THE WAGE PREMIUM OF NATURALIZED CITIZENSHIP

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ABSTRACT

We examine the potential effect of naturalization on the U.S. immigrants's earnings. We find the earning gap between naturalized citizens and non-citizens is positive over many years, with a tent shape across the wage distribution. We focus on a normalized metric entropy measure of the gap between distributions, and compare with conventional measures at the mean, median, and other quantiles. In addition, naturalized citizen earnings (at least) second-order stochastically dominate noncitizen earnings in many of the recent years. We construct two counterfactual distributions to further examine the potential sources of the earning gap, the "wage structure" effect and the "composition effect." Both of these sources contribute to the gap, but the composition effect, while diminishing somewhat after 2005, accounts for about 3/4 of the gap. The unconditional quantile regression (based on the Recentered Influence Function), and conditional quantile regressions confirm that naturalized citizens have generally higher wages, although the gap varies for different income groups, and has a tent shape in many years.

Keywords: Earning gap; citizenship; stochastic dominance tests; RIF regression; entropy measure; immigration

JEL classifications: C13; J70

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1. INTRODUCTION

Studies of immigrant wages go back to at least Chiswick (1978). Most studies are concerned with the analysis of earnings differences of immigrants compared with natives (see, e.g., Aldashev, Gernandt, & Thomsen, 2012; Bartolucci, 2014). The earning gap between naturalized citizens and noncitizens has received less attention. Besides political and social rights, citizenship provides economic benefits. Most federal, state, local public sector and certain licensed professional jobs are restricted to citizens. These government jobs are stable and offer higher wages. Most private employers prefer citizenship holders as well, due to the risk of knowingly or inadvertently hiring unauthorized immigrants, and the administrative cost of hiring noncitizens. Second, the 1996 US welfare reform sharply reduced welfare eligibility for noncitizens (permanent residents qualify for these benefits after at least 40 quarters of work with legal status).

In the literature, economists are interested in three main questions related to citizenship's impact on economic benefits to immigrants. (1) How large is the earning gap? (2) How could one separate out the earning gap due to "the composition effect," or human capital characteristics? (3) How to evaluate the changes in the distribution and quantiles of the unconditional (marginal) distribution of immigrant log wages? Our paper proposes to offer some answers to these questions and examines new concepts and techniques for this purpose.

Identification of the "citizenship" effect is more likely by focusing on immigrants alone as a more homogeneous group compared with natives. We also focus on immigrants who are actively in the labor market.

Previous research on wage differentials is often based on certain measures such as means and medians. Sumption and Flamm (2012) reports 50–70% gap for the median annual incomes during the period from 1993 to 2010, and naturalized citizens appear to have weathered the effects of the economic crisis more successfully as the median income fell only by 5% from 2006 to 2010, while the decline of noncitizens' median income is 19%.[1] However, the differences at "representative" parts of the earnings distribution (mean, median, or any percentile) may not be "representative." This type of heterogeneity challenges the status of any scalar measure of the gap, especially simple aggregators like the mean and median, or any single quantile. Maasoumi and Wang (2015) are the first to utilize a normalized metric entropy measure of the wage gap, adapted from Bhattacharay–Matusita–Hellinger, and developed in Granger, Maasoumi, and Racine (2004). They argue this measure is a more comprehensive welfare-theoretic metric of distance between two earnings distributions. This is important for credible complete, "cardinal rankings." For weaker uniform orderings, they proposed stochastic dominance (SD) tests to rank the earnings distributions over large classes of familiar welfare functions. Maasoumi, Pitts, and Wu (2014) implement similar methods for the wage gap between incumbent and newly hired employees. Our paper employs the same entropy measure and SD tests to explore the earning gap between naturalized citizens with noncitizens in the United States from 1994 to 2012. The raw earning gap is often tent shaped in each year, possibly peaking from 1995 to 1997, while the trough appears during 1999–2001. The SD rankings are inferred to a statistical degree of confidence, allowing uniform ranking of naturalized citizens wages over noncitizens for most years. First-order SD rankings before 2003 are not statistically significant (significance level considered is 5%), but we find second-order significant SD for more than half of time after (including) 2003.

Moving beyond raw wages comparisons, we examine which part of the wage gap may be due to differences in the composition effects (human capital characteristics), and due to wage structure (market returns). The latter is considered by some as an indication of "discrimination" in the context of gender or race gaps. Our paper follows the counterfactual analysis proposed by Maasoumi and Wang (2015) by identifying and estimating two types of counterfactual distributions. This provides a decomposition of the gap into the aforementioned components. This decomposition procedure is described in Firpo, Fortin, and Lemieux (2007) and generalizes the Oaxaca-Blinder-type decomposition (at the conditional mean) to the whole distribution.

Based on the counterfactual analysis, the entropy gap estimates suggest a potential very small market structural gap from 1994 to 2012, holding human capital characteristics. SD tests seldom show significant ranking between the (two) noncitizen counterfactual distributions compared with the actual noncitizen wage distributions. Human capital characteristics appear to account for most of the differences in the hourly wage distributions. Entropy estimates quantify the magnitude of this human capital effect over the entire distribution of wages.

Most of the previous studies on the earning gap between naturalized citizens and noncitizens place "citizenship" as an explanatory variable in a Mincer-type earnings regression. Based on a linear (conditional mean) regression analysis, Pastor and Scoggins (2012) find that in 2010, naturalized citizens earned 7.9% on average more than noncitizens after controlling for numerous human capital characteristics. Bratsberg, Ragan, and Nasir (2002) track the same young male immigrants group from 1979 through 1991, showing an average wage gain of around 5.6% from naturalization. These results focus on the coefficient of the citizenship variable in the conditional mean. By contrast, we are interested in possibly heterogeneous effect of citizenship at different quantiles. Our paper examines the effect of changing the proportion of naturalization on the τth quantile of the unconditional distribution of log wages. This kind of analysis follows methods that have been developed only recently, such as in Firpo, Fortin, and Lemieux (2009). The approach consists of running a regression of the Recentered Influence Function (RIF) of the unconditional quantile on desired explanatory variables. For each year from 1994 to 2012, we discover a tent shape for the citizenship effect, implying that this effect is different for different levels of income, and is highest between the median and the 75-th percentile. For comparison, we also implement the traditional conditional quantile regressions (Koenker, 2005; Koenker & Bassett, 1978).[2] The findings from different methods provide a robustness check, and generally agree, but can differ quantitatively at different quantiles.

In Section 2, we will present the methods, data description is provided in Section 3. In Section 4, we provide the results, and conclude our paper in Section 5.

2. EMPIRICAL METHODOLOGY

2.1. Basic Notation

Let $\ln(\omega^0)$ and $\ln(\omega^1)$ denote the log wages of naturalized citizens and noncitizens, respectively. We observe a random sample of $N = N_0 + N_1$ immigrants. N_0 and N_1 denote the sample sizes of naturalized citizens and noncitizens, respectively. Let $F_0(y) \equiv Pr[\ln(\omega^0) \leq y]$ represents the cumulative density function (CDF) of $\ln(\omega^0)$ (i.e., the log of earning for naturalized citizens) and $f_0(y)$ is the corresponding probability density function (PDF); $F_1(y)$ and $f_1(y)$ are similarly defined for $\ln(\omega^1)$.

Individual earnings are determined by both observable, X_i, and unobservable characteristics ϵ_i via an unknown wage functions g_d

$$\ln(\omega_i^d) = g_d(X_i^d, \epsilon_i^d), \quad d = 0, 1 \tag{1}$$

The wage gap between naturalized citizens and noncitizens stems from two sources in Eq. (1): (1) differences in the distributions of both observable and unobservable characteristics, X_i^d and ϵ_i^d, respectively; (2) differences in the wage structures, $g_d(\cdot)$.

2.2. Decision-Theoretics: Entropy as a Distributional Measure of the Earnings Gap

The need for careful decision/welfare-theoretic understanding of measures of earnings gap has led to a reevaluation of suitable functions of the earnings distributions. A brief review of the issues is given in Maasoumi and Wang (2015). Flexible Evaluative Functions (EFs) that account for different outcomes at different parts of the earnings distribution provide better support for functionals that go beyond the mean and median, any single quantile, or merely reporting a set of quantiles. The classical literature on ideal measures of inequality provides the relevant backdrop and guidance. This literature identifies Entropy measure as "ideal" distribution functions.[3] As argued in Maasoumi and Wang (2015), the "gap" between two distribution is conveniently seen as the distance between the entropies (inequality measures) of the relevant distributions. When "metricness" is further required for distance functions (rather than mere divergence), a metric entropy member of the Generalized Entropy family emerges which is a normalization of the Bhattacharya–Matusita–Hellinger measure proposed by Granger et al. (2004). Other entropy measures can be employed with qualitatively consistent results. But only a metric measure that satisfies the triangularity rule may support coherent statements about respective "distances" amongst three or more distributions.

$$S_\rho = \frac{1}{2}\int_{-\infty}^{\infty}\left(f_1^{\frac{1}{2}} - f_0^{\frac{1}{2}}\right)^2 dy \tag{2}$$

This entropy measure possess several properties: (1) it can be applied to discrete and continuous variables;[4] (2) if $f_1 = f_0$, the two distribution are equal, then $S_\rho = 0$, and lies between 0 and 1 as it is normalized; (3) it is a metric, accommodating assessment across multiple distributions because triangularity property is satisfied; (4) it is invariant under continuous and strictly increasing transformation on the underlying variables; and (5) it is dimensionless, accommodating multivariable assessments.

Following Granger et al. (2004), Maasoumi and Racine (2002), and Maasoumi and Wang (2015), we consider a kernel-based implementation of Eq. (2). We use Gaussian kernels and the "normal reference rule-of-thumb" bandwidth $(=1.06 \cdot \min(\sigma_d, \frac{IQR^d}{1.349}) \cdot n^{-\frac{1}{5}}$, where $\sigma_d, d = 0, 1$ is the sample standard deviation of $\ln(\omega_i^d)_{i=1}^{N_d}$, IRQ^d is the interquartile range of the sample d). Interestingly, Gaussian kernels also enjoy an entropic justification as the Maximum Entropy choice when only the first two moments of data are utilized.

The entropy values S_ρ may not be statistically significantly different from 0, thus in this paper, we obtain critical values to test the hypothesis $H_0 : S_\rho = 0$ based on 299 bootstrap resamples. The critical values are reported in Table 1.

2.3. *Stochastic Dominance*

In our paper, we employ statistical tests for the first- and the second-order SD. This is motivated by the fact that there is no universally accepted Evaluation Function, and SD rankings, or lack of them, reveal whether (weak) uniform rankings hold across large classes of EFs, or else, how restrictive such functions need to be to provide (cardinal) complete rankings.

Table 1. Critical Values for Testing of $H_0 : S_\rho = 0$.

Year	Noncitizen versus Naturalized			C1 versus Noncitizen			C2 versus Noncitizen		
	90th	95th	99th	90th	95th	99th	90th	95th	99th
1994	0.29	0.31	0.35	0.32	0.34	0.40	0.34	0.38	0.49
1995	0.34	0.39	0.45	0.23	0.27	0.34	0.27	0.30	0.37
1996	0.34	0.38	0.44	0.51	0.65	0.78	0.35	0.39	0.44
1997	0.33	0.37	0.44	0.52	0.58	0.79	0.30	0.35	0.42
1998	0.29	0.34	0.40	0.28	0.30	0.38	0.28	0.33	0.41
1999	0.26	0.29	0.36	0.46	0.51	0.60	0.39	0.41	0.51
2000	0.26	0.28	0.37	0.30	0.33	0.39	0.56	0.60	0.75
2001	0.22	0.25	0.29	0.21	0.23	0.28	0.27	0.30	0.34
2002	0.18	0.20	0.23	0.22	0.23	0.28	0.24	0.27	0.35
2003	0.19	0.20	0.24	0.37	0.45	0.53	0.23	0.25	0.30
2004	0.18	0.20	0.25	0.19	0.20	0.27	0.26	0.31	0.37
2005	0.20	0.24	0.28	0.23	0.27	0.30	0.21	0.23	0.27
2006	0.16	0.18	0.24	0.25	0.27	0.33	0.24	0.27	0.32
2007	0.25	0.27	0.31	0.26	0.28	0.33	0.27	0.30	0.36
2008	0.21	0.22	0.29	0.19	0.21	0.27	0.27	0.29	0.33
2009	0.19	0.20	0.29	0.17	0.19	0.24	0.19	0.21	0.30
2010	0.18	0.20	0.24	0.17	0.19	0.22	0.27	0.29	0.36
2011	0.21	0.22	0.28	0.25	0.27	0.35	0.28	0.31	0.37
2012	0.21	0.23	0.28	0.24	0.27	0.31	0.22	0.24	0.27

Source: IPUMS CPS (http://cps.ipums.org/cps/).
Notes: The entropy ($\times 100$) 90th, 95th, and 99th percentile critical values under the null of no entropic difference between two wage distributions. C1 is noncitizen counterfactual #1, C2 is noncitizen counterfactual #2. Critical values obtained from 299 bootstrap resamples.

First-Order Dominance: *Naturalized citizen earnings* $(\ln(\omega^0))$ *first-order stochastically dominate noncitizen earnings* $(\ln(\omega^1))$ *(denoted* $\ln(\omega^0)$ *FSD* $\ln(\omega^1)$*) if and only if*

1. $E[u(\ln(\omega^0))] \geq E[u(\ln(\omega^1))]$ *for all* $u \in U_1$ *with strict inequality for some* u*;*
2. *Or,* $F_0(y) \leq F_1(y)$ *for all* y *with strict inequality for some* y*,*

where U_1 denotes the class of all (increasing) von Neumann–Morgenstern-type of social welfare functions u such that welfare is increasing in wages (i.e., $u' \geq 0$).

Second-Order Dominance: *Naturalized citizen earnings* $(\ln(\omega^0))$ *second-order stochastically dominate noncitizen earnings* $(\ln(\omega^1))$ *(denoted* $\ln(\omega^0)$ *SSD* $\ln(\omega^1)$*) if and only if*

1. $E[u(\ln(\omega^0))] \geq E[u(\ln(\omega^1))]$ *for all* $u \in U_2$ *with strict inequality for some* u*;*
2. *Or,* $\int_{-\infty}^{y} F_0(t)dt \leq \int_{-\infty}^{y} F_1(t)dt$ *for all* y *with strict inequality for some* y*,*

where U_2 denotes the class of social welfare functions in U_1 such that $u'' \leq 0$ (i.e., concavity).

Then a generalized Kolmogorov–Smirnov test discussed in Linton, Maasoumi, and Whang (2005) and Maasoumi and Heshmati (2000) is used to conduct SD tests. The Kolmogorov–Smirnov test statistics for FSD and SSD are based on empirical counterparts of the following:

$$d = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\{\sup\,[F_1(y) - F_0(y)], \sup\,[F_0(y) - F_1(y)]\} \tag{3}$$

$$s = \sqrt{\frac{N_0 N_1}{N_0 + N_1}} \min\left\{\sup \int_{-\infty}^{y} [F_1(t) - F_0(t)]dt, \sup \int_{-\infty}^{y} [F_0(t) - F_1(t)]dt\right\} \tag{4}$$

To estimate these test statistics, we replace CDFs by empirical CDFs (e.g., $\hat{F}_0(y) = \frac{1}{N_0} \sum_{i=1}^{N_0} I(\ln(\omega_i^0) \leq y))$, where $I(\cdot)$ is an indicator function. Additionally, 99 replications of bootstrap technique following the literature (e.g., Maasoumi & Heshmati, 2000; Maasoumi & Wang, 2015), implemented here to obtain the robustness check of the results. If Probability $[d \leq 0]$ is large enough, say 0.95, and $\hat{d} \leq 0$, then FSD is statistically significant. Similar definition for SSD.

2.4. Counterfactual Distributions

The identification of contributing components of the earning gap has been mostly conducted by Oaxaca-Blinder regression decompositions at the conditional mean. In our context, we conduct decompositions that are both robust to wage equation specifications and consider the whole distribution of wages. This is done first by inverse probability techniques, describe immediately below, and later by direct quantile regression and RIF regressions. The goal is to separate wage/market structure and the human capital characteristics components. The different techniques of identifying quantiles/distributions provide a check on robustness of findings. The conditional quantile regressions are further limited by functional specification choices.

Consider two counterfactual cases, as follows:

$$\ln(\omega_i^{c1}) = g_0(X_{i1}, \epsilon_{i1}) \quad (\mathit{Counterfactual} \quad \mathit{Outcome}\#1) \tag{5}$$

$$\ln(\omega_i^{c2}) = g_1(X_{i0}, \epsilon_{i0}) \quad (\mathit{Counterfactual} \quad \mathit{Outcome}\#2) \tag{6}$$

$F_{c1}(f_{c1})$ represents the corresponding CDF (pdf) of the counterfactual outcome $\ln(\omega_i^{c1})$, thus the differences in the distributions of F_{c1} and F_1 ($\ln(\omega_i^{c1})$ vs $\ln(\omega_i^{1})$)

only come from differences in wage structures or potential discrimination. $F_{c2}(f_{c2})$ represents the corresponding CDF (pdf) of the counterfactual outcome $\ln(\omega_i^{c2})$, as a result, the differences between the distributions of F_{c2} and F_1 ($\ln(\omega_i^{c2})$ vs $\ln(\omega_i^1)$) come from the differences in human capital characteristics.

There are many identification strategies for these two counterfactual distributions. We adopt the common assumptions of Ignorability (Unconfoundedness) and Overlapping Support, as employed by Firpo (2007) and Firpo et al. (2007).

Assumption 1. (*Ignorability*).
Let (D, X, ϵ) have a joint distribution. For all x in X, ϵ is independent of D given $X = x$; D=1 for noncitizens.

Assumption 2. (*Overlapping Support*).
For all x in X, $0 < p(x) = Pr[D = 1|X = x] < 1$, here $p(x)$ is called "propensity-score." In practical, we estimate the propensity score using logistic regression.[5]

Consider the following three inverse probability weighing functions:

$$\omega_1(D) = \frac{D}{p}, \quad \omega_0(D) = \frac{1-D}{1-p}, \quad \omega_c(D, X) = \left(\frac{p(X)}{1-p(X)}\right) \cdot \left(\frac{1-D}{p}\right)$$

here p is the probability that an individual is in group 1.

With these reweighing functions, we transform the marginal distribution of $\ln(\omega)$ to the conditional distributions of $\ln(\omega^1)$ given $D = 1$, $\ln(\omega^0)$ given $D = 0$, and $\ln(\omega^0)$ given $D = 1$.

We can identify F_1, F_0, F_{c1}, and F_{c2} as follows.

Theorem 2.1. *Under Assumptions 1 and 2:*

(1) $$F_d(y) = \mathbb{E}[\omega_d(D) \cdot \mathbb{I}(\ln(\omega)) \le y], \quad d = 0, 1 \tag{7}$$

(2) $$F_{ct}(y) = \mathbb{E}[\omega_{ct}(D, X) \cdot \mathbb{I}(\ln(\omega)) \le y], \quad t = 1, 2 \tag{8}$$

$\omega_{c2}(D, X) = \omega_c(D, X)$ if we let naturalized citizens to be the treatment group taking dummy value of 1, while $\omega_{c1}(D, X) = \omega_c(D, X)$ if setting noncitizens as the treatment group instead.

2.5. *Decomposition of the Distributional Statistics*

Armed with the conditional distributions $F_d(y), d = 0, 1$ and $F_{ct}(y), t = 0, 1$, we can decompose the wage gap into two parts, as suggested by Firpo et al. (2007).

Let ν be a functional of the conditional joint distribution of $(\ln(\omega)_0, \ln(\omega)_1)|D$, that is, $\nu : \mathcal{F}_\nu \to \mathbb{R}$, and $\mathcal{F}_\nu$ is a class of distribution functions such that $F \in \mathcal{F}_\nu$ if $\|\nu(F)\| < +\infty$. The difference in the ν's between the two groups is called the ν-overall wage gap.

$$\Delta_O^\nu = \nu(F_0) - \nu(F_1) = \nu_0 - \nu_1 \tag{9}$$

Then the difference (9) in wages can be decomposed into two parts:

$$\Delta_O^\nu = (\nu_0 - \nu_{c2}) + (\nu_{c2} - \nu_1) = \Delta_S^\nu + \Delta_X^\nu \tag{10}$$

The first term Δ_S^ν is the difference in the wage structure, since it is the gap between $g_1(\cdot,\cdot)$ to $g_0(\cdot,\cdot)$ keeping the the distribution of human capital characteristics constant. The second term Δ_X^ν reflects the difference in composition effect. In the last part of this paper, we also provide decompositions of the total difference in mean wages (as in Oaxaca-Blinder decomposition) as well as in at quantiles, based on common index (parametric) specifications. This will provide a check on the consistency of the two different approaches.

2.6. *Unconditional Quantile Partial Effects (UQPE)*

Following the RIF regression method provided by Firpo et al. (2009), we can obtain the effect of increasing the proportion of naturalized immigrants on the τth quantile of the unconditional distribution of $\ln(\omega)$.

$$IF(\ln(\omega); q_\tau; F) = \lim_{\varepsilon \to 0} \frac{q_\tau(F_\varepsilon) - q_\tau(F)}{\varepsilon} = \frac{\tau - \mathbb{I}\{\ln(\omega) \le q_\tau\}}{f(q_\tau)} \tag{11}$$

$$RIF(\ln(\omega); q_\tau; F) = q_\tau + IF(\ln(\omega); q_\tau; F) = q_\tau + \frac{\tau - \mathbb{I}\{\ln(\omega) \le q_\tau\}}{f(q_\tau)} \tag{12}$$

where q_τ is the τth quantile. $F_\varepsilon(y) = (1-\varepsilon)F + \varepsilon\delta_y, 0 \le \varepsilon \le 1$ and δ_y is a distribution that only puts mass at the value y. We use $RIF(\ln(\omega); q_\tau)$ instead of $RIF(\ln(\omega); q_\tau; F)$ to simplify the notation.

The Unconditional Quantile Partial Effect (UQPE)

$$\alpha(\tau) = \frac{\partial q_\tau(F_{\ln(\omega), t\cdot G_Y^*})}{\partial t}\Big|_{t=0} = E\left[\frac{dE[RIF(\ln(\omega), q_\tau)|X]}{dX}\right] \tag{13}$$

here, $F_{\ln(\omega), t\cdot G^*_{\ln(\omega)}} = (1-t)\cdot F_{\ln(\omega)} + t\cdot G^*_{\ln(\omega)}$. $G^*_{\ln(\omega)}$ is the counterfactual distribution of $\ln(\omega)$, which can be obtained by replacing $F_X(x)$ with $G_X(x)$. $G_Y^* = \int F_{Y|X}(y|X=x)\cdot dG_X(x)$. The new distribution G_X is the distribution of a random $k \times 1$ vector Z, where $Z_i = X_i$ for $i \neq j$ and $i = 1, \ldots, K$, and $Z_j = X_j + t$, here j is the specific dimension we interested in.

From Eq. (12),

$$RIF(\ln(\omega); q_\tau) = c_{1,\tau} \cdot I\{\ln(\omega) > q_\tau\} + c_{2,\tau}$$

where $c_{1,\tau} = \frac{1}{f(q_\tau)}$, $c_{2,\tau} = q_\tau - c_{1,\tau} \cdot (1 - \tau)$.

Take the expectation,

$$E[RIF(\ln(\omega); q_\tau)|X = x] = c_{1,\tau} \cdot Pr[\ln(\omega) > q_\tau|X = x] + c_{2,\tau}$$

suppose $Pr[\ln(\omega) > q_\tau|X = x]$ is linear in x, then from Eq. (13), we know $\alpha(\tau) = E[\frac{dE[RIF(\ln(\omega), q_\tau)|X]}{dX}]$ is the same as the coefficient of regression RIF on X.

The estimator of RIF is

$$\widehat{RIF}(\ln(\omega); \widehat{q}_\tau) = \widehat{c}_{1,\tau} \cdot \mathbb{I}\{\ln(\omega) > \widehat{q}_\tau\} + \widehat{c}_{2,\tau}$$

here $\widehat{c}_{1,\tau} = \frac{1}{\widehat{f}(\widehat{q}_\tau)}$ and $\widehat{c}_{2,\tau} = \widehat{q}_\tau - \widehat{c}_{1,\tau} \cdot (1 - \tau)$. Then the average marginal effect or the UQPE-$\alpha(\tau)$ could be obtained by regressing $\widehat{RIF}(\ln(\omega); \widehat{q}_\tau)$ on X, we call it RIF-OLS method. Firpo et al. (2009) also mentioned logistic and polynomial series nonparamentric methods; however, the results are very close to the RIF-OLS method for the example in Firpo et al.'s (2009) paper.

3. DATA

In this paper, we examine the 1994–2012 Integrated Public Use Microdata Series, March Current Population Survey (King et al., 2010) (IPUMS-CPS). There are 176,164 observations for the 19 years we considered. The average sample size from 1994 to 2012 is 3,706 for naturalized citizens, and 5,566 for noncitizens. The minimum numbers appeared in 1994 for both groups are 1,663 and 3,209 for naturalized and noncitizens, respectively. This data source contains detailed information on the labor market outcomes such as earnings and other characteristics. Thus, it is widely used in the literature.[6] 1994 is the first year when the citizenship information is collected within immigrants. We restrict our sample to individuals aged 18–64, with at least 20 working weeks and 35 working hours (inclusive) per week in the previous year. Hourly wages less than or equals to $1 are excluded.

We use the log of hourly wages, which is obtained by dividing an individual's wage and salary income by the hours worked in the previous year. This is the standard procedure in the literature (e.g., Maasoumi & Wang, 2015). In our counterfactual analysis, unconditional and conditional quantile regressions, we include age, age squared,[7] education dummies (five education groups: less than high school, high school, some college, college, graduate), current married dummy variable (1 if married and zero otherwise), race dummy (1 if non-white and zero otherwise), region dummies (Northeast, Midwest, South, and West), and three occupations dummies (high-skill for managerial and professional specialty occupations; medium-skill contains technical, sales, and administrative support occupations; low-skill consists of service, farming, forestry and other occupations).

4. EMPIRICAL RESULTS

4.1. Distributional Comparison and Analysis

First we look at the raw differences measured by the Bhattacharya–Matusita–Hellinger entropy, alongside specific quantile (or moment based) differences of the wage gap between naturalized and noncitizens. This is given in Panel A of Table 2. Generally speaking, the $S_\rho \times 100$ gap and 10th, 25th, 50th (Median), 75th, 90th percentile gaps including the mean difference are positive and consistent from 1994 to 2012, indicating that naturalized citizens earn more than noncitizens. In addition, from the Panel A, the gap is not constant at different quantiles. For example, at the 10th quantile, the earning gap is 0.24–0.36, while it is 0.37–0.49 for the 50th quantile. The earning gap increases for above median incomes, and then decreases to 0.21–0.38 for the 90th quantile again. Thus, it seems that the association of citizenship is higher for median and above median wages, and generally lower at both tails. A tent shape.

Continuing with the raw entropy differences, nominal peak appears in 1995–1997, while the trough emerges during the period 1999–2001 (shown in Fig. 1 as well[8]). 2001 is the collapse of the Dot-com bubble. At lower wages (10th quantile), the gap is increasing in the period 2007–2012 compared with the prior period, suggesting the financial crisis may have impacted low income noncitizens more than other income levels. Citizenship may be associated with more stable wages in uncertain economic environments. But this may also be partly due to more active enforcement of immigration laws in some periods.

Fig. 2 displays the empirical CDFs of naturalized citizens and noncitizens in some years. Predominantly, all noncitizens CDFs are to the left of those of naturalized citizens (except Year 1994 when there is a cross at the higher end).[9] These graphical impressions are confirmed statistically. In Table 2, we find generally significant SD of citizen immigrant wages.

As just mentioned, in Panel B of Table 2, we report SD tests based on 99 bootstrap replications. In all the years 1994–2012, naturalized citizen earnings

Table 2. Naturalized Citizen versus Noncitizen Wage Distributions.

Panel A: The Raw Wage Gap

Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	4.00	0.35	0.29	0.35	0.41	0.39	0.27
1995	5.80	0.41	0.36	0.45	0.49	0.43	0.36
1996	5.59	0.42	0.31	0.41	0.47	0.42	0.38
1997	5.16	0.40	0.29	0.40	0.46	0.48	0.33
1998	4.45	0.37	0.27	0.38	0.44	0.38	0.31
1999	3.75	0.36	0.24	0.33	0.41	0.39	0.32
2000	3.71	0.33	0.25	0.35	0.40	0.37	0.21
2001	3.40	0.32	0.25	0.35	0.37	0.38	0.24
2002	3.90	0.36	0.28	0.33	0.42	0.38	0.26
2003	3.87	0.36	0.27	0.34	0.39	0.36	0.33
2004	4.03	0.36	0.26	0.33	0.43	0.38	0.29
2005	4.18	0.36	0.22	0.38	0.43	0.37	0.29
2006	4.40	0.38	0.26	0.38	0.41	0.46	0.32
2007	3.96	0.37	0.29	0.36	0.39	0.43	0.38
2008	4.33	0.38	0.28	0.39	0.43	0.41	0.35
2009	3.79	0.35	0.30	0.33	0.43	0.36	0.26
2010	4.02	0.36	0.30	0.37	0.43	0.39	0.31
2011	4.02	0.36	0.27	0.36	0.43	0.39	0.31
2012	3.96	0.37	0.30	0.36	0.43	0.42	0.29

Panel B: Stochastic Dominance Tests

Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	SSD	0.04	8.44	0.04	0.36	−0.04	250.97	−0.04	0.91
1995	FSD	−0.01	10.50	−0.01	0.30	−0.04	322.73	−0.04	0.77
1996	FSD	−0.04	10.10	−0.04	0.85	−0.04	252.88	−0.04	0.94
1997	SSD	0.00	10.42	0.00	0.28	−0.05	278.53	−0.05	0.68
1998	FSD	−0.01	10.67	−0.01	0.23	−0.04	273.61	−0.04	0.79
1999	FSD	−0.04	9.74	−0.04	0.75	−0.08	236.08	−0.08	0.83
2000	FSD	−0.04	10.45	−0.04	0.76	−0.04	274.21	−0.04	0.86
2001	FSD	−0.05	11.40	−0.05	0.68	−0.05	269.71	−0.05	0.93
2002	FSD	−0.06	12.50	−0.06	0.84	−0.06	322.67	−0.06	0.87
2003	FSD	−0.07	12.61	−0.07	0.94	−0.07	303.39	−0.07	0.98
2004	FSD	−0.08	12.59	−0.08	0.65	−0.09	323.23	−0.09	0.68
2005	FSD	−0.09	12.77	−0.09	0.98	−0.09	298.37	−0.09	1.00
2006	FSD	−0.06	13.41	−0.06	0.55	−0.08	330.51	−0.08	0.57
2007	FSD	−0.06	13.22	−0.06	0.66	−0.07	334.96	−0.07	0.74
2008	FSD	−0.06	13.86	−0.06	0.91	−0.06	328.82	−0.06	1.00
2009	FSD	−0.07	12.83	−0.07	0.92	−0.07	323.90	−0.07	0.98
2010	FSD	−0.02	13.27	−0.02	0.63	−0.06	287.41	−0.06	0.96
2011	FSD	−0.06	13.31	−0.06	0.79	−0.06	273.41	−0.06	0.86
2012	FSD	−0.05	12.67	−0.05	0.83	−0.06	279.47	−0.06	0.98

Source: Panel A: IPUMS CPS (http://cps.ipums.org/cps/).
Notes: Panel A: Column 2: Entropy wage gap ($\times 100$) is invariant to log transformation. Columns 3–8: conventional measures of the log wage differences. Panel B: OR means observed ranking. $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap resampling produce.

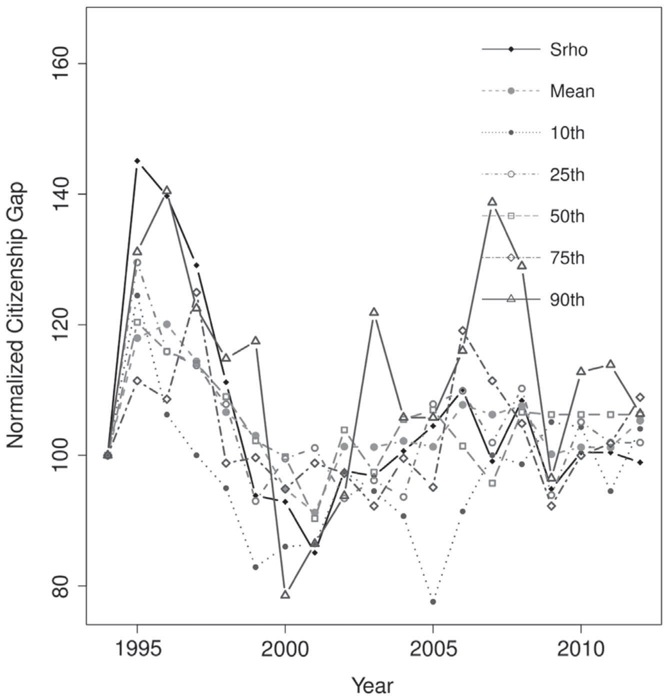

Fig. 1. The Time Trend of Citizenship Wage Gap.

stochastic dominate noncitizen earnings. Furthermore, we find first-order SD except for the years 1994 and 1997. The columns labeled d and s are the Kolmogorov–Smirnov test statistics for FSD and SSD, respectively (Expressions (3–4)), while the columns labeled $P[d \leq 0]$ and $P[s \leq 0]$ report the probabilities of first-order and second-order SD, respectively. From Panel B of Table 2, FSD is only significant in 2005, but SSD is significant for 2003, 2005, 2008–2010, and 2012. In 2011, the probability is 0.86, which is noteworthy. The earnings distribution of naturalized citizens is found to dominate from 2008 to 2012, indicating noncitizens have not faired well during the recent economic recession. Some regulations may have contributed to this outcome. For example, The U.S. Senate agreed on February, 2009 to set restrictions on the hiring of H-1B workers by financial services firms that received federal bailout funds.

4.2. *Counterfactual Analysis*

Comparing noncitizen counterfactual #1 and noncitizen, measures of earning gap and SD tests are displayed in Table 3 and Fig. 3. Other years graphs are in Fig. A.2.

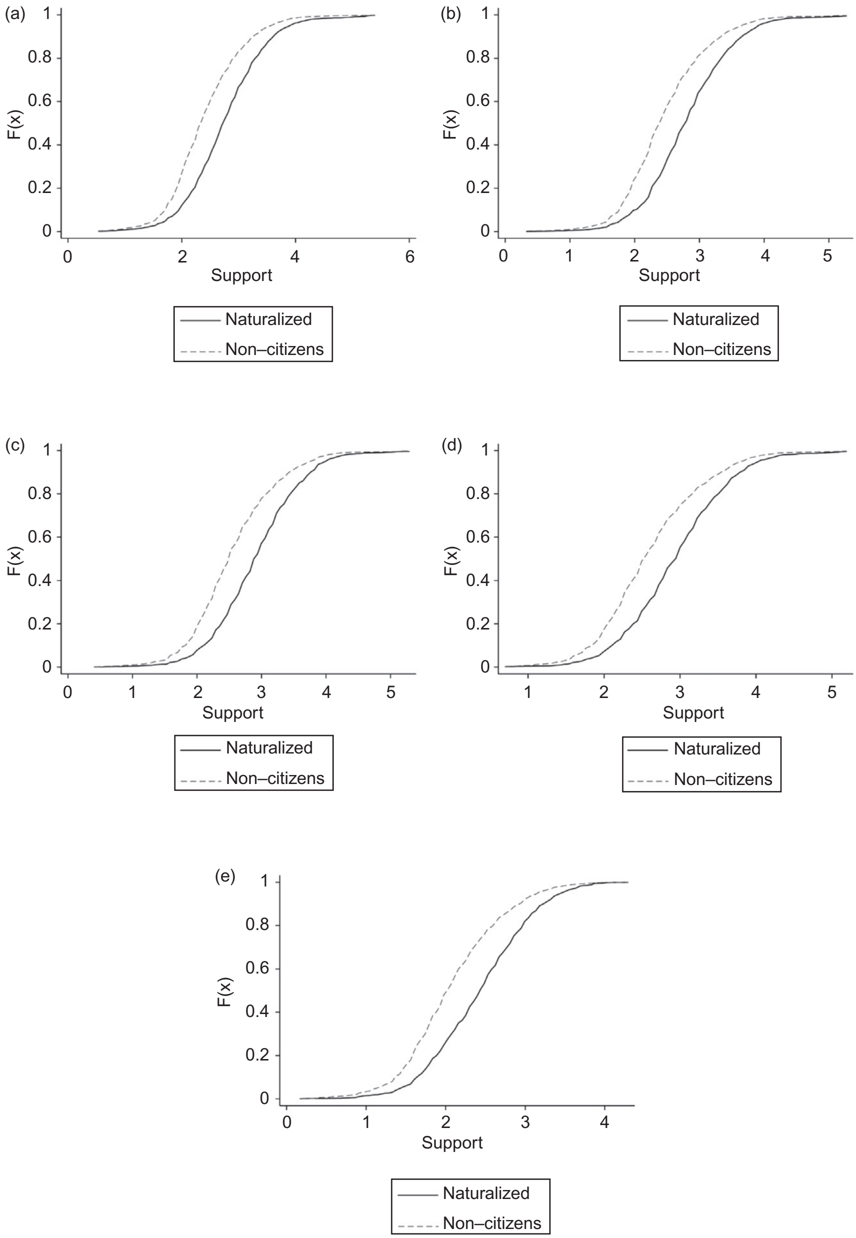

Fig. 2. CDF Comparisons of Naturalized Citizen and Noncitizen. (a) 2003; (b) 2005; (c) 2008; (d) 2009; and (e) 1994.

Table 3. Noncitizen Counterfactual #1 versus Noncitizen Distributions.

Panel A: Measures of Wage Differentials

Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	0.36	0.07	0.02	0.07	0.09	0.09	0.04
1995	1.23	0.17	0.17	0.15	0.22	0.18	0.12
1996	1.08	0.16	0.14	0.11	0.19	0.22	0.16
1997	1.25	0.14	0.07	0.18	0.21	0.18	0.13
1998	0.75	0.12	0.12	0.12	0.17	0.16	0.07
1999	0.80	0.14	0.06	0.11	0.14	0.17	0.13
2000	0.94	0.13	0.13	0.18	0.14	0.13	0.06
2001	0.68	0.11	0.14	0.13	0.15	0.14	0.03
2002	1.03	0.15	0.12	0.17	0.18	0.16	0.05
2003	0.78	0.12	0.04	0.16	0.17	0.11	0.11
2004	0.77	0.13	0.12	0.13	0.14	0.15	0.05
2005	0.99	0.13	0.08	0.18	0.18	0.13	0.08
2006	0.98	0.14	0.13	0.21	0.15	0.13	0.06
2007	0.90	0.15	0.19	0.16	0.18	0.15	0.13
2008	1.32	0.18	0.17	0.20	0.18	0.16	0.10
2009	0.85	0.14	0.14	0.12	0.16	0.13	0.05
2010	0.81	0.12	0.10	0.13	0.14	0.15	0.07
2011	0.98	0.14	0.08	0.15	0.18	0.14	0.09
2012	0.90	0.14	0.11	0.16	0.18	0.13	0.06

Panel B: Stochastic Dominance Tests

Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	SSD	0.06	3.24	0.06	0.06	−0.06	81.49	−0.06	0.94
1995	SSD	0.08	7.29	0.08	0.14	−0.07	212.94	−0.07	0.83
1996	None	0.18	6.48	0.18	0.07	0.14	145.28	0.14	0.40
1997	None	0.98	6.61	0.98	0.00	8.85	143.56	8.85	0.06
1998	SSD	0.18	6.81	0.18	0.00	−0.06	137.12	−0.06	0.77
1999	FSD	−0.06	6.18	−0.06	0.45	−0.06	136.05	−0.06	0.97
2000	SSD	0.13	7.74	0.13	0.07	−0.07	150.75	−0.07	0.45
2001	SSD	0.28	7.79	0.28	0.02	−0.09	137.45	−0.09	0.75
2002	None	0.09	9.70	0.09	0.19	0.42	196.17	0.42	0.36
2003	None	0.26	8.10	0.26	0.14	1.52	152.75	1.52	0.37
2004	FSD	−0.05	8.73	−0.05	0.20	−0.16	172.87	−0.16	0.49
2005	SSD	0.07	9.46	0.07	0.15	−0.08	166.08	−0.08	0.70
2006	FSD	−0.03	9.76	−0.03	0.15	−0.15	190.52	−0.15	0.83
2007	None	0.17	9.28	0.17	0.13	0.53	199.70	0.53	0.29
2008	FSD	−0.03	11.25	−0.03	0.66	−0.11	237.46	−0.11	1.00
2009	FSD	−0.05	8.65	−0.05	0.27	−0.11	185.39	−0.11	0.92
2010	SSD	0.10	9.23	0.10	0.05	−0.09	149.57	−0.09	0.75
2011	SSD	0.02	9.92	0.02	0.17	−0.10	161.76	−0.10	0.73
2012	FSD	−0.01	8.91	−0.01	0.19	−0.10	158.71	−0.10	0.77

Source: Panle A: IPUMS CPS (http://cps.ipums.org/cps/).
Notes: Panel A: Column 2 is entropy gap ($\times$100). Columns 3–8 report conventional measures of the log wages gap. Panel B: OR means observed ranking. $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap resampling produce.

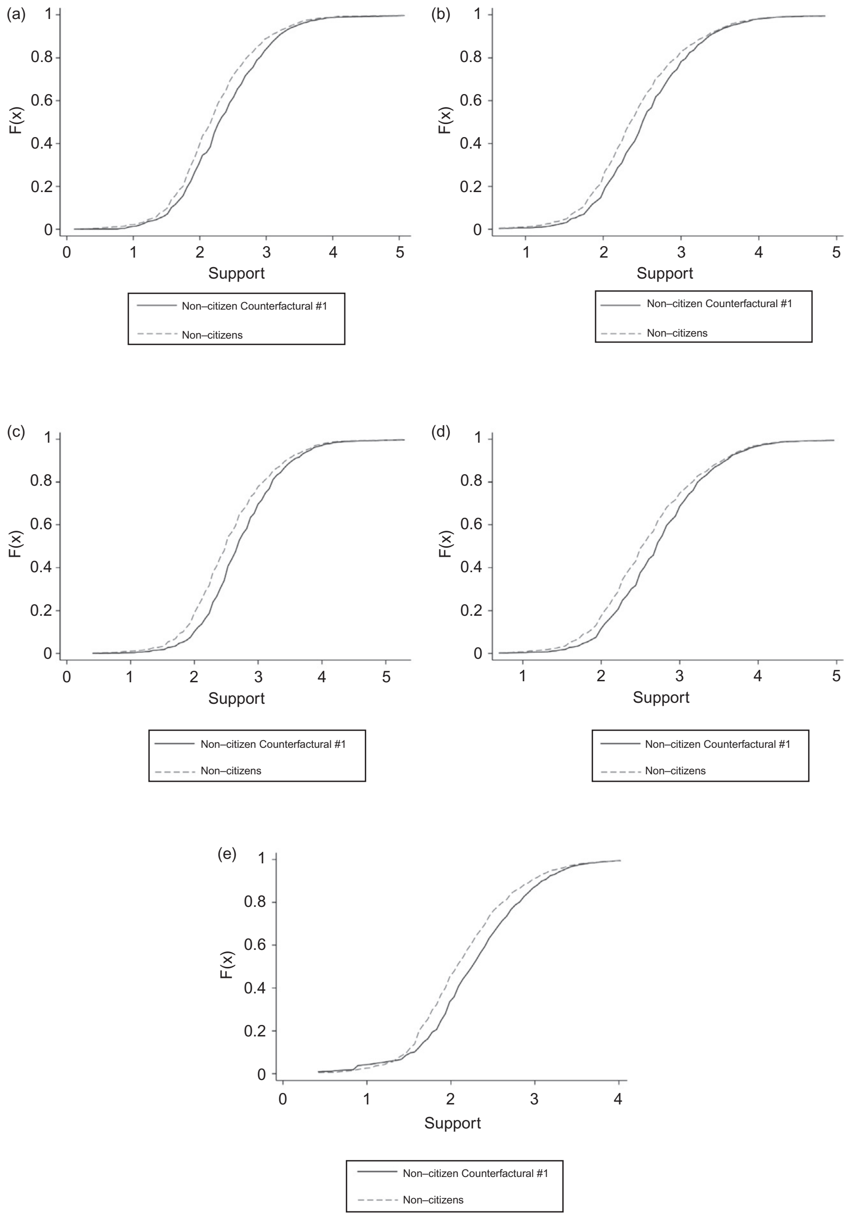

Fig. 3. CDF Comparisons of Noncitizen Counterfactual # 1 and Noncitizen. (a) 1999; (b) 2004; (c) 2008; (d) 2009; and (e) 1997.

Table 4. Noncitizen Counterfactual #2 versus Noncitizen Distributions.

Panel A: Measures of Wage Differentials

Year	$S_\rho \times 100$	Mean	10th	25th	50th	75th	90th
1994	1.62	0.23	0.14	0.18	0.25	0.33	0.24
1995	1.60	0.22	0.15	0.17	0.27	0.29	0.26
1996	1.42	0.21	0.08	0.16	0.21	0.29	0.25
1997	1.61	0.22	0.11	0.17	0.26	0.31	0.24
1998	1.39	0.21	0.10	0.16	0.21	0.27	0.25
1999	1.36	0.21	0.07	0.16	0.22	0.26	0.31
2000	1.71	0.24	0.13	0.16	0.26	0.36	0.31
2001	1.34	0.21	0.14	0.15	0.22	0.30	0.26
2002	1.59	0.23	0.10	0.17	0.26	0.29	0.24
2003	1.33	0.20	0.10	0.15	0.25	0.27	0.24
2004	1.50	0.22	0.13	0.15	0.25	0.29	0.27
2005	1.70	0.24	0.13	0.21	0.30	0.34	0.25
2006	1.65	0.24	0.15	0.22	0.26	0.36	0.30
2007	1.65	0.24	0.17	0.16	0.25	0.27	0.29
2008	1.40	0.22	0.16	0.15	0.22	0.26	0.23
2009	1.28	0.21	0.14	0.15	0.24	0.30	0.20
2010	1.23	0.21	0.10	0.15	0.22	0.29	0.24
2011	1.31	0.22	0.08	0.14	0.24	0.31	0.27
2012	1.11	0.20	0.07	0.13	0.23	0.29	0.18

Panel B: Stochastic Dominance Tests

Year	OR	$d_{1,max}$	$d_{2,max}$	d	$P[d \leq 0]$	$s_{1,max}$	$s_{2,max}$	s	$P[s \leq 0]$
1994	FSD	−0.05	8.05	−0.05	0.48	−0.06	240.58	−0.06	0.64
1995	FSD	−0.06	8.60	−0.06	0.60	−0.06	275.01	−0.06	0.94
1996	FSD	−0.04	7.43	−0.04	0.51	−0.06	190.10	−0.06	0.85
1997	None	0.13	8.70	0.13	0.12	1.00	225.37	1.00	0.16
1998	None	0.15	8.02	0.15	0.11	0.77	219.97	0.77	0.20
1999	None	0.07	8.13	0.07	0.13	0.29	201.42	0.29	0.27
2000	FSD	−0.04	9.64	−0.04	0.62	−0.07	274.66	−0.07	0.78
2001	FSD	−0.07	10.63	−0.07	0.34	−0.08	264.87	−0.08	0.51
2002	FSD	−0.08	12.02	−0.08	0.68	−0.08	308.49	−0.08	0.78
2003	None	0.08	10.37	0.08	0.25	0.08	251.36	0.08	0.45
2004	FSD	−0.05	10.80	−0.05	0.58	−0.07	299.83	−0.07	0.88
2005	FSD	−0.10	11.86	−0.10	0.51	−0.10	293.64	−0.10	0.55
2006	FSD	−0.12	11.94	−0.12	0.95	−0.12	331.67	−0.12	0.97
2007	FSD	−0.11	12.38	−0.11	0.37	−0.11	319.73	−0.11	0.60
2008	FSD	−0.08	11.77	−0.08	0.72	−0.10	287.03	−0.10	0.79
2009	FSD	−0.08	11.13	−0.08	0.31	−0.16	292.81	−0.16	0.42
2010	FSD	−0.11	10.63	−0.11	0.84	−0.11	250.11	−0.11	0.90
2011	FSD	−0.09	10.91	−0.09	0.63	−0.10	250.18	−0.10	0.77
2012	FSD	−0.08	9.92	−0.08	0.64	−0.15	228.67	−0.15	0.84

Source: Panel A: IPUMS CPS (http://cps.ipums.org/cps/).
Notes: Panel A: Column 2 reports Entropy gap ($\times$100). Columns 3–8 report conventional measures of log wage differences. Panel B: OR means observed ranking. $P[d] \leq 0$ and $P[s] \leq 0$ results are based on 99 replications of bootstrap resampling produce.

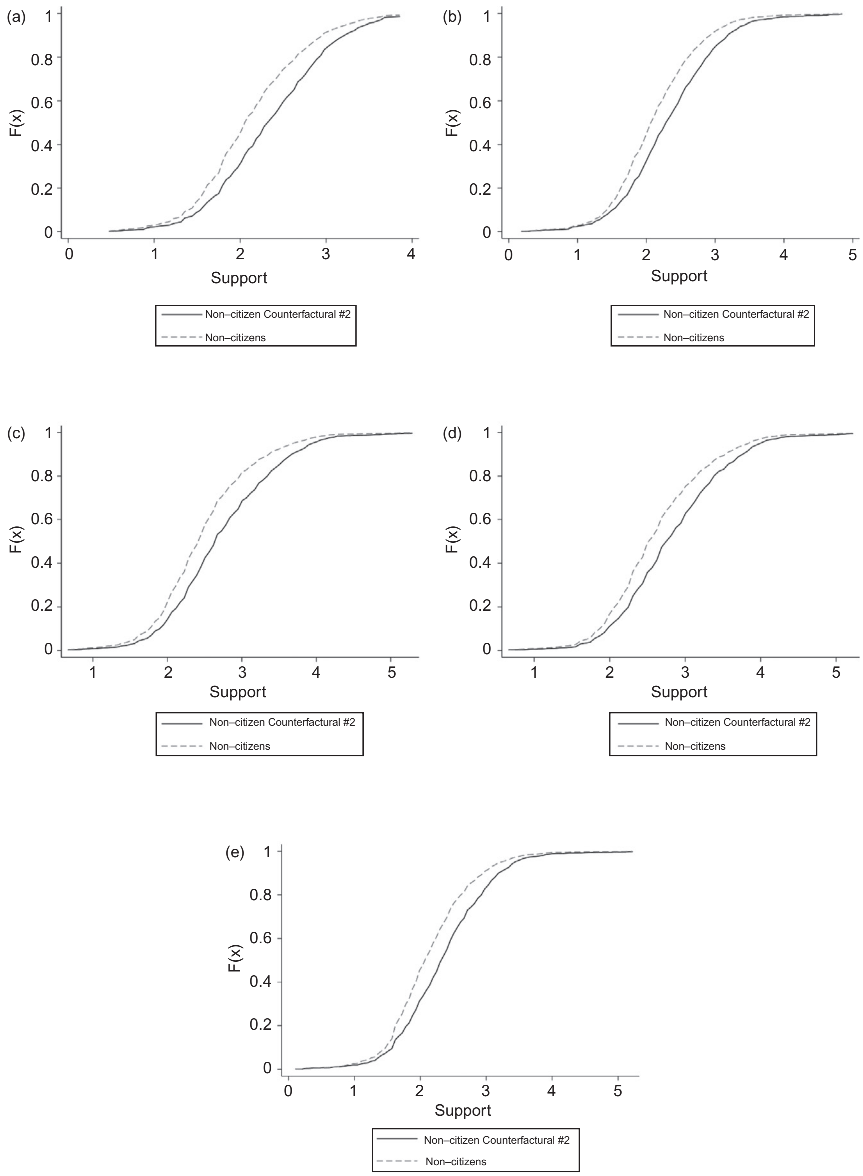

Fig. 4. CDF Comparisons of Noncitizen Counterfactual # 2 and Noncitizen. (a) 1995; (b) 1996; (c) 2006; (d) 2010; and (e) 1997.

Table 5. Wage Gap Decomposition.

Panel A: The Wage Structure Component of the Gap

Year	Mean	10th	25th	50th	75th	90th
1994	0.12	0.14	0.16	0.16	0.08	0.07
1995	0.17	0.20	0.24	0.20	0.14	0.07
1996	0.21	0.25	0.21	0.24	0.18	0.10
1997	0.18	0.18	0.20	0.20	0.16	0.14
1998	0.17	0.18	0.20	0.21	0.12	0.09
1999	0.15	0.17	0.17	0.18	0.15	0.04
2000	0.11	0.10	0.16	0.18	0.05	−0.01
2001	0.10	0.12	0.20	0.16	0.08	0.01
2002	0.12	0.16	0.12	0.11	0.12	0.06
2003	0.15	0.13	0.17	0.16	0.12	0.11
2004	0.12	0.14	0.14	0.13	0.08	0.06
2005	0.11	0.13	0.14	0.11	0.06	0.06
2006	0.11	0.10	0.15	0.13	0.08	−0.01
2007	0.12	0.11	0.18	0.12	0.13	0.09
2008	0.14	0.13	0.22	0.17	0.11	0.09
2009	0.12	0.13	0.17	0.17	0.05	0.05
2010	0.13	0.18	0.19	0.18	0.09	0.05
2011	0.12	0.18	0.20	0.16	0.05	0.01
2012	0.14	0.19	0.21	0.17	0.09	0.07

Panel B: Composition Effect Component of the Gap

Year	Mean	10th	25th	50th	75th	90th
1994	0.23	0.14	0.18	0.25	0.33	0.24
1995	0.22	0.15	0.17	0.27	0.29	0.26
1996	0.21	0.08	0.16	0.21	0.29	0.25
1997	0.22	0.11	0.17	0.26	0.31	0.24
1998	0.21	0.10	0.16	0.21	0.27	0.25
1999	0.21	0.07	0.16	0.22	0.26	0.31
2000	0.24	0.13	0.16	0.26	0.36	0.31
2001	0.21	0.14	0.15	0.22	0.30	0.26
2002	0.23	0.10	0.17	0.26	0.29	0.24
2003	0.20	0.10	0.15	0.25	0.27	0.24
2004	0.22	0.13	0.15	0.25	0.29	0.27
2005	0.24	0.13	0.21	0.30	0.34	0.25
2006	0.24	0.15	0.22	0.26	0.36	0.30
2007	0.24	0.17	0.16	0.25	0.27	0.29
2008	0.22	0.16	0.15	0.22	0.26	0.23
2009	0.21	0.14	0.15	0.24	0.30	0.20
2010	0.21	0.10	0.15	0.22	0.29	0.24
2011	0.22	0.08	0.14	0.24	0.31	0.27
2012	0.20	0.07	0.13	0.23	0.29	0.18

Source: IPUMS CPS (http://cps.ipums.org/cps/).
Notes: Panel A: Column 2: The Standard Oaxaca-Blinder decomposition. Columns 3–7 are quantile "wage structure" source of the earning gap. Panel B: Column 2: Composition effect from the Standard Oaxaca-Blinder decomposition. Columns 3–7, composition effects at quantiles.

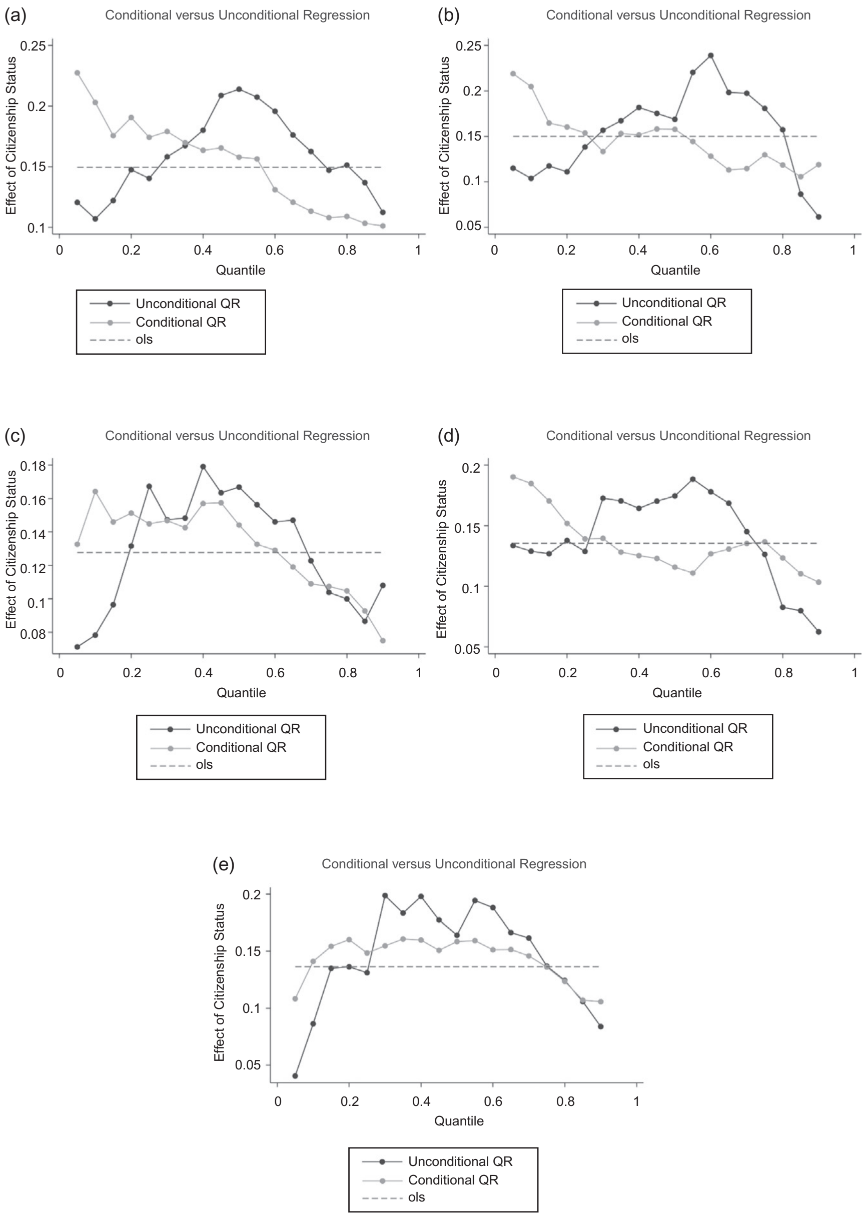

Fig. 5. Unconditional and Conditional Quantile Regression Estimates of the Effect of Citizenship Status on Log Wages. (a) 1995; (b) 1998; (c) 2005; (d) 2009; and (e) 2010.

Table 6. Comparing OLS, Unconditional Quantile Regressions (UQR), and Conditional Quantile Regressions (CQR): Citizenship Status Effect.

Year	OLS	10th Centile		50th Centile		90th Centile	
		UQR	CQR	UQR	CQR	UQR	CQR
1994	0.13	0.08	0.21	0.16	0.13	0.10	0.09
1995	0.15	0.11	0.20	0.21	0.16	0.11	0.10
1996	0.16	0.13	0.21	0.20	0.17	0.16	0.14
1997	0.14	0.07	0.16	0.19	0.17	0.14	0.11
1998	0.15	0.10	0.20	0.17	0.16	0.06	0.12
1999	0.15	0.10	0.14	0.16	0.14	0.09	0.14
2000	0.13	0.08	0.15	0.17	0.15	0.05	0.09
2001	0.12	0.11	0.15	0.15	0.13	0.06	0.08
2002	0.14	0.10	0.16	0.15	0.15	0.06	0.10
2003	0.14	0.06	0.14	0.18	0.14	0.14	0.11
2004	0.13	0.10	0.15	0.17	0.14	0.09	0.08
2005	0.13	0.08	0.16	0.17	0.14	0.11	0.07
2006	0.12	0.09	0.16	0.15	0.12	0.03	0.09
2007	0.13	0.12	0.16	0.17	0.13	0.10	0.09
2008	0.14	0.11	0.16	0.17	0.15	0.09	0.13
2009	0.14	0.13	0.18	0.17	0.12	0.06	0.10
2010	0.14	0.09	0.14	0.16	0.16	0.08	0.11
2011	0.12	0.09	0.14	0.14	0.14	0.04	0.09
2012	0.14	0.11	0.16	0.18	0.16	0.04	0.11

Notes: All robust standard errors (OLS) and bootstrapped standard errors (99 replications) for UQR and CQR are less than 0.01, thus are neglected in this table.

Comparison of F_{c1} and F_1 controls for "human capital characteristics," reflecting wage structure components. From Panel B of Table 3, there is generally no statistically significant first- or second-order SD (except in 1999 and 2008, when probabilities are larger than 0.95). Thus, the noncitizen wage distribution #1 and the counterfactual wage distribution #1 are generally unrankable. Market returns cannot account for the wage gap.

In Panel A of Table 3 entropy gap S_ρ peaks in 2008 (1.32) but is otherwise quite stable and much smaller than the raw values observed in prior tables. This is consistent with the SD tests. Only other, possibly very narrow decision-theoretic definitions of the gap can possibly order these distributions.

Table 4 and Fig. 4 show the comparison results for noncitizen counterfactual #2 and noncitizens. Graphs for remaining years are in Fig. A.3. Here, noncitizen counterfactual #2 represents the corresponding earning distributions, if we use the distribution of the naturalized citizens' human capital instead of noncitizens' while keeping the wage structure unchanged. The gap is generally positive in Panel A,

Table 4, accounting for most of the total gap reported in the raw comparisons. There is no discernible general trend in the human capital/characteristics component of the gap. It is stable around 1.33–1.65, with peaks in 2000 and 2005, and troughs in 2009–2012. In the recent recession years, we find the impact of the "skills gap" is declining amongst immigrants. Accordingly, the entropy gap S_ρ has decreased from 1.70 in 2005 to 1.11 in 2012.

The earnings distributions of noncitizen counterfactual #2 graphically FSD the earnings distributions of noncitizen; see Fig. 4. For FSD, these are not statistically significance except for 2006, as can be seen in Panel B, Table 4 for many years. But there is a fairly strong evidence of statistical SSD. The high probabilities for SSD suggest the likelihood of general third-order SD for all years. This suggests that EFs that are (increasingly) inequality averse would order these two outcomes. Skills matter, especially so with increasing inequality aversion, which values upward mobility at lower wages more highly than at higher wages.

4.3. Decomposition of the Gap in Conditional Means and Quantiles

In this section, we examine alternative methods to the nonparametric distribution-based analysis provided so far. Thus, we reexamine decompositions of the wage gap based on modeling of the conditional means (Mincer-type earnings equations), and conditional quantile regressions. For comparison purposes in this context, we also obtain the corresponding partial effects of "citizenship" on immigrant wages based on the RIF Regressions described in prior sections.

Table 5 reports the gap due to "wage structure" and composition effect. These are reported at the mean and select quantiles. The results at the conditional mean are known as the Oaxaca-Blinder decompositions.

4.4. The UQPE and the Conditional Quantile Partial Effect (CQPE) of Citizenship

If citizenship effect is "causal," one may wish to find the partial impact of it on immigrants' wages. In this part, we treat citizenship as a factor contributing to immigrants' income. Firpo et al. (2009) suggests a different measure to obtain UQPE, instead of the coefficient of the factor from the traditional conditional quantile regression. The reason is that the coefficient $\beta_\tau = F^{-1}(\tau|D=1) - F^{-1}(\tau|D=0)$ from a conditional quantile regression is generally different from $dq_\tau(p)/dp, p = P[D=1]$. $D=1$ for a citizen immigrant. $p = P[D=1]$ denotes the proportion of naturalized immigrants.

Table 6 and Fig. 5 report unconditional quantile regression estimates (labeled UQR), standard OLS (conditional mean) estimates, and standard (conditional) quantile regression estimates (labeled CQR) of the effect of citizenship status on log wages.[10] The estimates are uniformly positive each year, however, the magnitudes are varied for different quantiles. Although the shape of the UQPE is slightly different every year, it is generally the tent shape, illustrating citizenship is more important to middle and upper middle wages, compared to very low-income and high-incomes. This result also indicates that citizenship increases inequality in the lower tail of the distribution while decreases inequality for the upper tail. For example, in year 2012 in Table 6, the difference between entries for the 50th and the 10th quantiles is 0.07 ($=0.18-0.11$), and the difference between the 90th and the 50th quantiles is -0.14 ($=0.04-0.18$). Thus, a 10% increase in the citizenship rate is associated with an increase of 0.007 in the 50–10 gap, but a decrease of the 90–50 gap by 0.014. For comparison, the CQPE results are also positive, but due to the decreasing magnitudes corresponding with larger quantiles, the increase in citizenship ratio will reduce the conditional earning distribution inequality. Bootstrapped standard errors (for UQR and CQR) and robust OLS standard errors are not reported in Table 6, since the largest value is $0.00358618 < 0.01$.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we implement entropy and SD tests for the comparison of the wage distributions between naturalized and noncitizen immigrants in the United States. We construct two counterfactual wage distributions to clarify the sources of the wage gap. In addition, we obtain the estimate of the UQPE of citizenship. We use CPS data 1994–2012 here. The findings by the two different approaches of inverse probability weighting and quantile regression decompositions are in general agreement. Our main conclusions are as follows:

(1) The wage gap between naturalized and noncitizen is generally stable during 1994–2012, and its has a tent shape, suggesting heterogeneity over the wage distribution.
(2) The Raw Naturalized citizen earnings at least SSD noncitizen earnings for most years.
(3) Decomposition of the gap into "wage structure" and "composition" components reveals that human capital characteristics, and skills (observed or otherwise) are the primary source of the wage gap between immigrants.
(4) When wage outcomes cannot be uniformly ranked, as when characteristics are controlled for, our decision-theoretic approach makes clear that only narrow EFs would rank wage distributions and outcomes. In such cases, the metric

entropy proposed in this paper presents an attractive function of the whole distribution of earnings with a set of weights to different wage earners that is better supported than assessments based on the mean, median, or individual quantiles. Other entropy measures, such as the symmetrized Kullback–Leibler, would provide interesting measures of “divergence,” with different underlying welfare functions. The patterns of the gap discovered in this paper are likely to be robust to the choice of entropy functionals.

CPS data do not contain English proficiency information. Neglecting this information may result in overestimates of the effect of “citizenship.” Literature on program evaluation that accounts for separate grades in maths and English suggests this is an important distinction. These different skills are also likely differently correlated with length of residency which is often higher for naturalized immigrants.

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NOTES

1. For immigrants with at least 10 years of residence in the United States.
2. The conditional quantile regression coefficient can be interpreted as the marginal effect of citizenship ratio at the τth quantile of the conditional distribution of log wages. Our unconditional quantile approach, following Firpo et al. (2009), provides the marginal effect on the unconditional τth quantile, averaged over conditioning sets.
3. Earlier literature expositing welfare functions associated with entropy measures includes insightful accounts in Cowell and Kuga (1981) and Cowell (1977).
4. For the discrete variables, $S_\rho = \frac{1}{2}\sum(p_1^{1/2} - p_0^{1/2})^2$.
5. In our paper, we use linear regression, nonparametric regression can be implemented to relieve the parametric functional form restriction.
6. The IPUMS-USA(IPUMS American Community Survey) provides data from 2001 to 2011, including information on English proficiency, but is less complete on education level, and covers fewer years.
7. We include the squared age to reflect the idea that there are declining returns to additional age after some period of time.
8. Fig. 1 shows the plot of the normalized values of S_ρ, mean, 10th, 25th, 50th, 75th, and 90th percentiles.

9. Graphs for other years are in Fig. A.1.
10. Other years graphs are in Fig. A.4.

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APPENDIX

In this appendix, we provide the other years CDF Comparisons between different groups, and unconditional, conditional quantile regression estimates of the effect of citizenship status on log wages.

A.1. CDF Comparisons

Fig. A.1 shows the empirical CDFs of naturalized citizens and noncitizens in other years different from years shown in the main text. Figs. A.2 and A.3 display the empirical CDFs comparison results for noncitizen counterfactual #1 versus noncitizen and noncitizen counterfactual #2 versus noncitizens, respectively.

A.2. Unconditional and Conditional Quantile Regression Estimates

Fig. A.4 shows the unconditional and conditional quantile regression estimates of the effect of citizenship status on log wages in other years from 1994 to 2012.

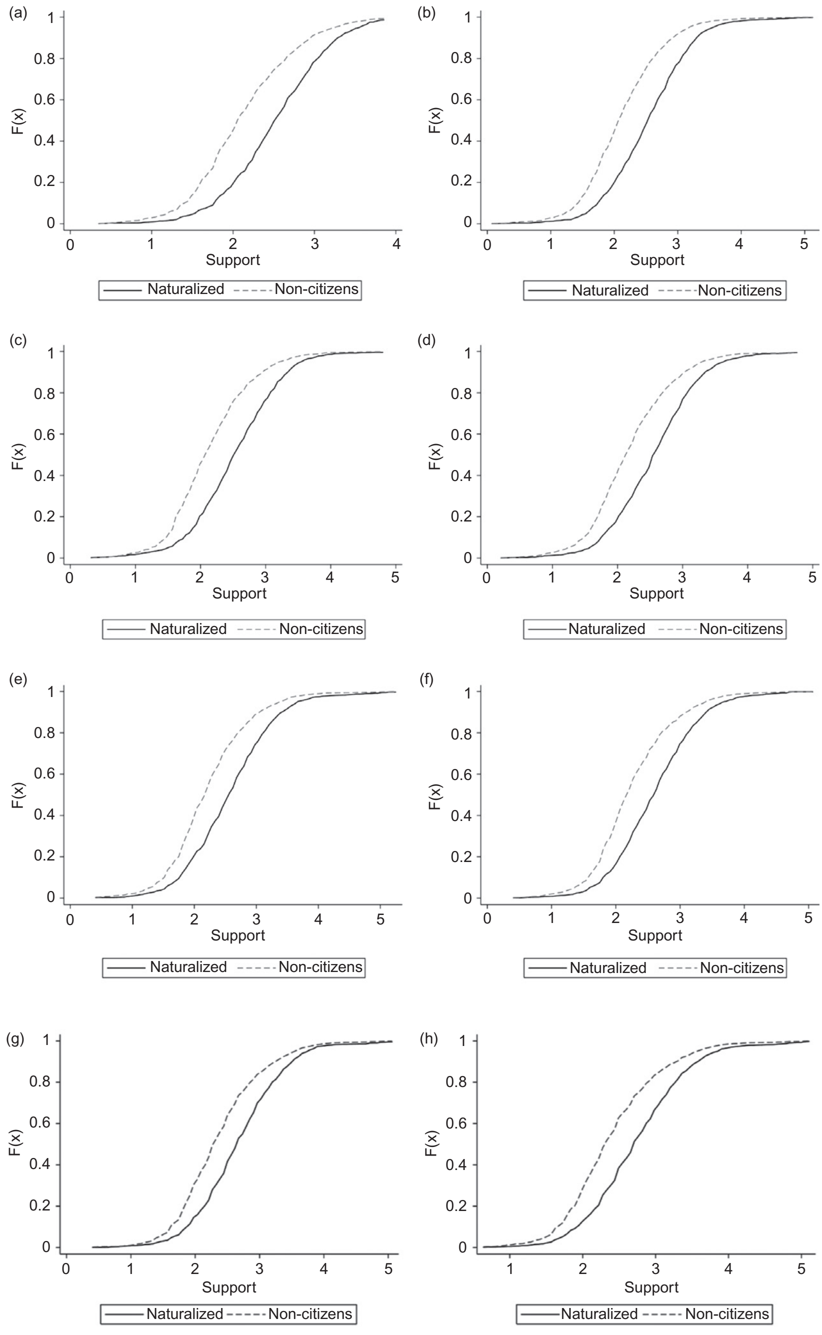

Fig. A.1. CDF Comparisons of Naturalized Citizen and Noncitizen (1994–2012). (a) 1995; (b) 1996; (c) 1997; (d) 1998; (e) 1999; (f) 2000; (g) 2001; (h) 2002; (i) 2004; (j) 2006; (k) 2007; (l) 2010; (m) 2011; and (n) 2012.

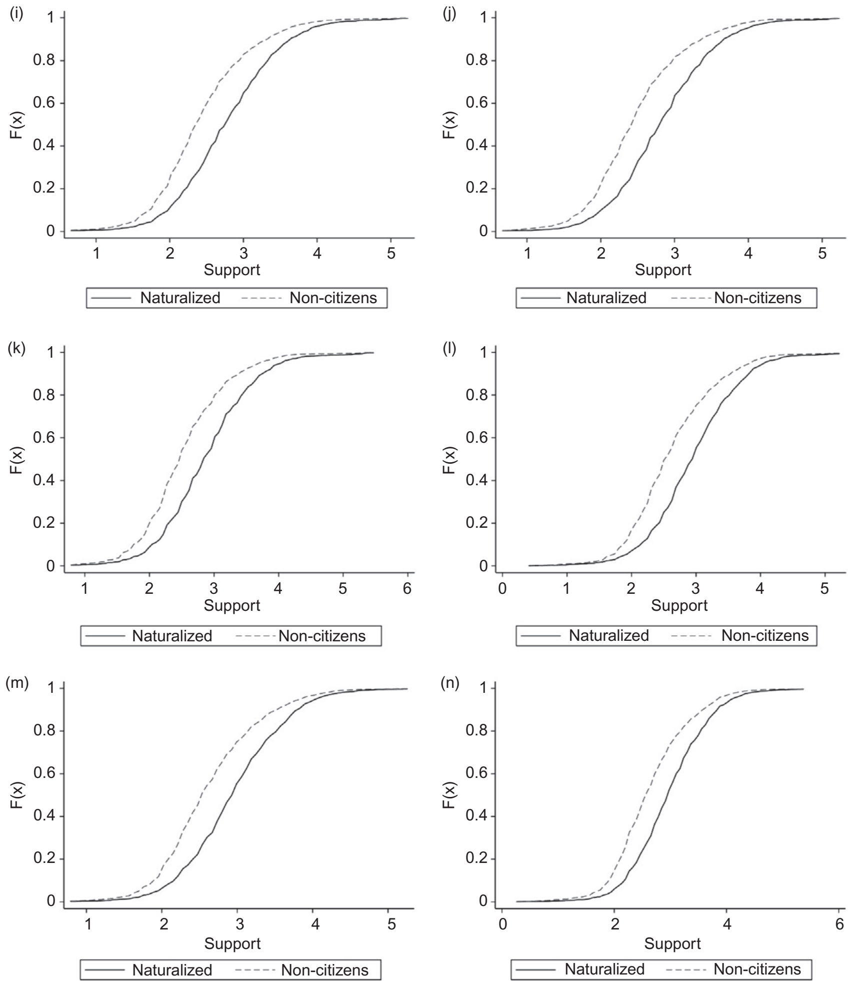

Fig. A.1. (*Continued*)

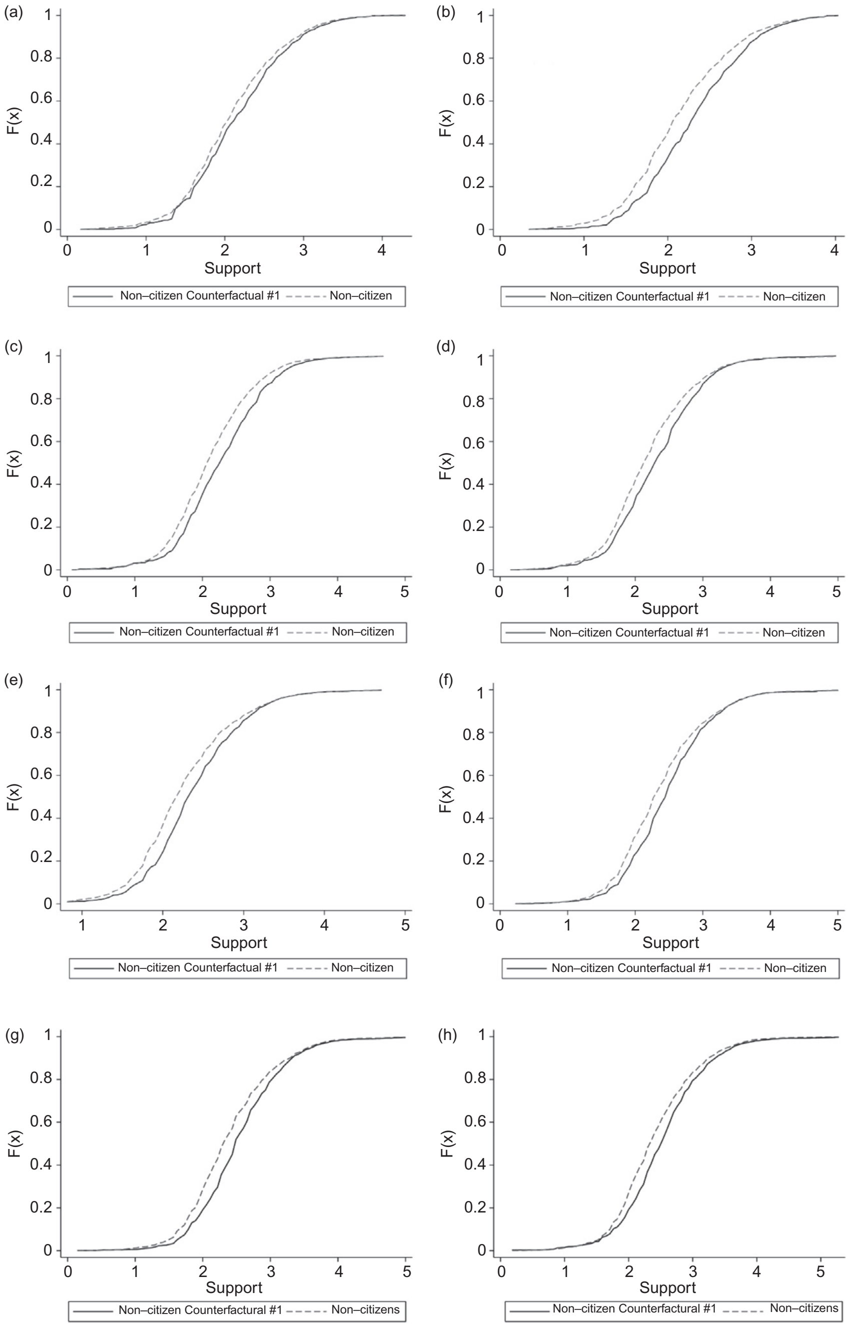

Fig. A.2. CDF Comparisons of Noncitizen Counterfactual # 1 and Noncitizen (1994–2012). (a) 1994; (b) 1995; (c) 1996; (d) 1998; (e) 2000; (f) 2001; (g) 2002; (h) 2003; (i) 2005; (j) 2006; (k) 2007; (l) 2010; (m) 2011; and (n) 2012.

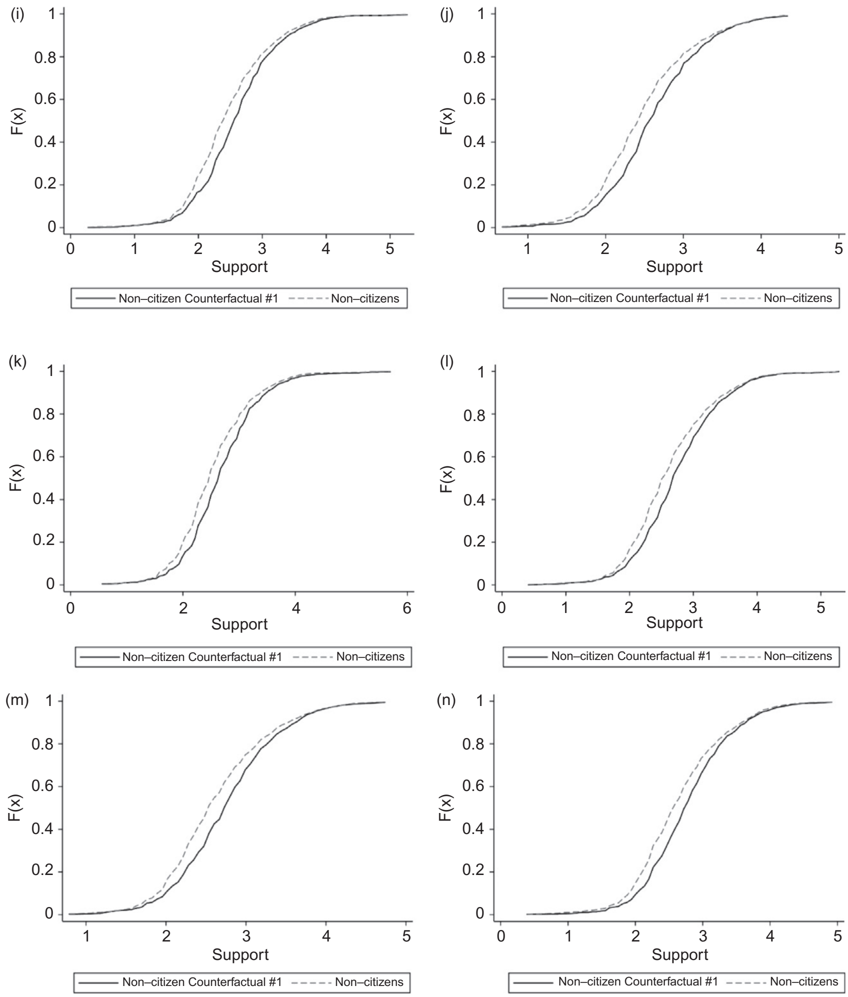

Fig. A.2. (*Continued*)

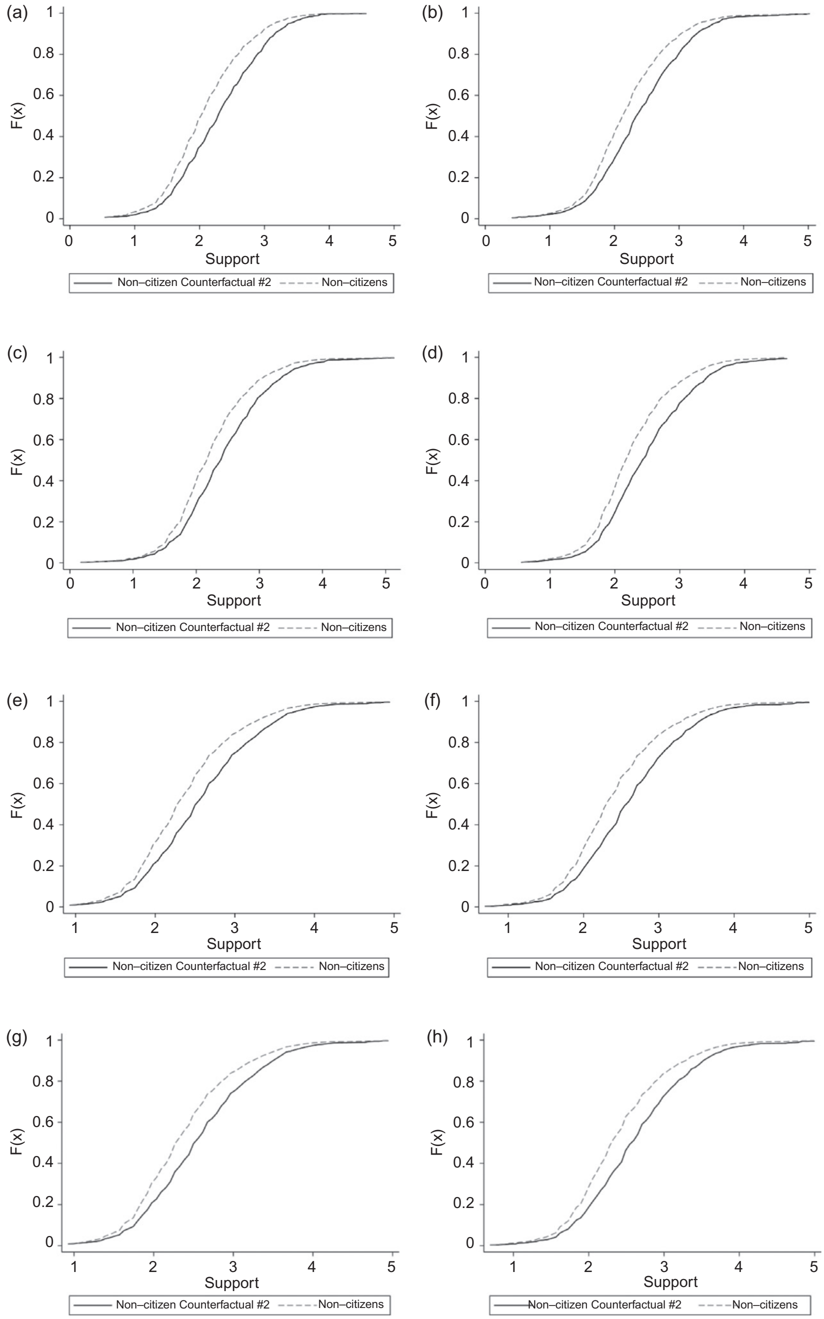

Fig. A.3. CDF Comparisons of Noncitizen Counterfactual # 2 and Noncitizen (1994–2012). "(a) 1994; (b) 1998; (c) 1999; (d) 2000; (e) 2001; (f) 2002; (g) 2003; (h) 2004; (i) 2005; (j) 2007; (k) 2008; (l) 2009; (m) 2011; and (n) 2012.

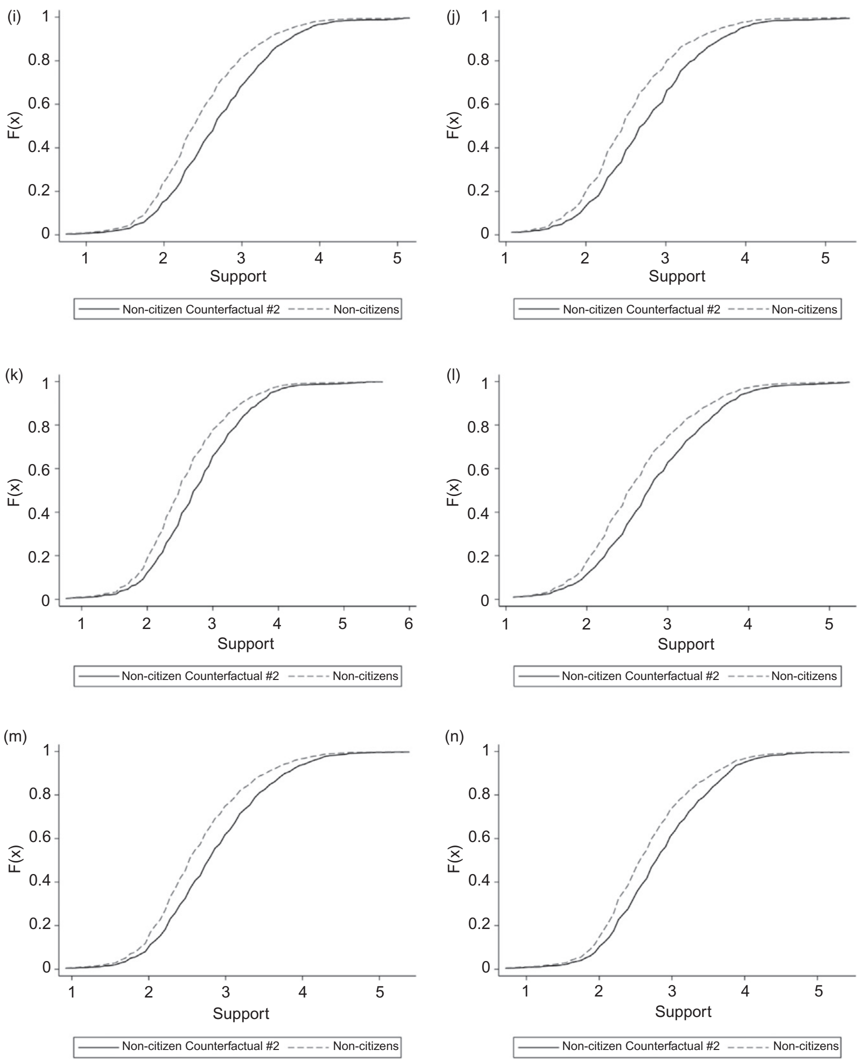

Fig. A.3. (*Continued*)

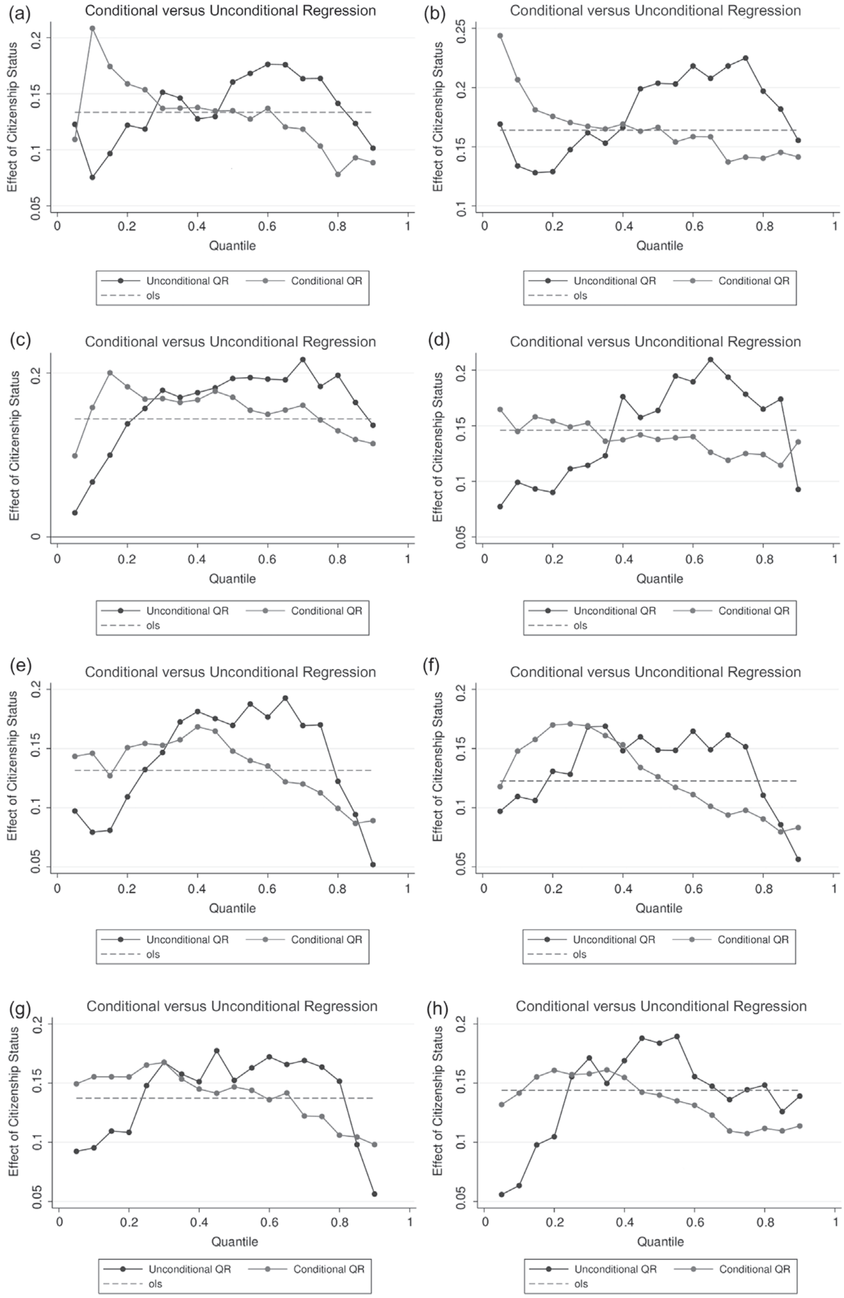

Fig. A.4. Unconditional and Conditional Quantile Regression Estimates of the Effect of Citizenship Status on Log Wages (1994–2012). (a) 1994; (b) 1996; (c) 1997; (d) 1999; (e) 2000; (f) 2001; (g) 2002; (h) 2003; (i) 2004; (j) 2006; (k) 2007; (l) 2008; (m) 2011; (n) 2012.

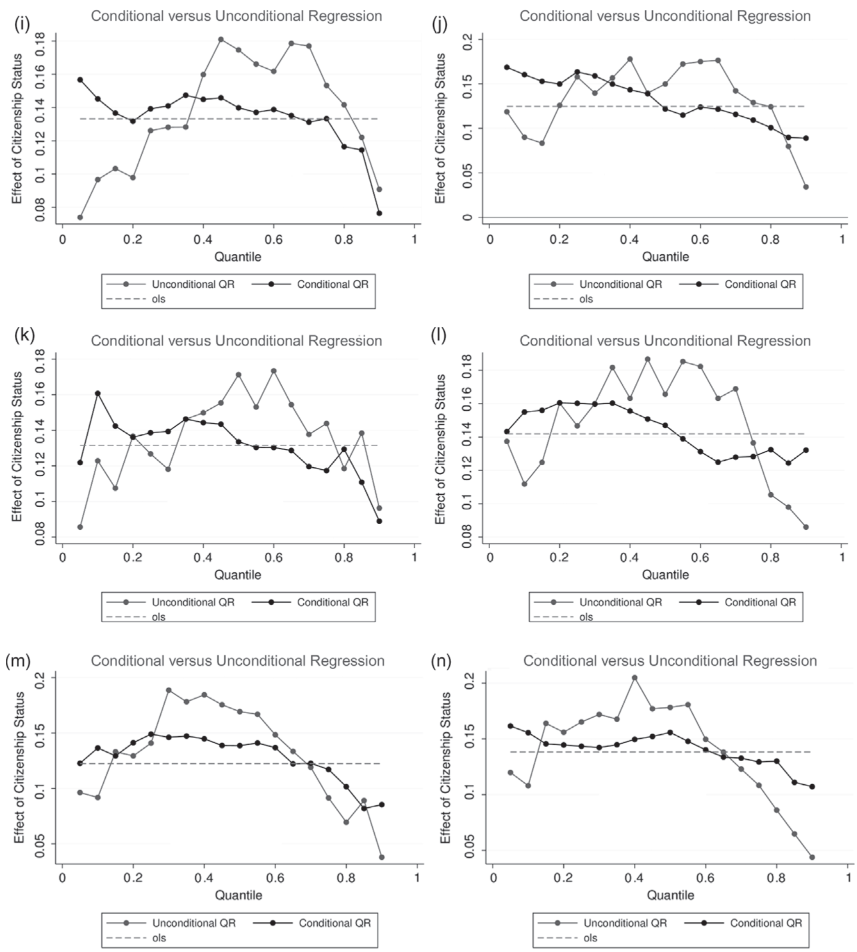

Fig. A.4. (*Continued*)

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