The labor supply of undocumented immigrants

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ABSTRACT

Over 11 million undocumented persons reside in the United States. This paper examines the labor supply of this population. Using newly developed methods that impute undocumented status for persons in the Current Population Surveys, the study documents a number of findings. The labor force participation rate of undocumented men is larger than that of natives or legal immigrants; this gap widened over the past two decades; and the labor supply of undocumented men is more inelastic than that of other groups. In contrast, the participation rate of undocumented women is far below that of both legal immigrants and natives.

1. Introduction

The Department of Homeland Security (DHS) estimates that 11.4 million undocumented persons reside in the United States (as of January 2012).[1] In the past few years, Congress considered a number of proposals to regularize the status of this undocumented population and provide a "path to citizenship," while President Obama issued executive orders, which were never fully implemented due to interventions by the judicial system, that attempted to grant some form of amnesty to about half of this population.

Given the size of the undocumented population, any future change in the immigration status of this group may have significant effects on the labor market, on the number of persons that qualify for various government-provided benefits, on the timing of retirement, on the size of the population receiving Social Security benefits, and on the funding of almost all of these government programs.

Any evaluation that attempts to predict the economic impact of the regularization of immigration status for the undocumented population immediately runs into a major roadblock: It is difficult to conduct such a calculation because we know little about the economic status and well-being of the 11.4 million undocumented persons. We do not have detailed information on their employment histories (so, for example, we do not know how many would potentially meet the 40-quarter eligibility requirement for Social Security). We lack information on the shape of the age-earnings profiles, on the individual histories of contributions to various government programs, or on how those earnings and contributions would change if the undocumented worker's status were regularized.[2] We also have no basis for predicting how

the labor supply decisions of the undocumented population would change after their status is regularized. For example, the regularization of status might increase their average wage simply because undocumented workers may then choose from a much wider set of employment options. But how would these wage changes affect labor supply over the life cycle?

This paper represents an initial attempt at providing some of the requisite background information involved in conducting any such future evaluation.[3] In particular, the paper provides a comprehensive empirical study of the labor supply behavior of undocumented immigrants in the United States.

The empirical study of the labor supply of a hard-to-detect and hard-to-identify population is made possible by the fact that some researchers have developed methods to impute the undocumented status of foreign-born persons in micro data sets, such as the American Community Surveys or the Current Population Surveys. These attempts build on the framework first advanced by Warren and Passel (1987) to estimate the size of the undocumented population. The Warren-Passel methodology, in fact, underlies the "official" estimates of this population reported by DHS.

Jeffrey Passel (now at the Pew Research Center) and various colleagues have improved and extended the initial methodology over the past two decades. This additional work led to the creation of some micro-level CPS files that contain a variable indicating if a foreign-born person is "likely authorized" or "likely unauthorized." I was granted access to the 2012–2013 Annual Socioeconomic and Economic Supplements (ASEC) created by the Pew Research Center that contains the undocumented status identifier. After carefully examining the Pew

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[1] More recent estimates by the Pew Research Center (Passel and Cohn, 2016) suggest that this number has held steady since the end of the Great Recession.

[2] The Social Security Administration, however, can calculate the total amount of Social Security taxes paid by persons where the worker's name and Social Security number do not match, and most of those taxes were probably paid by workers who are not authorized to work in the United States.

[3] Goss et al. (2013) report calculations linking immigration and the Trust Funds of the Social Security System made by the Actuaries of the Social Security Administration. See also Bohn and Lofstrom (2012), Bohn et al. (2014), Hotchkiss and Quispe-Agnoli (2013) for related work.

data, I adapted and extended their approach so that I could create an undocumented status identifier in all the ASEC files where foreign-born status is reported (i.e., the ASEC files beginning in 1994). This extension of the Pew approach yields a time series of micro data that allows an examination of the labor supply of undocumented immigrants, as well as a study of the factors that distinguish the trends in the labor supply of this group from those of the native-born and of legal immigrants.

The analysis of the various CPS cross-sections yields a number of important findings:

1. The labor supply of undocumented immigrant men, as measured by the labor force participation rate during the CPS reference week, is higher for undocumented immigrant men than for legal immigrant men, which in turn is higher than for native men.
2. The probability that undocumented immigrant women are in the labor force is lower than the respective probability for legal immigrant women, which in turn is lower than the probability for native women.
3. The already large difference in labor force participation rates between undocumented men and native men widens dramatically after controlling for differences in skills and other socioeconomic characteristics. In contrast, the difference in the participation probability between undocumented women and native women narrows after such controls.
4. The absolute and relative participation rates of undocumented men rose during the 1994–2014 period. The gap in participation rates between undocumented men and native men widened by about 5 percentage points. The relative participation rates of undocumented women also rose, but at a much slower rate.
5. The labor supply of undocumented men is less responsive to wage changes than that of legal immigrants, which in turn is less responsive that of natives. It would not be difficult to infer that the labor supply of undocumented men is very inelastic.[4]

This diverse set of findings provides a foundation upon which an eventual assessment of the various regularization proposals can be based. It is crucial to acknowledge at the outset, however, that the robustness of the evidence depends on the validity of the procedure used to impute undocumented status at the micro level. As a result, the empirical analysis is subject to various types of unknowable and non-classical measurement errors. Nevertheless, any assessment of regularization proposals will require that much more be known about the economic life cycle of the undocumented population in the United States. A more systematic application of the imputation methods described in this paper may help provide a unique opportunity for such an assessment to begin.

2. Counting and identifying undocumented immigrants

The statutes regulating legal immigration to the United States have not changed in significant ways since 1965. The 1965 Amendments to the Immigration and Nationality Act introduced a "family preference" system that favors visa applicants who already have relatives residing in the United States (as either citizens or permanent residents). The 1965 Amendments also allocated a relatively small number of visas to persons who apply to enter the United States for employment purposes. Partly because of the numerical statutory limits, the number of legal immigrants entering the United States has hovered around 1 million persons per year for over a decade, and more than two-thirds of those immigrants are granted entry visas under the family preference

system.

Despite the relative constancy in the statutes that regulate legal immigration since 1965, a new development has become increasingly more important: illegal immigration. The initial flow of Mexican undocumented immigrants began soon after the discontinuation of the Bracero program in the 1960s.[5] The persistence of undocumented immigration in the 1970s and 1980s led to the enactment of the Immigration Reform and Control Act (IRCA) in 1986, a statute that granted amnesty to 2.7 million persons and that made it illegal (for the first time) for employers to knowingly hire undocumented immigrants.

The Department of Homeland Security (DHS) publishes annual estimates of the size of the undocumented population (Baker and Rytina, 2013) (Hoefer et al., 2012). As of January 2012 (the most recent calculation), there were 11.4 million undocumented immigrants residing in the country, a number that (again according to DHS estimates) has held relatively steady since January 2005.

The "residual" methodology used by the DHS to estimate the size of the undocumented population was developed by Warren and Passel (1987) and is easy to describe. The first step in the calculation involves estimating how many legal immigrants should reside in the United States at a point in time. Over the years, the DHS and its precursor (the Immigration and Naturalization Service) have kept track of the number of legal immigrants admitted (i.e., the number of "green cards" granted to foreign-born persons each year). We also "know" how many foreign-born persons live in the United States temporarily (e.g., foreign students, business visitors, diplomats, etc.). These data allow us to apply mortality tables to the cumulative count of green cards awarded and predict how many legal immigrants *should be* alive and residing in the United States at any point in time.

At the same time, many government surveys, including the decadal censuses, the American Community Surveys (ACS), and the Current Population Surveys (CPS), periodically sample the U.S. population and specifically ask where each person was born. These surveys provide estimates of how many foreign-born people are *actually* living in the country. In rough terms, the difference between the number of foreign-born persons who are actually living in the United States and the number of legal immigrants who should be living in the United States is the Warren-Passel (and now official DHS) estimate of the number of undocumented persons.

The residual methodology obviously faces one important obstacle. The enumerations in the decadal censuses or the CPS miss many people whenever the enumerators go out and attempt to count (or sample) the population. Some of the people that the enumerators miss are undocumented immigrants who wish to avoid being detected. To calculate an estimate of the size of the undocumented population, therefore, the Warren-Passel methodology must make an assumption about the undercount rate. The DHS uses the assumption that the government enumerators miss 10% of the undocumented immigrants (Baker and Rytina, 2013, p. 6).

Jeffrey Passel, who was a statistician with the Bureau of the Census at the time that he and Robert Warren developed the residual method, has continued working on the identification and enumeration of undocumented immigrants over the past two decades. As a result of these efforts, Passell (and colleagues at the Pew Research Center) have developed a methodology that attempts to identify the undocumented immigrants at the *individual level* in survey data. Specifically, this work attempts to predict which of the foreign-born persons sampled in a microdata file are legal immigrants and which are undocumented. This important extension of the Warren-Passel methodology relies on the same residual approach that was initially introduced to calculate the size of the undocumented population.

Passel and Cohn (2014) provide a detailed description of the

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[4] Hotchkiss and Quispe-Agnoli (2013, Table 2) use firm-level administrative data for the state of Georgia and also document that the labor supply of undocumented workers is less responsive to wage changes than that of other workers.

[5] The Bracero program allowed some Mexicans to enter the United States temporarily and work in the agricultural sector. The program was discontinued in 1964.

methodology used to add a "likely unauthorized" identifier to the Annual Social and Economic Supplement (ASEC) files of the CPS. In rough terms, their methodology identifies the foreign-born persons in the sample who are likely to be legal, and then classifies the remainder as likely to be undocumented. In particular:

All immigrants entering the U.S. before 1980 are assumed to be legal immigrants. Then, the CPS data are corrected for known over-reporting of naturalized citizenship on the part of recently arrived immigrants...and all remaining naturalized citizens from countries other than Mexico and those in Central America are assigned as legal. Persons entering the U.S. as refugees are identified on the basis of country of birth and year of immigration...Then, individuals holding certain kinds of temporary visas (including students, diplomats and "high-tech guest workers") are...assigned a specific legal temporary migration status...Finally, some individuals are assigned as legal immigrants because they are in certain occupations (e.g., police officer, lawyer, military occupation, federal job) that require legal status or because they are receiving public benefits (e.g., welfare or food stamps) that are limited to legal immigrants. As result of these steps, the foreign-born population is divided between individuals with "definitely legal" status...and a group of "potentially unauthorized" migrants...[There is also] a check to ensure that the legal statuses of family members are consistent; for example, all family members entering the country at the same time are assumed to have the same legal status (Passel and Cohn, p. 23).

Passel and Cohn (2014) note that this approach leads to "too many" undocumented immigrants. In other words, the residual number of persons predicted to be likely undocumented is larger than what would be expected from the DHS official estimates. Passel and Cohn then apply a final filter to ensure that the counts from the microdata conform with the reported DHS numbers: "To have a result consistent with the residual estimate of legal and unauthorized immigrants, probabilistic methods are employed to assign legal or unauthorized status to these potentially unauthorized individuals." The CPS sample is then reweighted so that the aggregate count of undocumented immigrants matches as closely as possible the DHS estimates, including the estimates of undocumented immigrants for the six largest states.

I was granted access to the 2012–2013 ASEC files that Passel and colleagues constructed and that are archived at the Pew Research Center. Table 1 summarizes some summary statistics for natives, legal immigrants, and undocumented immigrants in the sample of persons aged 20–64. In the pooled 2012–2013 cross-sections, 5.4% of the population aged 20–64 was predicted to be composed of undocumented immigrants, and another 12.4% was composed of legal immigrants. The Pew imputation also suggest that undocumented immigrants are, on average, around 4–5 years younger than either natives or legal immigrants. The undocumented immigrants are also more likely to be male (54% as compared to around 49 percent for the other two groups). And, finally, the undocumented are much more likely to be high school dropouts: 42% of the undocumented lack a high school diploma, as compared to only 19.2% of legal immigrants, and 7.1% of natives. Given these large skill differences, it is not surprising that undocumented immigrants suffer a large wage disadvantage (of around 40% relative to natives).

The top panel of Fig. 1 illustrates the percent of the U.S. population by age that is imputed to be undocumented in the Pew ASEC files. The DHS official counts imply that 3.7% of the U.S. population is undocumented. The Pew files suggest that a very high fraction (almost 10%) of persons in their early 30s is undocumented.

Table 1 also reports the fraction of each group that participated in the labor force during the CPS reference week—the key labor supply variable that will be used throughout the study. There are interesting differences both across the three nativity groups and between men and women. In particular, undocumented men have by far the *highest* participation rates of any of the groups, while undocumented women have the *lowest* participation rates. The participation rate of undocumented men is 92.0%, as compared to 80.7% for natives and 84.8% for legal immigrants. In contrast, the participation rate of undocumented women is 60.7%, as compared to 71.8% for natives, and 63.9% for legal immigrants. Note that the differences in the employment rate among the groups (defined as the fraction working at some point during the previous calendar year) mirror the participation rate differentials, with undocumented men having the highest employment rates and undocumented women having the smallest.

After being granted access to the Pew ASEC files (but not to the underlying code that creates the undocumented status identifier), I

Table 1
Summary statistics in pooled 2012–2013 CPS-ASEC files.

	Pew CPS files			Reconstruction of undocumented identifier		
	Natives	Legal	Undocumented	Natives	Legal	Undocumented
Percent of population	82.2	12.4	5.4	82.9	11.5	5.7
Percent male	48.9	48.2	54.3	48.9	46.8	55.9
Average age	41.7	42.4	37.6	41.7	43.3	37.6
Education:						
High school dropouts	7.1	19.2	42.0	7.1	19.9	39.5
High school graduates	29.3	24.0	28.8	29.3	25.2	26.9
Some college	32.7	21.0	13.2	32.7	21.2	13.5
College graduates	30.9	35.8	16.0	30.9	33.8	20.1
State of residence:						
California	9.7	26.7	22.2	9.7	26.2	23.6
New York	5.6	11.8	6.9	5.6	11.6	7.5
Texas	7.7	9.5	14.7	7.8	9.3	14.8
Percent wage differential (relative to natives)						
Men	0.0	−5.0	−42.6	0.0	−4.1	−40.8
Women	0.0	−1.5	−36.0	0.0	−0.7	−37.3
Labor force participation rate						
Men	80.7	84.8	92.0	80.7	86.2	90.0
Women	71.8	63.9	60.7	71.8	65.6	58.0
Employment rate						
Men	80.9	83.2	90.4	80.9	84.7	88.1
Women	72.6	62.8	58.9	72.6	64.4	56.7
Sample size	193,417	42,047	18,077	191,768	28,074	13,566

Notes: All statistics are calculated in the sample of persons aged 20–64. The percent log wage differential equals 100 times the respective difference in the log hourly wage rate.

A. Percent legal and undocumented in Pew files
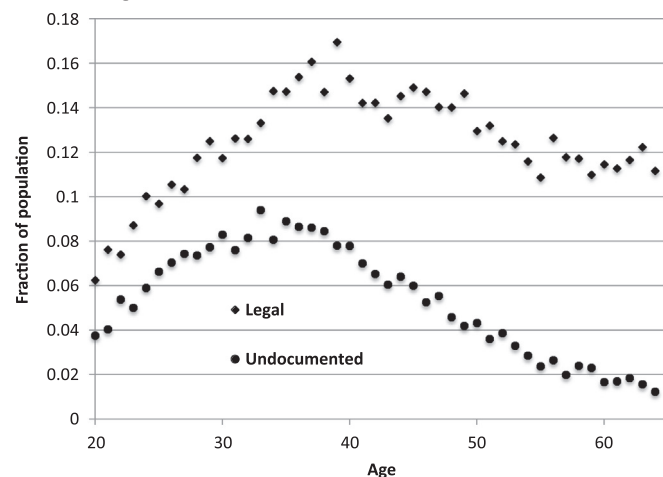
B. Percent undocumented in Pew files and in reconstruction
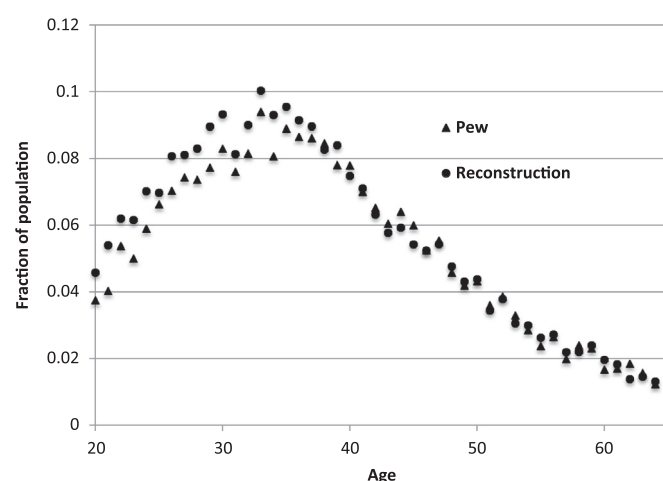
Fig. 1. Percent foreign-born in population, by age. (Pooled CPS-ASEC files, 2012–2013). A. Percent legal and undocumented in Pew files. B. Percent undocumented in Pew files and in reconstruction. Notes: The figures show the fraction of the population (at a particular age) that is foreign-born and is classified as either "likely authorized" or "likely unauthorized." See text for details on the construction of the likely unauthorized status identifier.

conducted a careful examination of the demographic characteristics of those persons identified as undocumented immigrants in the pooled 2012–2013 cross-section. Despite the inherent complexity in the residual method of identifying the subsample of the likely undocumented, it turns out that only a relatively small number of variables really "matter" in the identification of undocumented persons. This fact suggests that it may be possible to reverse engineer the Pew residual method to create a comparable undocumented identifier in *all* of the ASEC files since 1994 (the year in which immigration status began to be collected by the CPS).

The algorithm I use to create a comparable undocumented status identifier in all the relevant ASEC files is as follows. A foreign-born person is classified as a legal immigrant if any one of these conditions applies:

a. That person arrived before 1980;
b. That person is a citizen;
c. That person receives Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance;
d. That person is a veteran, or is currently in the Armed Forces;
e. That person works in the government sector;
f. That person resides in public housing or receives rental subsidies, or

that person is a spouse of someone who resides in public housing or receives rental subsidies;
g. That person was born in Cuba (as practically all Cuban immigrants were granted refugee status before 2017);
h. That person's occupation requires some form of licensing (such as physicians, registered nurses, air traffic controllers, and lawyers);
i. That person's spouse is a legal immigrant or citizen.

The residual group of all other foreign-born persons is then classified as undocumented. Unlike the Pew methodology, my reconstruction of the undocumented identifier does not carry out any kind of probabilistic sampling to account for the "excess" number of undocumented immigrants that this residual method yields, nor does it reweight the data in any fashion to ensure that the total counts of the undocumented match the DHS official counts. Throughout the analysis, the sample weights employed when I use the ASEC files that contain my reconstruction of the undocumented status identifier are the original CPS sampling weights.

As Table 1 shows, there is a lot of similarity between the summary statistics from the Pew files and from my reconstruction of the pooled 2012–2013 ASEC cross-sections.[6] Both methods yield a similar population of undocumented immigrants (5.4% in Pew and 5.7% in my reconstruction). Further, the percent male in the undocumented population is 54.3% in the Pew files and 55.9% in my reconstruction. The average age of undocumented immigrants is 37.6 years in both files. Similarly, 42.0% of the undocumented lack a high school diploma in the Pew cross-sections, while my reconstruction predicts that this statistic is 39.5%. Finally, as in the Pew files, the labor force participation rate for undocumented men in the reconstructed files is far higher than that of native men or legal immigrant men, while the participation rate for undocumented women is far lower than that of native women or legal immigrant women.

It is important to note that although my reconstruction does not conduct any probabilistic sampling of the data nor any type of reweighting, my approach yields a very similar geographic distribution for the location of the undocumented population: Around 23% of the undocumented live in California, 7.0% live in New York, and 15% live in Texas regardless of the method used.[7]

Finally, as the bottom panel of Fig. 1 documents, the predicted fraction of undocumented immigrants in the population at any particular age is similar in the two files, although the fraction of young persons (below the age of 35) who are predicted to be undocumented is about 1 percentage point percent higher in the reconstructed CPS file. The general similarity between the two data sets suggests that it is possible to extend the exercise to create an undocumented status identifier for all foreign-born persons sampled by the CPS in the post-1994 period. This extension allows for an examination of the differential long-term labor supply trends among natives, legal immigrants, and undocumented immigrants.[8]

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[6] I experimented with a variety of sensitivity tests in the imputation of undocumented status. These alternative exercises include the "correction" of a reported naturalized citizenship status for any foreign-born person who has been in the country fewer than 5 years, or slightly different lists for the set of occupations that requires licensing. The results generated by the undocumented status identifier used in this paper are very representative of a wide array of alternative definitions.

[7] Note that the number of observations for the pooled 2012–2013 ASEC cross-sections is larger in the Pew files because of the probabilistic sampling methods used to create those extracts. The actual number of observations in the CPS files (as released by the BLS) is the one given in Panel B of Table 1.

[8] I also obtained an alternative ASEC file from the Heritage Foundation for the 2011 cross-section that imputes an alternative undocumented status identifier. The Heritage methodology identifies a sample of undocumented persons that has very similar socioeconomic characteristics to the undocumented samples in both the Pew files and in my reconstructed samples.

3. Differences in labor supply across groups

I begin by documenting the differences in labor force participation across the various nativity groups. The analysis initially uses the pooled 2012–2013 ASEC files created by the Pew Research Center and is restricted to persons aged 20–64. I pool the two cross-sections and treat them as a single data set. The key measure of labor supply indicates if the person participated in the labor force during the CPS reference week.[9]

To document the differences in labor supply across the various groups—and to examine the source of these differences—I estimated the following logit regression model:

$$\log \frac{p_i}{1 - p_i} = \beta_1 L_i + \beta_2 U_i + \mathbf{X_i}\theta + \delta_t + \varepsilon_i, \tag{1}$$

where p_i is a dummy variable indicating if the person is in the labor force during the reference week; δ_t is a dummy variable indicating if the observation is drawn from the 2012 or 2013 ASEC cross-section; $\mathbf{X_i}$ is a vector of socioeconomic characteristics described below; L_i is a dummy variable indicating if the person is a legal immigrant; U_i is a dummy variable indicating if the person is an undocumented immigrant; and the excluded group indicates if person i is native-born. The marginal effects implied by the coefficients β_1 and β_2 measure the participation rate of the two foreign-born groups relative to that of natives. The regressions are estimated separately for men and women.

The first two columns of Table 2 report the marginal effects implied by the coefficients in the vector β. The top panel of the table reports the effects estimated in the sample of men. It is evident that, on average, both legal and undocumented immigrants are more likely to be in the labor force than native-born workers, and that this gap in participation propensities remains when the regression adds a fourth-order polynomial in age. The age-adjusted difference in the participation probability between legal immigrants and natives is around 3 percentage points, and that gap rises to 11 percentage points for undocumented immigrants. The finding that undocumented immigrant men are much more likely to be employed than either native or legal immigrant men is one of the key implications of the empirical analysis, and will be robust throughout the paper.

As the third row of the table shows, this gap becomes even larger after the regression controls for differences in educational attainment among the groups. As we saw from the summary statistics reported in the previous section, undocumented immigrants have far less education than either natives or legal immigrants. Once the regression controls for these differences in educational attainment, the participation gap between undocumented immigrants and natives widens from 11 to 16 percentage points, while the gap between legal immigrants and natives only widens by about 1 percentage point.[10] Finally, as row 4 of the table shows, these gaps in participation rates remain stable when the regression model is expanded further to include a vector of state-of-residence fixed effects and an indicator of whether the person lives in a metropolitan area to account for the different geographic settlement of the three groups.

The last two columns of Table 2 re-estimate the regression in Eq. (1) using the comparable ASEC files (i.e., for the pooled 2012–2013 cross-sections) that contain my reconstructed undocumented status indicator. It is evident that the labor supply gaps across the three groups are roughly similar to those obtained from the Pew files. For example, the participation rate gap between undocumented immigrants and natives in the most general specification (in row 4) is 16 percentage points in the Pew files and 12 percentage points in my

Table 2
Differences in labor supply in pooled 2012–2013 CPS-ASEC files.

Regression specification:	Pew files		Reconstructed files	
	Legal immigrants	Undocumented immigrants	Legal immigrants	Undocumented immigrants
A. Men				
1. No controls	0.043	0.150	0.059	0.114
	(0.005)	(0.008)	(0.005)	(0.007)
2. Adds age	0.029	0.114	0.046	0.081
	(0.004)	(0.007)	(0.005)	(0.007)
3. Adds age, education	0.039	0.164	0.060	0.124
	(0.005)	(0.008)	(0.005)	(0.007)
4. Adds age, education, geography	0.041	0.161	0.062	0.122
	(0.005)	(0.008)	(0.005)	(0.008)
B. Women				
1. No controls	−0.075	−0.104	−0.058	−0.127
	(0.004)	(0.006)	(0.004)	(0.006)
2. Adds age	−0.084	−0.127	−0.067	−0.148
	(0.004)	(0.006)	(0.004)	(0.006)
3. Adds age, education	−0.062	−0.043	−0.041	−0.074
	(0.004)	(0.006)	(0.004)	(0.007)
4. Adds age, education, geography	−0.063	−0.045	−0.042	−0.076
	(0.005)	(0.006)	(0.005)	(0.007)

Notes: Standard errors are reported in parentheses. The dependent variable indicates if the person was in the labor force during the CPS reference week, and the reported coefficients give the average marginal effect in a logit regression. The regressions control for age by including a vector of fixed effects indicating the person's age in five-year bands (20–24, 25–29, and so on). The regression controls for educational attainment by including a vector of fixed effects indicating if the person is a high school dropout, a high school graduate, has some college, or is a college graduate. The controls for geography include a vector of fixed effects indicating the person's state of residence and a dummy variable indicating if the person lives in a metropolitan area. All regressions also include a dummy variable indicating if the observation was drawn from the 2013 cross-section. The male (female) regressions estimated in the Pew files have 122,520 (131,014) observations. The male (female) regressions estimated in the reconstructed files have 112,127 (121,281) observations.

reconstruction.

The bottom panel of the table estimates the regressions using the sample of women in both the Pew files and the reconstructed CPS files. As suggested by the summary statistics, the regressions indicate that legal immigrant women are less likely to participate in the labor force than native women, and that undocumented women have the lowest participation rates. Interestingly, the results for immigrant women are essentially a reverse image of the results for immigrant men.

Specifically, the age-adjusted probability that a legal immigrant woman participates in the labor force is about 8 percentage points lower than that of a native women, and that gap widens to over 13% points for undocumented women. Moreover, as row 3 of the table indicates, these gaps *narrow* (rather than widen as in the case of men) after we control for differences in educational attainment among the groups. Both legal and undocumented immigrant women have participation rates that are about 5–8 percentage points lower than those of comparably skilled native women.

It is useful to continue the descriptive analysis by examining the labor force participation gaps at various points in the life cycle. I smooth out the age-participation profiles by estimating the following logit regression in the pooled 2012–2013 ASEC cross-sections:

$$\log \frac{p_i}{1 - p_i} = \beta_1 L_i + \beta_2 U_i + \mathbf{A}_i \theta_0 + (L_i \times \mathbf{A}_i) \theta_1 + (U_i \times \mathbf{A}_i) \theta_2 + \delta_t + \varepsilon_i, \tag{2}$$

where $\mathbf{A_i}$ is a vector of variables containing a fourth-order polynomial

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[9] I also conducted a parallel analysis where the dependent variable indicates if the person worked during the CPS reference week. The results are similar to those reported below.

[10] The vector of fixed effects indicating educational attainment indicate if the person is a high school dropout, a high school graduate, has some college, or is a college graduate.

A. Pew CPS, men

B. Reconstructed CPS, men

C. Pew CPS, women

D. Reconstructed CPS, women
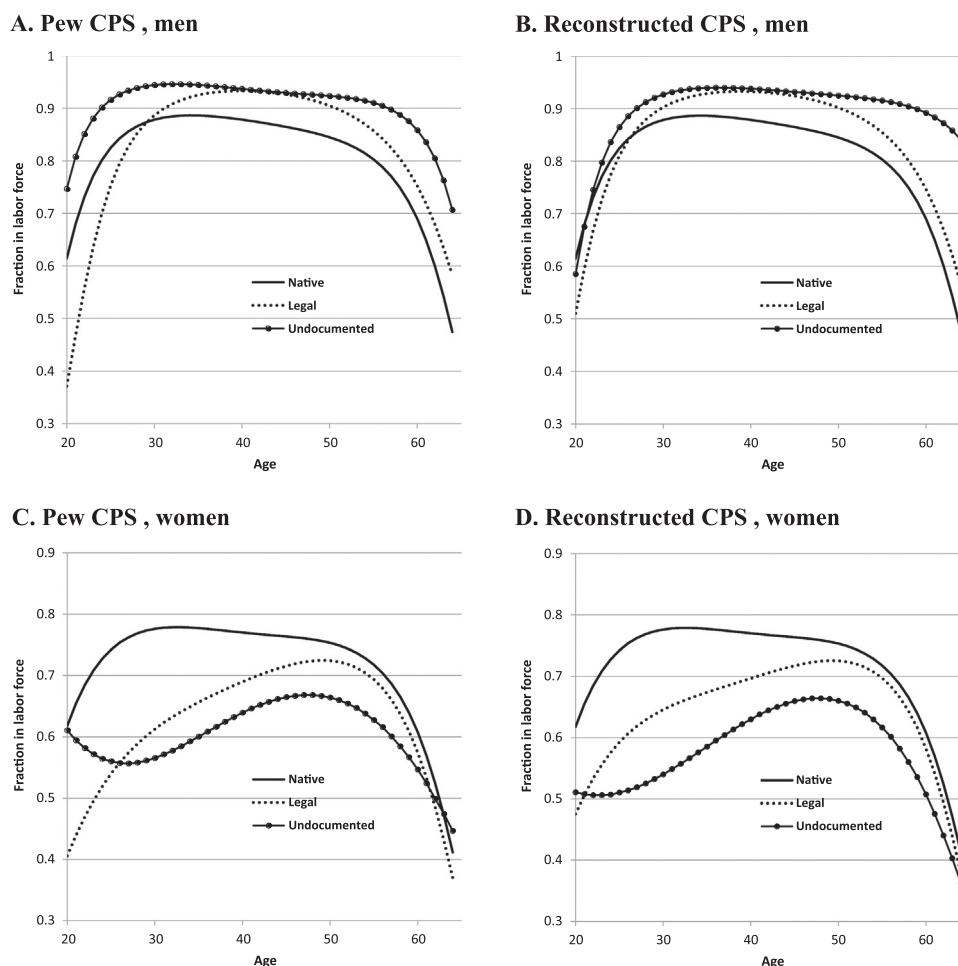
Fig. 2. Predicted labor force participation profiles, 2012–2013. A. Pew CPS, men. B. Reconstructed CPS, men. C. Pew CPS, women. D. Reconstructed CPS, women. Notes: The predicted age-participation profiles are obtained from a logit regression of the probability that a person is in the labor force during the CPS reference week on age (entered as a fourth-order polynomial), using the pooled 2012–2013 CPS-ASEC files.

in person *i*'s age. The interactions between the immigration status indicators and the age vector, of course, allow for the age-participation profiles to vary across the three groups. The logit regressions are estimated separately for men and women. The predicted age-participation profiles from the logistic regression very closely track the raw data for all the nativity groups.

Panels A and C of Fig. 2 illustrate the predicted participation profiles for men and women implied by the data in the Pew files. It is evident that the participation gap between undocumented and native men is present over the entire life cycle. It is of interest to note that the gap is quite large (about 20 percentage points) when the two groups near retirement age, and narrower (about 6 percentage points) in the middle of the life cycle when the men are in their 40 s. In contrast, undocumented women are far less likely to work than both natives and legal immigrant women throughout much of the life cycle, and that gap is about 15–20 percentage points when the women are in their 30 s and 40 s.

It is important to document the similarity in the predicted age-participation profiles when I estimate the regression model in (2) using my reconstruction of the undocumented status indicator. Panels B and D of Fig. 2 show the comparable profiles. It is evident that my reconstruction leads to age-participation profiles that are roughly similar in the two data sets (although the participation gap between undocumented men and natives is somewhat smaller in the reconstructed data, especially at the younger ages where I find a larger fraction of undocumented persons). The overall similarity suggests that the reconstructed CPS files can be used to examine the labor supply

trends of the various groups over a longer span of time.[11]

4. Trends in the labor supply of undocumented immigrants

It is well known that there has been a steep and long-term decline in the labor supply of men over the past few decades, and that this decline perhaps accelerated after the onset of the Great Recession in 2008 (Aaronson et al., 2006; Aaronson et al., 2014; Farber, 2011). This section documents the differences in the secular trends among the three nativity groups using the reconstruction of the undocumented indicator status in the ASEC files between 1994 and 2014.

Panel A of Fig. 3 illustrates the long-term trends in the male labor force participation rate. There was a noticeable divergence in participation rates between immigrants and natives, and particularly between undocumented immigrants and natives. In the late 1990 s, the participation rate of legal immigrants was only about 2 percentage

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[11] As implied by the regression analysis in Table 2, it is also the case that adjusting for education widens the gap in participation rates over the life cycle between undocumented and native men and narrows the equivalent gap for women. I re-estimated the logit regression in (2) by adding the vector of education fixed effects. The various panels of Appendix Fig. A1 illustrate the predicted education-adjusted age-participation profiles for men and women (where the adjusted labor force participation rate is calculated at the mean educational attainment of undocumented workers). In the case of men, the gap in participation rates between undocumented and native men is much larger at every age and is over 20 percentage points for older men. In contrast, adjusting for differences in educational attainment eliminates the participation gap after age 40 across the three groups of women.
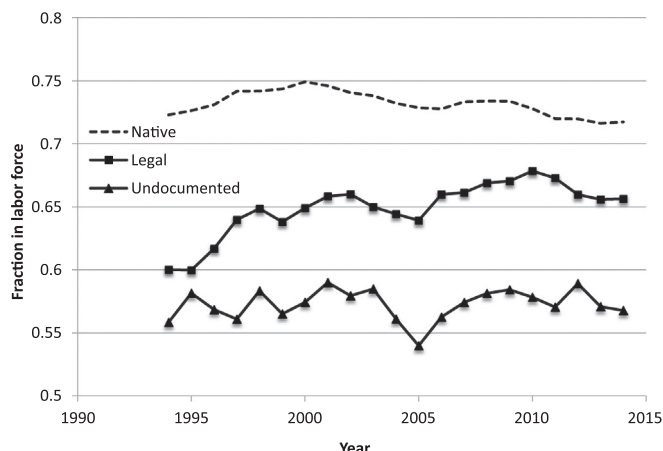
A. Raw Data
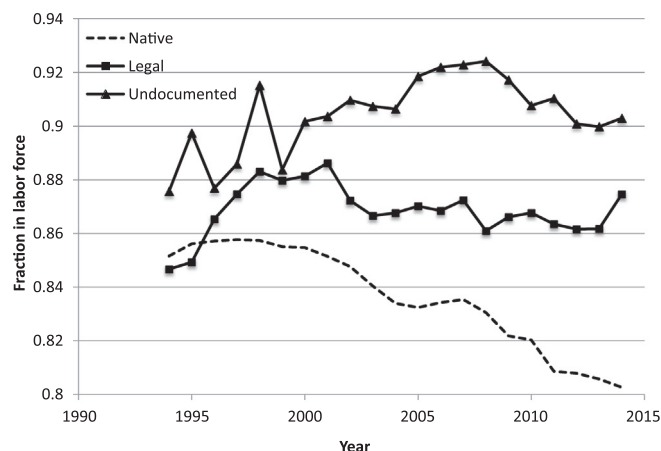
B. Netting out year effects
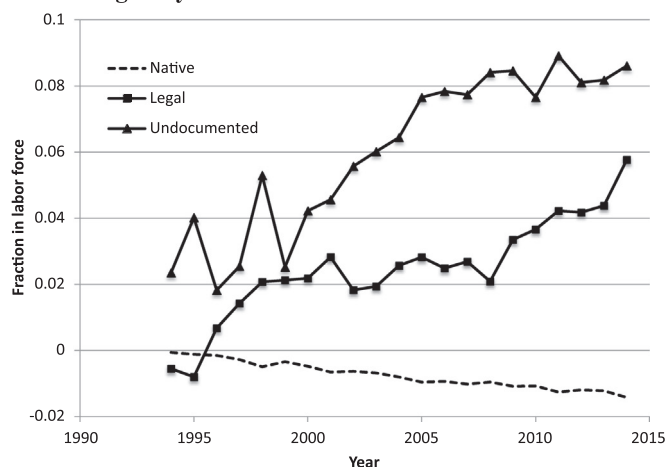
Fig. 3. Trends in labor supply for men, 1994–2014. A. Raw Data. B. Netting out year effects. Notes: The figure illustrates the trend in the probability that a person is in the labor force during the CPS reference week, using the 1994–2014 CPS-ASEC files that contain my reconstruction of the undocumented status indicator.

A. Raw data

B. Netting out year effects

Fig. 4. Trends in labor supply for women, 1994–2014. A. Raw data. B. Netting out year effects. Notes: The figure illustrates the trend in the probability that a person is in the labor force during the CPS reference week, using the 1994–2014 CPS-ASEC files that contain my reconstruction of the undocumented status indicator.

points higher than that of natives, while the participation rate of undocumented immigrants was about 3 or 4 percentage points higher. After 2000, however, the participation rate of native men declined precipitously, while that of legal immigrants remained stable and that of undocumented immigrants rose. By 2014, the participation rate of undocumented immigrants had risen to about 90 percent, that of legal immigrants stood at 87 percent, and that of natives had fallen to 80 percent.
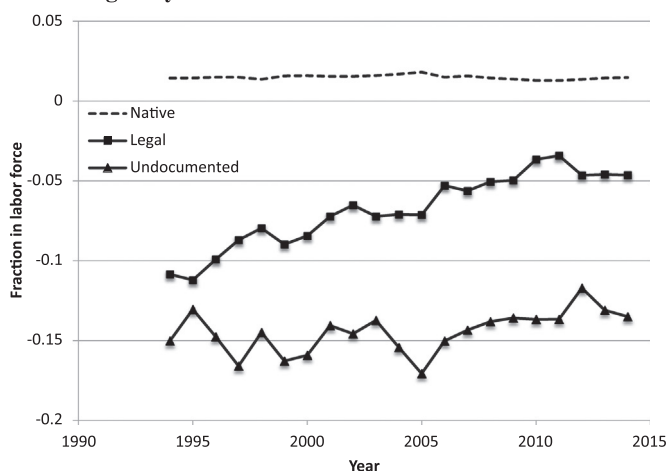
It is easy to visualize the divergence across the three groups by netting out year-specific cyclical factors from each group's trend. In particular, the bottom panel of Fig. 3 redraws the trends after subtracting from each of the trend lines the average labor force participation rate of the population aged 20–64 in each year. There was a long-term decline in the trend-adjusted participation rate of native men—amounting to almost 2 percentage point over the 20-year period. Similarly, there was a steady increase in the participation rate of legal immigrant men, amounting to over 5 percentage points over the period. And there was a steeper increase in the participation rate of undocumented men, amounting to over 6 percentage points.[12] Note also that the cyclically adjusted trend line for the participation rate in each of the groups can be reasonably approximated by a linear trend.

This fact provides a simple way for determining which factors may be responsible for these differential long-term trends in labor force participation.

The two panels of Fig. 4 present the analogous long-term participation trends for women. There are a number of key differences in the trends between men and women. First, the cyclically-adjusted participation rate of native women shown in panel B—unlike that of native men—did not decline over the past two decades; instead, it was very stable. Second, the participation rate of immigrant women—both undocumented and legal—is not higher than those of natives, but is instead lower. Finally, the long-term increase in the participation rate for women was strongest among legal immigrants, rather than among undocumented immigrants.

The trends illustrated in Figs. 3 and 4 raise an important question: Which factors account for the differential trends among natives, legal immigrants, and undocumented immigrants? Even apart from the cyclical fluctuations, the 1994–2014 period witnessed many other important economic shocks, including the well-documented changes in the wage structure that have been studied extensively in the literature (Lemieux, 2006).

To isolate the factors that may be responsible for the differential trends in labor force participation, I use a generalized regression specification that allows me to account for changes in the returns to skills. Specifically, I classify workers into skill groups defined by

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[12] These descriptive differential trends should *not* be interpreted as evidence of a causal relationship between the increase in the participation rate of undocumented men and the concurrent decline in the participation rate of native men.

education and age. I categorize workers into one of four education groups: persons who are high school dropouts (i.e., they have less than 12 years of completed schooling), high school graduates (they have exactly 12 years of schooling), persons who have some college (they have between 13 and 15 years of schooling), and college graduates (they have at least 16 years of schooling). Further, I classify workers into age groups that are composed of 5-year bands: 20–24, 25–29, 30–34, etc. There are, therefore, a total of 36 skill groups in the analysis (i.e., 4 education groups and 9 age groups).

I then stack all the 1994–2014 ASEC cross-sections that contain my reconstruction of the undocumented status identifier and estimate the following logit model in the stacked data:

$$\log \frac{p_i}{1 - p_i} = \beta_1 L_i + \beta_2 U_i + \gamma_1 (L_i \times T) + \gamma_2 (U_i \times T) + \mathbf{X}_i \theta + \delta_t + \varepsilon_i,$$

(3)

where δ_t represents a vector of fixed effects indicating the year of the ASEC cross-section; T is a linear trend (set equal to 1 in 1994); and L_i and U_i are again the dummy variables indicating whether person i is a legal or an undocumented immigrant, respectively. The interactions between the linear trend T and the legal and undocumented status indicator variables, of course, effectively estimate the differential slopes in the cyclically adjusted labor supply trends (relative to natives) illustrated in the bottom panels of Figs. 3 and 4. The regression is estimated using alternative sets of variables in the vector $\mathbf{X}$ to determine the extent to which these background characteristics can "explain" the differences in the labor force participation trends. The regressions are estimated separately in the samples of men and women.

The first column in Panel A of Table 3 estimates the basic regression where there are no controlling socioeconomic characteristics in the vector $\mathbf{X}$, and the coefficients in the vector γ are essentially imposing a linear path on the cyclically adjusted differential trend between each type of immigrant and natives. Consider initially the results in the male sample. The marginal effect implied by the coefficient γ_1 for legal immigrant men is .002, implying that over a 20-year period (the span of the data), the participation rate of legal immigrants increased by about 4 percentage points relative to that of natives (or .002×20).

Table 3
Determinants of differential trends in labor supply (Pooled 1994–2014 ASEC-CPS files).

	Specification			
	(1)	(2)	(3)	(4)
A. Men				
Trend×legal immigrant	0.0022	0.0014	0.0009	0.0011
	(0.0009)	(0.0004)	(0.0003)	(0.0003)
Trend×undocumented	0.0075	0.0025	0.0020	0.0018
	(0.0029)	(0.0011)	(0.0010)	(0.0010)
B. Women				
Trend×legal immigrant	0.0028	0.0018	0.0013	0.0014
	(0.0006)	(0.0002)	(0.0002)	(0.0002)
Trend×undocumented	0.0033	0.0010	0.0004	0.0008
	(0.0016)	(0.0005)	(0.0005)	(0.0005)
Fixed effects included:				
Year	Yes	Yes	Yes	Yes
Skill-year	No	Yes	Yes	Yes
State-year	No	No	Yes	Yes
Country of birth	No	No	No	Yes

Notes: Standard errors are reported in parentheses and are clustered at the skill group level. The dependent variable indicates if the person was in the labor force during the CPS reference week, and the reported coefficients give the average marginal effect in a logit regression. The "trend" variable is a linear trend set to 1 in 1994. The skill-year fixed effects interact the age-education fixed effects with year fixed effects. The state-year fixed effects interact state of residence fixed effects with year fixed effects. The regressions estimated in the male (female) sample have 1,741,119 (1,856,095) observations.

Similarly, the coefficient for undocumented immigrant men is .0075, so that over the 20-year span the relative participation rate of undocumented immigrants increased by about 15 percentage points (or .0075×20).

The remaining columns of the table re-estimate the model by adding variables to the vector $\mathbf{X}$ to determine the sensitivity of the coefficients γ_1 and γ_2 to the inclusion of these socioeconomic characteristics. Column 2, for example, includes a vector of fixed effects indicating the person's skill group (i.e., the person's particular combination of education and age), and these skill fixed effects are allowed to vary over time. The interaction of the skill and period fixed effects, of course, allow for the possibility that the dramatic changes that occurred in the wage structure had independent effects on labor supply. Despite the very general way in which the changes in the wage structure (as well as any other skill-year shocks that independently affect labor supply) are incorporated into the regression, the *relative* participation rate of legal immigrant men is still predicted to increase by around 3 percentage points over a 20-year period, and that of undocumented men by around 5 percentage points over the period.

Although the regression controls for aggregate cyclical effects, and for skill-specific cyclical effects, it may be possible that because the three groups settle in distinct geographic areas, the cyclical effects that affect each of the groups is different due to this diverse geographic clustering. The clustering might matter because of geographic differences in industrial structure, the occupational composition of jobs, and the economic policies pursued by different localities that might affect the three groups differentially.

The specification of the regression model in equation (3) allows me to again determine the extent to which these geographic-cyclical interactions affect the differential trends in labor force participation in a general way. Specifically, the third column of Table 3 adds a vector that interacts the year fixed effects with a vector of state of residence fixed effects, allowing for the possibility that there are state-year specific shocks that affect the labor supply of the three nativity groups differentially.

The marginal effects reported in the third column of Table 3 show that the relevant coefficients γ_1 and γ_2 are still positive and significant. Even after controlling for differential trends in the returns to skills across skill groups and for differential impacts of cyclical trends across geographic regions, a simple fact remains: the relative participation rate of legal immigrants increased by about 2 percentage points over the 1994–2014 period, while the relative participation rate of undocumented immigrants increased by 4 percentage points.

The last column of the table adds a vector of country-of-birth fixed effects to the regression model to account for potential differences in labor supply behavior across different nationalities. Although there are well-known differences in the national origin mix of legal and undocumented immigrants, the inclusion of the country-of-birth fixed effects does not alter the key result that the participation rate of undocumented immigrants grew relative to both that of natives and legal immigrants over the past two decades.

This exercise implies that the "usual suspects" cannot fully explain why the three nativity groups experienced such differential trends in labor force participation over the 1994–2014 period. Even after the regression adjusts for the possibility that economic conditions varied dramatically over time for each of the narrowly defined skill groups, as well as for the possibility that economic conditions varied dramatically among the different geographic regions where the three groups tend to settle, it is still the case that the participation rate of immigrants, and particularly that of undocumented immigrant men, increased relative to that of native-born men.

The fact that there are sizable "unexplained" shifts in labor supply in this period is consistent with other research. Barnichon and Figure (2015), for example, argue that some of the employment decline observed for the average person cannot be traced back to changing economic conditions *per se*, but rather to changes in the "desire" to

work.[13] We do not yet understand, however, which factors are driving these changing preferences towards leisure. The regression analysis summarized in Table 3 suggests that these factors, whatever they may be, are not correlated with specific skill or geographic trends. As a result, about a third of the relative increase in labor force attachment for legal and undocumented immigrant men remains unexplained.[14]

The bottom panel of Table 3 re-estimates the regression model in the sample of women. As with men, the key finding is that the inclusion of the various variables that attempt to control for changes in skill prices or in cyclical conditions cannot explain why the relative labor force participation rate of immigrant women increased relative to that of native women over the 20-year period. Even after adjusting for skill and geographic differences, the relative participation rate of undocumented women increased by about 2 percentage points over the 20-year period, while that of legal immigrant women increased by almost 3 percentage points.

5. Estimates of the labor supply elasticity

The previous section documented that adjusting for differences in the usual list of socioeconomic characteristics cannot fully explain why the labor supply of immigrant men—and particularly that of undocumented men—rose over the past two decades both in absolute and relative terms. This section of the paper explores a related question by examining the extent to which the labor supply of the three nativity groups is linked to systematic changes in the wage. It turns out that the labor supply of immigrants—and particularly the labor supply of undocumented immigrants—is less responsive to wage changes than the labor supply of natives. In fact, it may be reasonable to infer that the labor supply of undocumented men tends to be quite inelastic.

For obvious reasons, it is not possible to easily estimate the responsiveness of labor supply to wage changes at the individual level simply because the wage is not observed for non-workers. Although it is potentially feasible to predict selectivity-corrected wages for the sample of non-workers, and then use a more sophisticated model to estimate various measures of labor supply responsiveness to wage changes, I opt for a simpler (and probably more empirically robust) method. In particular, I aggregate the data into age-education-nativity groups in each of the ASEC cross-sections, and estimate various types of labor supply functions using this aggregate data.

Specifically, I classify persons into the 36 skill groups defined in the previous section. The four education groups indicate if a person is: a high school dropouts; a high school graduate; has some college; or is a college graduate. Similarly, the nine age groups specify if a person is: 20–24 years old, 25–29 years old, and so on. Within each of these skill groups, there are three types of persons: the native-born, the legal immigrants, and the undocumented immigrants.

For each of these age-education-nativity cells, I then calculated (separately by gender) four alternative measures of labor supply at time t: the fraction of the group that is in the labor force in the CPS reference week; the fraction of the group that worked at some point in the previous calendar year; the average log hours worked annually in the sample of workers; and the log of the average hours worked annually across all persons in the age-education-nativity group, including non-

workers.

For each skill group, I also estimated the "market wage" facing the particular age-education group at a point in time. This market wage is given by the average of the hourly wage rate across all workers in the age-education group in each ASEC cross-section.[15] I calculated the average log wage for the skill group at time t separately in the sample of men and women.

By stacking the aggregated annual data for the 108 age-education-nativity groups across all CPS cross-sections between 1994 and 2014, it is then possible to estimate the regression model:

$$S_{asnt} = \phi_a + \phi_s + \phi_n + \phi_t + \phi_{at} + \phi_{st} + \phi_{nt} + \phi_{asn} + \sigma_N(\log \; w_{ast} \times N)$$
$$+ \sigma_L(\log \; w_{ast} \times L) + \sigma_U(\log \; w_{ast} \times U) + \varepsilon_{asnt}, \qquad (4)$$

where S_{asnt} is the averaged measure of labor supply for cell (a, s, n, t), and $\log w_{ast}$ is the mean log wage of workers in the particular age-education group at time t. Note that the log wage is interacted with indicators of whether the cell represents persons who are native born (N), legal immigrants (L), or undocumented immigrants (U), so that the regression allows the wage effect on labor supply to vary across the three nativity groups.

The vectors ϕ_a, ϕ_s, ϕ_n, and ϕ_t represent fixed effects indicating the group's age, education, nativity status, and the year in which the cross-section is observed. The interactions ϕ_{at}, ϕ_{nt}, and ϕ_{st} allow for the impact of the age, education, and nativity fixed effects to vary over time. Finally, the inclusion of the age-education-nativity interactions ϕ_{asn} implies that the impact of the wage on labor supply is being identified from changes that occur *within* an age-education-nativity group, and this wage response is allowed to vary among the three nativity groups.

The top panel of Table 4 reports the estimates of the regression coefficients in the vector $(\sigma_N, \sigma_L, \sigma_U)$ estimated in the sample of men. It is evident that the correlation between labor supply and wages is much stronger for natives than it is for legal immigrant, which in turn is much stronger than it is for undocumented immigrants.

Consider, for example, the coefficients reported in the first column, where the dependent variable is the fraction of the group that is in the labor force in the CPS reference week. The parameter σ_N is 0.170 (with a standard error of 0.018). The effect drops by more than half for legal immigrants, to 0.061 (0.029), and is even smaller and statistically insignificant for undocumented men, or 0.050 (0.030). Similarly, the second column shows the responsiveness of the fraction employed to the wage, again suggesting that the employment rate of natives is far more responsive to wage changes than that of legal immigrants, while the estimate of the elasticity for undocumented immigrants is not statistically different from zero.

It is worth noting that these regressions of the labor force participation or employment rates on the log wage do not estimate what is usually referred to as the "labor supply elasticity" in the neoclassical model of labor-leisure choice. The typical elasticity estimated in that model captures the net of income and substitution effects resulting from a wage change with an interior solution.[16] The estimates of σ_N in the first two columns are instead estimates of the labor supply

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[13] See also Fujita (2014) and Hotchkiss and Rios-Avila (2013). The low explanatory power of the usual economic variables in determining the decline in labor force participation is also noted by Fujita: "Almost all of the decline (80%) in the participation rate since the first quarter of 2012 is accounted for by the increase in nonparticipation due to retirement...The likelihood of those who left the labor force due to retirement or disability rejoining the labor force is small and has been largely insensitive to business cycle conditions in the past, suggesting that the decision to leave the labor force for those two reasons is more or less permanent" (Fujita, 2014, p. 1).

[14] One possible hypothesis is that the participation rate of undocumented workers remained high because the flow of undocumented immigrants slowed down or was reversed due to poor economic conditions, making the supply of undocumented workers relatively more scarce in recent years; see Nakamura (2013).

[15] Because the sample size of some of the age-education-nativity groups is very small, the market wage is calculated at the age-education group level throughout this section, rather than at the age-education-nativity group level. This aggregation helps to minimize the measurement error in the key independent variable in the regression model. The regression model will also include fixed effects for nativity groups, which help to absorb most of the expected wage differences between comparable natives, legal immigrants, and undocumented immigrants.

[16] Hotchkiss and Quispe-Agnoli (2013) provide the only other available estimates of the labor supply response of undocumented workers to wage changes. Using administrative firm-level data for Georgia, they estimate a parameter that measures a person's "willingness to supply their labor to a specific firm" as firms adjust their wages (Hotchkiss and Quispe-Agnoli, 2013, p. 66). Despite the conceptual difference in the parameter being estimated, they also find that the labor supply response for undocumented workers is about 25% smaller than the response for "documented" workers (which include both natives and legal immigrants).

Table 4
Estimates of labor supply elasticities (using 1994–2014 reconstructed CPS-ASEC files).

	Dependent variable				
	Labor force participation	Employment	Average Log hours worked	Log average hours worked (includes non-workers)	
A. Men					
Native	0.170	0.237	0.066	0.357	0.289
	(0.018)	(0.016)	(0.026)	(0.043)	(0.027)
Legal immigrants	0.061	0.101	−0.070	0.106	0.154
	(0.029)	(0.025)	(0.036)	(0.036)	(0.012)
Undocumented	0.051	0.027	−0.062	−0.024	0.080
	(0.030)	(0.043)	(0.066)	(0.089)	(0.012)
A. Women					
Native	0.278	0.312	0.094	0.530	0.463
	(0.013)	(0.014)	(0.031)	(0.035)	(0.032)
Legal immigrants	0.258	0.269	0.178	0.551	0.451
	(0.030)	(0.032)	(0.088)	(0.086)	(0.034)
Undocumented	0.236	0.253	−0.078	0.416	0.497
	(0.050)	(0.059)	(0.115)	(0.140)	(0.047)
Includes state-year and state-skill fixed effects	No	No	No	No	Yes

Notes: Standard errors are reported in parentheses and are clustered at the education-age group level. The unit of analysis in the regressions reported in the first four columns is an age-education-nativity-year cell. All of the regressions include vectors of age fixed effects, education fixed effects, nativity fixed effects, and year fixed effects, as well as age-year, education-year, nativity-year, and age-education-nativity fixed effects. The unit of analysis in the regressions reported in the last column is a state-age-education-nativity-year cell. This regression adds vectors of state-year and state-skill fixed effects. The regressions reported in the first three columns have 2268 observations; the regressions reported in the last column have 75,457 observations.

response at the extensive margin, giving the percentage point change in the labor force participation or employment rate due to a one-percent change in the wage. The point estimates suggest that a 10% change in the wage is associated with a 1.7 point increase in the labor force participation rate of native men, a 0.6 point increase for legal immigrants, and a 0.5 (and insignificant) increase for undocumented immigrants.

The coefficients reported in column 3 of the table are obtained from a regression where the dependent variable is the average log annual hours worked by the sample of workers within an age-education-nativity group, and these coefficients indeed measure the neoclassical labor supply elasticities. The elasticity estimates are positive for natives, negative and statistically significant for legal immigrants, and negative but insignificantly different from zero for undocumented immigrants.
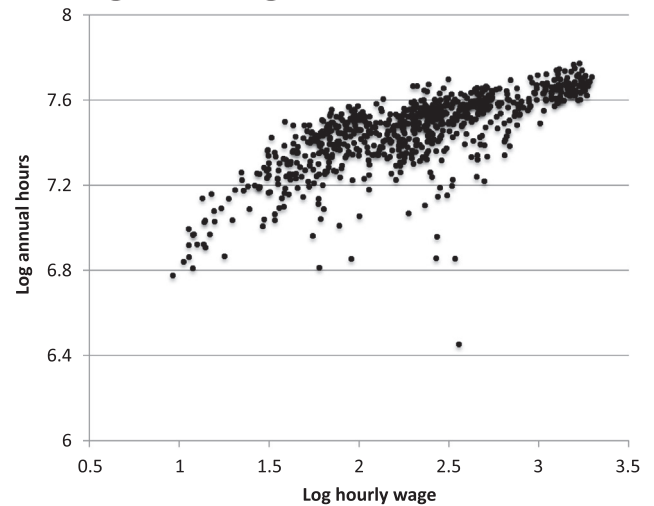
The last two columns of the table report the regression coefficients when the dependent variable is the log of the average number of hours worked across all persons in the (a, s, n, t) cell, including non-workers. In column 4, the elasticity of labor supply for natives, capturing the response at both the extensive and intensive margins, is again positive and significant (the coefficient is 0.357, with a standard error of 0.045). It is less positive, but still significant, for legal immigrants (the coefficient is 0.106 with a standard error of 0.036). And it is statistically equal to zero for undocumented immigrants.

In short, the top panel of Table 4 suggests that the labor supply of undocumented immigrants is far less responsive to systematic changes in the price of skills than that of either legal immigrants, and far less responsive that of native-born persons. In fact, it seems that the labor supply of undocumented immigrant men is very inelastic as the elasticity is not statistically different from zero. This finding is
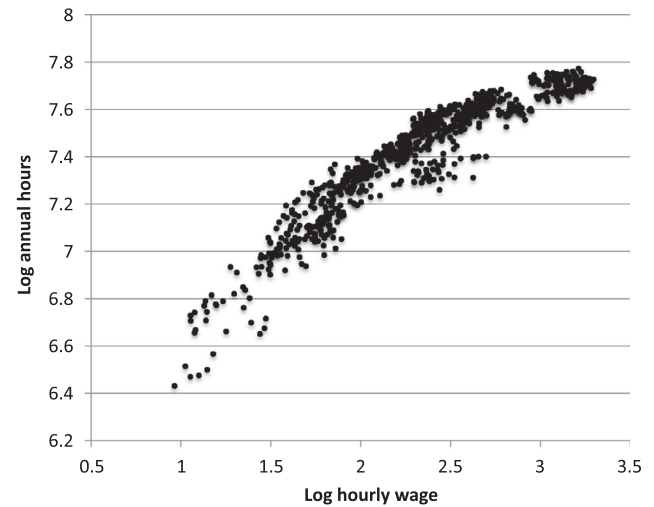
Fig. 5. Relation between hours of work and wages for men (by skill group and year). A. Natives. B. Legal immigrants. C. Undocumented immigrants. Notes: The scatter diagrams illustrate the relation between the log of average annual hours worked (including non-workers) and the log hourly wage of a particular age-education-year group, using the 1994–2014 CPS-ASEC files that contain my reconstruction of the undocumented status indicator.

consistent with a frequent conjecture that is made about undocumented immigration—that "undocumented immigrant men come to the United States to work." The data seem to support this conjecture. Undocumented immigrant men, as identified by the residual method of imputation pioneered by Pew, remain in the labor force or remain employed regardless of the surrounding economic conditions.

It is helpful to visually illustrate the evidence. Fig. 5 presents the raw data—without any type of statistical adjustment—relating the group average of log hours worked (including non-workers) to the group average wage in the sample of men across cells (*a*, *s*, *n*, *t*). It is visually obvious that the "labor supply curve" is quite steep and positively sloped for native men; that the curve is positively sloped, but not quite as steep, for legal immigrant men; and that the curve is essentially flat for undocumented men.

The fact that labor supply is inelastic for undocumented men may have implications for any future analysis that attempts to predict the consequences of legislation or executive orders that regularize the status of undocumented immigrants. Such regularization is likely to be accompanied by an increase in the average wage of undocumented immigrant men. This wage increase is not surprising because the newly legalized status opens up many additional employment opportunities for the previously undocumented workers. A number of studies have examined what happened to the earnings of persons who received amnesty in 1986 as part of the Immigration Reform and Control Act (IRCA). Nearly 3 million illegal immigrants received amnesty at the time, and contemporaneous surveys tracked those immigrants as they received their legal working papers. Their wage rose by around 6 percent between 1989 and 1992 (Kossoudji and Cobb-Clark, 2002; Kaushal, 2006).

The wage increase resulting from any regularization of immigration status would, of course, generate an increase in the labor force participation of the previously undocumented workforce at the extensive margin, as well as income and substitution effects on labor supply at the intensive margin. If the labor supply elasticities estimated in Table 3 were to remain constant after the regularization takes place, the evidence would suggest that we should not expect much of a change in the labor supply of undocumented immigrant men.

However, the regularization of immigration status may change not only the wage that employers offer to previously undocumented immigrants, but also the parameter that measures the labor supply response to the change in the wage. Unfortunately, there does not exist any information that would allow us to reliably assess how the labor supply elasticity may be affected by undocumented status *per se*.

Put differently, the elasticity of labor supply (however defined) is unlikely to be constant along the labor supply curve. Undocumented immigrants are obvious outliers in their labor force participation and employment propensities. The elasticity calculated at such an extreme point in the labor supply curve may be quite different than what would be measured for an "average" person. This implies, of course, that regularization of status might also affect the value of the elasticity as it might change the preference mapping of undocumented immigrants, complicating attempts to predict the final impact of a change in undocumented status.

The bottom panel of the table re-estimates the regression models in the sample of women. The labor supply elasticities for native women are roughly similar as those estimated for native men. In column 4, for example, the labor supply elasticity is 0.357 (0.043) for men and 0.530 (0.035) for women. This finding is consistent with recent evidence showing a dramatic convergence in the magnitude of the labor supply elasticities for men and women (Blau and Kahn, 2007). Given the nature of the evidence for female labor supply reported in earlier sections of this paper, however, it is not surprising that the gender similarity in labor supply elasticities does not hold for immigrants. Immigrant women—both legal and undocumented—have much higher labor supply elasticities than immigrant men. As a result, any wage increase resulting from the potential regularization of status for

undocumented immigrant women is likely to increase their labor supply.

It is possible that the lack of responsiveness of labor supply to wages in the sample of undocumented immigrant men could arise because the various nativity groups were differentially affected by cyclical fluctuations in the past two decades. Although the overall impact of the business cycle is netted out through the period effects (as well as the interaction of these period fixed effects with education, experience, and nativity group fixed effects), it may well be that the different groups are affected differentially by cyclical fluctuations because the three groups tend to settle in different geographic regions. It is easy to expand the regression model in equation (4) to account for region-specific differences in economic conditions.

Specifically, I conduct an alternative aggregation of the data by classifying persons into region-age-education-nativity cells. The generic regression model then becomes:

$$
\begin{aligned}
S_{rasnt} = {} & \phi_r + \phi_a + \phi_s + \phi_n + \phi_t + \phi_{rt} + \phi_{at} + \phi_{st} + \phi_{nt} + \phi_{asn} \\
& + \sigma_N(\log\ w_{rast}\ \times N) + \sigma_L(\log\ w_{rast}\ \times L) + \sigma_U(\log\ w_{rast}\ \times U) \\
& + \varepsilon_{asnt},
\end{aligned} \tag{5}
$$

where *r* indicates the state of residence of person *i*; the vector ϕ_r represents a vector of state fixed effects; and the interaction $\phi_{r \cdot t}$ allows these state effects to vary over time.

The last column of Table 4 reports the labor supply elasticities resulting from these alternative regressions using the measure of labor supply that gives the log of the average annual hours worked (including non-workers). It is clear that the labor supply of native men continues to be most responsive to wage changes, while the labor supply of undocumented men continues to be least responsive. Note, however, that the elasticity for undocumented men, though about 70% smaller than the respective elasticity for native men and half the size of the elasticity for legal immigrants, is no longer insignificantly different from zero.[17]

6. Summary

The last decade has witnessed a series of attempts by both the legislative and executive branches to enact some form of comprehensive immigration reform. A central component of such reform involves the creation of some type of "path to citizenship" for the 11.4 million undocumented immigrants currently residing in the United States.

This paper uses newly developed methods that attempt to impute undocumented status for each person sampled in the Current Population Surveys. The existence of such an undocumented identifier at the individual level allows a full examination of the differences in various economic outcomes that distinguish the undocumented population from the population of legal immigrants, as well as from the native-born.

In particular, the paper examines the labor supply behavior of undocumented immigrants, both at a point in time as well as the trends over the 1994–2014 period, a period marked both by rapid economic growth as well as a deep recession. The analysis yields a number of new insights into the labor supply behavior of this large population:

1. Undocumented immigrant men are far more likely to participate in

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[17] The estimates of the labor supply elasticities reported in Table 4 rely on my reconstruction of the undocumented status indicator in all ASEC files between 1994 and 2014. It is easy to show that the finding of relatively inelastic labor supply for undocumented workers is not an artifact of my imputation method. Appendix Table A1 shows that the evidence is very similar if I estimated the comparable regressions in the cross-section obtained by pooling the 2012–2013 ASEC files provided by the Pew Research Center. In short, to the extent that the residual method pioneered by Pew to impute undocumented status at the micro level is reasonably accurate, the evidence is unambiguous: The labor supply of undocumented men is relatively inelastic.

the labor force than other groups, while undocumented immigrant women are far less likely to be in the labor force.

2. The participation gap that distinguishes undocumented men from the other groups widened over the past twenty years. By 2014, the probability that an undocumented man participated in the labor force in the CPS reference week was about 10 percentage points larger than that of native men.

3. The labor supply of undocumented workers is not as responsive to wage changes as the labor supply of other groups in the population. In fact, the data clearly suggest that the labor supply of undocumented men tends to be quite inelastic.

It is important to emphasize that the analysis reported in this paper represents but a first step in any evaluation of alternative regularization proposals. Many more facts need to be established about the economic status and well being of the undocumented population before a full assessment can be conducted. It is equally important to further assess the accuracy of the imputation methods used to impute a person's undocumented status at the micro level. The empirical analysis reported in this paper, however, illustrates the promise and importance of the availability of microdata files that contain an undocumented identifier.

Appendix A

See Appendix Fig. A1
See Appendix Table A1
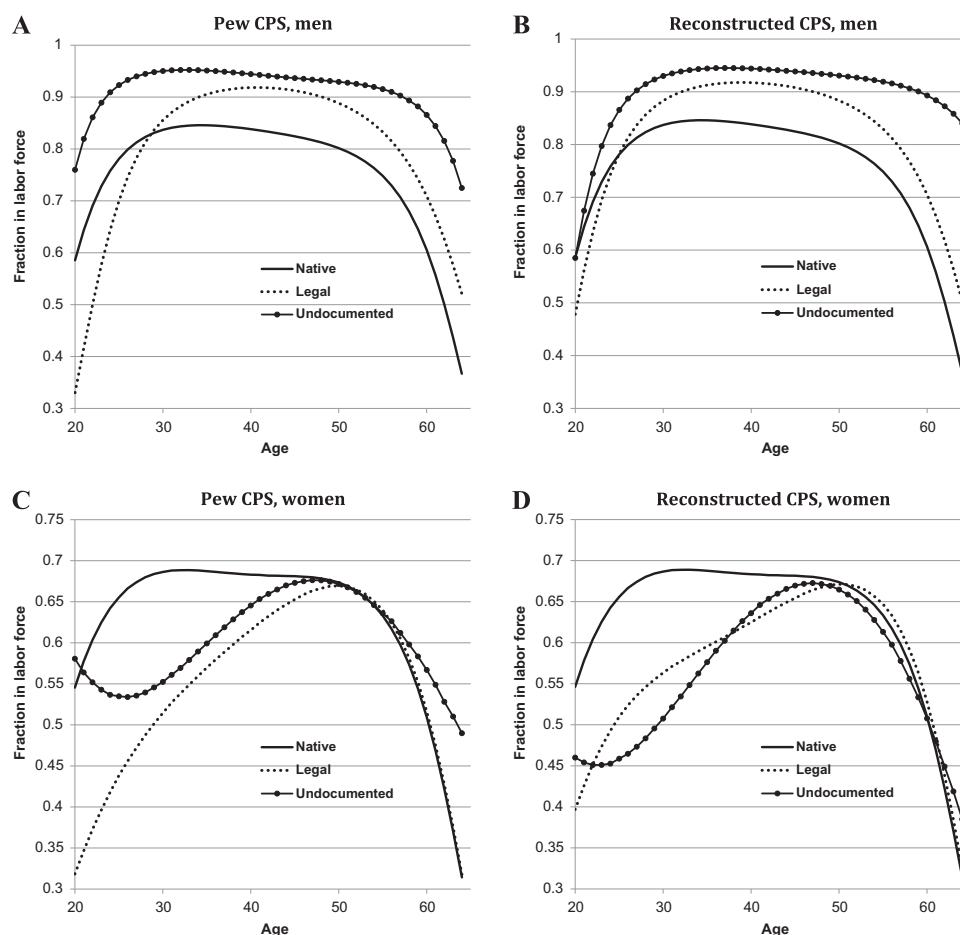
Fig. A1. Predicted labor force participation profiles adjusted for education, 2012–2013. A. Pew CPS, men. B. Reconstructed CPS, men. C. Pew CPS, women. D. Reconstructed CPS, women. Notes: The predicted age-participation profiles are obtained from a logit regression of the probability that a person is in the labor force during the CPS reference week on age (entered as a fourth-order polynomial), using the pooled 2012–2013 CPS-ASEC files.

Table A1

Labor supply elasticities in Pew and in reconstructed data (Pooled 2012–2013 CPS files).

	Dependent variable				
	Labor force participation	Employment	Average log hours worked	Log average hours worked (includes non-workers)	
Pew ASEC files					
A. Men					
Native	0.214	0.196	0.096	0.356	0.400
	(0.044)	(0.038)	(0.043)	(0.060)	(0.043)
Legal	0.102	0.069	0.021	0.139	0.172
	(0.037)	(0.034)	(0.049)	(0.062)	(0.039)
Undocumented	0.031	−0.004	−0.040	−0.006	0.075
	(0.041)	(0.034)	(0.058)	(0.065)	(0.036)
B. Women					
Native	0.198	0.263	0.405	0.524	0.575
	(0.056)	(0.060)	(0.103)	(0.179)	(0.049)
Legal	0.120	0.176	0.338	0.378	0.467
	(0.060)	(0.064)	(0.105)	(0.186)	(0.042)
Undocumented	0.047	0.106	0.258	0.202	0.390
	(0.063)	(0.065)	(0.106)	(0.194)	(0.062)
Reconstructed ASEC files					
C. Men					
Native	0.202	0.176	0.045	0.302	0.j388
	(0.045)	(0.036)	(0.049)	(0.060)	(0.041)
Legal	0.100	0.064	−0.017	0.113	0.204
	(0.037)	(0.030)	(0.052)	(0.059)	(0.037)
Undocumented	0.004	−0.049	−0.097	−0.008	0.012
	(0.046)	(0.035)	(0.067)	(0.076)	(0.032)
D. Women					
Native	0.206	0.275	0.417	0.510	0.560
	(0.055)	(0.055)	(0.104)	(0.164)	(0.047)
Legal	0.153	0.201	0.360	0.402	0.480
	(0.059)	(059)	(0.108)	(0.174)	(0.042)
Undocumented	−0.015	0.048	0.255	0.085	0.202
	(0.059)	(0.059)	(0.106)	(0.171)	(0.059)
Includes state-skill fixed effects	No	No	No	No	Yes

Notes: Standard errors are reported in parentheses and are clustered at the education-age group level. The pooled 2012–2013 CPS data are treated as a single cross-section, and the unit of analysis in the first four columns is an age-education-nativity cell. All regressions include vectors of education fixed effects, age fixed effects, and nativity fixed effects. The unit of analysis in the last column is a state-age-education-nativity cell, and this regressions adds vectors of state-education and state-age fixed effects. The regressions in the first four columns have 108 observations; the regressions in the last column have 4,401 observations.

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