an increasing function of $L$. So is the output $Y = A \cdot L^{\beta}$. The wage rate is now:

$$w = C_3 \bar{a} L^{-\frac{1-\alpha-\beta}{1-\alpha}}. \tag{B4}$$

Note that with an exogenous technology level $\bar{a}(L) = \bar{a}$, the wage rate is a decreasing function of $L$. This results from the decreasing return to scale production function, together with the constant price of machines. However, when the technology level $\bar{a}$ is endogenous, it increases when $L$ increases. This effect dampens the wage response to a change in the labor supply and might even change the sign of the effect.

### B.2 Labor-Saving Improvements:

***Definition of equilibrium:*** Given the labor supply, $L$, marginal cost of machines production $\psi_L$, entry cost function $g_L(l)$, and the Cobb-Douglas parameter $\beta$, an equilibrium is defined by the wage rate $w$, machine prices $\{p_L(l)\}$, manual labor demand $\{e(l)\}$, machine quantities $\{x_L(l)\}$, and the set of technologies available $\{q_L(l)\}$, such that:

1. Given the prices and the set of technologies available, $\{x_L(l)\}$ and $\{e(l)\}$ maximize the producer's profits.
2. For each task $l \in [0, 1]$ such that $q_L(l) = 1$, the machine price $p_L(l)$ maximizes the monopolist's gross profits.
3. Free entry condition: for each task $l \in [0, 1]$, the monopolist chooses $q_L(l) = 1$ if and only if her net profits are positive.
4. The labor market clears: $\int_0^1 e(l)dl = L$

***Full solution of the model:*** The gross profits of the inventor are now:

$$\Pi_L(l) = (p_L(l) - \psi_L)\, p_L(l)^{-\frac{1}{1-\beta}} (\beta A)^{\frac{1}{1-\beta}}. \tag{B5}$$

Taking the first order condition with respect to the price, the optimal price is $p_A(a) = p_A = \frac{\psi_A}{1-\beta}$. However, where $w < \frac{\psi_A}{1-\beta}$, because machines and labor are perfect substitutes, if the monopolistic charged this price, the producers would choose to produce with labor and to pay a lower price. Therefore, the monopolistic price is:

$$p_L(l) = min(\frac{\psi_L}{\beta}, w). \tag{B6}$$

Additionally, if $w < \psi_L$, the producers would lose from the production of every machine (even without the entry cost), and therefore will choose not to produce (even if the technology already exists).

We can distinguish between three cases: 1) $w \geq \frac{\psi_L}{\beta}$, 2) $\psi_L \leq w \leq \frac{\psi_L}{\beta}$, and 3) $w \leq \psi_L$.

**Case 1:** $w \geq \frac{\psi_L}{\beta}$. In this range, the price of the machines does not depend on $l$ or $L$. The gross profits $\Pi_L^* = \left(\frac{\psi_L}{\beta} - \psi_L\right)\left(\frac{\psi_L}{\beta}\right)^{-\frac{1}{1-\beta}} (\beta A)^{\frac{1}{1-\beta}}$ are fixed and positive. Because of the continuity and monotonicity of $g_L(l)$ and the Inada conditions, a unique equilibrium technology level exists that satisfies $\bar{l} \in (0,1)$. This technology level is independent of $L$: $\frac{\partial \bar{l}}{\partial L} = 0$.

**Case 2:** $\psi_L \leq w \leq \frac{\psi_L}{\beta}$. In this case $p_L = w$. Note that $\frac{\partial \Pi_L}{\partial w} > 0$ for $w < \frac{\psi_L}{\beta}$. Again, because $g_L(l)$ is continuous, monotonically increasing in $l$, and satisfies the Inada conditions, for each level of $\Pi_L \geq 0$ a unique $\bar{l} \in [0,1)$ exists such that $g_L(\bar{l}) = \Pi_L$ and $\frac{\partial \bar{l}}{\partial \Pi_L} > 0$. Hence, we can write $w = h(\bar{l})$ such that $h'(\bar{l}) > 0$. Using the simplifying assumption that if a producer is indifferent between manual labor and machines she will use machines only, together with the uniform wage rate and the decreasing return to scale in each task ($\beta < 1$), we obtain $e(l) = \frac{L}{1-l}$. Substituting into equation 16, we obtain:

$$L = \left(\frac{h(\bar{l})}{\beta A}\right)^{-\frac{1}{1-\beta}} (1 - \bar{l}) \tag{B7}$$

Differentiating $L$ with respect to $\bar{l}$, we get:

$$\frac{\partial L}{\partial \bar{l}} = -\left(\frac{h(\bar{l})}{\beta A}\right)^{-\frac{1}{1-\beta}} - \frac{h'(\bar{l})}{\beta A(1-\beta)}\left(\frac{h(\bar{l})}{\beta A}\right)^{\frac{\beta-2}{1-\beta}}. \tag{B8}$$

Because $h(\bar{l}) > 0$ and $h'(\bar{l}) > 0$, both terms are negative, so we have $\frac{\partial L}{\partial \bar{l}} < 0$ and hence $\frac{\partial \bar{l}}{\partial L} < 0$. Finally, $\frac{\partial w}{\partial L} = \frac{\partial h(\bar{l})}{\partial L} = \frac{\partial h(\bar{l})}{\partial \bar{l}} \frac{\partial \bar{l}}{\partial L} < 0$

**Case 3:** $w < \psi_L$. In this case, the gross profits of the inventor are negative for every positive amount of production. Hence, there is no reason to pay the fixed cost of the invention and no machine is invented ($\bar{l} = 0$). Changes in the labor supply in this range do not affect the technology level $\frac{\partial \bar{l}}{\partial L} = 0$.

In what follows, I show that we can divide the parameters space into three disjoint groups that correspond to the three cases (see Figure B1). First, note that in all three cases $\frac{\partial w}{\partial L} < 0$. I have already demonstrated this for case 2. For cases 1 and 3, it can be seen from the producer's F.O.C:

$$w = \beta A \left(\frac{L}{1 - \bar{l}}\right)^{\beta - 1}, \tag{B9}$$

and the fact that $\frac{\partial \bar{l}}{\partial L} = 0$.

***Claim:*** For each set of parameters $L$, $\psi_L$, $\beta$, and entry cost function $g_L(l)$, there exist a unique equilibrium $(w, p_L, x_L, e.\bar{l})$. Moreover, let $\bar{L} = \left(\frac{\psi_L}{\beta A}\right)^{-\frac{1}{1-\beta}}$ and $\underline{L} = \left(\frac{\psi_L}{\beta^2 A}\right)^{-\frac{1}{1-\beta}} \left(1 - g_L^{-1}(\Pi_L^*)\right)$,

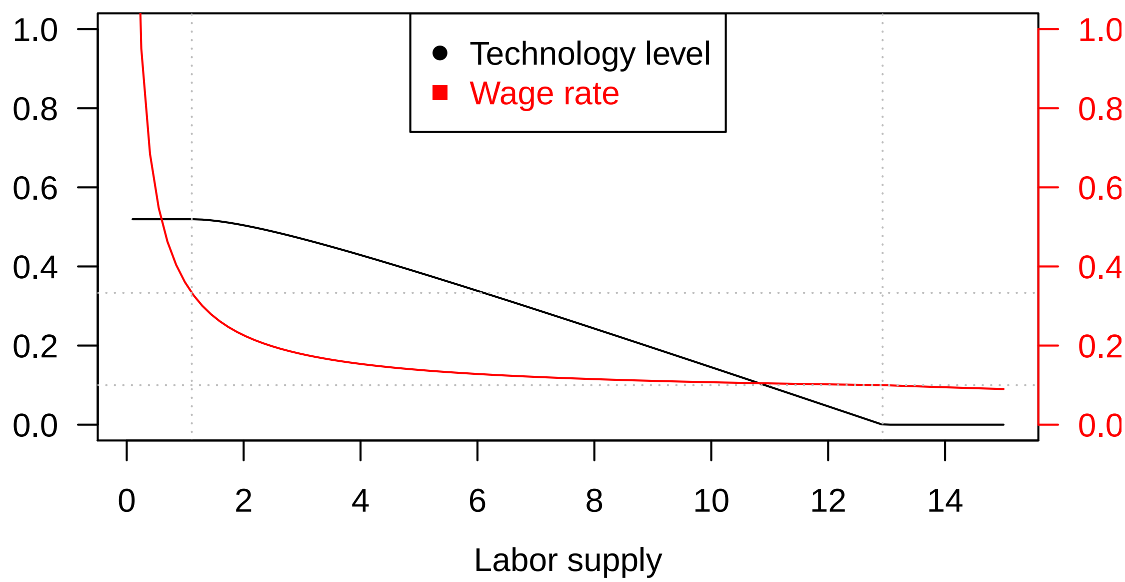


**Figure B1:** Equilibrium technology level and wage rate of the model with labor-saving improvements $(A = 2, \beta = 0.3, \psi_L = 0.1, g_L(l) = \frac{l}{2(1-l)})$

then:

1. $w \geq \frac{\psi_L}{\beta} \iff L \leq \underline{L}$.

2. $\psi_L \leq w \leq \frac{\psi_L}{\beta} \iff \underline{L} \geq L \geq \bar{L}$.

3. $w \leq \psi_L \iff L \geq \bar{L}$.

***Proof:*** Assume $w \geq \frac{\psi_L}{\beta}$ and let $L = \underline{L}$. Because we are at the range of case 1, $\Pi_L = \Pi_L^*$ and therefore $\bar{l} = g_L^{-1}(\Pi_L^*)$. From equation B9 we obtain $w = \frac{\psi_L}{\beta}$, so we can verify that indeed $w \geq \frac{\psi_L}{\beta}$. Now, assume that $L < \underline{L}$. Because $w$ is strictly decreasing in $L$, we have $w > w(\underline{L}) = \frac{\psi_L}{\beta}$. On the other hand, for $L < \underline{L}$ we have $w < \frac{\psi_L}{\beta}$. Therefore, a solution of the type $w \geq \frac{\psi_L}{\beta}$ exists only if $L \leq \underline{L}$, and exists and is unique if $L \leq \underline{L}$.

Now, consider a solution of the type $w \leq \psi_L$. In this case $\bar{l} = 0$ and $w = \beta A L^{\beta-1}$. For $L = \bar{L}$, we have $w = \psi_L$. Because $w$ is strictly decreasing in $L$, a solution of this type exists if only if $L \geq \bar{L}$ and is unique if $L \geq \bar{L}$.

Finally, consider the case of $\psi_L \leq w \leq \frac{\psi_L}{\beta}$. If $L = \bar{L}$, $w = \psi_L$ and $\bar{l} = 0$ solve the system of equations 19 and B9. Similarly, If $L = \underline{L}$, the unique solution is $w = \frac{\psi_L}{\beta}$ and $\bar{l} = g_L^{-1}(\Pi_L^*)$. Again, because $w$ is strictly decreasing in $L$, a solution of this type exists if only if $\underline{L} \geq L \geq \bar{L}$ and is unique if $\underline{L} \geq L \geq \bar{L}$.

Notice that for each of the three ranges of $w$, a solution exists only if $L$ satisfies the corresponding parametric condition; therefore there cannot be more than one equilibrium for a given set of parameters. $\square$

***Comparative statics*** We have already shown that the technology level $\bar{l}$ does not depend on the labor supply when $L \leq \underline{L}$ and $L \geq \bar{L}$, and is decreasing in $L$ otherwise. I have also shown that $w$ is decreasing in $L$ in all regions. Next, I turn to explore what happens to the other elements of the model.

**Case 1:** In this region, the technology level and the monopolistic price of the machines are constant in $L$; therefore the quantity of machines $x_L(l)$ is also constant for each $l \leq \bar{l}$ (denote it by $x_L(l) = x^*$). The output in this case is $Y = A\left[\bar{l}x^{*\beta} + (1-\bar{l})\left(\frac{L}{1-\bar{l}}\right)^{\beta}\right]$ which increases in $L$.

**Case 2:** In this case we have $w = p_L(l)$ and $e(l) = x(l)$. As $w = \beta Ae(l)^{\beta-1}$ and $\frac{\partial w}{\partial L} < 0$ , we know that $\frac{\partial e(l)}{\partial L} = \frac{\partial x(l)}{\partial L} > 0$. The output is $Y = Ae(l)^{\beta}$, increases in $L$.

**Case 3:** In this case we have $w = \beta AL^{\beta-1}$ and $e(l) = L$. There are no machines. The output is $Y = AL^{\beta}$, increases in $L$.

# C Data Appendix

## C.1 US Patents

Patent data were collected from Google Patents for successful applications for patents between 1940-1990. The data include the full text of the patent (title, abstract, claims, and description) as well as patent identification numbers, number of citations, CPC classification, and application and publication (issue) years. I used the application, rather than publication year, to define the timing of invention, because the application date is closer to the date of the invention. Publication dates are typically delayed by several years. For patents with missing application dates, I proxy the application date by subtracting the median lag between application and publication dates (2.6 years) from the publication date.

In Appendix D, I also used data on the USPTO classification of patents. This data was collected from USPTO historical master-file.[20]

## C.2 Crop-level information

Total and foreign seasonal labor by crop for the years 1964-1965 was collected from (Secretary of Labor 1966, Table 5, p. 11). Total and foreign seasonal labor by crop at the date of peak foreign employment was collected from (Secretary of Labor 1966, Table 21, p. 48). Information for the total

[20] Available at https://www.uspto.gov/learning-and-resources/electronic-data-products/historical-patent-data-files.

and Mexican seasonal labor in California for the additional ten crops was collected from (University of California 1963, Table 5, p. 17)

To construct the labor-intensity measures, I collected data on labor-requirements per acre (in terms of hours and cost of labor) by task and crop in California in 1960 from the State of California's "Report and Recommendations of the Agricultural Labor Commission" (State of California 1963). This data includes information on person-hours and labor cost per acre for the various tasks required for the production process for California's twenty-five most valuable crops in 1960.

Production, acreage, and value by crop for the years 1940-1990 was collected from various publications of the Department of Agriculture (see Table C1).

**Table C1:** Sources of data on acreage, production, and value by crop

| Crop | Acreage | Production | Value (current prices) |
|---|---|---|---|
| Sugarbeets | NASS (40-90) | NASS (40-90) | NASS (40-90) |
| Sugarcane | NASS (40-90) | NASS (40-90) | NASS (78-90) |
| Bean | NASS (40-90) | NASS (40-90) | NASS (40-90) |
| Cotton | NASS (40-90) | NASS (40-90) | NASS (40-90) |
| Tobacco | NASS (40-90) | NASS (40-90) | NASS (40-90) |
| Grapes | NASS (47-90) | NASS (44-90) | NASS (44-90) |
| Potatoes | NASS (40-90) | NASS (40-90) | NASS (40-90) |
| Tomatoes | RE (40-59), ERS (60-90) | RE (40-59), ERS (60-90) | RE (40-59), ERS (60-90) |
| Lettuce | RE (40-49), ERS (50-90) | RE (40-49), ERS (50-90) | RE (40-49), ERS (50-90) |
| Asparagus | RE (40-49), ERS (50-81,83-90 ) | RE (40-49), ERS (50-81,83-90 ) | RE (40-49), ERS (50-81,83-90 ) |
| Straebwrries | RE (40-59, 64-69), AS (60-63), ERS (70-90) | RE (40-59, 64-69), AS (60-63), ERS (70-90) | RE (40-59, 64-69), AS (60-63), ERS (70-90) |
| Celery | RE (40-59, 64-81), AS (60-63) | RE (40-59, 64-81), AS (60-63) | RE (40-59, 64-81), AS (60-63) |
| Cucumbers | RE (40-59, 64-70, 74-81) | RE (40-59, 64-70, 74-81) | RE (40-59, 64-70, 74-81) |
| Mellons | RE (40-81) | RE (40-81) | RE (40-81) |
| Citrus | No Data | CF (40-81) | CF (40-81) |
| Apples | No Data | No Data | No Data |

*Notes:* This table uses the following abbreviations for the Department of Agriculture's publications. NASS: National Agricultural Statistics Service. RE: Revised Estimates. ERS: Economic Research Service. AS: Annual Summary. CF: Citrus Fruits.

### C.3 County-level information

Share of Mexicans by county is calculated from the 1940 US population census 1% sample.[21] Distance from Mexico is the minimal distance between the Mexico border and the center of the county. To calculate the weight of each county in the production of each crop, I use information on the total acreage by crop and county from the 1964 census of agriculture. Farm values per acre were collected from the census of agriculture for the years 1950, 1954, 1959, 1964, 1969, 1974, 1978, and 1982. Finally, the list of bracero and non-bracero states used in section 7 are from (Clemens et al. 2018, Figure 2, p. 1476).

## D Evidence for Technology Spillovers

An interesting question is whether there was a diffusion of the effect for a broader range of innovations. To answer this question, I compared USPTO sub-classes of patents that contain agricultural patents of crops with different exposures to the labor shock.

[21] Available at https://usa.ipums.org/usa/.

**Table D1:** Effects of *Bracero* Exclusion on Invention: Spillovers

| | (1)<br>All patents | (2)<br>Without original patents |
|---|---|---|
| Average Foreign percentage × post | 0.025*** | 0.021** |
| | (0.009) | (0.010) |
| N (subclasses × years) | 8,702 | 7,752 |
| Mean patents before 1965 | 1.47 | 1.38 |
| Year FE | Yes | Yes |
| Subclass FE | Yes | Yes |

**Notes:** Difference-in-differences Poisson regressions. Observations are USPTO subclass-year pairs. Treatment is the weighted average of foreign share by crop, where the weights are the number of "crop-specific patents" for each crop in the subclass. Crop-specific patents are the patents which were assigned to each crop and used in the main analysis. Outcome is the number of patents in a subclass-year for subclasses with more than two original patents over the period 1948-1985. The second column subtracts the number of crop-specific patents from the sum of patents. All specifications include subclass and year fixed effects. Standard errors are clustered at the subclass.

For each sub-class, I constructed a measure of exposure to the shock by looking for patents in the sub-class that assigned to one of the crops using the procedure described above, and I calculate the weighted average of the foreign share over these original patents. With this exposure measure in hand, I estimated the following equation using a Poisson Quasi Maximum-likelihood Estimator:

$$ln\left[\mathbb{E}(Patents_{st}|X_{st})\right] = \beta \cdot Exposure_s \cdot post_t + \gamma_s + \delta_t \tag{D1}$$

where $Patents_{st}$ is the number of patents in a sub-class $s$ at year $t$. To ensure that the exposure is measured accurately, I use only sub-classes with at least two original patents during the period 1948-1985. Estimates of this regression imply an increase in US invention by 2.5 percent for an increase of one percentage point in the exposure measure (Table D1, column 1).

In the next step, I isolated the spillovers by focusing on patents that do not explicitly mention one of the crops. As expected, the estimators are slightly smaller but still statistically significant and at similar magnitude (Table D1, column 2).