Employer sanctions on hiring illegal labor: An experimental analysis of firm compliance

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Abstract

The employer sanctions provision of the 1986 Immigration Reform and Control Act penalizes employers who knowingly hire unauthorized workers. Under IRCA, employers are subject to civil and/or criminal penalties; however, given the widespread availability of counterfeit documentation, in some cases it becomes difficult to discern the employment eligibility status of some workers. Using experimental methods, this study provides some evidence that marginal increases in employer compliance rates are significantly higher when employers have perfect information on the employment eligibility status of its potential workers than when they do not. The experimental results suggest that increases in government spending for employer sanctions enforcement may be more effective if the informational asymmetry faced by employers is solved first. A possible solution to this problem may lie in the adoption of tamper-proof documentation such as a national identification card.

JEL classification: C91; D82; K42

Keywords: Experimental economics; Asymmetric and private information; Illegal behavior and the enforcement of law

1. Introduction

During the early part of the 1980s, the United States experienced a surge in both legal and illegal immigration (Borjas, 1994). The increase in immigration led to the passage of the Immigration Reform and Control Act (IRCA) in November 1986. IRCA's main
objective was to reduce the U.S. illegal alien population through employer sanctions on
those who employ unauthorized labor, increase in border enforcement resources, and an
amnesty program (Rivera-Batiz, 1991, Borjas, 1994). When complying with the
employer sanctions provision, however, employers may face uncertainty at the time of
verifying the employment eligibility of ‘unauthorized-looking’ potential workers given
the relative ease of obtaining counterfeit documentation (Pagan and Davila, 1996). Since
employers are supposed to readily accept documents if they seem genuine (otherwise they
may face potential discrimination charges if mistaken), employers may have difficulties
complying with this IRCA provision.

This study contributes to the understanding of the impact of IRCA on U.S. labor
markets. Given the recent calls for increased Immigration and Naturalization Service
(INS) funding for employer sanctions enforcement, it becomes important to understand
the mechanisms by which informational asymmetries created by the Act affect
employer’s behavior. It is possible that increasing the INS budget for employer sanctions
enforcement may only be marginally effective in deterring illegal immigration and may
even confuse employers due to the difficulties in identifying the employment eligibility
status of potential workers (for example, Cobb-Clark, Shiells and Lowell, 1995).¹ A
solution to this problem may lie in the implementation of a national identification card
(for example, Pagan, 1995).

Using experimental methods, this paper analyzes how IRCA’s employer compliance
rates would behave when enforcement funding increases under two possible scenarios:
one in which employers have perfect information on each worker’s employment
eligibility status and the other in which they do not. If employer compliance is
significantly more responsive to increased enforcement under a perfect information
environment, then it makes sense to first solve the employer’s ‘information problem’
before allocating more resources to the INS.

Our findings suggest that employer compliance with IRCA is relatively higher when
there exists perfect information on the employment eligibility status of potential workers.
Hence, the study suggests that a national ID card may significantly increase employer
compliance with IRCA. This result has important public policy implications since
employer sanctions may have a deterrent effect on illegal immigration by reducing the
expected post-migration earnings of potential migrants (for example, Pagan, 1995).

2. Conceptual issues

The early 1980s encompass a period of significant increases in both legal and illegal
immigration to the United States. For example, Passel et al., 1987 estimated the annual
increase in the illegal alien population to be between 100,000 and 300,000 during this
period (see also Warren and Passel, 1986, Hill and Pearce, 1990). These increases in the
undocumented population led the U.S. Congress to enact the Immigration Reform and

¹ Davila et al., 1995 present a theoretical and empirical discussion on the impact of employer sanctions on the
labor market outcomes of undocumented-appearing legal workers. Also, employer sanctions may have a
significant deterrent effect since they reduce the expected earnings of migrants to the U.S.
Control Act (IRCA) in November, 1986. IRCA's main objective was to reduce the U.S. illegal alien population through employer sanctions, allocating more resources for border enforcement, and implementing an amnesty program for those undocumented immigrants who arrived to the U.S. before 1982. Congress designated the U.S. Immigration and Naturalization Service (INS) as IRCA's principal law enforcement agency.

Of particular relevance to this paper is the employer sanctions provision of IRCA. The 1986 Act made it unlawful for employers to knowingly hire undocumented workers. Employers found in violation of the law are subject to monetary fines and/or jail sentences, the severity of the penalty dependent upon the number of unauthorized workers employed and the number of employer repeat offenses (Hill and Pearce, 1990). IRCA requires employers to check the employment eligibility of job applicants before hiring potential workers (U.S. Department of Justice, 1991). However, under further IRCA revisions (contained in the 1990 Immigration Act), employers who refuse to accept genuine-looking worker identification cards may be charged with employment discrimination.

The employer sanctions provision contained in IRCA, coupled with the anti-discrimination provisions of the 1990 Immigration Act and the lack of difficulty in obtaining counterfeit documentation, have created an environment of confusion among all parties affected by immigration reform (see U.S. Department of Labor, 1991). In particular, employers may face uncertainty when verifying the employment eligibility of ‘unauthorized-looking’ potential workers. The biggest problem is that unauthorized workers can easily obtain counterfeit documentation (Lelyveld, 1994) and employers are supposed to accept the documents at face value, if they seem genuine, or they risk making an identification mistake and may possibly face discrimination charges (Fry, Lowell and Haghighat, 1995). This asymmetric information dilemma makes it difficult for employers to fully comply with IRCA provisions.

Some policy-makers have suggested that substantial increase in funding for INS’s employer sanctions enforcement are needed given the recent upsurge in illegal immigration (for example, Chiswick, 1991). However, increasing the INS budget for employer sanctions enforcement may only confuse employers more due to the difficulties in identifying the employment eligibility status of potential workers (for example, Cobb-Clark, Shiells and Lowell, 1995). Some economists have proposed a kind of national identification card as a possible way of solving this informational asymmetry (see, for

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2 IRCA’s employer sanctions provision imposes civil and/or criminal penalties to employers who knowingly hire or continue to employ illegal aliens. The fines range from $250 to $3000 per employee, but repeat offenders could be fined up to $10,000 per worker or receive a criminal penalty of $3000 and/or six months imprisonment (U.S. Department of Justice, 1991).

3 Although the new law protects workers against employer discrimination “... on the basis of national origin or citizenship, or to require (from employment applicants) more or different documents from a particular individual” (see U.S. Immigration and Naturalization Service, 1991: p. 1), employers are not held responsible for the authenticity of the documentation provided by potential workers. The employer is not liable for hiring an unauthorized worker as long as the employee’s documents appear genuine and they relate to the individual presenting them.

4 Pagan and Dávila (1996) have shown that the employer uncertainty created by IRCA with regard to employment eligibility status may have resulted in a reduction of the quantity and quality of the on-the-job training provided to foreign-appearing native workers, particularly Mexican–Americans.
example, Pagán, 1995). Supposedly, under the perfect information scenario created by a national identification card, employers will not have incentives both to discriminate against the undocumented-appearing and to claim ignorance on the employment eligibility of potential workers. Hence, they may have more incentives to comply with the employer sanctions provision of IRCA.

This line of inquiry has important public policy implications since IRCA’s employer sanctions compliance rates, given an increase in INS enforcement funding, may differ depending on the degree of information faced by employers. As such, it then becomes policy relevant to focus on how IRCA’s employer compliance rates would behave when enforcement funding increases under different degrees of employer information on the worker’s employment eligibility status. If employer compliance is more responsive to increased enforcement under perfect information, then policymakers should solve these asymmetries first before embarking in any INS budgetary increases.

There are two major difficulties that arise when attempting to provide empirical answers to the above public policy issues. First, and for obvious reasons, employers may have an incentive to hide information if asked about their compliance behavior with IRCA provisions. Second, a counter proof national identification card has never existed. It is this difficulty in collecting reliable data that does not allow us to directly test the implications of increases in employer sanctions’ enforcement resources.

One possible solution to this data constraint is the use of experimental methods. For example, laboratory experiments have been widely used to analyze individual income tax compliance under differing enforcement schemes (Alm et al., 1992a, 1992b, 1993). A laboratory setting provides a way of analyzing employer behavior to changes in, for example, IRCA’s penalty structure, the probability of being investigated by the INS, and other policy issues for which data is nonexistent and/or difficult to collect. Further, some economists argue that experimental methods can be used in public policy analysis as long as the assumptions of induced-value theory are satisfied and as long as the experimental design captures the main properties of the ‘naturally occurring processes’ that are being studied (Friedman and Sunder, 1994; Chapter 2).

3. Employer sanctions: Experimental design

The experimental setting is designed to capture the main features of the employer sanctions provision of IRCA. During each session, subjects act as employers who have to decide the profit-maximizing share of legal and illegal workers, represented in the experiment by blue and red tokens, respectively. Basically, subjects have to decide the optimal combination of blue and red tokens to be held in order to maximize profits (or points in the experimental setting). The red tokens represent a higher potential ‘value’ to the subject, where value can be interpreted as the difference between the marginal revenue product and the wage rate of each worker. That is, given the same marginal

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5 For example, employers may not wish to answer questions with regard to whom they hire and/or their workers’ employment eligibility status for fear of retribution by the INS. For other examples in the compliance literature, see Klepper and Nagin (1989).
revenue product for both legal and illegal labor, employers pay a lower wage to those that are illegal (that is, the red tokens; see Isé and Perloff, 1995). This lower wage may arise mainly due to three factors: a risk premium charged by employers to those that appear undocumented, a ‘monopsonistic’ lower wage due to the reduction in employment opportunities faced by illegals after IRCA, or, simply, a distaste for foreign-appearing labor (see Todaro and Maruszko, 1987, Dávila et al., 1995).

Given this experimental framework, the probability of being investigated by the enforcement authority, as well as the degree of employer knowledge on each worker’s employment eligibility status, are manipulated to investigate their effects on employer compliance with IRCA. In passing, note that it is implicitly assumed that increase in the employer sanctions enforcement budget results in a higher probability of being investigated by immigration authorities.

Subjects were recruited from undergraduate economics classes at The University of New Mexico and The University of Texas-Pan American during the fall semesters of 1994 and 1996. A total of 30 subjects were divided into six experimental groups. During each session we manipulated two parameters, the probability of being detected with red tokens (0.1, 0.5 and 0.9), and the subjects’ knowledge of the employment eligibility status of workers (later referred to as blue token uncertainty). To induce students to participate in the experiment, the subjects were paid a $5 participation fee and competed for a $20 cash price. None of the subjects had any previous experience in decision-making under uncertainty experiments. Each session began with three practice rounds, and each lasted from 35 min to 1 h.

A total of five subjects participated in each session and they were identified by a number from 1 to 5. A set of printed instructions was provided to each individual and read aloud by the experimenter before the beginning of each session (see Appendix A). The instructions were written in neutral terminology to avoid potential context or framing effects (Smith, 1982, Davis and Holt, 1993). Subjects were told that the sessions would last for an unknown number of rounds but the rounds were predetermined at 25. During each round, subjects were given an endowment (a number written by the experimenter on a blackboard) of tokens ranging from 50 to 100. Subjects were told that they could hold their endowment in either red or blue tokens and received the same endowment in a given round. Red tokens were assigned a value of 3 points each while blue tokens were valued at 1 point each. A record sheet was provided to each subject to keep track of the total token allocation and experimental outcomes (see Appendix B).

After each subject had selected their token distribution, some were randomly selected for a ‘check’ by the experimenter. Individuals that were selected for a check lost all their red tokens (in that round) and, in addition, paid a penalty of 1 point per red token held.

Using the National Agricultural Worker’s Survey, Isé and Perloff, 1995 find that legal agricultural workers earn 15 percent more on average than do undocumented workers. They also find that the wage differential varies by region and levels of human capital. Taylor, 1992 finds a much higher wage differential in this sector. Todaro and Maruszko, 1987) call it the ‘illegality tax’ and discuss some studies that have found a substantial wage differential between legals and illegals in the U.S. (Todaro and Maruszko, 1987: p. 112, endnote 7).

The cash prize was awarded to the individual who accumulated more points in a randomly selected round. This remuneration scheme was used for two reasons: first, due to the availability of funds and, second, to control for ‘wealth’ effects of early round points on late round behavior (see Friedman and Sunder, 1994; p. 51).
This reflects the fact that those employers who knowingly hire undocumented workers lose them through deportation and also pay a set fine per employed worker (see U.S. Department of Justice, 1991).

In three of the six sessions, subjects faced a second lottery that incorporated the asymmetric information problem faced by employers with respect to employment-eligibility documentation. This feature of the employer–worker interaction is captured by allowing for blue token uncertainty. That is, in these sessions subjects selected between blue and red tokens but they did not know whether blue tokens (representing legal potential workers) were really blue. As such, in the ‘blue token uncertainty’ sessions (that is, no national ID), individuals selected for a check also faced a second lottery with a 1 in 2 chance of losing half of their blue tokens.8

Note that in this second lottery employers (subjects) were not fined but lost the points they would have earned if there was no blue token uncertainty. This captures the fact that employers who unknowingly hire undocumented workers are not fined by the INS but lose the worker through voluntary departure or, in some cases, forced deportation (U.S. Department of Labor, 1991). Also, this implicitly captures the costs of rehiring workers to substitute for those deported by immigration authorities.

At the end of each round, subjects scored (in points) the value of their tokens left in a Record Sheet. The checking procedure was determined by drawing numbered balls from a bingo cage in full view of the audience. The bingo cage contained 10 balls: five with each subject’s assigned number plus five other balls.9 In the sessions with blue token uncertainty a second individual draw was conducted for those who were selected for a check. If the number selected was from 1 to 5, the individual would lose 50 percent of the blue tokens held (that is, a 50 percent chance of losing 50 percent of the blue tokens). A summarized description of the six sessions conducted is provided in Table 1, Columns 1–3.10

The theoretical expected value for the individual choice when there is no uncertainty about the blue tokens is given by:11

\[ EV = 3R + 1B - 4pR, \]  

where \( R \) and \( B \) represent the number of red and blue tokens selected, respectively, and \( p \) is the probability of a check. Taking the derivative with respect to \( R \) and recognizing that \( R \) and \( B \) must sum to the per-round endowment, the individual will choose all \( R \) if and only if \( 2 - 4p > 0 \), all \( B \) if \( 2 - 4p < 0 \), and will be indifferent between \( R \) and \( B \) if \( 2 - 4p = 0 \).

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8 For example, if a subject divided his/her endowment between 25 red and 30 blue tokens and was not selected for a check, (s)he would accumulate 105 points in that round. If (s)he was selected for a check in the first draw (s)he would have lost all 25 red tokens and pay an additional penalty of 25 points, for a total of 5 points in the round. If (s)he was also selected in the second draw then the total points would have been –10 (15 from the blue tokens left minus 25 penalty points from the red tokens initially held).

9 For example, if the probability of being checked was 10 percent, one ball was drawn from the bingo cage and then replaced for subsequent rounds. For a probability of 50 percent, 5 balls (without replacement) were drawn from the bingo cage and then replaced for subsequent rounds.

10 The expected per round payoffs (in points) of holding red/blue tokens are: S1: red = 2.6, blue = 0.975 S2: red = 1, blue = 0.875 S3: red = –0.6, blue = 0.775 S4: red = 2.6, blue = 1 S5: red = 1, blue = 1 S6: red = 1, blue = 1

11 This analysis was suggested by one of the referees.
Therefore, under no blue token uncertainty, the critical value at which the subject is indifferent between $B$ and $R$ tokens is simply $p^c = 1/2$. Consequently, if we allow $p$ to attain different values between 0 and 1, then subjects will choose all $R$ if $p = 0.1$, be indifferent when $p = 0.5$, and choose all $B$ if $p = 0.9$ (that is, these are the three different $p$’s selected for the experiment).

When there is uncertainty about the blue tokens, however, the expected value for the individual choice becomes:

$$EV' = 3R + 1B - 4pR - qpB/2$$  \hspace{1cm} (2)

where $q$ is the probability of being selected for a second check (that is, sessions with blue token uncertainty). It is easy to show that subjects will choose all $R$ when $2 - 4p + pq > 0$. The critical value of the $p$ probability is now $p^c' = 1/[2 - (q/4)]$. Since we chose $q = 0.5$, the critical value becomes 0.533. Again, the same values for $p$ are used in the three sessions with blue token uncertainty. Note that, assuming risk-neutrality, subjects should exhibit all-or-none behavior in the sessions.

Econometric analysis of the data was conducted by the Tobit maximum likelihood\(^\text{12}\) estimation of a regression of the form

$$B_{it} = \alpha_0 + \alpha_1 TT_{it} + \alpha_2 P50_{it} + \alpha_3 P90_{it} + \alpha_4 BU_{it} + \alpha_5 p50 \times BU_{it} + \epsilon_{it} \text{ if } B_{it} > 0$$  \hspace{1cm} (3)

$$B_{it} = 0 \text{ otherwise,}$$

where $B_{it}$ is the total number of blue tokens held by subject $i$ ($i = 1 \cdots 30$) at round $t$ ($t = 1 \cdots 25$), $TT_{it}$ represents the total number of endowed tokens, $P50_{it}$ and $P90_{it}$ are dummy variables that take the value of one if the probability of being checked is 0.50 and 0.90, respectively, and zero otherwise, $BU_{it}$ is a dummy variable that takes the value of one if there is blue uncertainty and zero otherwise, $p50 \times BU_{it}$ and $p90 \times BU_{it}$ are interaction terms, and $\epsilon_{it} \sim N(0, \sigma^2)$. The a priori signs of the coefficients are $\alpha_1 > 0$, $\alpha_2 > 0$, $\alpha_3 > 0$, $\alpha_4 < 0$, $\alpha_5 < 0$, and $\alpha_6 < 0$. Maximum likelihood estimation of Eq. (3) assures consistent estimates of the equation parameters (Maddala, 1983, Breen, 1996).

\(^\text{12}\) Tobit estimation was used because there were a significant number of zero values for the dependent variable ($B$). That is, the dependent variable is censored at zero. For other examples of using Tobit estimation in this context, see Alm et al., 1992a, 1993).

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**Table 1**

<table>
<thead>
<tr>
<th>Session</th>
<th>Blue token uncertainty</th>
<th>Mean blue tokens’ percentage</th>
<th>Checks per round</th>
<th>Average total points</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Yes</td>
<td>0.180</td>
<td>0.096</td>
<td>176.96</td>
</tr>
<tr>
<td>S2</td>
<td>Yes</td>
<td>0.456</td>
<td>0.488</td>
<td>54.58</td>
</tr>
<tr>
<td>S3</td>
<td>Yes</td>
<td>0.784</td>
<td>0.912</td>
<td>45.76</td>
</tr>
<tr>
<td>S4</td>
<td>No</td>
<td>0.018</td>
<td>0.088</td>
<td>191.96</td>
</tr>
<tr>
<td>S5</td>
<td>No</td>
<td>0.545</td>
<td>0.432</td>
<td>68.00</td>
</tr>
<tr>
<td>S6</td>
<td>No</td>
<td>0.897</td>
<td>0.904</td>
<td>51.92</td>
</tr>
</tbody>
</table>
4. Experimental results

The experiment results are summarized in Table 1 and graphically displayed in Figs. 1 and 2. Note the differences in the compliance rates in Column 4 of Table 1. The

Fig. 1. Average compliance rates by session and round.

Fig. 2. Average compliance rates by probability of being selected for a check.
compliance rate is defined as the (per session) average ratio of blue to total tokens (in other words, the legally employed share of the employer’s total labor force). In the sessions with blue token uncertainty (S1, S2 and S3; no national ID), for example, an increase in the probability of detection from 0.10 to 0.50 increases compliance rates from 0.18 to 0.45, a 153 percent increase. However, in the sessions where each subject knew the exact value of blue tokens (S4, S5, and S6; national ID), an identical increase in the probability of being checked leads to an increase in compliance rates from 0.02 to 0.55. That is, an increase in the probability of detection seems to be significantly more effective (in terms of increasing compliance rates) when the subjects have perfect information (no blue token uncertainty).

Fig. 1 plots the compliance rates over the 25 period sessions. A visual inspection of the graph confirms that average per period compliance rates were almost always higher when there was no blue token uncertainty. Note also that there was a slight learning effect since compliance rates decreased somewhat in all the sessions.

Fig. 2 shows the results from Table 1 graphically. Note that compliance rates are higher under perfect information (a national ID) when you move from $p = 0.1$ to $0.5$ and $0.9$. In other words, increases in funding for employer sanctions enforcement may be more effective under an environment of perfect employer knowledge of the employment eligibility status of its work force. Note also, in Table 1, that the average total points for sessions S4, S5 and S6 are higher when there is no blue token uncertainty. That is, the average returns (profits) are higher when there is perfect information (S4, S5 and S6) even though the average checks per round (for red tokens only) were higher in sessions S1, S2 and S3.

Table 2 reports the Tobit maximum likelihood estimates of Eq. (3). Since the estimated parameters reflect how changes in the regressors affect the unobserved latent variable $B_{it}$, we also report the marginal effects of changes in the independent variables on $B_{it}$ for ease of interpretation ($\partial E(B_{it})/\partial x_j = \Phi(\alpha'x/\sigma)\alpha_j$, where $x$ represents the regressors and $\alpha$ is

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimates</th>
<th>Marginal effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$-75.683^a (6.847)$</td>
<td>0.001</td>
</tr>
<tr>
<td>Total tokens ($TT$)</td>
<td>0.474 $^a (0.063)$</td>
<td>0.227</td>
</tr>
<tr>
<td>Prob. 50 ($P50$)</td>
<td>76.664 $^a (5.272)$</td>
<td>0.294</td>
</tr>
<tr>
<td>Prob. 90 ($P90$)</td>
<td>99.319 $^a (5.293)$</td>
<td>0.294</td>
</tr>
<tr>
<td>Blue uncertainty ($BU$)</td>
<td>43.213 $^a (5.305)$</td>
<td>0.294</td>
</tr>
<tr>
<td>$P50 \times BU$</td>
<td>$-51.153^a (6.415)$</td>
<td>$-0.152$</td>
</tr>
<tr>
<td>$P90 \times BU$</td>
<td>$-34.573^a (6.344)$</td>
<td>$-0.103$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>27.505</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>$-2.499.033$</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>750</td>
<td></td>
</tr>
</tbody>
</table>

Notes: (i) The dependent variable is the total number of blue tokens held per round per individual,
(ii) $P50$ and $P90$ are dummy variables taking the value of one if the probability of being checked is 0.50 or 0.90, and zero otherwise. The base category is $P10$.
(iii) $BU$ is a dummy variable that takes the value of one if there is blue uncertainty and zero otherwise.
(iv) Standard errors are reported in parentheses; $^a =$ significant at the one percent level.
a vector of $J$ parameters ($j = 1 \cdots J$). Note that, as expected, compliance significantly increases with increase in the total endowment of tokens ($TT$) and the probability of detection (see the coefficients of $P50$ and $P90$). Note also that compliance under blue token uncertainty is lower for two of the three different detection probabilities being analyzed. This is reflected in the negative and statistically significant interaction terms of blue token uncertainty with $P50$ and $P90$ (see also the sign of the marginal effects).

A puzzling result is that the coefficient for $BU$ is positive and statistically significant. Since this result applies to the session with a 10 percent chance of being selected for a check, however, it may be arising due to the low probability of losing blue tokens in sessions S1 and S4 (see related results in Appendix C). That is, given the low chance of being selected for a check, subjects proportionally (and systematically) choose more red than blue tokens and, hence, are not concerned with blue token uncertainty as we clearly see in the 50 and 90 percent sessions. In sum, the results from this analysis provide partial support to the assertion that blue token uncertainty does affect compliance behavior and that compliance rates are higher when there is perfect information.

5. Conclusion

This experimental work presents some evidence to support the notion that employers who hire undocumented workers are responsive to increases in the probability of being apprehended and fined by the enforcement authorities. Indeed, employer compliance is relatively higher when employers have perfect information on the employment eligibility status of its potential workers than when they do not. These results suggest that some kind of national ID card may be beneficial in achieving a higher employer compliance rate with IRCA. Thus, any budgetary increase for employer sanctions enforcement should be preceded by a solution to the asymmetric information problem faced by employers. These policy recommendations may be worth considering if the benefits of increased employer compliance with IRCA outweighs the monetary and social/political costs of implementing a national ID card. For example, employer sanctions may have a deterrent effect on illegal immigration by reducing the expected post-migration earnings of workers from immigrant source countries (see, for example, Pagán (1995), Dávila and Pagán (1997)). As such, employer sanctions may have an important role in stemming illegal immigration by complementing a border enforcement strategy and increasing migration costs.

Although these results contribute to the understanding of the enforcement mechanism of employer sanctions, they should be considered with caution given the nature of experimental methods. Nevertheless, results from laboratory experiments are the only current sources of data that can provide answers on how individuals behave to the changes in policy parameters that are of interest to enforcement agencies such as the INS. Future research should look at how other enforcement schemes may be implemented (such as changes in the employer penalty structure and/or endogenous enforcement rules) to increase employer compliance with IRCA.

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13 Aggregation biases may also play a role since the Tobit estimation procedure implicitly assumes that each individual’s rounds are independent.
Acknowledgements

I am grateful to Alberto Dávila, Micha Gisser, Michael McKee, Montserrat Viladrich-Grau, the editor and two referees for their helpful suggestions and comments.

Appendix A

Experiment instructions (S1)

This is an experiment about economic decision making under uncertainty. Please read the instructions carefully, and raise your hand if you have a question. If you follow the instructions and make good decisions, you will have the opportunity to earn a $20 cash prize, which will be paid to you at the end of the experiment. In addition, you will earn a $5 participation fee.

The experiment will last for several rounds. The exact number is unknown. In each round you will be required to make a decision and your points per round will depend on these decisions. The more points you accumulate the more likely you win the $20 prize. There will be three practice rounds to familiarize you with the experiment procedures.

At the beginning of each round you will be assigned a maximum quantity of tokens you can buy or hold. The exact quantity will be between 50 and 100 tokens. You can hold either BLUE or RED tokens and combine them as you wish. BLUE tokens are valued at 1 point each. RED tokens are valued at 3 points each. Each round will proceed as follows:

1. The experimenter will write on the blackboard the total number of tokens you will be able to buy or hold in that round. You must decide how many BLUE and RED tokens you will buy. Record the total number of tokens given to you as well as the number of RED and BLUE tokens you wish to hold on the RECORD SHEET in front of you.

<table>
<thead>
<tr>
<th>Record sheet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total tokens</td>
</tr>
<tr>
<td>Red tokens bought</td>
</tr>
<tr>
<td>Blue tokens bought</td>
</tr>
<tr>
<td>Blue tokens left</td>
</tr>
<tr>
<td>Total round points</td>
</tr>
</tbody>
</table>

Table 3

Record Sheet

<table>
<thead>
<tr>
<th>Total tokens</th>
<th>Red tokens bought</th>
<th>Blue tokens bought</th>
<th>Blue tokens left</th>
<th>Total round points</th>
</tr>
</thead>
</table>
2. After everyone has made their choices, up to 1 person may be selected for a check. If you are checked and you are found holding RED tokens, all of them will be taken away (i.e. crossed out from your RECORD SHEET by the experimenter) and, in addition, you will pay a penalty of one point per RED token held. You will also face a 1 in 2 chance of losing half of your BLUE tokens. Only the person checked will know the result of the check. At the end of each round you will score the value of your token holdings in terms of points.

Example: If you are holding 25 RED and 30 BLUE tokens and you are selected for a check, you will lose 25 RED tokens and pay a penalty of 25 points. If in the second gamble you are also selected you will lose an additional 15 BLUE tokens.

Table 4
Average individual blue/total token ratio

<table>
<thead>
<tr>
<th>Session</th>
<th>Individual</th>
<th>Mean blue tokens’ ratio (standard deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1</td>
<td>0.44 (0.26)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td></td>
<td>3</td>
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3. The checking procedure is as follows. Each RECORD SHEET has an ID number from 1 to 5. In the bingo cage in front of the classroom there are 10 balls numbered from 1 to 10. After everyone has recorded their purchases, one ball will be drawn from the cage. If your ID number is selected, your RECORD SHEET will be checked. If the number of the ball is 6 to 10, no one will be checked. You have a 1 in 10 (10 percent) chance of being selected for a check.

4. If you are selected for a check the experimenter will conduct a second draw from the bingo cage. If a number from 1 to 5 is drawn then you will also lose half of your BLUE tokens but will not be assessed a penalty. In other words, you have a 50 percent chance of losing 50 percent of your BLUE tokens.

At the end of the experiment one person will win a $20 prize. The prize winner will be determined as follows. One ball will be drawn from a bingo cage containing balls numbered from 1 to the last round number. The individual with the highest number of points in the selected round will win the $20 prize. Once again, remember that the more points you hold per session the higher the chance you win the $20 prize. Thank you for your participation. Are there any questions?

Appendix B

Table 3

Appendix C

Table 4

References


