HISPANICS IMMIGRANTS ON THE FIELDS: IS DISCRIMINATION A BARRIER TO GET NON-AGRICULTURAL JOBS?

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

This research presents evidence supporting the existence of differences in treatments received by Hispanics job-seekers on agricultural and non-agricultural labor markets found through an experimental labor market. Hispanics males' productivity predicted by agricultural employers was higher than the predicted by non-agricultural employers, suggesting that Hispanics males are believed to fit better in agricultural activities. This may imply an invisible barrier preventing Hispanics to access non-agricultural jobs. Employers' beliefs reactions to a more informative signal related to productivity sent to the labor market were tested. Hispanic job-seekers' signals did not significantly reduce the gap between agricultural and non-agricultural employers' beliefs; suggesting that this invisible barrier may also prevent Hispanic males mobility from agricultural to non-agricultural jobs over time, reducing the incentive to invest in costly signals' improvement (i.e. education, reputation). Results also support the existence of a non-neutral gender barrier, given no differences in treatments where found for female Hispanics.

Keywords: immigration, agricultural labor market, discrimination, Hispanics, social networks experimental economics, labor economics.

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DEDICATION

This thesis is dedicated to my family. To my sister Silvina and my brother in law Diego, this would never be possible without your advices and guidance. To my mother Cecilia, thanks for always supporting me even when the path takes me far from you. To my nephew Felipe and my coming niece, my two favorite persons in this world. And especially to my father Wilson, dad I know you would have enjoyed this more than anyone else.

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LIST OF ABBREVIATIONS

OLS……………………………………Ordinary Least Squares

p…………………………………………p-value

bic………………………………………Bayesian Information Criterion

F…………………………………………F-Snedecor

LIST OF SYMBOLS

μ……………………………………………………..Error Term

β……………………………………………………..Coefficient

γ……………………………………………………..Coefficient

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CHAPTER 1. INTRODUCTION

1.1. Hispanics in the US Labor market

It is well known that America is a country mostly made by immigrants and Hispanics[1] are a significant part of them. The US attracts 20% of the world's international migrants (Migration Policy Institute 2013) and, approximately 25% of the overall US population, is either first or second generation of immigrants (Migration Policy Institute 2013). This is due to international migrants moving from lower to higher wage labor markets: high-income countries with 16 percent of the world's workers have over 60 percent of the world's migrants (Martin 2005). Most of the immigrants that come to America are Hispanics or Latinos, this ethnic group represented 46% of US immigrants in 2013 (Migration Policy Institute 2013) and in particular Mexican-born were 28% of the US immigrants in 2013 (Migration Policy Institute 2013). As a consequence of immigration and their higher than average reproductive rates Hispanics, share in the US population and its relevance has increased significantly. While from 1980 to 2012 the number of children per Hispanic women variated between 2.69 and 2.65, the number of children per White women variated between 1.6 and 1.79 (Drozd 2015). Hispanics are the largest and fastest-growing minority group in the US representing 17% of the U.S population at 54 million (US Census Bureau 2014a), increasing from 10.7 million in 1990 to 24.8 million in 2013 (Bureau of Labor Statistics 2010).

There is a significant amount of literature supporting the existence of differences in labor market outcomes and wealth fare levels between Hispanics and Whites in the US (Abowd and Killingsworth 1984; Borjas and Tienda 1985; Hoynes 1999; Orrenius and Zavodny 2009). Hispanics show higher long-run rates of unemployment than Whites: the jobless rate for

[1] Hispanics and Latinos or Hispanics ethnicity groups are used indistinctly through this document.

Hispanics is 12.5% vs. 8.7% for Whites (Bureau of Labor Statistics 2010). Hispanics show official poverty rates at least twice as high as those of non-Hispanic Whites. Median income for Hispanic households $42,491 was significantly lower in 2013 than their White, non-Hispanic counterparts $60,256 (US Census Bureau 2014b). While food insecure affects 22% of Latino households affects 11% of White, non-Hispanic households and 14% households overall (USDA Economic Research Services 2014). In addition, Hispanics also suffer from a larger educational attainment gap (Gradín 2012).

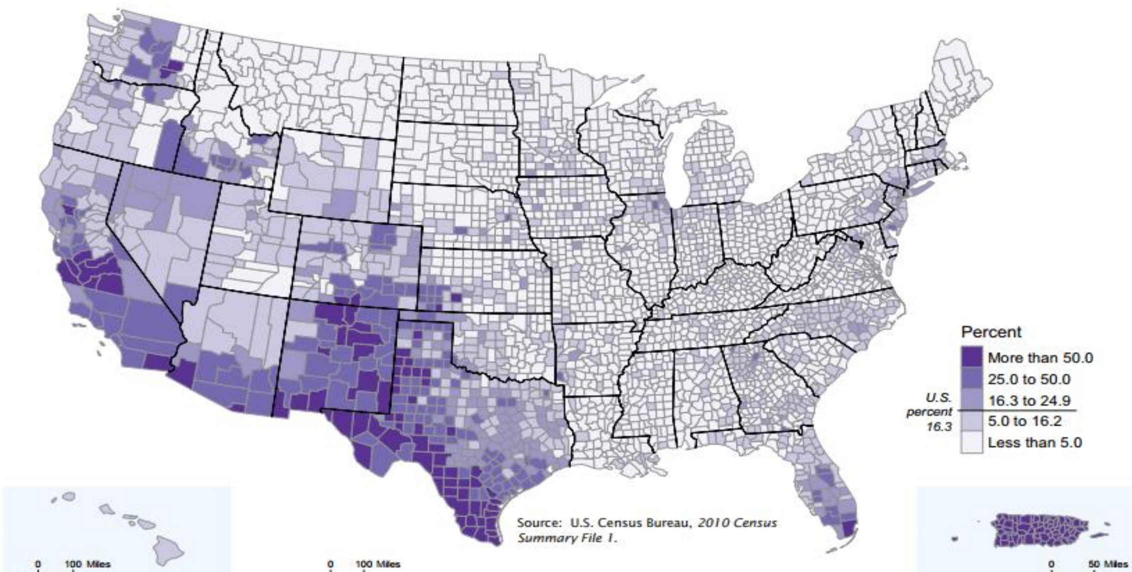

Figure 1. Hispanic or Latino population as a percentage of total population by county 2010
Source: US Census Bureau 2010 a

Areas close to the border with Mexico, and the West Coast show the highest rates of Hispanic or Latino population as percentage of the total population by county (Figure 1). Florida State is an exception outside those areas because of Cuban immigration: Cuban population represents 29% of the Hispanic population in Florida (Pew Research Center 2011), On the other hand, the Midwest and the East Coast have the lowest rates of Hispanic population as a percentage of the total population (Figure 1). Despite that, recent patterns show that Hispanics immigrants have increasingly dispersed to non-traditional areas throughout the US, especially in the Southeast and Midwest (Marrow 2009; Oropesa and Jensen 2010).

At least three reasons contributed to Hispanic population growth in rural areas outside the Southwest in recent years. One of those reasons is related to the dynamics in the job market: labor market saturation and weak economies in traditional urban destinations, such as big Cities in California State, encouraged Hispanics to seek work in nontraditional areas (Fennelly and Leitner, 2002; Suro and Singer, 2002). Another reason may be the employment availability and corporate recruitment, redirecting both domestic and foreign migration to new rural destinations (JohnsonWebb, 2002; Krissman, 2000). Finally, the increase on U.S. immigration border enforcement may have dispersed Hispanic immigrants away from areas close to the border to new U.S. destinations (Durand et al., 2000).

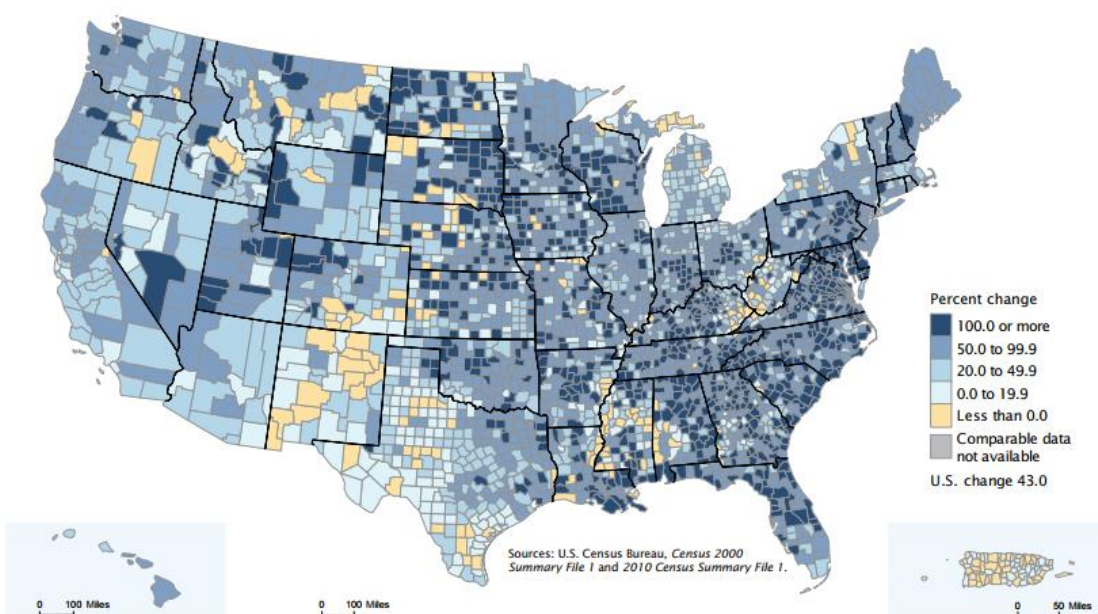

Figure 2. Percent change in Hispanics or Latino populations by county: 2000 to 2010
Source: US Census Bureau, 2009 Census

As a consequence of these reasons, the percent change in Hispanics or Latino populations by county, between 2000 and 2010, were highly greater in those regions in which the total population is lower (Figure 2). Particularly in the Midwest, Hispanic population change between 2000 and 2010 was 49.2%, while for the entire country was 43% (US Census Bureau 2010 b). Furthermore, the natural decrease of population in many rural counties in the US has been offset by new Hispanic population growth and high fertility (Johnson and Lichter 2013). Hispanic population growth throughout the rural United States, especially in the South and Midwest, reflects a growing presence in industries that require low-skill workers in this regions, this new Hispanic settlement patterns need attention from policymakers because they may affect the well-being of both, Hispanics and rural communities themselves (USDA Economic Research Service 2004).

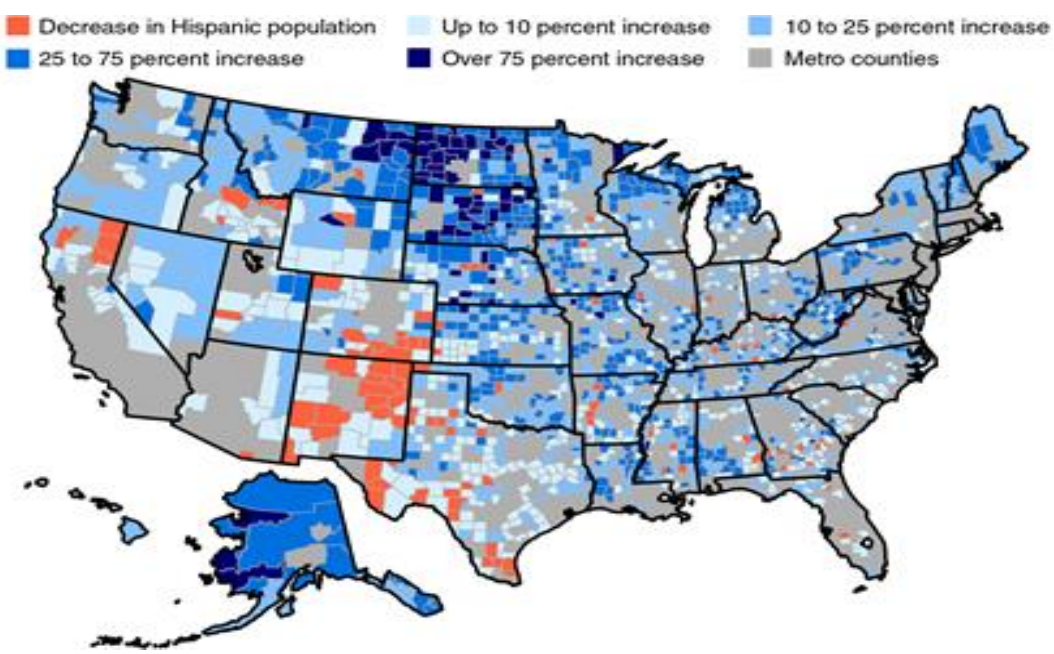

Figure 3. Hispanics or Latino populations change in rural counties, 2010 to 2014
Source: US Census Bureau, Economic Research Service

The percent of increase in Hispanics or Latinos population in rural areas is mostly concentrated in the Midwest, particularly in the Northern plains where most of the rural counties show in between 25% to 75% increase or even over 75% (Figure 3). This new trends on Hispanics' location may make them to face new socio-economic challenges.

There is evidence suggesting that discrimination against minorities is related to the minorities' share in the communities' population (Mobious, Rosenblat, and Wang 2016, Moody 2001; Boisjoly et al. 2006; and Van Laar et al. 2005). By increasing the level of exposure to people with diverse backgrounds, more diverse communities may lead to attenuate discrimination based on stereotypes and have more accurate perceptions about minorities. Mobious, Rosenblat, and Wang (2016) found that the bigger the minorities' share in the total community's population, the lower the level of discrimination against minorities in the labor market, through an experimental labor market realized in different communities in China. This result is consistent with other approaches: Moody (2001) found that friendship segregation, in American high schools, declines with school heterogeneity levels, and Boisjoly et al. (2006) and Van Laar et al. (2005) found that having a roommate of another ethnic group, in university dorms, improves attitudes toward that group. In addition, those destinations emerging and non-traditional for Hispanics immigrants are characterized by a more rigid black–white divide and are potentially less tolerant of racial difference. These destinations present strong linguistic, cultural, and racial boundaries that continue to separate Hispanics from Whites, and there is evidence supporting that discrimination by Whites is harming Hispanics' wellbeing in fundamental ways (Marrow 2009).

1.2. Labor scarcity and Farms' production in the Midwest

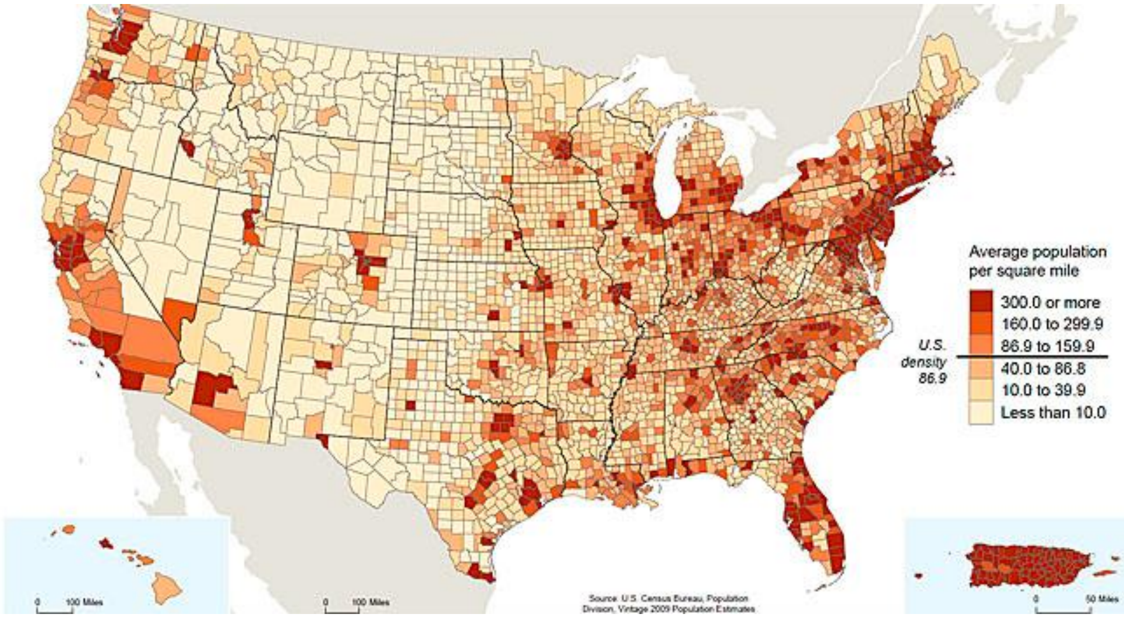

Figure 4. US population per-square mile
Source: US Census Bureau, 2000.

Labor is a scarce resource in agricultural production in the Midwest. It is cited by farmers as one of the most common limitations for the expansion of farms in the Midwest. Among the causes for the limited supply of labor in rural areas is the limited amount of the population living in rural areas, and in the case of the Midwest, the low total population (rural and urban) per square mile. Most of the counties in the Midwest show less than 39.9 as average population per square mile, which is less than half of the average population for the US, 86.9 (Figure 4). In addition, the population growth rate was 0.93% while in the US was 2.39% (US Census Bureau 2010 c). This low total population limits the labor supply in relation to rural labor demand, making labor supply a critical resource for agriculture. In recent years competing activities have reduced the limited Midwest labor supply even more in rural areas of the Northern Plains. In particular, the oil boom of the Bakken formation area has increased the regional demand for labor significantly (Casselman 2010). Because of the limited local labor supply, the oil boom brought immigration to the upper plains, drastically changing the labor market and the rural communities in the area. This limited labor supply occurs in a region where farmland is concentrated.

The Midwest region has been historically identified as the region of farms in the US. The percentage of land area designated to farming in US it is mostly concentrated in the Midwest. When compared with the rest of US an important difference between percentages of area devoted to farming can be observed. While most of the counties in the Midwest present between 80 % and 100 % of land area devoted to farming, in the rest of the US most of the counties present between 0 % and 20 % of land area devoted to farming (Figure 5).

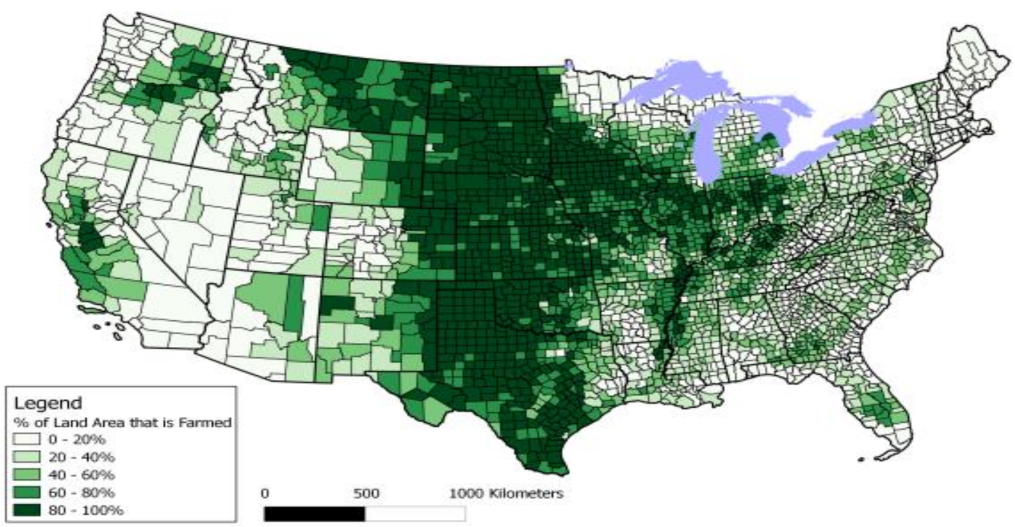

Figure 5. Percentage of land area devoted to farming by US county
Source: United States Department of Agriculture, National Agricultural Statistics Service, 2007.

The Midwest has become known as the Corn Belt[2] of America producing most of the US crops including corn and soybeans, and animal products like cattle, hogs, dairy products and

[2] The US's Corn Belt is defined to include: Iowa, Illinois, Indiana, southern Michigan, western Ohio, eastern Nebraska, eastern Kansas, southern Minnesota and parts of Missouri. Usually it is defined to include parts of South Dakota, North Dakota, Indiana, Ohio, Wisconsin, Michigan, and Kentucky as well (US Department of Agriculture, 2007).

eggs. During 2012 ten of the thirteen top Sates in Agricultural sales were in the Midwest, combined they sold USD 165.1 billion, 42% of the total agricultural sales in US[3] (USDA 2012). During 2008, the top four corn-producing Sates in the Midwest (Iowa, Illinois, Nebraska and Minnesota) combined produced more than half of the corn grown in the United States (USDA 2016).

Agriculture usually shows worse labor environment for employees when compared with non-agricultural jobs and most of the workers are Hispanics. Agriculture ranks among the most hazardous industries due to the use of chemicals and risk of injury. Farm workers are at high risk for fatal and nonfatal injuries, work-related lung diseases, noise-induced hearing loss, skin diseases, chemical-related illnesses, and certain cancers associated with chemical use and prolonged sun exposure (Center of Disease Control and Prevention). Furthermore, agriculture is the most dangerous industry for young workers, accounting for 42% of all work-related fatalities of young workers in the U.S. between 1992 and 2000 (US Department of Labor, 2013). The labor force in this type of production is mostly made-up by Hispanics or Latinos. During 2001-2002, 83% of the crop workers identified themselves as Hispanic or Latino (United States Department of Labor, 2003).

Migrant Hispanics are demanded as agricultural workers and they may face limitations to access non-agricultural jobs. Most of Mexican immigrants take agricultural jobs despite receiving 40% less income than Mexican immigrants on nonagricultural jobs. Almost 49% of Mexican immigrants take agricultural jobs and 24.9% take unskilled nonagricultural jobs (Munshi 2003).

[3] Top States in Agriculture sales in 2012 (in USD billion): California 42.6, Iowa 30.8, Texas 25.4, Nebraska 23.1, Minnesota 21.3, Kansas 18.5, Illinois 17.2, North Carolina12.6, Wisconsin 11.7, Indiana 11.2, North Dakota 11.0, South Dakota 10.2. Ohio 10.1. Total US agriculture sales in 2012= USD 394.6 billion. Source: USDA NASS, 2012 Census of Agriculture.

There is a need to better understand the potential effects of discrimination against Hispanics job-seekers, especially in regions where Hispanics show lower population's rates and higher population's growth rates because they are more exposed to face ethnic based discrimination barriers. From a research perspective, these emerging and non-traditional regions of destination can be considered a substantial source for investigating the social mechanisms harming Hispanics immigrants' wellbeing. While there is an overall lacking on research related to Hispanics and Latinos experience with discrimination, studies on discrimination in these emerging and non-traditional regions of Hispanics destination are even more scarce (Baker 2004; O'Neil and Tienda 2010; Oropesa and Jensen 2010; Flippen and Parrado 2015). These regions are both inexperienced to large immigrant populations, which potentially magnify the culture clash and Hispanics exposure to discrimination, and lack an established ethnic community that would provide Hispanics with more tools to handle with exclusion. Within these non-traditional destinations, it is of particular interest study the existence of the potential employers' wrong beliefs related Hispanics job-seekers in the Midwest, a region where labor is a scarce resource.

1.3. Need for the research and contributions

Given the significant growth of Hispanics in the U.S labor force and their significant share on the agricultural labor market, it is relevant to determine if there exists an invisible barrier restraining Hispanics job-seeker from non-agricultural jobs. There is a need to better understand if potential employers' wrong beliefs, based in ethnic stereotypes with respect to Hispanics job-seekers, are leading them to both sub-optimal decisions and hampering Hispanics from non-rural jobs. This study contributes to the existing literature by comparing discrimination against Hispanics in rural and non- rural labor markets in the Midwest, a region where the potential non-desirable effects of employers' sub-optimal decisions would be magnified by the labor scarcity.

The aim of this study is to determine if potential employers from non-agricultural labor market show differences in beliefs related to Hispanics job-seekers, based on ethnic stereotypes, when compared with potential employers from agricultural labor market. The specific objectives of this research are: (i) achieve a better understanding of employers' beliefs related to Hispanics potential employees in the labor market; and (ii) identify for the first time the existence of a potential discrimination barrier for Hispanics job-seekers to access to non-agricultural jobs.

We investigate employers' predictions about Hispanics' productivity in an experimental labor market to measure the effect of otherwise unobservable labor market characteristics on potential employers' beliefs related to Hispanic job-seekers, by following Mobius and Rosenblat (2005); Mobius, Rosenblat and Wang (2016), and Bertrand and Mullainathan (2003). Because of the significant Hispanic population growth and the relevance of agricultural production in the Midwest, the experiment participants are students, with diverse backgrounds, from a University in the Midwest. Students play both the role of job market candidates and the role of potential employers. As job market candidates they solve puzzles in order to provide a signal to the potential employer; as potential employers they make predictions about potential employees' productivity (Mobius and Rosenblat 2005; Mobius, Rosenblat and Wang 2016). Potential employers make productivities' predictions based on different sets of potential employees' information, allowing to investigate the possible existence of ethnic based differentiated treatment against Hispanic job-seekers. Agricultural and non-agricultural labor markets are simulated by controlling the student's answer to the following question: "Are you working now on a farm, ranch, or any other rural work, or planning to work when you graduate?"

The outcomes of this experiment may provide support to answer the following question:

(i) Is there an agricultural non-agricultural labor markets differentiated treatment against Hispanics job-seekers?

The results of this study may help to understand potential employers' beliefs in both, agricultural and non-agricultural labor markets that may affect Hispanic job-seekers' wellbeing. They may provide evidence to correct wrong beliefs that are potentially causing employers to take sub-optimal decisions, which are especially relevant, a region with labor scarcity and high Hispanic population growth such as the Midwest. Furthermore, they may provide valuable information for policy design to reduce market inefficiencies related to labor force in agriculture. The remaining of this paper presents the literature review, experimental design, and proposed models, followed by results' discussion, and conclusions.

CHAPERT 2. LITERATURE REVIEW

2.1. Discrimination in the labor market

Theoretical literature provides two major sources of racial discrimination in labor markets: statistical and taste-based. Statistical discrimination occurs in an environment of imperfect information where agents form decisions based on limited signals that correlate with race (Arrow and Phelps' 1972), in the other hand taste-based discrimination is related to racial prejudice (Becker 1957). While empirical literature focuses on documenting the presence of disparities and the effects of policies designed to counteract discrimination, theoretical literature based on each model has been split between statistical and taste-based models. Jonathan Guryan and Kerwin Kofi Charles (2013) provide an extensive review of this literature. Although no existing theory can account for all existing empirical regularities in the labor market, significant advances in models of discrimination have been made in recent years (Lang and Lehmann 2012).

Researchers usually measure differential treatment by comparing the labor market performance of minorities with non-minorities who have similar sets of skills (ex: Whites and African-Americans). Empirical economic literature typically measures differences in economic outcomes between genders, races, among others, that remain after statistically controlling for observable characteristics of workers. However, such kinds of comparisons have important limitations. Those methods can control for too little but they can also control for too much, and both can lead to the classical omitted variable bias.

Concerns about the limitations of regression-based methods have led researchers to search for alternative methods. One of those methodological advances is audit studies consisting of testing differences in treatment received between minorities and white job candidates through sending trained actors to respond similarly in real job interviews. The results of those studies indicate that auditor minorities tend to have on average worse performance (fewer job offers, fewer callbacks, etc.). One example of an audit study applied to the labor market was Neumark et al. (1996). They studied sex discrimination in hiring sending matched pairs of men and women to apply for jobs as waiters and waitresses at 65 restaurants in Philadelphia. The experiment was designed so that a male and female pair applied for a job at each restaurant, and so that, on paper at least, the male and female candidates were identical. They found statistically significant differences in outcomes between men and women applicants. Women had an estimated probability of receiving a job offer that was lower by about 0.4, and an estimated probability of receiving an interview that was lower by about 0.35. Some other examples of audits studies are Ayres and Siegelman (1995), Yinger (1998), Riach and Rich (2002), and Dymski (2006).

The use of audit studies is a useful method because it provides more direct evidence of discrimination than is provided by other empirical methods. However, it also has important limitations, such as the fact that it is impossible that the pair of applicants match in all relevant characteristics. Even in the situation that auditors' characteristics could match (on average), the differences between the distributions of their characteristics may explain different outcomes. Furthermore, even in the best conditions, audit methods can only make measurements about average differences in behavior by employers. Those limitations have been addressed by Heckman and Siegelman (1992), Heckman (1998), and Neumark (2012).

When audit methods are applied in labor markets research, the focus of the analysis switches from the worker to the employer. The discrimination measurement is based on the analysis of the different treatments received by minorities from potential employers in observable variables such as callbacks and job offers. Discrimination becomes a difference in the behavior of potential employers, but the difference in the distribution of auditors' characteristics, not just the presence of such characteristics, can generate differences in those outcomes. Considering this, the most important limitation of these methods is the inability to control the distribution of auditors' characteristics. In addition, it is possible to see the remarkable importance of considering how employers perceive gender, race and expected productivity in order to understand the different outcomes between minorities and non-minorities in the labor market. A new type of field experiments, known as "correspondence studies" was created because of these limitations.

Correspondence studies represent a significant methodological advance in the pursuit of measuring the effect of discrimination on economic outcomes. These studies are typically based on a set of conveniently developed resumes which are sent in response to a set of real job openings. The resumes are designed to be as realistic as possible, usually based on combinations of real resumes. The most important distinction between audit and correspondence studies is that correspondence studies are able to vary multiple attributes on the resumes randomly and independently. For example, researchers are able to signal the race or gender of the applicant by using a fantasy name on the resume, and then measure differences in callbacks between resumes that signaled that the applicant was black or female and resumes that signaled that the applicant was white or male.

An example of this kind of study is Bertrand and Mullainathan (2003), two researchers who studied the effect of ethnicity in the labor market by sending fictitious resumes to help wanted ads in Boston and Chicago newspapers. They used African-American- or White sounding names which were randomly assigned to CVs of differing qualifications in order to manipulate perceived race. They found a uniform gap across occupation, industry, and employer size between races. White-sounding names received 50 percent more callbacks for interviews. In addition, callbacks were also more sensitive to the level of qualifications on CVs with White sounding names than for African-American-sounding ones. One limitation of this research is that these findings are evidence only that employers discriminate against black workers when they review CVs, but there is no evidence supporting that African-American workers have differential treatment when compared with White workers at other stages in the job process such as hiring, firing, and promoting (Guryan & Charles 2013).

2.2. Behavioral economics and field experimentation

The basic core of behavioral economics is based on the idea that increasing the realism of the psychological underpinnings of economic analysis will improve the economy in its principal fields: theory, predictions, and economic policy. In recent years the economics of behavior has gone beyond experimentation and embraced the whole range of methods used by economists.

The first experiments in labor economics using principles of behavioral economics were known as "lighting experiments" in the Hawthorne plant. In this experiment between 1924 and 1927, the amount of light in the workplace was varied, in addition to other changes such as maintaining clean work stations, clearing floors of obstacles, relocating workstations, and systematically changing experimental groups in different departments; in order to measure the impact of those changes in workers' productivity. Workers in the departments were women who made wound wire coils and productivity was measured based on the number of units completed during the workday. The experiment's results suggest an increase of workers' productivity but only while the changes were made. It has been argued that the "Hawthorne effect" was caused by a positive emotional effect due to the perception of a sympathetic or interested observer (Mayo 1949). Despite the fact that many researchers questioned the validation of this experiment's results such as Franke and Kaul (1978), Jones (1992), and Levitt and List (2011), this marked the beginning of the first period in which a large number of such experiments were performed. Furthermore, the "Hawthorne effect" has had a profound influence on the design and direction of research in the social sciences since then.

Late in the second half of the twentieth century came the second period of field experiments in which interest was focused on labor economics. During this period, government agencies made a series of large-scale social experiments in order to evaluate the impacts of changes in different areas like employment programs, prices of electricity, and housing subsidies. In the US the series of the experiments known as "income maintenance experiments" were started by Heather Ross in 1966. Ross wanted to collect data that could be used to determine what lower-income people would do if they were provided with money. This is the first prominent example in which the technique of randomly assigning individuals was used to test the impact of social programs and has become a model for social experiments. The high cost and the long time needed do this kind of experiment have been stated as the most important weaknesses of this technique. However, with recent social experimentation timely results at a reasonable cost have been possible to produce (Munell 1986).

Field experimentations are the latest wave of experiments in economics. This type of experiment arose in the mid-1980 and included a new set of empirical strategies to identify causal effects that have entered the mainstream of empirical research in labor economics. To summarize, field experiments are based on fixed effects, difference-in-difference, instrumental variables, regression discontinuities, and natural experiments. Today a large range of research questions are addressed by labor economists.

The field experiment is a useful technique for labor economists because it allows the estimation of otherwise unmeasurable variables. Despite rarely having the possibility to randomly change the economic variables directly related to the individuals, such as investment in education decisions, the minimum wage faced by an individual, or retirement benefits, field experiments allow the researcher the ability to randomize key elements of the economic environment that determine such results. However, List and Rasul (2011) addressed an extensive review of many concerns with respect to the use of field experiments in social sciences related to the sample attrition, the sample selection, and to the intervention level.

2.3. A new approach to the measurement of discrimination in labor market

Another approach to solving the problem of isolating a single characteristic of an individual in order to measure the discriminatory differential in outcomes related to it in the labor market is to design an experimental labor market. These experiments in most cases produce replicable evidence and permit the implementation of truly exogenous ceteris paribus changes. Control is the most important asset behind running experiments; and it is also the most important advantage over other methods, no other empirical method allows a similarly tight control as do experiments. Particularly the implementation of experimental labor markets is useful in order to add realism in studies. The direct observation of human behavior in such experiments also has forced the researchers to take more seriously issues related to human motivation and bounded rationality (Falk & Fehr 2003).

One example of this is Mobius and Rosenblat (2005). They studied the beauty premium in an experimental labor market where “employers” determined wages of “workers” by estimating their ability to solve puzzles based on signals. The signal estimation was a real performance of the “workers”. They found a sizable beauty premium and identified three channels of transmission, higher levels of self-confidence of physically-attractive workers, better oral skills of physically-attractive workers, and wrong beliefs from employers that considered physically-attractive workers more able. The task of solving puzzles requires a true skill which they showed to be unaffected by physical attractiveness. An important contribution of this research is that the methodology used can be easily adapted in order to study the sources of discriminatory pay differentials in other settings and related to other characteristics such as gender, ethnicity, etc. After that Mobius, Rosenblat and Wang (2016) replicated this methodology in order to analyze how stereotype-based discrimination against ethnic minorities depended on the shares of ethnic groups in the population in an experimental labor market with university students in an ethnic non-diverse and an ethnic diverse province in China.

Statistical discrimination may be reduced by providing more information to the employer about the job market candidate. Dickinson and Oaxaca (2009) suggest that statistical discrimination is influenced by the level of information, related to the potential employee, that the potential employer has at the moment of making the decisions. "First-moment" statistical discrimination occurs when, for example, minority groups receive lower wages because are perceived to be less productive, on average, than non-minority workers. "Second-moment" statistical discrimination would occur when risk-averse employers offer minority workers lower wages based not on lower average productivity but on a higher variance, real or presumed, in their productivity. They reported results from controlled laboratory experiments designed to study second-moment (that is, risk-based) statistical discrimination in a labor market setting. They found that by reducing uncertainty about the performance of the minority "second-moment" statistical discrimination may be reduced.

CHAPTER 3. METHODOLOGY AND DATA

3.1. Conceptual framework

This study contributes to the statistical discrimination in the labor market literature, by comparing discrimination against Hispanics in agricultural and no-agricultural job markets. Statistical discrimination exists when differences in treatment between different demographic groups are made on the basis of beliefs related to statistical distinctions between the groups. One particular case of statistical discrimination occurs in the labor market, e.g. gender-based and ethnicity based profiling. When wrong, these beliefs may cause potential employers to make sub-optimal decisions in hiring, promotion, and firing workers. On the other hand, potential workers' beliefs about employers' discrimination in the labor market affects their self-confidence and this may cause job-seekers to make sub-optimal decisions in applications, human capital investment, among others (Lundberg and Startz1983; Schwab1986).

In this study, we investigate employers beliefs in an experimental labor market to measure the effect of otherwise unobservable labor market characteristics on employers' beliefs related to Hispanic job-seekers, by following Mobius and Rosenblat (2005); Mobius, Rosenblat and Wang (2016), Bertrand and Mullainathan (2003), and Dickinson and Oaxaca (2009). Because of the significant Hispanic population growth in the Midwest's rural areas and the relevance of agricultural production in the Midwest, the experiment participants are 152 Midwestern university students with diverse backgrounds. Students play the role of job market candidates and employers (Mobius and Rosenblat 2005; Mobius, Rosenblat and Wang 2016). Students playing as job market candidates solve puzzles to provide a signal to the "employer" that makes predictions about productivity (Mobius and Rosenblat 2005; Mobius, Rosenblat and Wang 2016). Predictions are made with different sets of potential employees' information (different CVs), allowing to research the possible existence of statistical discrimination. Following Bertrand and Mullainathan (2003), when fake names where provided in the CVs they were selected, according to their respective ethnicity, from the most common names and last names in the US Census 2000 and regionally statistics. We also provide a more informative signal related to workers' productivity sent to the labor following Dickinson and Oaxaca (2009) in order to investigate the impact of the increase of job seekers' observable characteristics on employers' beliefs.

Agricultural and non-agricultural labor markets were simulated by controlling the student's answer to the following question: "Are you working now on a farm, ranch, or any other rural work, or planning to work when you graduate?" By using the participants' answers to this question, we were able to split the sample between agricultural and non-agricultural potential employers. During the experiment both groups of potential employers, agricultural and non-agricultural, made predictions related to the same sample of job-seekers. By doing this we were able to isolate differences in predictions about potential employees' productivity caused by differences on potential employers' beliefs in agricultural and non-agricultural labor markets.

In this experiment we made the potential employers to make estimations by having access to different levels of information about the potential employees. The potential employer has to form an estimation about the productivity "Belief" of a job-seeker which is a function of a set of observable variables "X" (X is a vector that contains all the job-seeker observable characteristics relevant for the job application) and a set of unobservable characteristics "Y" (Y is a vector that contains all the job-seeker non-observable characteristics relevant for the job application).

$$\boldsymbol{Belief_i = \gamma_0 + \gamma_1 X_i + \gamma_2 Y_i} \tag{1}$$

By variating the relation of “X” and “Y” we are able to estimate in which way the increasing level of “X” (decreasing level of “Y”) affected potential employers’ predictions related to Hispanics’ productivity.

$$\boldsymbol{Belief'_i = \gamma_0 + \gamma_1 X'_i + \gamma_2 Y'_i} \qquad (2)$$

Particularly, in the first step we focused the research on finding the existence of differences between employers beliefs’ related to Hispanics job-seekers in agricultural labor market and Hispanic job-seekers in the non-agricultural labor market. In the second step we focused on understand how the increasing level of information, related to the Hispanic job-seeker, affected the potential employers’ beliefs.

3.2. Empirical approximation: Experimental labor market design

In this study an experimental labor market is designed in order to collect data that allows studying decision making processes in the labor market’s demand. The experiment is designed to find differences on treatment received by Hispanics job-seekers in the agricultural labor market with Hispanics job-seekers the non-agricultural labor market. In particular the experimental labor market design tries to achieve a better understanding and determine the existence of employers’ discrimination against Hispanics that may act as an invisible barrier to Hispanics’ access to non-agricultural jobs. In addition, the experimental labor market is designed to identify the potential effects of increase the level of information through a more informative signal related to workers’ productivity sent to the labor market, for example through a CV, in the potential employers’ beliefs related to Hispanics job-seekers, focusing in the comparison between agricultural and non-agricultural employers’ beliefs.

There are two roles in this experiment: workers and employers. All the participants in the experiment played both roles. The “dual role” in the experiment implies that the potential employer has good information on what the worker does in the experiment, the requested task related to his predictions. Self-experience provided the employer with better information on the worker's task than any other descriptive words would do.

The experiment is divided into two sections on two different days. The first day section's main purpose is to obtain data about the workers' productivity and potential employers' beliefs related to job seekers productivity. We were able to obtain data about participants' skills as workers, and their demographic characteristics. In addition, we obtained data about how demographic characteristics of potential employees affected the participants' beliefs, playing as potential employers, related to job seekers' productivity. The second day section's main purpose was to find how the potential employers' beliefs were affected by an increase in the level of information, through a more informative signal related to workers' productivity, with respect to the information available during the first day section's potential employers' predictions.

We offered participants monetary compensations mixing a fixed amount as participations' fee of 7 USD, per each day section, plus a variable amount in each day session based on their performance, their answers, and the rest of the participants' answers. Each section lasted 50 minutes. During both, first and second day section, the answers were collected by using the Turning Point's clickers and software.

3.2.1. Section day 1 description

At the beginning of the first day section, we asked all the participants to play the role of the worker. After having a two-minute period for practice, workers had the task of solving as many character puzzles as possible within a five-minute period. As well as in all the rest of the steps experiment during this task we offered the participants monetary compensations in order to ensure their best effort. The sequence of the puzzles in each step was identical for every subject, which means that the subjects were solving the same puzzles appearing in the same order.

PRACTICE 1

	1	2	3	4	5	6
1	R	S	O	A	B	J
2	I	S	Q	R	Y	I
3	A	S	P	G	S	Z
4	A	J	Z	T	Q	B
5	G	D	N	J	F	C
6	T	W	G	M	N	R
7	U	I	N	J	V	D

	1	2	3	4	5	6
1	R	S	O	A	G	J
2	I	S	Q	R	Y	I
3	A	S	P	G	S	Z
4	A	J	Z	T	V	B
5	G	D	N	J	F	C
6	T	W	G	M	N	R
7	U	I	N	J	V	D

Aswer code

	1	2	3	4	5	6
1	AA	AB	AC	AD	AE	AF
2	BA	BB	BC	BD	BE	BF
3	CA	CB	CC	CD	CE	CF
4	DA	DB	DC	DD	DE	DF
5	EA	EB	EC	ED	EE	EF
6	FA	FB	FC	FD	FE	FF
7	GA	GB	GC	GD	GE	GF

Figure 6. Example of puzzle asked during the task

PRACTICE 1

	1	2	3	4	5	6
1	R	S	O	A	$\boxed{B}$	J
2	I	S	Q	R	Y	I
3	A	S	P	G	S	Z
4	A	J	Z	T	$\boxed{Q}$	B
5	G	D	N	J	F	C
6	T	W	G	M	N	R
7	U	I	N	J	V	D

	1	2	3	4	5	6
1	R	S	O	A	$\boxed{G}$	J
2	I	S	Q	R	Y	I
3	A	S	P	G	S	Z
4	A	J	Z	T	$\boxed{V}$	B
5	G	D	N	J	F	C
6	T	W	G	M	N	R
7	U	I	N	J	V	D

Aswer code

	1	2	3	4	5	6
1	AA	AB	AC	AD	$\boxed{AE}$	AF
2	BA	BB	BC	BD	BE	BF
3	CA	CB	CC	CD	CE	CF
4	DA	DB	DC	DD	$\boxed{DE}$	DF
5	EA	EB	EC	ED	EE	EF
6	FA	FB	FC	FD	FE	FF
7	GA	GB	GC	GD	GE	GF

Figure 7. Illustration of one of the puzzles' solution we asked the participants to perform as a compensated task for a five-minute period using clickers

Participants had to find the differences between the two puzzles in the left side of the Figure 6 and answer by using the answer code in the right side of the Figure 6. A correct answer was a combination of two pairs of letters. In this example (Figure 7) AEDF or DFAE were the only two possible correct answers. Participants had two-minute period to practice and become familiar with the task. After that they were asked to solve as many puzzles as possible in five minutes. We created incentives in order to ensure the best effort from participants. For example in this step, for each puzzle correctly solved during the five minute period participants knew that they would receive 50 Tokens.[4]

[4] 1 Token = 1 Cent

In addition, participants knew that as workers they would be evaluated during the second day section of the experiment, by several potential employers, based on their performance during both, the two-minute practice period and the five-minute period of solving puzzles. Based on the two-minute practice period performances we developed workers' "signal 1" for the labor market. The "signal 1" is the time, in seconds, it took a participant until they correctly solve a puzzle during the practice period. For the "signal 1" each workers' timer was started at the moment they start the two-minute practice period and it was stopped once one puzzle was correctly solved, the total seconds showed by the timer at the end of the process is the "signal 1". The workers' "signal 2" for the labor market was developed using the five-minute period's performance. The "signal 2" is the number of puzzles correctly solved during the five-minute period of production during the first day section. [5]

After the five-minute period of solving puzzles, employers' beliefs were measured by using their predictions about job-seekers productivity. We asked the participants: "On average, how many puzzles do you think the Hispanic, Latino, or Spanish origin males (females) participants of this experiment solved?" and "On average, how many puzzles do you think the Whites origin males (females) participants of this experiment solved?" We split the sample between agricultural job and non-agricultural job employers by asking them: "Are you working now on a farm, ranch, or any other rural work, or planning to work when you graduate?"

After the first day section we asked participants a set of demographic questions, the same set of questions used in the US Census 2010. This group of demographic questions were asked through an online survey in order to avoid extending the experiment's duration. As well as in the

[5] The two signals were used as an input for the Section day 2's potential employer's estimations.

rest of the experiment, the online survey included monetary incentives for the participants in order to assure their answers would be as accurate as possible.

3.2.2. Section day 2 description

For the second day section we split the participants in the experiment between agricultural and non-agricultural labor market by using the information obtained in the first day section[6]. At the beginning of this section, we asked all the participants to play the role of the worker again. Similarly with the first day section, after giving them a two-minute practice period, we asked the participants to solve as much as puzzles as they could, but in this case during a ten-minute period[7] of production. Similarly to the first day section, we offered to the participants 50 Tokens per each puzzle correctly solved during the production period.

After they become completely familiar with the task of solving puzzles we asked participants to play the role of employers and make predictions about potential workers' performances. Since 97% of the participants during the second day section had already participated in the first the section, at this point of the experiment almost all of the participants have had two two-minute periods to practice, one compensated five-minute period solving puzzles, and one compensated ten-minute period solving puzzles. Two different sets of predictions were asked by giving two different levels of information, related to the worker being evaluated, to the potential employers' (predictors).

For the first set of predictions we gave to the employers a set of ten potential employees' fake names, names representative of gender and ethnicity, with their respective "signal 1", the

[6] By using the answers to the question "Are you working now on a farm, ranch, or any other rural work, or planning to work when you graduate?" asked during the first day section.

[7] For the second day section we used a complete new set of analogous puzzles of the ones used for the first day section .Again, the sequence of the puzzles in each step was identical for every subject, which means that the subjects were solving the same puzzles appearing in the same order.

time it took a participant until they correctly solve a puzzle during the practice period of the first day section [8]. The fake names, representative of ethnicity and gender, were made based on US statistics about most popular used names per each ethnicity group (US Census Bureau 2000; Mongabay 2005 a). In addition, we used regionally popular names and last names in the Midwest for Whites males and females based on regional statistics about popular names and last names for the range of ages in which most of the participants were included (Mongabay 2005 b).
With that set of information we asked participants to make predictions about each of those ten potential employees' productivity in the five-minute period of solving puzzles. In addition, with exactly the same set of information we asked participants to make predictions about each of those potential employees' performances during the ten-minute period of solving puzzles.

How many puzzles do you think each applicant can solve in 5 minutes? For each answer that matches the 5 minutes performance, you will receive additional 20 tokens.

Question 11	Fake name:	John White Bull	Signal:	25
Question 12	Fake name:	Sofia Martinez	Signal:	78
Question 13	Fake name:	Emma Little Eagle	Signal:	33
Question 14	Fake name:	Ebony Williams	Signal:	67
Question 15	Fake name:	Jacob Smith	Signal:	128
Question 16	Fake name:	Alexander Olsen	Signal:	102
Question 17	Fake name:	Hannah Larsen	Signal:	78
Question 18	Fake name:	John Garcia	Signal:	77
Question 19	Fake name:	Jamal Davis	Signal:	60
Question 20	Fake name:	Emily Johnson	Signal:	97

Figure 8. Example of a set of information containing ten fake-names and their respective "signal 1". In this case asking them to make predictions for five minutes performance

[8] The "signal 1" was developed with the data obtained in the first day section. The timer for the signal started at the moment they start the practice period and ended once one puzzle was correctly solved.

All the sets presented to the participants in this step of the experiment contained the same population distribution of fake names observed in Figure 8: 2 Hispanics (1 male and 1 female), 2 Native Americans (1 male and one female), 2 African Americans (1 male and 1 female), and 4 Whites (2males and 2 females). In the case of Whites males and females regionally popular in the Midwest were also used. The order, in which fake names were presented, as well as levels and he differences among signals were randomized. Each employer was asked to make predictions related to employers' ten-minute productivity based on exactly the same set of information.

After these two sets of predictions we increased again the level of information related to employees' relevant characteristics for the task being evaluated that we were giving to the potential employers through a more informative signal related to workers' productivity. At this step of the experiment we gave the participants a set of ten potentials' fake-names with their respective "signal 2". The "signal 2" is workers' productivity during the five-minute productivity in the first day section, is the number of puzzles correctly solved by the potential employee during the five-minute period of production. With that set of information we asked the potential employers to make predictions about those potential employees' performance during a ten-minute period of solving puzzles.

The set of fake-names used in the predictions based on "signal 1" and "signal 2" were different, since we wanted to avoid the get confused while they were predicting five-minute period's performance (based on "signal 1") by "taking a look" on the page that was next. However, as well as with the sets of information that contained "signal 1" we were consistent with the fake names' population distribution and we randomized the order of the names, the level and the differences between "signals 2".

In this case you know the 5 minutes performance of the applicants. How many puzzles do you think each applicant can solve <u>in 10 minutes</u>? For each answer that matches the 10 minutes performance, you will receive additional 20 tokens.

Question 1	Fake name:	John Garcia	Puzzles(5min):	10
Question 2	Fake name:	Sofia Martinez	Puzzles(5min):	11
Question 3	Fake name:	John White Bull	Puzzles(5min):	11
Question 4	Fake name:	Hannah Larsen	Puzzles(5min):	11
Question 5	Fake name:	Jacob Smith	Puzzles(5min):	3
Question 6	Fake name:	Emily Johnson	Puzzles(5min):	7
Question 7	Fake name:	Ebony Williams	Puzzles(5min):	7
Question 8	Fake name:	Alexander Olsen	Puzzles(5min):	5
Question 9	Fake name:	Jamal Davis	Puzzles(5min):	7
Question 10	Fake name:	Emma Little Eagle	Puzzles(5min):	14

Figure 9. Example of a set of information containing ten fake-names and their respective "signal 2"

3.3. Econometric specification and empirical model

In order to measure the discrimination of Hispanics and Latinos in the labor market we developed three groups of linear regressions. The first group of regressions was developed with the estimations obtained during the first day section and corresponds to potential employers' beliefs when they only knew the requested task for the job and the potential employees' ethnicity. The dependent variable $Avpredhlm_i$ captures employers' beliefs about Hispanics job-seekers' productivity through their answer to the question[9] "On average, how many puzzles do you think the Hispanic, Latino, or Spanish origin male (female) participants of this experiment solved?"

Employers' beliefs about Hispanics job-seekers' productivity were regressed with potential employers' socio-economic characteristics, and their prediction about Whites

[9] The question was asked right after participants finished the five-minute solving puzzles period during the first day section.

employers' productivity as explanatory variables. Following this strategy, we developed the following model based in two linear regressions[10]:

$$Avpredhlm_{\,i} = \beta_0 + \beta_1 agjob_i + \beta_2 white_i + \beta_3 male_i + \beta_4 avpredwhitem_i + \beta_5 religious_i + \mu \qquad (3)$$

$$Avpredhlf_{\,i} = \beta_0 + \beta_1 agjob_i + \beta_2 white_i + \beta_3 male_i + \beta_4 avpredwhitef_i + \beta_5 religious_i + \mu \qquad (4)$$

Where $Avpredhlm(f)_{\,i}$ is the i's participants' prediction of Hispanics males' (females') average productivity, $white_i$ is a dummy variable (1= i's participant's race is White, 0= i's participant's race is any but White), $male_i$ is a dummy variable (1= i's participant is male, 0= i's participant is female), $avpredwhitem(f)_i$ is the i's participant's prediction of Whites males' (females) average productivity[11], $agjob_i$ is a dummy variable (1= i's participant's is involved in the agricultural labor market , 0= i's participant's is not involved in the agricultural labor market)[12], $religious_i$ is a dummy variable (1= i's participant's profess any religion , 0= i's participant's does not profess any religion).

The second day section's groups of regressions were developed by increasing the level of available information about employees (with respect to the first group) through a more informative signal with strong linkage with potential employees' productivity, at the moment of their predictions. During the second day, predictions were made based on an employee's "signal" to the labor market. It could be argued that the level of the evaluated employee's "signal", the

[10] Both linear estimations were robust regressed with-out and with some relevant interaction terms.
[11] Employers beliefs about Whites job-seekers' productivity was measured during the first day section by asking them: "On average, how many puzzles do you think the White origin male (female) participants of this experiment solved?" just after they finish the five-minute period of solving puzzles.
[12] We split the simple by using the answers to the question "Are you working now on a farm, ranch, or any other rural work, or planning to work when you graduate?". Asked during the first day section.

level of the other employees' "signals", and furthermore the differences between the "signals" presented in the set of information, could have an effect in the employees' prediction. In order to avoid that problem we followed a group of strategies. First of all we randomized the order, the level, and the differences between Hispanics job-seekers' and non-Hispanics' job-seekers' "signals" among the different sets of information presented to employers during the experiment.

In addition, to measure the participants' estimation bias of Hispanics' productivity, we used as an unbiased productivity estimation a Poisson model based on the signal provided to the employer and real performances of all participants in the experiment. The difference between the participants' productivity estimation of a job seeker and the Poisson model estimation based on the signal provided is defined as the participants' estimation bias. The calculation was done in three steps. In the first step we captured employers' beliefs about Hispanics job-seekers' productivity by their answers to the question "How many puzzles do you think each applicant can solve in 5 minutes? For each answer that matches the 5 minutes performance, you will receive additional 20 tokens." We repeated the same question for the case of 10 minutes. In the second step we created an a "synthetic" real performances by using an unbiased productivity estimation Poisson model, based on the signal provided to the employer and real performances of all participants in the experiment [13] per each level of "signal" presented to potential employers. Synthetic "real" performances were developed based in two main assumptions:

(1) Ethnicity is not relevant to predict workers' productivity, which is consistent with Mobious, Rosenblat, and Wang (2016) and with our results (Tables 2 and 3) and

[13] The original idea was use real performances instead of synthetic "real" performances but we had to proceed this way because of the number of observations. Synthetic "real" performances per each level of "signals" presented during the experiment are presented in appendix (Tables A4 and A5).

(2) The “solving a correct puzzle” process follows a Poisson distribution[14]. The “real” performances based on “signal 1” were developed using a Poisson model with the “signal 1” and its square as explanatory variables[15]. For five-minute’s “real” performances the number of observations used were 129, the R^2= 0.0424, and the estimated equation was:

$$Fiveminsig1 = 2.781083^{**} - 0.0210369^{**} signal1 + 0.00013^{**}\, signal1^2 \quad (5)$$

For ten-minute’s “real” performances the number of observations used were 45, the R^2= 0.0176, and the estimated equation was:

$$Tenminsig1 = 3.264328^{**} - 0.00449563\, signal1 + 0.0000152\, signal1^{\,2} \quad (6)$$

The “real” performances based on “signal 2” were developed using a Poisson model with the “signal 2” as explanatory variable[16]. For these “real” performances the number of observations used were 60, the R^2= 0.0619, and the estimated equation was:

$$Tenminsig2 = 2.805387^{**} + 0.030634^{**} signal2 \quad (7)$$

In the third step we created the dependent variables “errors in predictions” as the differences between the employers’ estimations (step 1) and the synthetic “real” performances forecasts (step 2). Hence, the dependent variables in second day section’s models are “errors in predictions”, the difference between the employers’ prediction about Hispanics’ performances and Hispanics real performances. Finally, we checked if “signals” have effects in the dependent

[14] Poisson regression is widely used when the dependent variable is a count, for instance of events such as the arrival of a telephone call at a call center, or in this case a correctly solved puzzle. Poisson regression may also be appropriate for rate data, where the rate is a count of events divided by some measure of that unit's exposure (a particular unit of observation,). More generally, event rates can be calculated as events per unit time, which allows the observation window to vary for each unit.

[15] Forecasted five and ten-minute “real’ performances per each level of “signal 1” are presented in Table A4 in the Appendix.

[16] Forecasted ten-minute “real’ performances per each level of “signal 2” are presented in Table A5 in the Appendix.

variables. We find no evidence that “signals” predicts “errors in predictions” in any of the specifications that we estimate below.[17]

Model 3 was developed with employers’ predictions made based in “signal 1”. We asked participants to make predictions related to a set of 10 potential employees’ potential productivity in five-minute period and in ten-minute period of solving puzzles[18] by giving them the potential employees’ fake names representative of gender and ethnicity, and the “signal 1” [19] of each of the ten potential employees. When compared with the first group of estimations the inclusion of “signal 1” in the set of information implies an increasing on the level of information available for potential employers. By doing this, we increased the level of available job–seekers’ observable characteristics relevant for the position and reduced the level of unobservable on. After that, potential employees’ estimations were compared with potential employees’ “real” productivity. Employers’ beliefs were captured by their errors in estimations. Errors were calculated by subtracting the real performance to the employees’ estimations. We captured employers’ beliefs (errors in predictions) related to Hispanics job-seekers by using:

$$Errorpredh_{\,i} = \beta_0 + \beta_1 agjob_i + \beta_2 white_i + \beta_3 male_i + \beta_4 errorpredw_i + \beta_5 religious_i + \beta_6 malepred_i + \beta_8 errorpredh10_i + \mu \quad (8)$$[20]

Where $Errorpredh_{\,i}$ is the i’s participants’ error in prediction with respect of a Hispanic’s real productivity, $agjob_i$ is a dummy variable (1= i’s participant’s is involved in the agricultural labor market , 0= i’s participant’s is not involved in the agricultural labor market),

[17]Regressions including “signals” as explanatory variables are presented in appendix (Tables A2 and A3).
[18] We requested them to make the predictions just after they finished to complete a ten-minute period of solving puzzles.
[19] The “signal 1” was developed with the data obtained during the first day section. The timer for the signal started at the moment that the potential employee started the practice period and ended once one puzzle was correctly solved by him. The higher the “signal 1”, the lower the productivity of the employer.
[20] The linear estimations were regressed with-out and with some relevant interaction terms.

$white_i$ is a dummy variable (1= i's participant's race is White, 0= i's participant's race is any but White), $male_i$ is a dummy variable (1= i's participant is male, 0= i's participant is female), $averrorpredw_i$ is the i's participant's error in prediction with respect of a White employee real productivity, $religious_i$ is a dummy variable (1= i's participant's profess any religion , 0= i's participant's does not profess any religion), $malepred_i$ is a dummy variable (1= i's participant's error in prediction is related to a Hispanic male's productivity, 0= i's participant's error in prediction is related to a Hispanic female's productivity), $errorpredh10_i$ is a dummy variable (1= i's participant's error in prediction is related to a Hispanic's productivity performance in ten minutes, 0= i's participant's error in prediction is related to a Hispanic's productivity performance in five minutes).

Models 4 and 5 were developed based on employers' estimations made based on "signal 2'. When compared with Model 3' estimations, the inclusion of "signal 2" in the set of information determined an increasing on the level of information related to job-seekers' characteristics relevant for the job's task. When compared with "signal 1" the "signal 2" offers a better linkage to real productivity, since it is based in a way longer period of workers' real production plus it was developed with more experienced workers' productivity. While "signal 1" is based in the two-minute practice period, the first opportunity that workers were asked to do the task, the "signal 2' is based in the five-minute period of production right after the practice time. After that, potential employees' estimations were compared with potential employees' "real" productivity in ten minutes[21]. Employers' beliefs were captured by their errors in estimations. Errors were calculated by subtracting the real performance to the employees' estimations. We

[21] "Real" productions per each level of "signal 2" were estimated by using a Poisson model.

captured employers' beliefs (errors in predictions) related to Hispanics males and females job-seekers by using the following regressions:[22]

$$Errpredhm_{\ i} = \beta_0 + \beta_1 agjob_i + \beta_2 white_i + \beta_3 male_i + \beta_4 errpredwm_i + \beta_5 religious_i + \mu \tag{9}$$

$$Errpredhf_{\ i} = \beta_0 + \beta_1 agjob_i + \beta_2 white_i + \beta_3 male_i + \beta_4 errpredwf_i + \beta_5 religious_i + \mu \tag{10}$$

Where $Errorpredhm\ (f)_{\ i}$ is the i's participants' error in prediction with respect of a Hispanic males (females) real productivity in ten minutes, $white_i$ is a dummy variable (1= i's participant's race is White, 0= i's participant's race is any but White), $male_i$ is a dummy variable (1= i's participant is male, 0= i's participant is female), $errpredwm_i$ is the i's participant's average error in prediction of the two White male potential employees' productivity with respect to their real productivity, $errpredwf_i$ is the i's participant's error in prediction of the female potential employee's productivity with respect to her real productivity, $agjob_i$ is a dummy variable (1= i's participant's is involved in the agricultural labor market , 0= i's participant's is not involved in the agricultural labor market), $religious_i$ is a dummy variable (1= i's participant's profess any religion , 0= i's participant's does not profess any religion).

3.4. Data

The pool of participants consisted of students from a university in the Midwest. They were recruited in different ways: massive emails, meetings with minorities' social organizations (Latin Americans, African Americans, and Native Americans), and announcements made during agribusiness undergrad degrees' classes.

[22] Regressions with and with-out interaction terms were made.

Table 1. The subject pool description.

	Sample description	
	First day section	Second day section
Number of participants	105	47
Agjobs	53.20%	40.40%
Religious	91.17%	76.00%
Males	63.60%	57.40%
Females	35.40%	42.60%
Whites	88.70%	91.40%
Minorities	11.30%	8.60%

Table 2. General description of the participants' performance solving puzzles in five-minute period during the first day section.

	Productivity in five minutes			
	Average	Min	Max	St. Dev.
All Participants	7.27	0	17	3.66
Minorities[23]	6.9	0	11	3.31
Whites	7.72	0	17	3.47
Males	6.84	0	17	3.56
Females	8.38	0	16	3.47

We did not find significant differences when Hispanics or Latinos' performances were compared with Whites' performances. Furthermore, we did not find significant differences when males' performances were compared with females' performances (Table 2).

Table 3. General description of the participants' performance solving puzzles in ten-minute period during the second day section.

	Productivity in ten minutes			
	Average	Min	Max	St. Dev.
All Participants	19.28	0	33	6.83
Minorities	25	24	26	1.15
Whites	22.825	0	33	7.13
Males	22.32	0	33	8.26
Females	23.94	17	33	4.33

[23] During the first day section Hispanics were 87% of the minorities.

We did not find significant differences when minorities' performances were compared with Whites' performances. Furthermore, we did not find significant differences when males' performances were compared with females' performances (Table 3).

The data collected through our experimental labor market gives to our research some advantages when compared to studies based on observational data. Through the experimental labor market we were able to offer a signal that better links to the true productivity. Observational data based studies usually use the years of study as the signal in the labor market. College major and performance are frequently unavailable, making years of schooling a less convincing index for the quality of education. In our experiment we developed the "signals" in order to provides a precise measure of the needed skills to solve puzzles in five and in ten-minute period of solving puzzles based on three main reasons: (1) the task is the same: solving the same type of puzzles;(2) the worker is induced, by monetary incentives, to perform identically in both; and (3) given that employers previously played the role of workers, at the moment of estimations they were completely familiar with the task that was being evaluated.

CHAPTER 4. RESULTS AND DISCUSSION

4.1. General description

Models were estimated using STATA statistical software. SATA -13 has the required command (regress) to estimate the regression equations using the ordinary least square estimators. By adding the command (robust) we were able to obtain robust estimations in each model[24]. Further all the descriptive statistics estimation and data procession were also done using STATA. Results presented in this paper include regressions with some interaction terms that theory indicates should be relevant. Most of the farms' principal operators in the Midwest are White males, for example of the 74,542 principal operators in Minnesota, 73,984 (99.3 percent) were White in 2012 and 84.6% of farms principal operators were males in Minnesota during the same year (USDA, 2012). Therefore, it is relevant to analyze the interaction terms between agjob (the dummy variable used to split the sample between agricultural job's employers and non-agricultural job's employers) and those other potential employers' socio-economic characteristics (White, male, and religious).

The first group of regressions refers to results obtained during the first day section when the statistical discrimination of potential employers was tested splitting the sample for predictions related to Hispanics males job-seekers' productivity (Model 1) and Hispanics females job-seekers' productivity (Model 2). In this case we present robust estimations with and with-out interaction terms for both models in the Table 4.

During the second day section we tested the effects of increase the available information, related to the employee, on employers' beliefs about workers' productivity. Results related to Model 3 are presented in the Table A1 in appendix. Results related to the theoretical Models 4

[24] Robust estimations are presented per each regression as follows: for Example Model 3 means a non-robust estimation of Model 3 while Model 3' means a robust estimation of Model 3.

and 5 are presented in the Table 6. Tables with “signals” as explanatory variables for Models 3, 4, and 5 are presented in appendix (Tables A2 and A3). The total number of employees’ productivities predictions made per- each participant, playing the employer role, were 10, making the total number of observations 347.

4.2. First day section’s results (Models 1 and 2)

Table 4. Employers’ predictions about average Hispanics males’ and females’ productivities

	Model 1’	Model 1’	Model 2’	Model 2’
Interaction terms	NO	YES	NO	YES
	Avpredhlm	Avpredhlm	Avpredhlf	Avpredhlf
Agjob	-0.156	3.407**	0.249	2.129
Avpredwm	0.944***	0.929***		
Religious	-0.190	-2.958*	0.0190	-3.681*
White	-0.500	4.423**	0.514	5.607**
Male	0.341	0.687	-0.599	-0.481
*Agjob*male*		1.119		-0.0844
*Agjob*religious*		-0.755		0.405
*Agjob*white*		-3.057***		-1.908
Avpredwf			0.954***	0.940***
_cons	-0.0432	1.227	-0.260	0.848
Bic	477.7	488.6	428.5	440.9
N	105	105	105	105
F	68.75	40.24	91.21	60.14

* p < 0.10, * *p < 0.05, *** p < 0.01

Predictions related to average Hispanics males and females’ productivity in five minutes were regressed following theoretical Models 1 and 2 using as explanatory variables the predictions about average Whites males’ and females’ productivity and demographic characteristics of the participants. Robust regressions with and without interaction terms are presented for males, columns 1 and 2 respectively, and for females, columns 3 and 4 respectively (Table 4).

Results suggest that agricultural and non-agricultural potential employers have different stereotypes with respect to Hispanics males’ productivity. Hispanics males are perceived to be more productive by agricultural job's potential employers than by non-agricultural job's potential employers. Results show that Hispanics males are perceived to be 3.40 puzzles more productive (47% more than all the participants' average productivity in five minutes) by agricultural jobs' employers than by non-agricultural jobs' employers. However, we did not find statistically significant differences between agricultural and non-agricultural employers' predictions related to Hispanics females' average productivity.

Results also suggest that religious and non-religious potential employers have different stereotypes with respect to Hispanics' productivity. Hispanics are perceived to be less productive by religious potential employers than by non-religious potential employers. Results show that Hispanics males are perceived to be 2.95 puzzles less productive (41% of all the participants' average productivity in five minutes) by religious employers than by non-religious employers. In addition, Hispanics females are perceived to be 3.68 puzzles less productive (51% of all the participants' average productivity in five minutes) by religious employers than by non-religious employers.

Furthermore, results show that Whites and minorities potential employers have different stereotypes with respect to Hispanics' productivity. Hispanics are perceived to be less productive by minorities than by White employers, which suggests lack of self-confidence among minorities. Results show that Hispanics males are perceived to be 4.42 puzzles more productive (60% more than all the participants' average productivity in five minutes) by White employers than by non-White employers. In addition, Hispanics females are perceived to be 5.60 puzzles more productive (77% more than all the participants' average productivity in five minutes) by White employers than by non-White employers.

In addition, results suggest that male and female employers do not present different stereotypes with respect to Hispanics productivity. We did not find statistically significant differences between male and female potential employers' predictions related to Hispanics' productivity.

We also investigated the distribution of the difference in stereotype between agricultural and non-agricultural employers' predictions among the sub-groups of agricultural employers (White agricultural employers, male agricultural employers and religious agricultural employers).

- MODEL: $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$
- INTERPREATION:

Dummies	$X_2 = 0$	$X_2 = 1$
$X_1 = 0$	β_0	$\beta_0 + \beta_2$
$X_1 = 1$	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$

Figure 10. Coefficients' interpretation in models with interaction terms between dummy variables

Figure 10 illustrates how to interpret coefficients when interaction terms between dummy variables are added in the model. In order compare the predictions, related to Hispanics productivity, made by Whites agricultural employers with the predictions made by Whites non-agricultural employers we jointly tested the significance of the differences in predictions between those two sub-groups, by testing the null hypothesis ($\beta_1 + \beta_3$) = 0, where $\beta_1 =$ coefficient associated with agjob and $\beta_3 =$ coefficient associated with the interaction term between agjob and white. We did not reject the null hypothesis; hence we did not find statistically significant differences between White-agjob employers and White-non-agjob employers.

We repeated the same process in order compare the predictions, related to Hispanics' productivity, made by male agricultural employers with the predictions made by male non-agricultural employers. We found that Hispanics males are perceived to be 2.62 puzzles more productive (36% of all the participants' average productivity in five minutes) by male agricultural employers than by male non-agricultural employers. However, we did not find statistically significant differences between those two groups' predictions about Hispanics females' productivity.

Finally we repeated the same process in order compare the predictions, related to Hispanics productivity, made by religious agricultural employers with the predictions made by religious non-agricultural employers. We found that Hispanics males are perceived to be 4.63 puzzles more productive (64% of all the participants' average productivity in five minutes) by religious agricultural employers than by religious non-agricultural employers. However, we did not find statistically significant differences between those two groups' predictions about Hispanics females' productivity.

4.3. Second day section's results (Models 3, 4, and 5)

Errors in predictions about Hispanics' productivities where estimated following the theoretical Models 3, 4 , and 5 using as explanatory variables the errors in predictions about average white performance's and demographic characteristics of the potential employers. The errors in predictions were calculated by subtracting the potential employees' performance from the potential employers' prediction (error in prediction = employers' prediction – employees' real performance). Hence, a positive error means a positive bias estimation from potential employer.

For the Model 3, besides each potential employee's "fake name" during this group of estimations potential employers used "signal 1" , the time it took a potential employee to correctly solve one puzzle during the practice period in the first day section, to predict employees' productivity in five-minute and in ten-minute periods. It was observed a high variance in and a significant range in the errors of predictions associated with Model 3 (Table 5).

Table 5. Descriptive statistics of dependent variables developed during second day section

Variable	**Obs**	**Mean**	**Std.Dev.**	**Min**	**Max**
errorpredhm5	47	4.78	19.43	-98	29
errorpredm10	47	4.59	17.57	-83	48
5errpredhm	47	2.57	5.746	-22	8
errorpredhf5	47	-2.90	14.14	-93	14
errorpredm10	47	3.12	12.77	-66	24
5errpredhf	47	2.43	5.89	-22	8

We did not find statistically significant estimations for the Model 3 when the observations related to five-minute period of solving puzzles were separated from the ones related to ten-minute period of solving puzzles. We wanted to explore if this was problem could be fixed by increasing the number of observations, which lead us to unify predictions related to Hispanics' five and ten minutes period's estimations in order to increase the number of observations. Since the set of ten potential employers' "fake names", presented to the employer, for the five-minute and the ten- minute period's predictions were the same, we could easily make it by adding two dummy variables. Errorpredh10 was included to measure the difference between the errors in predictions related to the five-minute's and ten-minute's period of productivity and Malepred was included to measure the difference between predictions related to Hispanics females' and Hispanics males' productivity (Table A1 in the appendix).

For Model 4's and Model 5's estimations, besides each potential employee's "fake name" the potential employers used employees' "signal 2", the number of puzzles correctly solved during the five-minute period in the first day section, to predict employees' productivity in a ten-minute period of production. When compared with “signal 1” the “signal 2” offers a better linkage to real productivity, since it is based in a way longer period of workers’ real production plus it was developed with more experienced workers’ productivity. While “signal 1” is based in the two-minute practice period, the first opportunity that workers were asked to do the task, the “signal 2’ is based in the five-minute period of production right after the practice time.

Contrary to what we found in Model 3’s predictions, it was not observed a high variance or a big range in the errors in predictions related to Models 4 and 5 (Table 5). This reinforces the idea that “signal 2” offers a better linkage with real performance than “signal 1”. Hence, predictions related to Hispanics males were regressed separately from Hispanics females’ productivity predictions.

Table 6. Errors in predictions of Hispanics productivity in 10-min having “signal 2” in the mini-resume

Interaction terms	Model 4’ NO	Model 4’ YES	Model 5’ NO	Model 5’ YES
	Errpredhm	Errpredhm	Errpredhf	Errpredhf
Agjob	1.161	7.479***	0.833	0.785
Errpredwm	0.473***	0.469***		
Errpredwf			0.353*	0.354*
Male	-0.434	-1.285*	-0.0586	-1.392
Religious	-2.078**	-1.729*	-2.031**	-2.891**
White	7.706***	9.932***	8.090***	8.889***
Agjobreligious		1.624		3.681*
Agjobmale		2.923		-5.055
Agjobwhite		-10.20***		3.014**
_cons	-3.724*	-5.604**	-6.157***	-5.493*
Bic	231.4	227.1	249.3	248.1
N	47	47	47	47
F	7.526	.	5.178	.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Predictions related to average Hispanics males’ and females’ productivities in ten minutes were regressed following theoretical Models 4 and 5 using as explanatory variables the predictions about average Whites males’ and females’ productivities and demographic characteristics of the participants. Robust regressions with and without interaction terms are presented for males, columns 1 and 2 respectively, and for females, columns 3 and 4 respectively (Table 6). Similarly to Model 3, the error in prediction was calculated by subtracting the potential employees' real performances from the potential employers' predictions about those performances (error in prediction = employers' prediction – employees' real performance). Hence, a positive error means a positive bias estimation from potential employer.

Results suggest that agricultural and non-agricultural potential employers have different stereotypes with respect to Hispanics males' productivity. Hispanics males are perceived to be more productive by agricultural job's potential employers than by non-agricultural job's potential employers. Results show that Hispanics males are perceived to be 7.47 puzzles more productive (46 % more than all the participants' average productivity in ten minutes) by agricultural jobs' employers than by non-agricultural jobs' employers. However, we did not find statistically significant differences between agricultural and non-agricultural employers' predictions related to Hispanics females' productivity.

Results also suggest that male and female potential employers have different stereotypes with respect to Hispanics males' productivity. Hispanics males are perceived to be less productive by male potential employers than by female potential employers. Results show that Hispanics males are perceived to be 1.28 puzzles less productive (7 % more than all the participants' average productivity in ten minutes) by male employers than by female employers. However, we did not find statistically significant differences between males and females employers' predictions related to Hispanics females' productivity.

Results also suggest that religious and non-religious potential employers have different stereotypes with respect to Hispanics' productivity. Hispanics are perceived to be less productive by religious employers than by non-religious employers. Results show that Hispanics males are perceived to be 1.72 puzzles less productive (9% of all the participants' average productivity in ten minutes) by religious employers than by non-religious employers. In addition, Hispanics females are perceived to be 2.89 puzzles less productive (15% of all the participants' average productivity in ten minutes) by religious employers than by non-religious employers.

Furthermore, results show that Whites and minorities potential employers have different stereotypes with respect to Hispanics' productivity. Hispanics are perceived to be less productive by minorities than by White employers, which suggests lack of self-confidence among minorities. Results show that Hispanics males are perceived to be 9.93 puzzles more productive (51% of all the participants' average productivity in ten minutes) by White employers than by non-White employers. In addition, Hispanics females are perceived to be 8.88 puzzles more productive (77% of all the participants' average productivity in ten minutes) by White employers than by non-White employers.

We also investigated the distribution of the difference in stereotype between agricultural and non-agricultural employers' predictions among the sub-groups of agricultural employers (White agricultural employers, male agricultural employers and religious agricultural employers) following the same process presented in Figure 10. In order compare the predictions, related to Hispanics productivity, made by Whites agricultural employers with the predictions made by Whites non-agricultural employers we jointly tested the significance of the differences in predictions between those two sub-groups, by testing the null hypothesis ($\beta_1 + \beta_3$) = 0, where $\beta_1 =$ coefficient associated with agjob and $\beta_3 =$ coefficient associated with the interaction term between agjob and white. We did reject the null hypothesis; hence we did find statistically significant differences between White-agjob employers and White-non-agjob employers. We found that Hispanics males are perceived to be 2.72 puzzles less productive (14% of all the participants' average productivity in ten minutes) by White agricultural employers than by White non-agricultural employers.

We repeated the same process in order compare the predictions, related to Hispanics productivity, made by male agricultural employers with the predictions made by male non-agricultural employers. We found that Hispanics males are perceived to be 10.40 puzzles more productive (54% more than all the participants' average productivity in ten minutes) by male agricultural employers than by male non-agricultural employers. However, we did not find statistically significant differences between those two groups' predictions about Hispanics females' productivity.

Finally we repeated the same process in order compare the predictions, related to Hispanics productivity, made by religious agricultural employers with the predictions made by religious non-agricultural employers. We found that Hispanics males are perceived to be 9.10 puzzles more productive (47% of all the participants' average productivity in ten minutes) by religious agricultural employers than by religious non-agricultural employers. However, we did not find statistically significant differences between those two groups' predictions about Hispanics females' productivity.

CHAPTER 5. CONCLUSIONS

This paper presents evidence supporting the existence of differences in treatments received by Hispanics job-seekers on agricultural and non-agricultural markets. We found evidence suggesting an invisible barrier preventing Hispanics males to get non- agricultural jobs and their mobility from agricultural to non-agricultural jobs, which may have implications on Hispanics' job allocation, migration, education and welfare.

During the first day section of the experiment we tested how the job seekers' ethnicity, the fact of being Hispanic, affected employers' beliefs related to productivity. We found that average predicted productivity for Hispanic males in the agricultural labor market was higher than in non-agricultural labor market, 3.407 puzzles which is the equivalent to 47% of the overall average productivity during the first day section (Model 1). This result suggests that Hispanics male job-seekers are predicted by employers to fit better in agricultural activities which may imply an invisible barrier that prevents their possibilities to get non-agricultural jobs. However, we did not find significant differences in the average predicted productivity of Hispanic female workers, when agricultural employers' and non-agricultural employers' predictions were compared (Model 2). Analyzing the distribution of the founded differences in beliefs within the sub-groups of employers, agricultural-male employers perceived Hispanics males job-seekers to be 4.52 puzzles, 62% of the overall average productivity during the first day section, more productive when compared with non-agricultural male employers' perceptions, and agricultural-religious employers perceived Hispanics male job-seekers to be 2.62 puzzles more productive than non-agricultural religious employers perceptions. Given that most of principal operators in the Midwest's farms are males and religious, this potentially aggravates the invisible barrier for

Hispanics males job-seekers' to get non-agricultural jobs. Evidence about overrepresentation of Hispanics in agricultural jobs despite the existence of salary gaps supports these results.

During the second day section we attempted to understand how the increase of the Hispanics' observable characteristics relevant for the job-task, through a more informative signal related to workers' productivity, affected employers' beliefs. In this new step of our experimental labor market employers had access to information related to Hispanics' productivity, employers had access to a Hispanics job-seekers' "signal" with strong linkage to the real productivity. During the first day section of our experiment, results suggested that Hispanics immigrants arrive to non-traditional destinations in the US and they are perceived to fit better in agricultural jobs, therefore they may face an invisible barrier to get non-agricultural jobs. We wanted to investigate what happens after: are Hispanics able to significantly reduce employers' preconception that they fit better in agricultural than in non-agricultural jobs by showing their job-skills? We found that even after providing signals with strong linkage to real productivity to the job market Hispanics males are perceived to be more productive by agricultural job's potential employers than by non-agricultural job's potential employers. Results show that Hispanics males are perceived to be 7.47 puzzles more productive by agricultural employers than by non-agricultural employers, which is the equivalent to 46% of overall participants' average productivity during the second day section (Model 4). The magnitude of this result is similar in order of magnitude to the 40% salary gap between agricultural and non-agricultural jobs reported by Munshi (2003). When compared with the first day section's results, we did not find a significant reduction in employers' preconception that Hispanics fit better in agricultural jobs. This result suggests that Hispanics male job-seekers may face an invisible barrier that prevents their mobility from agricultural to non-agricultural jobs. Given more productivity information does not improve Hispanics males' chances to get a better paid non-agricultural job, optimal education investment for rural Hispanics is lower than for non-Hispanics, in line with Gradin 2012. Hence, this result may partially explain the educational gap between Hispanics and non-Hispanics through reducing Hispanics males' incentives to invest in human capital, in line with Lundberg and Startz 1983 and with Schwab 1986.

Results also suggest that Hispanics female job-seekers may not face the mentioned invisible barrier (Model 5). Analyzing the distribution of the founded differences in beliefs during the second day section within the sub-groups of employers, agricultural-male employers perceived Hispanics males job-seekers to be 10.40 puzzles more productive, 54% of the overall average productivity during the second day section, when compared with non-agricultural male employers' perceptions, and agricultural-religious employers perceived Hispanics male job-seekers to be 9.10 puzzles more productive than non-agricultural religious employers perceptions. Again, this potentially aggravates the invisible barrier that prevents Hispanics males job-seekers' mobility from agricultural to non-agricultural jobs. When compared with first day section's results, our findings suggest that the Hispanics male "signals" sent to the job market do not have a significant impact in employers' preconceptions that they fit better in agricultural activities than in non-agricultural ones.

Overall, the results presented on this study may have important implications for policy makers. Results suggest a difference in treatment against Hispanics males which segments the labor market on agricultural and non-agricultural labor market, independently of the Hispanic job seekers' skill level. Given Hispanics are believed to be better fitter for non-agricultural jobs, there is a barrier for Hispanic males that may create an excess supply of agricultural labor, which may at least partially explain the salary gap observed by Munshi (2003). Furthermore, results also suggests that the mentioned gap between agricultural and non-agricultural employers' beliefs are not reduced by Hispanic job-seekers' more informative signals to the labor market may also imply a distortion in the labor supply factor mobility by affecting Hispanics job seekers' incentives to invest in education, which may have an impact on second generation Hispanic immigrants via parent's educational level, and by making less effective the recommendations that potential Hispanics males jobs seekers receive from past employers. Therefore, policy designs should take account the differences in employers; beliefs' effects in both sides of the labor market, attempt to reduce the bias in employees' selection by the potential employers but also to increase potential employees incentives to invest in education.

Finally, this study may have some limitations in regards to sample selection bias, since most of students in the pool of participants were Midwest Whites and the number of Hispanic participants was a minor share of the pool. This prevented us to analyze in more detail the Hispanics' real performance during the experiment. Further research may be required to complement this study and reduce the limitations faced in it, possibly including other areas of the United States, especially more diverse ones.

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APPENDIX

A.1. Second day section's results with "signals 1" in the mini-resume

A.1.1. Model 3

Table A1. Errors in predictions of Hispanics' productivity having "signal 1" in the mini-resume

	Model 3	Model 3'	Model 3	Model 3'
Interaction terms	NO	NO	YES	YES
	Errorpredh	Errorpredh	Errorpredh	Errorpredh
Agjob	-4.254*	-4.254*	-78.57***	-78.57***
Averrorpredw	0.216***	0.216**	0.167***	0.167***
White	20.82***	20.82**	-2.964	-2.964
Male	4.459*	4.459**	2.506	2.506
Religious	7.140**	7.140*	-2.709	-2.709
Malepred	-1.259	-1.259	-1.212	-1.212
Errorpredh10	5.208**	5.208**	5.974***	5.974***
Agjobmale			-1.834	-1.834
Agjobwhite			81.11***	81.11***
Agjobreligious			0.999	0.999
_cons	-31.11***	-31.11***	-0.966	-0.966
Bic	1423.6	1423.6	1342.0	1342.0
F	14.79	3.404	30.08	22.94
N	172	172	172	172

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: "Model 3' " denotes robust OLS estimations of the models.*, **, and *** represent 91, 95 and 99% significance. "Agjob" is the dummy variable that splits rural labor market and urban labor market. "Malepred" is a dummy variable, Malepred=1 means is a prediction related to a Hispanic male's productivity, Malepred = 0 means is a prediction related to a Hispanic female. "Errorpredh10" is a dummy variable, Errorpredh10 = 1 means is a prediction related to a Hispanics' ten-minute productivity, Errorpredh = 0 means is a prediction related to a Hispanics' five-minute productivity.

A.2. Second day section's results with "signals" as explanatory variables

A.2.1. Model 3

Table A2. Errors in predictions of Hispanics' productivity having "signal 1" in the mini-resume

	Model 3	Model 3'	Model 3	Model 3'
Interaction terms	NO	NO	YES	YES
	Errorpredh	Errorpredh	Errorpredh	Errorpredh
Averrorpredw	0.211***	0.211**	0.148***	0.148**
Agjob	-4.261*	-4.261*	-84.13***	-84.13***
White	20.75***	20.75**	-3.577	-3.577
Male	4.518*	4.518**	2.829	2.829
Religious	7.350**	7.350*	-2.105	-2.105
Malepred	-1.270	-1.270	-1.261	-1.261
Avsignalh	-0.0183	-0.0183	-0.0811*	-0.0811
Errorpredh10	5.241**	5.241**	6.116***	6.116***
Agjobmale			-2.291	-2.291
Agjobwhite			83.30***	83.30***
Agjobreligious			-0.281	-0.281
Agjobavsignalh			0.103	0.103
_cons	-30.41***	-30.41***	2.665	2.665
Bic	1428.6	1428.6	1348.8	1348.8
F	12.90	3.084	25.53	20.36
N	172	172	172	172

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Table A2 presents robust OLS estimations of the models.*, **, and *** represent 91, 95 and 99% significance. "Agjob" is the dummy variable that splits rural labor market and urban labor market. "Malepred" is a dummy variable, Malepred=1 means is a prediction related to a Hispanic male's productivity, Malepred = 0 means is a prediction related to a Hispanic female. "Errorpredh10" is a dummy variable, Errorpredh10 = 1 means is a prediction related to a Hispanics' ten-minute productivity, Errorpredh = 0 means is a prediction related to a Hispanics' five-minute productivity. "Avsignalh" is the average between the Hispanics' "signals 1" received by the employer.

A.2.2. Models 4 and 5

Table A3. Errors in predictions of Hispanics productivity in 10-min having "signal 2" in the mini-resume

Interaction terms	Model 4' NO	Model 4' YES	Model 5' NO	Model 5' YES
	Errpredhm	Errpredhm	Errpredhf	Errpredhf
Agjob	1.187*	-9.692**	0.945	-15.71*
Av5errpredwm	0.475***	0.444***		
White	7.568**	12.24***	7.268***	9.272***
Male	-0.442	-1.379*	-0.0649	-1.577
Religious	-2.076**	-1.612	-1.889**	-2.837**
Minprodhm	0.0461	-0.741		
Agjobwhite		-17.90***		-7.966**
Agjobmale		1.734		1.557
Agjobreligious		2.244*		2.964**
Agjobminprodhm		2.387***		
Errpredwf			0.391*	0.401**
Minprodhf			0.344	-0.267
Agjobminprodhf				1.974**
_cons	-4.069	-0.0589	-9.085	-2.750
Bic	235.2	217.9	252.0	248.0
F	6.924	.	4.356	.
N	47	47	47	47

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Table A presents robust OLS estimations of the models.*, **, and *** represent 91, 95 and 99% significance. "Agjob" is the dummy variable that splits rural labor market and urban labor market. "Minprodhm" is the Hispanic male's "signals 2" received by the employer. "Minprodhf" is the Hispanic female's "signals 2" received by the employer.

A.3. Synthetic-forecasted “real” productivities per-each level of signal presented

Table A4. Synthetic “real” productivities per each level of “signal 1” presented

	"real" productivity	
"signal 1"	5 minutes	10 minutes
12	19	26
13	19	26
14	19	26
15	18	25
16	18	25
17	17	25
18	17	25
19	17	25
20	16	25
21	16	25
22	16	25
23	15	25
24	15	24
25	15	24
26	14	24
27	14	24
28	14	24
29	14	24
30	13	24
31	13	24
32	13	24
33	12	23
34	12	23
35	12	23
36	12	23
37	11	23
38	11	23
39	11	23
40	11	23
41	11	23
42	10	23
43	10	22
44	10	22
45	10	22
46	9	22
47	9	22
48	9	22
49	9	22
50	9	22
51	9	22

	"real" productivity	
"signal 1"	5 minutes	10 minutes
52	8	22
53	8	21
54	8	21
55	8	21
56	8	21
57	8	21
58	7	21
59	7	21
60	7	21
61	7	21
62	7	21
63	7	20
64	7	20
65	6	20
66	6	20
67	6	20
68	6	20
69	6	20
70	6	20
71	6	20
72	5	20
73	5	20
74	5	19
75	5	19
76	5	19
77	5	19
78	5	19
79	5	19
80	5	19
81	5	19
82	4	19
83	4	19
84	4	19
85	4	19
86	4	18
87	4	18
88	4	18
89	4	18
90	4	18
91	4	18

Table A4. Synthetic “real” productivities per each level of “signal 1” presented

	"real" productivity	
"signal 1"	5 minutes	10 minutes
92	4	18
93	4	18
94	3	18
95	3	18
96	3	18
97	3	18
98	3	18
99	3	17
100	3	17
101	3	17
102	3	17
103	3	17
104	3	17
105	3	17
106	3	17
107	3	17
108	3	17
109	3	17
110	2	17
111	2	17
112	2	16
113	2	16
114	2	16
115	2	16
116	2	16
117	2	16
118	2	16
119	2	16
120	2	16
121	2	16
122	2	16
123	2	16
124	2	16
125	2	16
126	2	15
127	2	15
128	2	15
129	2	15
130	2	15

Table A5. Synthetic “real” productivities per each level of “signal 2” presented.

“signal 2”	“Real” productivity in 10 minutes
1 2	17 17
3 4	18 18
5 6	19 19
7 8	20 20
9	21
10 11	22 22
12	23
13	24
14 15	25 25
16	26
17	27
18	28
19	29
20	30
21 22	31 31