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"CONSEGUENZE ECONOMICHE DI LEGGI ANTIDISCRIMINATORIE: IL CASO "BAN THE BOX"

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Firma (signature) ……Chiara Scenini……

TABLE OF CONTENTS

ABSTRACT (ITALIANO)
La selezione avversa è una delle due modalità con cui l'asimmetria informativa può manifestarsi e influenzare l'allocazione di un mercato. Questa accade quando un agente economico in una situazione strategica possiede maggiori informazioni rispetto alla sua controparte a proposito di una caratteristica che viene nascosta o non è osservabile in un evento casuale. Come enunciato dal primo teorema dell'economia del benessere, l'asimmetria informativa è considerata una delle cause del fallimento di mercato e per questa ragione è dato al policy maker il compito di individuare una soluzione per poter ottenere una allocazione più efficiente. Nonostante queste premesse, potrebbe essere il policy maker stesso con l'introduzione di una nuova legge ad introdurre asimmetria informativa nel mercato. Questo è successo negli Stati Uniti con l'introduzione di un insieme di leggi che prendono il nome da "Ban the Box", una campagna a sostegno degli ex-detenuto con l'obiettivo di aumentare il tasso di occupazione degli ex-carcerati. Per ottenere questo risultato, queste nuove leggi vietano ai datori di lavoro di richiedere informazioni sulla fedina penale dei candidati se non al termine del processo di assunzione. Tuttavia, queste nuove normi introducono asimmetrie informative tra i datori di lavoro e i candidati e alcuni studi dimostrano come queste riducano il tasso di occupazione tra la popolazione ispanica e nera giovane e poco qualificata.
Dopo una breve introduzione della campagna e della posizione economica e sociale degli ex-detenuti, nel secondo capitolo approfondisco gli studi svolti da diversi ricercatori che dimostrano con differenti metodologie empiriche questi effetti sul tasso di occupazione. Successivamente, analizzo con il modello di Rothschild e Stiglitz come un ipotetico mercato assicurativo possa cambiare ed evidenzio quali agenti economici ricevano benefici e quali ricevano danni dall'introduzione della legge. Nel terzo capitolo, analizzo l'impatto della legge sulla discriminazione nei confronti delle minoranze etniche secondo le teorie economiche discusse nella letteratura economica discriminando come una legge progettata per ridurla possa invece ottenere l'effetto contrario. Infine, evidenziamo il trade off presente tra la discriminazione e la privacy.

ABSTRACT
Adverse selection is one of the possible ways in which asymmetric information can influence the market. It occurs when one or more agents in a strategic situation possess better information on a random event than the other agents: in particular when the information concerns a characteristic that is hidden or not observable. As is known from the First Welfare Theorem, it is one of the determinants of market failure. As a result, the policy maker is usually given the role to find a solution to get a more efficient allocation.

However, it can be the same policymaker the one who creates a situation of asymmetric information while introducing a new policy, who causes unintentional effects in the market. This is what happened in the USA with the introduction of the “Ban the Box” policy: its objective is to increase the employment rate of ex-offenders by preventing employers from asking about job applicants’ criminal records until late in the hiring process. But this law introduces asymmetric information between employers and employees, with the unintentional outcome of a decrease in the employment rate between young and low-skilled Black and Hispanic men.

Firstly, we will focus on these unintended effects, found by different researchers using different empirical methodologies, understanding what the effects of the policy implementation in the American job market are.

Secondly, using the Rothschild and Stiglitz model, we hypothesize how an insurance market would transform after the introduction of the policy. We also try to point out who are the individuals that are made better off and who are made worse off after the change in the market.

Thirdly, we analyze the impact of the policy on discrimination against minority groups using the economic theories of taste-based discrimination and statistical discrimination and demonstrate how a supposedly anti-discrimination law could instead result in an increase in discrimination overall. Lastly, we highlight the tradeoff between discrimination and privacy.

CHAPTER 1: INTRODUCTION: THE “THE BAN THE BOX” LAWS

In the U.S., 37 states and over 150 cities and counties have adopted what is known as “Ban the Box” laws, which require employers to remove criminal-history questions from employment applications. The “Box” in question is the yes-no checkbox on a job application that asks whether the applicant has been convicted of a crime.

It all goes back to the Summer of 1998: a law prohibiting employers from considering a candidates' criminal history until presented with an employment offer, had passed in Hawaii. Following this example, the “All of Us or None” organization, a national civil rights movement of formerly incarcerated people and their families, started the “Ban the Box” campaign in 2004, which quickly spread and gained strength in other U.S. states. The campaign has the purpose to challenge the stereotypes associated with people with a criminal history by asking employers to pick their best candidates on a skill-based and qualification reasoning, and not past on past convictions.

It is, indeed, difficult for this group of people to find a job. Among the reasons, ex-offenders have less education, less job experience and weaker connection to the labor market than non-offenders. Moreover, they have higher rates of untreated mental illness, addiction, and emotional trauma (Raphael 2010; Wolff and Shi 2012), which could all represent valid concerns for employers.

However, it has been shown by Pager (2003) and others that employers discriminate against ex-offenders even when other observable characteristics are identical. Moreover, the unwillingness to hire ex-offenders is on average stronger than the employer unwillingness to hire other groups of stigmatized workers, i.e., welfare recipients, applicants with no high school diploma or applicants with gaps in their employment history (Holzer, Raphael and Stoll, 2006). In addition, some federal and state laws ban certain employers, including public-sector ones, from hiring ex-offenders for certain positions and/or mandate criminal background checks (Freeman, 2008).

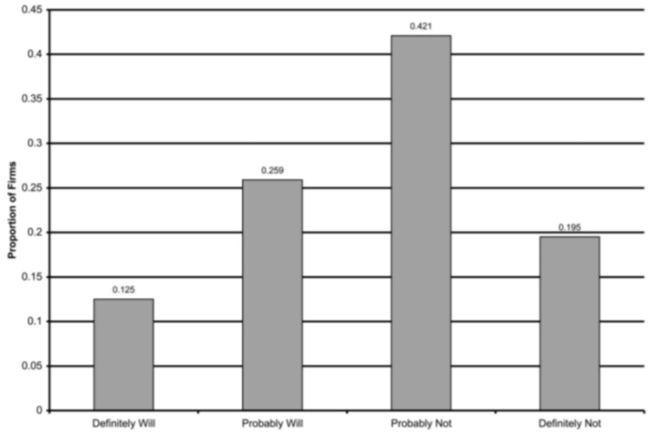

Figure 1: Distribution of employers' willingness to hire applicants with criminal records. Data collected in the early 1990s, it covers the Atlanta, Boston, Detroit, and Los Angeles metropolitan areas. From Holzer, Raphael and Stoll (2006)

All ban-the-box laws, therefore, prohibit employers from asking about criminal history on an initial job application. Subsequently, some laws require employers to wait until after they have conducted the first interview before allowing background checks, others even require waiting after a conditional offer, so that ex-offenders may be able to signal their otherwise-unobservable job readiness to the employer. A few laws also impose additional requirements: in California, for example, employers must conduct an individual analysis and, if they decide to deny employment, they must provide the applicant with notice and allow him to prove otherwise.

These policies were able to gain more momentum in recent years, with policies adopted at not only the state and local levels but also by the federal government. For example, President Obama endorsed ban-the-box in November 2015 by banning the box for federal government jobs. After that, in December 2019, the "Fair Chance to Compete for Jobs Act of 2019" became law: it prohibits most federal agencies and contractors from requesting information on a job applicant's criminal record until after conditionally offering the job to the applicant. These laws thus primarily cover the public sector; however, they also apply to the private sector in 12 states, including New Jersey, and in several cities, including New York. Some national private firms, like Walmart, Target, Home Depot, Starbucks, and Koch Industries, even banned the box voluntarily, in response to the social movement.

Supporters of the movement argue that these policies are important tools that can have positive results also for other economic and societal issues, helping reduce mass incarceration, increasing public safety, and reducing racial disparity in employment, especially by improving access to employment for black men.
In the U.S., 65 million people are estimated to have been arrested and/or convicted of criminal offenses and 2 million people are currently incarcerated. Mass incarceration has been used as an important crime-reduction policy for the past several decades, but recently it has been criticized since it is very costly.
Therefore, now offenders are being released from state and federal prisons more quickly than they are being admitted. According to the most recent data, more than 637.000 people are released each year (Carson and Golinelli 2014). However, from the data, it can be shown that approximately two-thirds of those released will be rearrested within the next 3 years (Cooper, Durose, and Snyder 2014). Connecting ox-offenders with jobs would keep them from reoffending, which would be a major benefit also for public safety. In the literature, even though the relationship between employment and recidivism is complex, it has been found that the probability of committing a crime depends partly on the prospect of having something to lose: individuals with good jobs and high earnings are found to commit less crime since they do not have the need to generate additional income to meet basic needs (Raphael, 2014). Hence, trying to help offenders reenter civilian life and break the recidivism cycle would help reduce incarceration rates.
In addition, there is a major racial disparity in incarceration rates. Bonczar (2003) shows that a black man born in 2001 has a 32% chance of being incarcerated at some point during his lifetime, compared with 17% for Hispanic men and 6% for white men. Women instead accounts for only 7% of the federal and state prison population, since they are convicted at much lower rates (Carson, 2015). Thus, if a clean record is a condition for employment, it could have particularly adverse consequences for minority groups and exacerbate racial inequality in employment. For this reason, the BTB policy in New York was passed as part of the Young Men’s Initiative, which was designed to address disparities faced by young Black and Hispanic men.
Furthermore, the availability of information about criminal histories is just one example of a larger debate about data availability, which is now more accessible than ever. In the latest years, an information boom has occurred in every market: in the labor market, employers can now check the applicant’s social media as well as their résumés; in the insurance market, health insurers can now evaluate the data from the patients’ home medical devices and not just from doctor visits; in the credit markets, lenders can now not to obtain financial information, such as bankruptcy records, credit records, or past loan repayment, but also borrowers’ SAT scores. Google and other search engines

have made it easier for decision-makers to obtain information on individuals that can have an impact on their fitness for a job, an apartment, a loan, or other opportunities.

On the other hand, there are different counterarguments against these policies. Firstly, employers, such as HR and hiring managers do employee screening practices to mitigate risk of fraud or criminal activity by employees (Hughes et al., 2013) to avoid be considered liable for negligent hiring (Connerley et al. 2001). The National Federation of Independent Businesses (NFIB) argues that hiding criminal-record information could have some effects on the safety and security of the business and its workers and customers since the policy does nothing to eliminate the concerns that employers may have.

Secondly, the hiring process becomes more difficult and more costly. Moreover, since the laws for private firms are diverse across the county, companies that hire across the U.S. must take into consideration completely different indications, preventing them from having a consistent and compliant hiring process. If firms want a standard procedure, they will have to adopt the most restrictive law, which only applies to 35% of the statutes.

Finally, researchers found out that these policies, which are supposed to be anti-discriminatory, produce some unintended effects creating discrimination against some racial groups. This is the result of the asymmetric information between the employer and the potential employee that originates with the adoption of the policy.

CHAPTER 2: UNINTENDED EFFECTS

Preventing employers from knowing the criminal record of a candidate creates an information asymmetry between the two economic agents. Assume that we can divide the population into two types: a bad type, the ex-offender, and a good type, the non-offender. The ex-offender can be considered a bad type since a criminal record is correlated with a lack of education and job experience or a lack of job readiness, and the policy does nothing to address this issue. Moreover, interviewing is costly, and a firm could even start training new hires before the information about the individual's type is obtained, wasting time and money, which is why employers would avoid hiring bad-type individuals. Thus, employers on average prefer non-offenders over ex-offenders, all else held equal.

In a Principal-Agent framework, the candidate is the Agent, since he knows what type of individual he is. Instead, the employer is the Principal, since he is unable to differentiate the two types, resulting in being the one with less information.

In the case of perfect information, the adverse consequences of criminal history will be borne entirely by bad-type individuals. Nonetheless, employers may be induced to hire ex-offenders if they could be hired at relatively lower wages. Risk-neutral employers don't need the incentives, while the wage discount required become larger if the employers are more risk-averse.

Raphael (2021) developed a model based on the Becker (1971) model of taste-based discrimination. After having ordered all the employers in terms of how adverse they are against ex-offenders, if the stock of job opportunities offered by risk-neutral employers is large enough to employ all ex-offenders, then there would be no wage or employment disparity. On the contrary, wages for ex-offenders would decline to equate supply and demand and the market equilibrium would be decided by the most reluctant employer since the other employers would then decide to pay an equal amount. However, if a characteristic of an economic agent is hidden, a problem of adverse selection arises. In the absence of individual information, employers may screen on factors they believe are correlated with criminal records, such as race (Phelps 1972, Stoll 2009), gender, and where one lives in a city, and respond by avoiding interviews with individuals they perceive more likely to be a bad type, i.e., black and Hispanic men. In other words, they make subjective assessments based on their judgments regarding who is likely to have been involved with the criminal justice system, as predicted by the theory of statistical discrimination.

Concerns about creating a situation for the rising of statistical discrimination arise from the fact that the likelihood of having a criminal history record is characterized by huge racial and gender disparities and that the entanglement with the criminal justice system is far from random. Different empirical studies found out about the unintended effects.

2.1) Empirical Evidence

In early contributions, Bushway (2004) argues that allowing employers to access to criminal history records may increase the wages of non-offenders, specifically those of groups of individuals with large number of ex-offenders, such as Black males. In addition, Holzer et al. (2006) analyzed how criminal background checks affect the likelihood of employment for African Americans. They claim that employers who check backgrounds are more likely to hire Black people, especially men; the effect being stronger among more adverse employers. They confirm that in the absence of a background check, statistical discrimination against black men and/or those with weak employment records occurs.

However, criminal background checks have an ambiguous net effect on the employment of Black people: if employers check, they are more likely to eliminate black applicants based on the information revealed, while if they don't check, they are more likely to eliminate black applicants based on perceived criminality. Moreover, it's not clear what effect predominates, and it is essential to understand the extent to which employers statistically discriminate in the absence of information.

To assess this, they estimate a series of linear probability models in which the dependent variable is a dummy to indicate the race of the most recent hire, and the key explanatory variable is an indicator variable: it is set to one if the employer used a criminal background check in the hiring process. The results indicate that the use of criminal background checks is associated with a higher likelihood that the most recent hire was African American. They also exploit the imperfect association between the employer's self-reported unwillingness to hire and whether they use criminal background checks. The results show a strong association between aversion to hire and the use of criminal background checks, although the correlation is far from perfect.

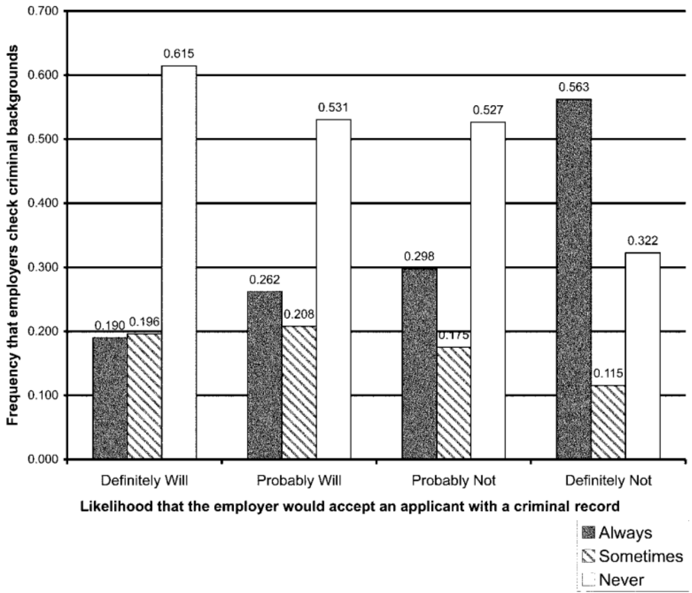

Figure 2: Frequency of criminal history record checks by employer willingness to hire applicants with criminal records. From Holzer, Raphael and Stoll (2006)

Afterwards, with the introduction of the first BTB laws, researchers were able to assess the degree of the statistical discrimination against minority caused by the policy, using both experimental methods or panel data. Agan and Starr (2018) conducted a field experiment about the probability of getting an interview in New York City and New Jersey, both before and after the adoption of BTB policies. They created 15.000 fictitious job application for entry-level positions, targeting private, for-profit employers. The applicants were young and low-skilled, and they were matched in pairs on race (white and black), that was signaled by the name of the applicant. They randomly assigned their criminal histories as well as whether the applicant had a GES and whether he had a one-year employment gap. These are characteristics that can potentially signal criminal history to employers. Afterwards, the pairs were assigned to the same store in the same period of time.

They found out that the effect of having a criminal record is significant and large: non-offenders are 63% more likely to be called back than ex-offenders, averaged across races. However, the introduction of the policy increases racial disparities since the callback rates gap between white applicants and black applicants increases six times: before the policy, white applicants received 7% more callbacks than similar black applicants, but after the policy the gap grew to 45%. This effect is the result of a combination of losses for black men and gains for white men, specifically:

- White ex-offenders benefited the most from the policy change: there is no effect for white non-offenders and a substantial increase in callbacks for white ex-offenders.
  After the introduction of the policy, employers seem to assume that all white applicants are nonoffenders.
- Black applicants were called back at a rate between the ex-offender and nonoffender callback rates from before the policy: for black non-offenders a substantial decrease in callbacks happens, while there is no effect for black ex-offenders
  So, those with records were helped, but those without records were hurt.

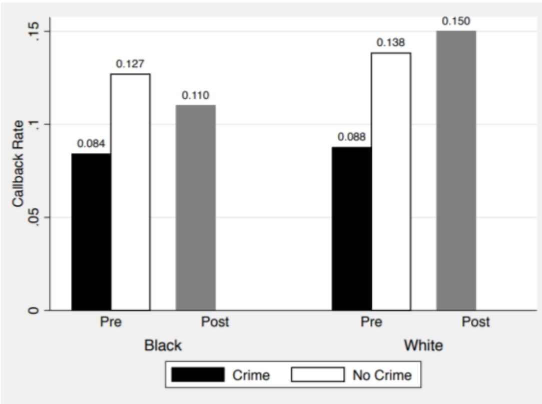

Figure 3: Callback Rates by Race, Criminal Record and Period of companies that required a criminal background check before the introduction of BTB. From Agan and Starr (2016)

These results suggest that employers, in the case of asymmetric information, tend to generalize that white applicants are more likely to be good-type individuals and that black applicants are more bad-type individuals.

However, this method has the limitation that the fake applicants can't do the interview, making it impossible to study if an ex-offender who proceed with the job interview is able to convince the employers to give them the job. In this case, the true social welfare consequences can't be calculated: an average callback rates decrease doesn't mean a lower employment rate if the policy is able to generate a sufficient proportion of hires among Black ex-offenders.

Doleac and Hansen (2020) tried to calculate this social welfare, finding a lower employment rate among Black and Hispanic individuals. They use individual-level data from the 2004-2014 Current Population Survey, a repeated cross section that targets individuals eligible to work, i.e., it excludes anyone under 15 years old and those in the Armed Force or in institutions such as a prison. It provides information on age, sex, race, ethnicity, education level and current employment status and it is usually used to assess the employment situation in the U.S.

Using this data, they use variation in the adoption and timing of state and local BTB policies to test their effects on employment outcomes. The target is black and Hispanic men who are young (age 25-34) and low skilled (no college degree), who are more likely to have served time in prison, being, at the same time, the most intended beneficiaries and potentially the most unintended damaged group by the policy.

So, they restricted the data to US citizens who are white, black and Hispanic, and don't consider themselves retired, considering three levels of education achievement, i.e., no high school diploma, no college degree and college degree. Since they measure the effect in the local labor market, they assign the individuals to their state or metropolitan statistical areas (MSA) and check if a BTB policy is applied in the area.

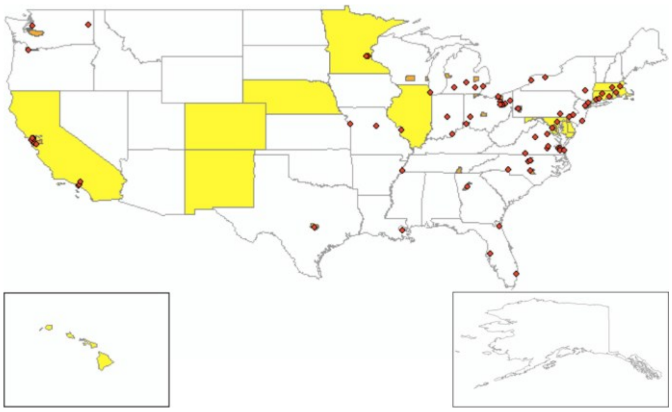

Figure 4: Jurisdictions with ban the box (BTB) policies by December 2014. Jurisdictions with BTB policies are represented by yellow shading (state-level policies), orange shading (county-level policies), and red circles (city-level policies). From Doleac and Hansen (2020)

To study the effect of the policy, they use a linear probability model for the probability that individuals are employed:

$$Employed_i = \alpha + \beta_1 BTB_{m,t} \times White_i + \beta_2 BTB_{m,t} \times Black_i + \beta_3 BTB_{m,t} \times Hispanic_i + \beta_4 \delta_{MSA} + \beta_5 D_i + \beta_6 \lambda_{time \times region} + \beta_7 \delta_{MSA} \times f(time) + e_i$$

where i indicated an individual and m the MSAs. δ_{MSA} denotes MSA fixed effects; D_i is a vector of individual characteristics that can help explain variation in employment, including race/ethnicity, age, education and whether the individual is currently enrolled in school; $\lambda_{time \times region}$ denotes time-by-region effects and $\delta_{MSA} \times f(time)$ denotes MSA-specific time trends. These variables are introduced to exclude the possibility of omitted variables. BTB is a dummy that is equal to 1 if any policy is in effect in the individual i's MSA.

The coefficients of interests are β_1, β_2 and β_3. They represent the effect that a BTB policy has on the probability that a white, black or Hispanic man is employed, respectively.

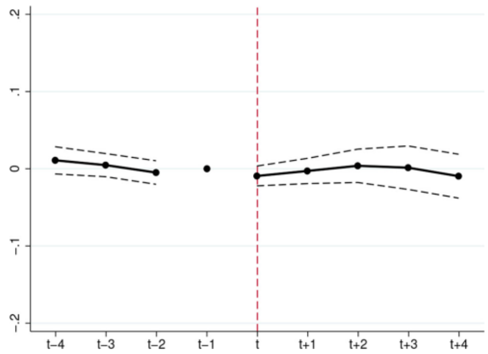

Figure 5: Effect of policy on the probability of employment for white men aged 25-34, no college degree. From Doleac and Hansen (2020)

Figure 3 is the coefficient plot for young, low-skilled white men. On the X-Axis the year relative to the effective date of the policy is shown, on the Y-Axis the effect of the policy on the probability of being employed. Year t-1 is the excluded category, so the coefficient is forced to be zero. The dashed lines are the 95% confidence intervals around the coefficients.
The policy has no effect on the employment for young, low-skilled white men.

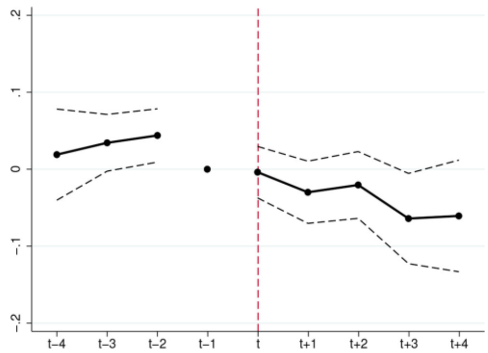

Figure 6: Effect of policy on the probability of employment for black men aged 25-34, no college degree. From Doleac and Hansen (2020)

Figure 4 is the coefficient plot for young, low-skilled black men. Estimates are less precise due to the smaller sample. It is shown that before the policy the employment for this group may have been increasing, probably indicating that the policy was adopted to try to support further young, low-skilled black men. But after the implementation of the policy, employment begins to fall and the negative effect of BTB worsens over time.

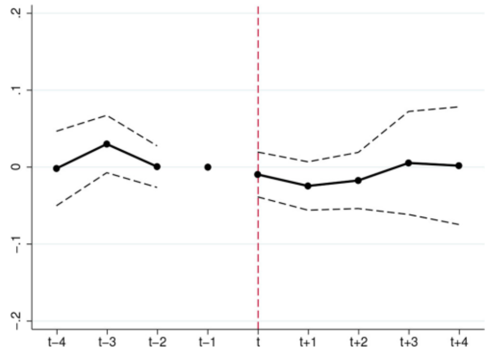

Figure 7: Effect of policy on the probability of employment for Hispanic men aged 25-34, no college degree. From Doleac and Hansen (2020)

Figure 5 is the coefficient plot for young, low-skilled Hispanic men. The estimates are flat before the introduction of the policy, then there is a decrease in employment, but after 3 years the effect returns to zero.

Effects on Employment for Men Aged 25–34 with No College Degree, Main Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White × BTB	−.0501***	−.0420***	−.0100	−.0072	−.0028	−.0091	−.0048	−.0088
	(.0088)	(.0089)	(.0073)	(.0058)	(.0061)	(.0064)	(.0077)	(.0061)
Black × BTB	−.0716***	−.0605***	−.0320***	−.0296***	−.0342**	−.0291**	−.0311**	−.0306**
	(.0113)	(.0118)	(.0115)	(.0103)	(.0149)	(.0143)	(.0136)	(.0145)
Hispanic × BTB	−.0489***	−.0476***	−.0120	−.0046	−.0234*	−.0228*	−.0196	−.0229*
	(.0088)	(.0097)	(.0113)	(.0126)	(.0130)	(.0120)	(.0147)	(.0119)
N	503,419	503,419	503,419	503,419	503,419	336,641	231,933	336,641
Pre-BTB baseline:								
White	.8219	.8219	.8219	.8219	.8219	.8226	.8219	.8226
Black	.6770	.6770	.6770	.6770	.6770	.6770	.6770	.6770
Hispanic	.7994	.7994	.7994	.7994	.7994	.7985	.7994	.7985
Controls:								
MSA fixed effects	X	X	X	X	X	X	X	X
Demographics		X	X	X	X	X	X	X
Time × region fixed effects			X	X	X	X	X	X
MSA-specific trends				X	X	X	X	X
Fully interacted with race					X	X	X	X
MSA unemployment								X
Sample:								
Full sample	X	X	X	X	X			
MSAs only						X		X
BTB-adopting only							X	

Source.—2004–14 Current Population Survey.
Note.—Standard errors are clustered at the state level. Coefficients show the effect (in percentage points) of ban the box (BTB) on the probability of employment.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Figure 8: Results of the linear regression. From Doleac and Hansen (2020)

In the table above, the main results from the regression used by Doleac and Hansen are shown. The first column shows the effects of the policy in the full sample of men aged 25-34 with no college degree, controlling only the MSA fixed effects. In this case, with no further information about the individual or the time period, the policy reduces the probability of getting employed for each race, it being larger for black men. The second column adds additional detailed information about the individual, i.e., age fixed effects, fixed effects for years of education and whether the individual is currently in school. This new control variables reduce the magnitude of the effects, but they are still similar. The third column adds additional information about the labor market trends not related to the policy, considering time-by-region fixed effects. Since the sample period 2004-2014 includes the Great Recession, it's important to consider these market trends. The coefficients of the effects of the policy on the employment of white and Hispanic men become statistically insignificant, removing in

particular the correlation between the decrease in employment for white men and the introduction of the policy. In the fourth column the MSA-specific trends variable is included in the regression.
However, all the control variables could affect the individuals differently based on their race, i.e., the employment trend in a MSA varies between white and Black men. The fifth column presents the results of a fully interacted model, where the effectts of all the variables differ across different ethnicity groups in order to isolate in the best way possible the effect of the policy. In this specification of the model, the policy reduces employment rate both for Black and Hispanic men: young, low-skilled men are 5.1% less likely to be employed after the policy implementation while for young, low-skilled Hispanic men employment rates decreases by 2.9%.
In the last three columns, they restrict the full sample used in the regression model. In the sixth column, the sample considers only individuals living in MSAs, excluding therefore more rural areas with a smaller black population. The results remain consistent with the ones found in the previous case. In the seventh column, the sample includes only jurisdictions that implemented the policy. The idea behind this sample is to isolate these specific job markets, that could have fundamentally different labor market trends that motivated the introduction of the policy. In this regression the results still show a negative effect for black and Hispanic men, even though the coefficient for the Hispanic is statistically insignificant.
Finally, in the last column they added another control variable for the MSA unemployment rate using the MSA sample. This could generate endogeneity issues, since it is possible that the policy would reduce employment overall, but the introduction of a control variable for unemployment rate could mask this effect. However, they argue that using this control variable will not be a problem in the case that the policy just simply shifts employment from one group to another, leaving the overall unemployment unchanged. Since controlling this new variable has little effect on the estimates, so it could be a sign that in the short run the policy creates substitution effects,
Due to the differences in racial composition across the U.S., Doleac and Hansen also focused on the effects of the policy in different regions of the country. They found out that, for black individuals, the employment rate decreases in the Northeast (7,4%), the Midwest (7,7%) and the West (8,8%) regions. On the other hand, in the South region, the effect is smaller (2,3%), but not statistically significant. These effects are not homogenous across the country since they depend also on the local labor market context. They find evidence that if there is a larger share of a minority population, the effects are not that strong for that minority. For instance, there is a larger population of Black people in the South, so in that area the effects are reduced for Black applicants; a similar situation happens in the West for Hispanic people, who are a larger share of the population of that area. This may suggest that employers are less likely to use race as a proxy in areas where the minority population of interest is

larger. This could depend on the fact that there are more Black and Hispanic employers and more minority-owned firms, who are less likely to use race as a proxy for criminality.
However, other researchers don't agree with the previous results. Evidence shows that these policies were able to raise the employment between residents of the top quartile of high-crime neighborhoods at least by 4%. This robust increase depends largely on the individuals getting hired in the public sector, the central target of these bans, and in the lowest-wage jobs; the industries with a large increase in high-crime area resident employment are government (12.1%), information (5.3%), education (4.2%) and real estate (4.1%) (Shoag and Veuger, 2018). It is indeed estimated that, on average, the probability of getting employed for ex-offenders raises by about 30% after the implementation of these laws (Craigie, 2019)
Furthermore, Shoag and Veuger (2018) highlight the experience of Wall Mart, the largest private – sector employer in the United States, which decided to voluntarily "ban the box" in 2010. The figure shows the log difference between Walmart's total employee demographics and the EE=-1 benchmark, both before and after they "banned the box", taken from Walmart Diversity and Development reports. We see that the ratio between the percentage of female employees and the benchmark decreases, while the ratio for the Black employees increases. Figure 9 shows that these variations were both concentrated among non-managerial job categories.

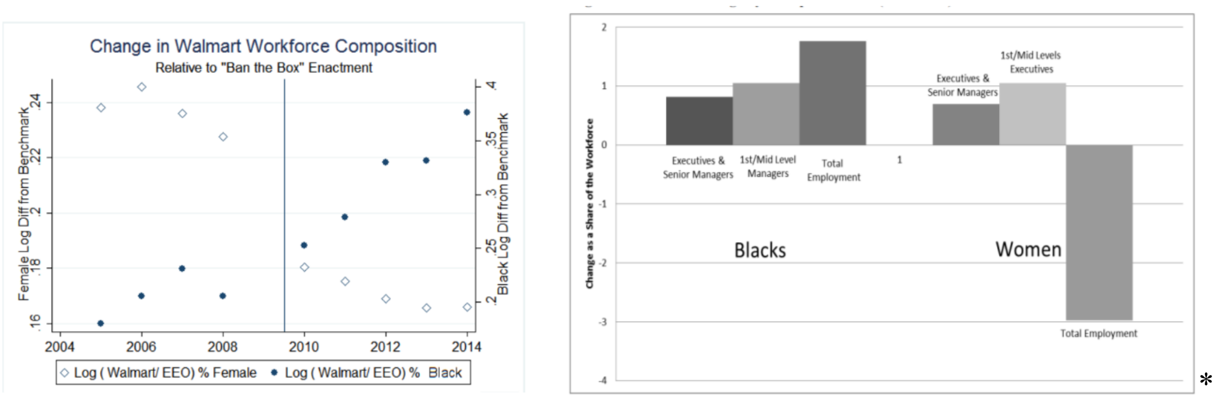

Figure 9: On the left, log difference between Walmart's total employee demographics and its EEO-1 benchmark before and after they "banned the box". On the right, change in the share of Wal-Mart employees from 2008 to 2012. From Shoag and Veuger (2016)

There is disagreement also on the impact of the policies on racial groups. Using American Community Survey (ACS) data, Shoag and Veuger (2016) found out that black men benefit from the policy since their employment goes up by around 3%. They point out that also Doleac and Hansen (2016) find that BTB increases the employment of Black men overall by between 1 and 2%, and that different results are obtained by concentrating on the different subgroups that they studied. On the other hand women, especially black ones, who are likely to have been less convicted of crimes, see their labor market outcomes deteriorate by a significant 2%. They argue that the Holzier et al's cross-sectional comparison may reflect a significant amount of statistical discrimination as well as other factors and that Agan and Starr' results are related to the that specific small subgroup, and it is not probably the case for the full population of young black applicants.

However, even though researchers do not agree on the target of the unintended effects, they all agree on the fact that the possible gain doesn't consist in an aggregate employment increase, but rather a substitution across workers. For Doleac and Hansen (2020), employment shifts towards older, low-skilled black men and older, low-skilled Hispanic women and highly educated Black women, in order to avoid the subgroups that are most correlated with criminal activity. The other option for employers is to substitute away from criminal background questions to other signals of employment quality: an "upskilling" occurs since firms responds to the ban by changing the requirement for college degrees and by raising the number of years of experience in job advertisements (Shoag and Veuger, 2018).

The implementation of BTB laws is surely not supported if we adopt a Paretian approach, but it could be justified by the Kaldow-Hicks Potential Compensation Principle. However, as proved by the previous studies, it's also difficult to understand if this gain is positive, since it depends on the extent to which ex-offenders benefit from suppressing information, the extent to which non-offenders lose, and the relative size of these two classes of applicants within each demographic group. Within some subgroups it seems also to be only negative.

Nonetheless, other problems could arise and cause other losses. For instance, for firms the expected cost of interviewing job applicants increases due to the higher chance that any interview could end in a failed background check. In addition, the option of "upskilling" may not meet enough offer from the job markets: individuals who have college degrees or that are clearly job ready may not be willing to accept a low-skilled job at the wage the employer is willing to pay. There is the risk that market unravels, with no transaction made at the end.

2.2) Analyzing a hypothetical insurance market

To better understand the negative effects that the BTB policy can have by adding asymmetric information to the market, we could analyze the economic situation in light of the theoretical model by Rothschild and Stiglitz, developed in 1976. By applying this model, we theorize how a hypothetical insurance market that covers the losses generated by the risk of not getting employed would react after the implementation of BTB, focusing also on its qualitative efficiency and its distributional effects.

In Rothschild and Stiglitz (1976), there are two types of individuals who are indistinguishable to the insurance company, that offer a contract identified by both a particular price and a particular quantity of insurance. In our case, the accident that decreases the individual's income would be not getting employed, thus ex-offenders would face a higher for the causes already explained in the previous pages. We assume that the individuals are all risk-averse, and the insurance company is risk-neutral and concerned only with the expected profits.

If individuals reveal their criminal records, everybody could be made better off. By their very being, ex-offenders cause an externality in this insurance market: the non-offenders are worse off than they would be in the absence of the ex-offenders. However, ex-offenders are no better off than they would be in the absence of the non-offenders.

The equilibrium in this competitive insurance market is a set of contracts such that, when customers choose contracts to maximize their expected utility:

i) no contract in the equilibrium set makes negative expected profits

ii) there is no contract outside the equilibrium set that, if offered, will make a nonnegative profit

In the competitive equilibrium, due to the perfect competition and the free entry, the firms make zero expected profits, and the set of all the contracts that break-even is referred to as the fair-odds line. In equilibrium and with perfect information, each risk-averse individual buys complete insurance at actuarial odds. This result is a Cournot-Nash equilibrium since this equilibrium contract maximizes the individual's expected utility and breaks even, and it satisfies the two previous conditions since i) the insurance companies make zero profits and ii) selling any contract preferred to it will bring expected losses to the insurance companies.

In the case of a heterogeneous population, such as the one we are talking about, two types of equilibria can exist: a pooling equilibrium in which both non-offenders and ex-offenders buy the same contract, and a separating equilibrium in which non-offenders and ex-offenders purchase different contracts.

It's already proved by Rothschild and Stiglitz (1976) that there cannot be a pooling equilibrium in perfect competition, since either insurance companies have negative profits or there is a better contract that could be offered to individuals. And in any case, if the contract is compared to the homogenous population benchmark, the good type, the non-offenders, is worse off while the bad type, the ex-offenders, is better off.

So, each type must purchase a separate contract to have an equilibrium in the insurance market. The results are similar both in perfect competition and in a monopoly framework, the only thing changing the break-even condition. We denote the ex-offender, our high-risk individual, and the non-offender, our low-type individual, by H and L respectively. We identify $V^i(\alpha)$ as the indirect utility achieved by type i when she purchases insurance contract α and $\Pi^i(\alpha)$ as the expected profit a firm earns by selling contract α to type i. Given that λ is the proportion of high-risk types, the market equilibrium will be:

$\max(\alpha^L, \alpha^H) \qquad V^L(\alpha^L) \qquad$ subject to

$$(IC_H) = V^H(\alpha^H) \geq V^H(\alpha^L)$$
$$(IC_L) = V^L(\alpha^L) \geq V^L(\alpha^H)$$
$$(MU) = V^H(\alpha^H) \geq \bar{V}^H$$
$$(BC) = (1-\lambda)\Pi^L(\alpha^L) + \lambda\Pi^H(\alpha^H) \geq 0$$

where (IC_i) is the incentive compatibility constraint stating that i types must find the contract intended for them to be preferable to the contract designed for the other type, thus will not have the incentive to mimic the other type, (BC) is the budget constraint that requires that on average policies break even or make positive profits, and (MU) is the minimum utility constraint for the high-risk type (Finkelstein, 2009). The equilibrium for the market consists of ex-offenders being fully insured while non-offenders being partially insured at a lower premium. Compared to the benchmark, the non-offenders are made better off. The policy, by creating the information asymmetry in the market, creates a redistribution from non-offenders to ex-offenders. Information asymmetry generates a welfare cost in the insurance market. This is another example to show how even a small amount of imperfect information could have a significant effect on markets and how ex-offenders could exert a negative externality on non-offenders.

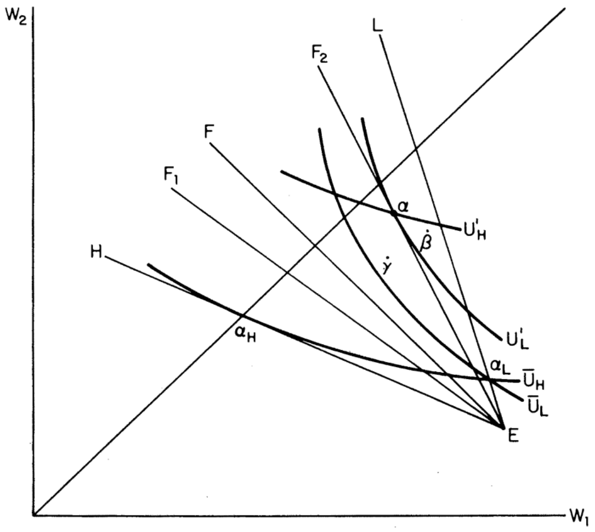

Figure 10: Insurance equilibrium (Hoy, 1982)

In figure 10, the separating equilibrium of Rothschild and Stiglitz is represented. Point E is the endowment position of both types of individuals, when the individuals buy no insurance (W_1 is the net wealth of the individual in the good state and W_2 is the net wealth in the bad state, the one where the accident happens). EL is the fair odds line for low-risk individuals while EH is the fair odds line for high-risk individuals. The contract pair of equilibrium are (α_H, α_L): we can see that high-risk individuals are fully insured at their fair odds line while low-risk individuals are partially insured at a lower premium. If the proportion of high-risk individuals is sufficiently high to have the pooled fair odds line EF or EF$_1$, on the left of $\overline{U_L}$, then the separating equilibrium exists. Otherwise, if the proportion is too low and the pooled fair odds line EF_2 is on the right of $\overline{U_L}$, then a pooled contract such as γ will be preferred over the previous separating contract both by the high-risk and low-risk individual and it will create positive profits. However, it can't be an equilibrium, as already stated, because then a pooling contract such as α will be preferred. But α, even though it is not possible to offer a contract on EF_2 neither above (it doesn't attract high-risk type) nor under α (it doesn't attract low-risk types), is still not an equilibrium. A firm could indeed adopt a strategy of cream skipping and choose a contract such as β, that attracts only the low-risk individuals and makes positive profits since it's left of EL, leaving only high-risk types in the contract α, which generates losses due to α lying at the right of EH. Contract α is then removed from the market, causing high-risk individuals to buy β, which generates losses due to β lying at the right of EF_2.

However, in the market in which the BTB is introduced, the insurance firms can make some predictions about the individual's type (whether he is an ex-offender or non-offender), because of other observable characteristics. Thus, we still consider two risk types, not directly observable, but the firms are able to observe an unalterable and costless signal correlated with the risk type. We identify the fraction λ_k as the fraction of individuals who are high-risk types, that in our case are the ex-offenders. There are two possible signals, X and Y, which are respectively white and black. Based on this correlated characteristic, the firm determines two risk categories: black people, who account for a fraction θ of the total population, are the high-risk category and white people, who the remaining fraction 1- θ of the total population, are the low-risk category. The high-risk category needs to have, by definition, a higher proportion of high-risk individuals, while the low-risk category has a smaller proportion of low-risk type individuals. Since black men have a 32% probability of getting involved with the criminal justice system, in opposition to the 6% probability for white men (Bonczar, 2003), we can adopt this association. Thus, according to the model, category Y is the higher-risk category, but it still includes some low-risk type individuals. This is equivalent to the employer's assumption that black people are more likely to be ex-offenders, even though there are black non-offenders.

In order to better analyze the situation, we assume the Wilson E2 equilibrium (Wilson, 1976), which allows the existence of the pooling equilibrium α by assuming that firms have enough insight to understand that the contract β will inevitably lead to losses in the long run. Hence, in terms of the pooled equilibrium (single contract), the individuals who are part of the high-risk category must pay a higher actuarially fair price of insurance, while individuals of the low-risk category have a lower one, in comparison to the benchmark situation (Hoy, 1982; Finkelstein, 2009). As a result, we have that black non-offenders must pay more than they should while white ex-offenders pay less. This means that white non-offenders are made better off by the introduction of the policy and a redistribution from black non-offenders to white ex-offenders occurs.

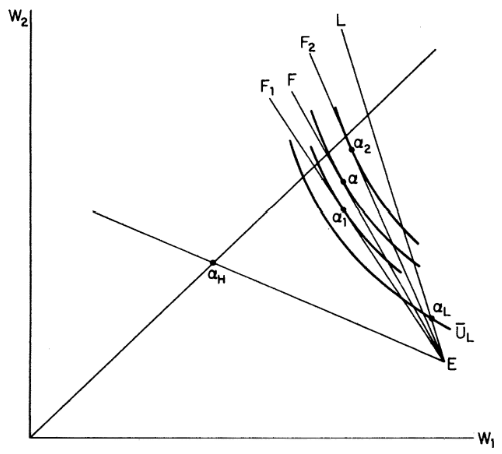

Figure 11: Insurance equilibrium CASE 1 (Hoy, 1982)

Moreover, this imperfect categorization alters the fair odds line, which is now based on the new probabilities that the firms hypothesize. We consider EF in figure 11 as the initial pooled fair odds line. After categorization, firms estimate EF_1 as the fair odds line for the high-risk category due to its higher proportion of high-risk individuals and EF_2 as the fair odds line for the low-risk category owing to its lower proportion of high-risk individuals. We consider the first case with the contract α as the initial Wilson E2 equilibrium before categorization. Assume that firms use race to assess the likelihood of being involved with the criminal justice system and determine α_2 as the pooling equilibrium for the low-risk category and α_1 as the pooling equilibrium for the high-risk category. Both the low-risk and high-risk individuals in the low-risk category, such as white non-offenders and ex-offenders, are made better off in respect to the pooling equilibrium meanwhile both low-risk and high-risk individuals in the high-risk category, such as black non-offenders and ex-offenders, are made worse off (Hoy, 1982).

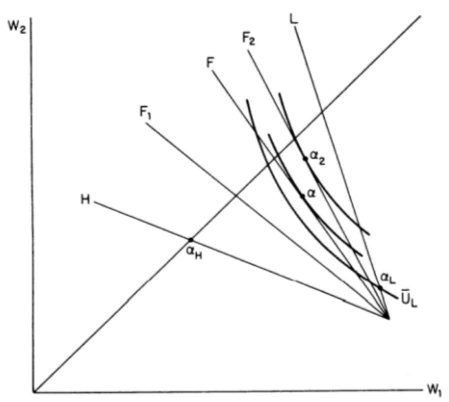

Figure 12: Insurance equilibrium CASE 2 (Hoy, 1982)

In this second case, however, the fair odds line EF_1 is at the left of $\overline{U_L}$ and they will be offered the separating pair of contracts (α_H, α_L). Compared to the benchmark α, individuals in the high-risk category are still made worse off even with the option of having a separating contract for their category. For the low-risk category, we still have the pooling equilibrium α_2 , thus all the individuals in the low-risk category are made better off by the categorization (Hoy, 1982).

CHAPTER 3: DISCRIMINATION AND INFORMATION

The topic of discrimination has always spiked interest in economic literature due to its pervasiveness across political, social, and economic settings, including the housing, credit and labor market. Even though it has a wide range of definitions, in this context we suppose that "discrimination occurs whenever a decision-maker treats one group of applicants differently than another group, simply as a function of their group memberships (i.e., holding all other factors equal)" (Patty, 2022).

Based on the findings of Agan and Starr (2018) and Doleac and Hansen (2020), we can argue that, even though BTB is designed as an anti-discrimination law, it increases discrimination against some minority groups. This outcome is consistent with the two theories for discrimination already established in the literature: taste-based discrimination theory and statistical discrimination theory.

Taste-based discrimination occurs when individuals discriminate between demographic groups simply based on the individual's prejudice and bias. Individuals are assumed to have a "taste for discrimination" that influences their preference, and they are willing to pay a price to avoid interacting with a member of a targeted group (Becker, 1971). Becker doesn't address why people have "taste for discrimination" and racial or gender animus, or preference bias, are taken as given, but psychological and sociological research distinguish between individual-level explanation, that would stem from personal dispositions or negative socialization experiences, and group-level explanations.

Statistical discrimination, on the other hand, arises in a context of uncertainty. It doesn't assume that prejudice can only be explained by emotional and irrational motives. It assumes that individuals are rational, and that discrimination is the outcome of rational actions carried out by agents who seeks to maximize their utility or profits from selection decisions in a framework of uncertainty. In the case that an unobservable, but outcome-relevant information about the employee is too costly to obtain or absent, the employer tries to assess it from the observable information that he possesses. Hence, he will use race, or sex, or other recognizable physical traits correlated with the missing information as proxy (Phelps, 1972; Arrow, 1973).

The discrimination that employers put through ex-offenders, even when other observable characteristics are identical (Pager, 2003), can be explained by both theories. Some employers simply do not like ex-offenders and their discrimination could be taste-based. In this case, no additional information can be given to the employer to change their idea. Other employers, in the process of evaluating the productivity of the applicant, are influenced by their priori belief about the productivity of ex-lawbreakers. Taking this into account, the idea of removing this information could seem reasonable. However, owing to the fact that the implementation of the BTB policy has discriminatory effects on black and Hispanic people, it seems that the problem represented by the discrimination against ex-offenders has not been eliminated, but only transformed. This happens because the policy does not really address its roots, but just simply changes the uncertainty framework in which the employer make his decision. Therefore, employers don't change their beliefs, but just change the proxies that he uses and the direct discrimination against ex-offenders becomes an indirect discrimination against those individuals who are more statistical likely to be one (given that the employers do not have any pre-existent biases towards black and Hispanic people).

To better understand this, we assume that the employer can choose between a population of job applicants. We assume there are two identifiable groups i=1,2 that represent whites and Black people. The worker ability is distributed as:

$$Q \sim N(\mu_i, \sigma^2)$$

with means μ_1 and μ_2 and standard deviation σ. The means thus depend on the demographic group while the variance is independent. The population parameters are known by the firm.

Workers produce output $f(q) = q$. Productivity and ability are thus synonymous. We assume that the employer will hire an applicant whose ability q exceeds a given threshold k and that $\mu_1 > k > \mu_2$. This assumption is done because Black people are statistically more likely to have been involved with the criminal justice system.

The employer observes the demographic characteristics of the individual as well as a noisy signal of the ability of each applicant, that we assume is conveyed in the resume. In our case, we assume that the information about the criminal history of the applicant, y, may measure the individual's true ability, q, plus an error term, ε. The signal y would indicate the "job-readiness" of the applicant that the employer receives from the criminal record, that he obtains from the types of crimes and their duration.

$y = q + \varepsilon$ where ε is normally distributed with mean zero and standard deviation γ

$$\varepsilon \sim N(0, \gamma^2)$$

In the absence of perfect information, the individual's prediction is the weighted average between the individual-specific signal and the average productivity of the applicant's demographic group (Phelps, 1972; Arrow). The conditional distribution of q given y, since the ability and the signal are jointly normally distributed, is:

$$E[ability|y] = \frac{\gamma^2}{\gamma^2 + \sigma^2}\mu_i + \frac{\sigma^2}{\gamma^2 + \sigma^2}y$$

If this expected quality $E[ability|y] > k$ the applicant is hired.

Intuitively, the more complete the information about the individual's signal is, the greater importance it has for the employer. This means that if it is precise (γ close to zero), the signal is able to provide the precise estimate of the applicant's ability. However, the less informative the signal is, the higher the importance the average productivity of the applicant's demographic has for the employer. Indeed, if the signal is noisy (the variance of ε is very high), the expected conditional ability will be closer to the population average regardless of the signal's value. Fundamentally, it's the lack of information that leads the employer to treat the individuals as members of groups and discrimination takes the form of stereotyping based on group memberships (Shoag and Veuger, 2016).

Other than the BTB policy case, there are plenty of other empirical findings about the rising of statistical discrimination when the policy maker limits the amount of information given to employers. Black employment rates increase by 7%-30%, with the largest effect among low-skilled black men, when a drug test is required during the hiring process (Wozniak, 2015). Banning background checks on applicants' credit histories has a negative effect on employment outcomes for groups that on average have lower credit scores, reducing the job-finding rates for black men by 7%-16%. (Bartik, Sott, 2016).

On this account, in order to better address discrimination in a better way, it is necessary to implement policies that deconstruct both prejudices and stereotypes. Prejudices (or prejudgments) are the source of taste-based discrimination since they are beliefs formed without actual knowledge of the relevant facts, while stereotypes, mental representations used to describe differences between groups, are the cause of statistical discrimination. A punitive approach, which consists of legally banning and sanctioning discrimination, is often not enough. It is necessary to try to change the beliefs that generate discrimination (Valfort, 2018).

A strategy to reduce the stereotypes around ex-offenders could be, contrary to the BTB recommendation, to supply better information regarding the crime history of the individuals. Researchers found out that the likelihood of ex-offenders being rearrested decreases with time till the point where it's back to the level of the general population, which is estimated to happen 7 to 10 years after release, and that one third of ex-offenders will never interact again with the criminal justice system. These individuals that have not reoffended for 7 years are identified by criminologists as "immediate desistors" and it's supposed that their likelihood of offending again is low from the day they left the prison. If we assume that this sub-group of ex-offenders is immediately identifiable from the rest, it could be presumed that employers would be more willing to hire them as the signal given by the information regarding their past is clearer and it's less necessary to rely on the average idea of productivity and reliability of the total group. By hiring these individuals earlier, more resources for reentry services could be made available for high-risk releases. (Raphael, 2014). Naturally, it can't be possible to identify immediate desistors from the passing of time since it is not possible to wait for 7 years. However, some post-release programs could be done to identify them, i.e., good behavior, job-training programs, educational achievements, abstention from drugs or alcohols use etc. with the necessity of the signal of being an immediate desistor being costly to keep its credibility. Some studies indeed show large differences in recidivism between participants and not participants. For instance, only the 10% of individuals who participated in New York's program didn't recidivate within a year while the 44% of those who did not participate did. As a result, reentry programs, especially transitional employment programs, could improve the precision of the information given about individual recidivism risk and certifies their low risk and compliance, playing a role of screening for employers. (Bushway and Apel, 2012).

Moreover, it could be also useful to mitigate the risk of prisoner reentry faced by employers by sharing it with the government. For instance, the federal bonding program that issues business insurance policies for six months to cover employers for high-risk hirings could be extended to cover an entire year. (Raphael, 2014).

Finally, it's interesting to analyze the relationship between privacy and antidiscrimination. Economics is interested in the matter of privacy, defined as "the control over and safeguarding of personal information" (Warren and Brandeis, 1890; Acquisti, Taylor and Wagman, 2016), due to its informational dimension and for the trade-offs that arise from it. Nowadays it is a central topic of discussion due to the growing importance of digital platforms, the extensive availability of information about individuals and the reduction of cost of storing information. Privacy law has therefore grown suddenly in the last decades. Among the new implementations, for example, the European law has introduced the "right to be forgotten", which is the legal entitlement that allows individuals to ask for the removal of information about themselves upon request. There has been extensive discussion in the literature regarding privacy at an individual level, framing the problem as a legal debate between the right of the individual and the free speech rights of the entity that has the information. However, it is essential also to analyze the impact of privacy on society, since we have seen how the unobservability of information can generate statistical discrimination. This suggests a trade-off between information privacy protection and antidiscrimination principals. Policies with the objective of "color blinding" the American population by depriving information about a candidates' race, religious or race could decrease statistical discrimination (such as the Racial Privacy Initiative, defeated at the polls in 2003, that wanted to prevent the government from collecting and sharing data regarding individuals' race), however, in the information age, this approach could be very difficult to enforce. Increasing instead the availability of information about individuals reduces the uncertainty of an employment decision and the reliance on problematic proxies. For this reason, it's important for the policy maker to understand that, in addition to traditional antidiscrimination law, it is possible to use information policy as a tool to decrease discrimination (Strahilevitz, 2007).

CONCLUSION

It is undeniable that individuals with past convictions face huge barriers in entering and staying in the job market, as proven by the lower callback rates, the lower employment rate and the lower wages.

However, empirical evidence demonstrates how BTB policy may not be the correct answer to reduce these barriers. This situation shows how asymmetric information can prevent the market from reaching the Pareto-efficient allocation by generating statical discrimination. Due to this unintended effect, researchers are not able to find an agreement on the impact of the policy in the public and private sector and the existence of a societal gain. The policy is not able to increase the employment rate, but rather generate a substitution across workers.

This analysis provides a better understanding of the role that information plays in the job market and how its removal may not give the expected results. It is highlighted, indeed, the trade off between information and discrimination. Hence, some better solutions for the discrimination faced by ex-offenders would be to either offer better information, through reentry programs and signals of good behavior, or by mitigating the risk associated with this information, through a societal sharing of the risk for negligent hiring or longer public insurances for new hires.

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