The Expected Impact of State Immigration Legislation on Labor Market Outcomes

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Abstract

In response to the dramatic rise in the number of unauthorized immigrants to the United States, every state has passed some form of immigration legislation. These laws appear to be predicated on a belief that unauthorized immigrants impose greater costs than benefits to state and local communities, including the labor market. The purpose of this paper is to examine some evidence on what workers should expect if the immigration legislation is successful in eliminating undocumented workers from states' labor markets. © 2012 by the Association for Public Policy Analysis and Management.

INTRODUCTION

> "The State of Alabama [Oklahoma] finds that illegal immigration is causing economic hardship and lawlessness in this state . . . "
>
> Alabama HB 56 (http://www.ncsl.org/documents/statefed/AlabamaH56.pdf)
> [Oklahoma HB 1804 (http://ssl.csg.org/dockets/29cycle/29A/2009adocketbills/1929A04ok.pdf)]

> "The legislature declares that the intent of this act is to make attrition through enforcement the public policy of all state and local government agencies in Arizona. The provisions of this act are intended to work together to discourage and deter the unlawful entry and presence of aliens and economic activity by persons unlawfully present in the United States."
>
> Arizona SB 1070 (http://www.azleg.gov/legtext/49leg/2r/bills/sb1070s.pdf)

> "Illegal immigration matters."
>
> Indiana SB 590 (http://www.in.gov/legislative/bills/2011/PDF/IN/IN0590.1.pdf)

According the National Conference of State Legislatures (NCSL), state legislative interest in immigration issues spiked in 2005, when 300 immigration bills were introduced into state legislatures; 39 of them survived to become law that year.[1] Activity nearly doubled in 2006, then exploded in 2007 with 1,562 bills introduced and 240 becoming law. Legislative activity on immigration remained roughly at this

[1] Details of state laws introduced and passed from 2005 through 2011 can be found on the National Conference of State Legislatures Immigration Issues Web site (http://www.ncsl.org/issues-research.aspx?tabs=951,119,851#951).

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level through 2011. The NCSL attributes this level of growth in state-level legislative activity to frustration about inaction at the federal level addressing the significant growth in unauthorized immigration that has occurred in the United States over the past 20 years. Between 1990 and 2010, it is estimated that the unauthorized population in the United States has grown at an average rate of 9 percent per year (see Passel & Cohn, 2011; U.S. Immigration and Naturalization Service, Office of Policy and Planning, 2003). The total U.S. population grew at under 1 percent per year over the same time period (Mackun & Wilson, 2011).

Since 2005, nine states have passed high-profile, omnibus immigration legislation. Arizona SB 1070 has been among the most visible (although Oklahoma appears to be the first) and has provided a template for other states attempting to pass similar legislation. Many of the legislative Acts have been titled *Taxpayer and Citizen Protection Act*, emphasizing the political environment in which these laws have been considered by various state legislatures. The language above reflects the expectation that if all of the unauthorized immigrants were to disappear (or, *attrit*, using Arizona's language), economic conditions (primarily labor market conditions) and lawlessness would improve. In fact, legislators in Alabama have claimed that the postrecession drop in Alabama's unemployment rate is a direct result of Alabama's new immigration law (Munro, 2011). These and hundreds of state laws addressing concerns about unauthorized immigration have been passed without the benefit of much research on the impact of or expected benefit from arresting the flow of unauthorized immigrants. The purpose of this paper is to provide some evidence as to what documented workers might experience in terms of employment and wages if these laws are successful in what they are designed to do—the removal of unauthorized immigrants.

DeFreitas (1988) and Hotchkiss, Quispe-Agnoli, and Rios-Avila (2012) investigate the wage impact of the presence of undocumented workers, finding only modest impacts that vary across worker skill level and across sectors. Brown, Hotchkiss, and Quispe-Agnoli (2012) present evidence that employing undocumented workers gives firms a competitive advantage, suggesting that the lower wages paid to undocumented workers likely derives from firms taking advantage of the workers' limited job opportunities and mobility, rather than reflecting merely lower productivity of the workers. And this is where the concern lies. If equally productive undocumented workers are willing to work for much lower wages than documented workers, then documented workers cannot compete for jobs unless they, too, accept the lower wages. One major assumption is required to come to this conclusion: Documented and undocumented workers are equally productive and are, therefore, competing for the same jobs.

This paper investigates that assumption directly by asking the question: How much of the observed wage differential between documented and undocumented workers is accounted for by undocumented workers' willingness to accept lower wages, and how much is accounted for by differences in productivity? We are also able to directly explore whether documented workers are displaced as their firms employ undocumented workers. The answers to these questions will provide a reality check for the unmistakable expectation of improved labor market conditions for documented workers that state legislatures held when passing immigration reform bills.

THEORETICAL FOUNDATION

The possibility that the wage differential observed between documented and undocumented workers merely reflects undocumented workers' willingness to accept lower wages because of limited grievance and job opportunities lies at the heart of legislatures' concerns about the *economic hardship* imposed by undocumented workers. The ability of employers to pay wages not fully reflecting a worker's productivity because that worker is less sensitive/responsive to wages is referred to as monopsonistic discrimination. The model of monopsonistic discrimination was developed by Robinson (1933) to describe a labor market in which two groups of equally productive workers (men and women) are paid different wages because they differ in their elasticities of labor supply (sensitivity to wages). Robinson theorized that women were paid less than men because they were limited in their alternative labor market options as a result of their husbands' employment situations. Boraas and Rodgers (2003), among others, provide empirical evidence that, in occupations where women are plentiful, downward pressure on male wages results from having to compete with a substitute labor input that is less sensitive to wage changes.

The argument is analogous for undocumented workers. If undocumented workers are less sensitive to wages, and they are substitutes for documented worker labor, then their presence in the labor market puts downward pressure on wages of documented workers, and getting rid of them will improve the labor market outcomes of documented workers. The empirical question, then, is how much of the lower wage paid to undocumented workers reflects their lower sensitivity to wages. If most of the lower wage is actually the result of the lower productivity of undocumented workers (rather than their lower labor supply elasticity), then getting rid of undocumented workers through restrictive immigration legislation will not necessarily improve the labor market outcomes of documented workers. In fact, if documented and undocumented workers differ in productivities in such a way that they are complementary inputs to the production process, eliminating undocumented workers may adversely affect employment of documented workers.

The key to determining whether the wages paid to undocumented workers are likely to put downward pressure on wages of documented workers is the determination of the degree to which employers exercise monopsonistic power over undocumented workers. The presence of monopsonistic employer power has been identified in a number of settings. Manning's (2011) contribution to the *Handbook of Labor Economics* thoroughly explores the empirical evidence and theoretical foundation for the presence of monopsony power in a variety of labor markets, concluding that "All labor economists should take imperfect competition seriously" (p. 1031). In addition, the April 2010 issue of *Journal of Labor Economics* contains eight articles finding various degrees of monopsony power, both in the United States and in other countries. Earlier evidence of monopsony power, and an environment ripe for monopsony power, has been found in labor markets for women (Barth & Dale-Olsen, 2009; Hirsch, Schank, & Schnabel, 2010; Ofek & Merrill, 1997), for blacks (Raphael & Riker, 1999), and even in the world of sports (Scott, Long, & Somppi, 1985; Scully, 1989; Zimbalist, 1992).

The labor market for undocumented workers meets the classic conditions in which employers can be successful in practicing monopsonistic discrimination—identifiable characteristics on which groups of workers can be segmented, and one of the groups of workers being limited in their employment opportunities. First of all, documented and undocumented workers in the United States are believed to be distinguishable from one another without much effort. Data from the U.S. Census American Community Survey (ACS) and from the Department of Homeland Security (DHS) suggest that between 40 and 60 percent of Mexicans in the United States are undocumented.[2] In addition, DHS estimates for January 2008 that 61 percent

[2] The 2008 ACS estimates that 11.4 million people in the United States were born in Mexico (http://www.census.gov/population/www/socdemo/hispanic/cps2008.html). The DHS estimates that 7.03 million undocumented workers from Mexico were in the United States in 2008. (http://www.dhs.gov/xlibrary/assets/statistics/publications/ois_ill_pe_2008.pdf).

of unauthorized immigrants come from Mexico (Hoefer, Rytina, & Baker, 2009). Clearly not all Hispanics are undocumented, but in the absence of time-consuming document verification, ethnicity and language proficiency may be used by employers as a proxy for their best guess of whether a worker is undocumented (see Dávila, Bohara, & Saenz, 1993 for evidence that merely an accent can lead employers to assume an English-proficient Mexican worker is undocumented).

Second, because of fear of being deported, undocumented workers are likely unwilling to complain about low wages or poor work environments, which necessarily limits employment opportunities. It is also not unreasonable to expect that the more employers to whom undocumented workers expose themselves, the higher the risk of deportation. And indeed, it is likely that there are many firms who will simply refuse to hire undocumented workers or that undocumented workers are geographically constrained by the support (or lack) of social networks. Kossoudji and Cobb-Clark (2000) document the limited occupational mobility among a group of undocumented male Mexican workers and note the apparent "lack of relationship between wages and job mobility of any kind" (p. 94).[3] All of these factors reduce employment opportunities of undocumented workers, everything else held constant, and is why we would expect labor supply elasticities to be lower among undocumented workers than among documented workers. Stark (2007) presents a compelling theoretical mechanism through which the work effort of undocumented workers is increased as their probability of deportation increases, which in turn expands the wedge between undocumented worker productivity and their wage. Semple (2008) offers anecdotal evidence that undocumented workers are at the mercy of their employers. An undocumented worker reported to Semple that an employer refused to pay him about $1,000 he was owed for work performed, but that "fear [of being deported] kept my mouth shut." In addition, Orrenius and Zavodny (2009a) find that recent legislative actions by states have weakened the labor market position of undocumented workers even further, increasing the opportunity of employers to pay wages below productivity levels.

Using employer-employee matched data, this paper estimates labor supply elasticities among documented and undocumented workers in the state of Georgia. With those elasticities, we are then be able to determine how much of the observed wage differential between documented and undocumented workers results from differences in labor supply elasticities and how much is reflective of differences in worker productivity. Based on these calculations, we can estimate how much economic hardship in the labor market is expected to be eliminated with successful removal of undocumented workers.

THE DATA

The primary data used for the analyses in this paper are the Employer File and the Individual Wage File, compiled by the Georgia Department of Labor for the purposes of administering the state's Unemployment Insurance (UI) program. These data are highly confidential and strictly limited in their distribution. The data are available from the first quarter of 1990 through the fourth quarter of 2006. The Employer File provides an almost complete census of firms, covering approximately 99.7 percent of all wage and salary workers (Committee on Ways and Means, 2004).[4]

[3] Also see further evidence of wage reductions that derive from restriction of employment opportunities in the postbellum hiring restrictions in the South (Naidu, 2010).

[4] Certain jobs in agriculture, domestic services, and nonprofit organizations are excluded from UI coverage (Committee on Ways and Means, 2004). For information about which workers are covered, see U.S. Department of Labor (2008).

The establishment-level information includes the number of employees, the total wage bill, and the NAICS classification of each establishment. The Individual Wage File, which links individual workers to their employer, is used to construct workforce characteristics at the firm level, such as workforce churning and the share of new hires that is undocumented. We take advantage of the longitudinal nature of the data to calculate the firm's age, turnover rates, and worker tenure and labor market experience. The data also contain a six-digit NAICS industry code and the county of location, allowing us to construct or merge in industry- and county-level indicators, such as county unemployment rate.

Regrettably, the data set contains no information about workers' demographics or, more importantly, immigration status. However, again making use of the longitudinal nature of the data, we estimate an individual fixed effects model, allowing us to control for individual characteristics that do not vary over time (e.g., innate human capital, native born).

Using SSNs to Identify Undocumented Workers

Details of how the Social Security number (SSN) is used to identify undocumented workers are contained in Appendix A.[5] The abbreviated version is that there are some easily identifiable ways in which an SSN is determined to be invalid. We conclude that some of those reasons are either errors or the result of incomplete record keeping by the firm. We restrict our identification of undocumented workers to invalid SSNs that are more likely to have been generated by the worker—numbers that look valid, but are not. Workers with invalid SSNs for any other reason are considered neither undocumented nor documented and thus are excluded from the analysis; this will clearly undercount the actual number of undocumented workers. However, all workers, regardless of SSN classification, are included in counts of aggregate firm employment.[6]

Figure 1 plots the prevalence of undocumented workers in the seven broadly defined sectors with the highest incidences. The concentration of workers in these sectors is confirmed nationally by Fortuny, Capps, and Passel (2007).[7] The pattern of growth is also consistent with their estimate that 72 percent of unauthorized immigrants in Georgia arrived in the last 10 years.

Fortuny, Capps, and Passel (2007) estimate that 4.5 percent of the workforce in Georgia was undocumented in 2004. In our sample, 1.0 percent of workers are classified as undocumented in 2004, implying that the sample used for the analysis in this paper is capturing about 22 percent of all undocumented workers in the state of Georgia. This is a respectable representation, given that to be included in the sample all workers have been included on the firm's wage report in the

[5] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[6] As pointed out by an anonymous referee, workers with invalid SSNs excluded from the analysis demonstrate a noted seasonality to their employment (see Figure A1 in Appendix A). Because seasonal undocumented workers are likely to be even less sensitive to wages than nonseasonal undocumented workers, their exclusion from the analysis will likely result in an estimate of labor supply elasticities that are larger than would be estimated if seasonal workers were included in the undocumented worker sample. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[7] Fortuny, Capps, and Passel (2007) estimate that nationally in 2004, the percent of workers in leisure and hospitality and construction that was undocumented was 10 percent each, 9 percent of workers in agriculture, and 6 percent each in manufacturing, professional, and business services, and other services. Also see Pena (2010).

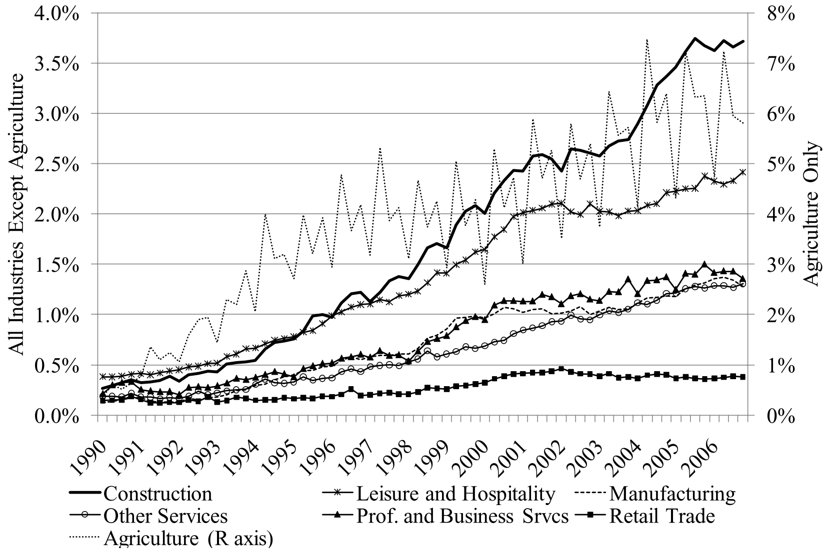

Figure 1. Percent of Workers That Is Undocumented by Broad Industry, 1990:1 to 2006:4.

first place, and we are being very conservative in the identification of workers as undocumented. Note that the identification process we use in this paper does not make any assumptions about whether the employer knows a worker is documented or undocumented. In addition, the goal of the conservative identification process is to end up with a sample in which we can have a high degree of confidence that the sample is representative of the undocumented workforce, not to actually count the number of undocumented workers in Georgia. Evidence supporting that confidence is detailed in Appendix A.[8]

Further, it is not essential for an employer to be able to distinguish between valid and invalid SSNs to practice monopsonistic discrimination. All that is necessary is that the employer is able to use some identifying characteristic(s) to distinguish between groups of workers. In this case, ethnic Hispanic characteristics and limited English skills are features that employers use to identify (within a certain degree of accuracy) which workers are likely undocumented.

A subset of workers identified as undocumented will have what is called an Individual Tax Identification Number (ITIN) reported as their SSN. In 1996, the Internal Revenue Service (IRS) introduced the ITIN to allow individuals who had income from the United States to file a tax return (the first ITIN was issued in 1997). It is simply a *tax processing number*, and does not authorize an individual to work in the United States. Employers are instructed by the IRS to "not accept an ITIN in place of an SSN for employee identification for work. An ITIN is only available to resident and nonresident aliens who are not eligible for U.S. employment and need identification for other tax purposes."[9] ITIN numbers have a specific numbering scheme

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[9] See Internal Revenue Service (2011) and Internal Revenue Service (2012).

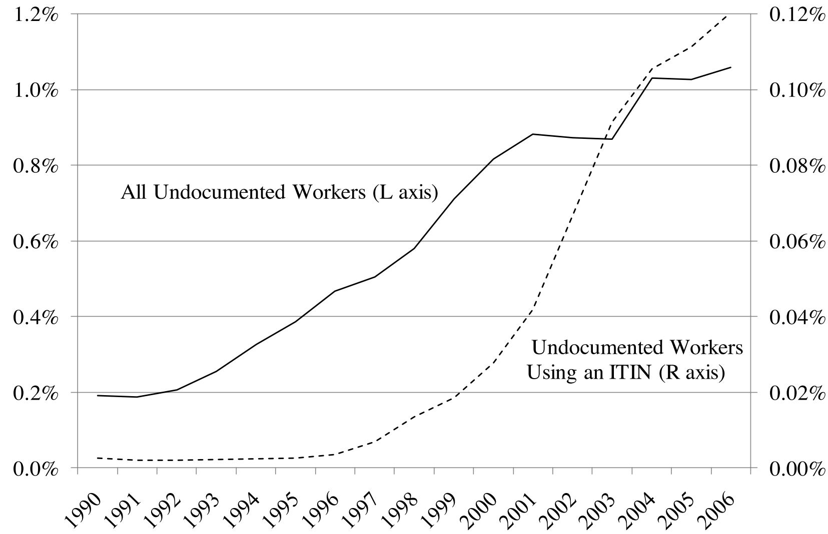

Figure 2. Percent of All Workers Undocumented and Percent Using ITIN, 1990: 1 to 2006:4.

that makes them readily identifiable (see Appendix A).[10] Figure 2 plots all workers identified as undocumented and the subset using ITIN numbers. The sample of workers with ITIN numbers is much smaller, and this subset of undocumented workers is likely to be more established in the U.S. economy and to have developed more extensive networks. These factors would likely result in an estimate of labor supply elasticities that are larger than would be estimated for the population of undocumented workers. However, these workers, among the undocumented, are also the most likely to use the same SSN across employers; this is necessary to control for individual worker fixed effects.

Sample Means

1997 is the first year of analysis, as this is the first year in which ITIN numbers were issued. Table 1 presents some means for four groups of workers: (1) the full sample of documented workers, (2) a three of 1,000 random sample of documented workers, (3) the full sample of undocumented workers, and (3) undocumented workers using an ITIN as their SSN. The full sample of documented workers of over 62 million observations is too large for estimation with two sets of high-order fixed effects, so a three of 1,000 sample is used. The sample is constructed by selecting a random sample of all unique, valid SSNs, then including all observations corresponding to each SSN.

Undocumented workers, on average, earn roughly half of the average documented worker wages (quarterly earnings, unconditional means). Some of this wage differential is likely because of the concentration of undocumented workers in lower paying industries or occupations, undocumented workers working fewer hours, or

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the upward push in the occupational chain of documented workers with the arrival of lower skilled undocumented workers (Pedace, 2006). The undocumented wage gap increases as workers move up the wage distribution. There is virtually no difference in earnings, on average, among lower paid workers (those earning less than $3,000 in real terms per quarter). As will be discussed in more detail below, a

Table 1. Sample means, 1997 to 2006.

	Documented		Undocumented	
	Full sample	Three of 1,000 random sample	Full sample	ITIN only
Wage (real quarterly earnings)	$8,514	$8,575	$4,190	$4,886
	(11,974)	(11,805)	(6,112)	(4,547)
Workers earning less than R$3,000/quarter	$1,202	$1,204	$1,140	$1,342
	(880)	(880)	(880)	(888)
Workers earning at least R$3,000/quarter	$11,878	$11,827	$6,836	$6,848
	(13,156)	(12,883)	(7,351)	(4,569)
Worker tenure (number of quarters)	12.64	12.99	4.20	4.11
	(14.32)	(14.46)	(5.12)	(3.84)
Worker labor market experience (number of quarters since 1990)	27.31	27.66	6.75	4.96
	(16.80)	(16.85)	(7.47)	(4.40)
Percent of workers separating	17.0%	16.4%	35.6%	24.1%
Separating to employment	*na*	9.0%	7.6%	3.7%
Separating to nonemployment	*na*	7.5%	28.0%	20.4%
Percent of workers newly hired	17.2%	16.5%	37.3%	28.6%
Recruited from employment	*na*	9.0%	7.2%	3.7%
Recruited from nonemployment	*na*	7.5%	30.1%	24.9%
Share of firms' new hires that is undocumented	1.0%	1.0%	12.2%	17.9%
Percent of workers in firm's six-digit NAICS industry that is undocumented	0.81%	0.79%	3.39%	3.24%
Age of employer (number of quarters since 1990)	36.70	37.18	31.75	30.52
	(16.48)	(16.13)	(17.55)	(19.33)
Employer size (number of workers)	2,796.9	2,943.7	1,287.4	330.7
	(6,772)	(6,915)	(4,081)	(1,636)
Worker churning among documented workers employed at the firm	26.5%	25.8%	46.2%	31.1%
Distribution by sector skill classification				
Low skill	*na*	12.9%	33.2%	27.8%
Medium skill	*na*	58.2%	62.4%	68.2%
High skill	*na*	28.9%	4.4%	3.9%
NAICS sector shares (U.S. share)[a]				
Natural Resources and Agriculture (1%)	1%	1%	6%	3%
Construction (6%)	6%	5%	16%	28%
Manufacturing (15%)	13%	14%	16%	8%
Transportation and Utilities (4%)	5%	5%	2%	1%
Wholesale Trade (5%)	5%	5%	4%	4%
Retail Trade (13%)	14%	14%	6%	7%
Financial Activities (7%)	6%	6%	2%	2%
Information (3%)	4%	4%	0%	0%
Professional and Business Services (17%) (includes temporary services)	16%	16%	19%	15%
Education and Health Services (15%)	18%	19%	2%	2%

Table 1. Continued.

	Documented		Undocumented	
	Full sample	Three of 1,000 random sample	Full sample	ITIN only
Leisure and Hospitality (10%)	11%	10%	23%	23%
Other Services (5%) (includes private household, laundry, and repair and maintenance services)	3%	3%	3%	7%
Number of observations	152,941,364	427,687	1,231,379	71,430

Notes: Standard errors are in parentheses. Wages are real quarterly earnings, deflated by the chained price index for personal consumption expenditure as of 2006, quarter 4. Full-time status is defined as earning at least $3,000 (real $) per quarter (see Dardia et al. 2005; Hotchkiss, Pitts, and Robertson, 2006). Sample means correspond to workers observed from 1997 to 2000 inclusively. Numbers in these cells do not reflect number of observations used in estimation as the estimation procedure requires two observations per worker to identify the fixed effect, thus reducing the usable sample size. Quartile ranges are defined within group. Worker flows is the sum of hires and separations and job flows is net employment change. *na* = not available (sample too large to calculate in Stata).

$CHURN_{jt} = \frac{[Hires+Separations]-[|N_{jt}-N_{jt-1}|]}{[(N_{jt}+N_{jt-1})/2]}$, N_{jt} is number of workers at firm j in time t (Burgess, Lane, & Stevens, 2001).

[a]*Source:* U.S. Census County Business Patterns (http://censtats.census.gov/cbpnaic/cbpnaic.shtml), March 2000.

more relevant wage comparison will be one that is calculated within firm (a comparison between workers employed by the same firm). The average wage of documented workers in firms that hire undocumented workers is $5,847, and the average undocumented worker earnings at the same firms is $4,789, putting the within-firm undocumented worker wage penalty at roughly 18 percent. Others have found wage penalties associated with being unauthorized ranging from 14 (Kossoudji & Cobb-Clark, 2002) to 42 percent (Rivera-Batiz, 1999). A penalty falling on the lower end of this wage penalty range is likely reflecting the higher average wages typically earned by undocumented workers using an ITIN number.

Undocumented workers are likely to have been on their current job a shorter amount of time, have less labor market experience, and reflect greater separation behavior (not holding anything else constant). Undocumented workers appear to be concentrated among smaller employers who experience a greater degree of churning among its documented workforce, suggesting a need for workforce flexibility, as has been documented among firms that employ undocumented workers (Morales, 1983–1984). The smaller firm size could be reflecting the typical size of firms in industries more likely to hire undocumented workers. The larger separation and new hire rates among the full sample of undocumented workers (vs. ITIN workers) validates our restriction to undocumented workers with ITIN numbers only; if multiple workers are using the same invalid SSN across different employers at different time (which is more likely among the non-ITIN group), that SSN will register more separations and new hires than an SSN that is used more consistently by only one person, which is expected to be the case with ITINs.

There are some notable differences in the distribution of workers across industry skill intensity and NAICS classification (Appendix B defines the sector classifications and describes the construction of skill classifications).[11] Most notably, undocumented workers are more concentrated in agriculture, construction, and leisure and hospitality. In addition, although similar shares of documented and undocumented workers are found in industries classified as medium skill, there is a much greater (less) concentration of undocumented workers in low (high) skill industries. Note that the distribution of documented workers across industries matches the U.S. distribution (in parentheses) fairly closely.

EMPIRICAL FRAMEWORK AND ESTIMATION

The full theoretical derivation of the estimating equations is found in Appendix C.[11] In this section, the final estimating equations are presented and interpreted.

Empirical Specification of Worker Separations

As seen in the derivation provided in the Appendix C, estimating workers' elasticities of labor supply comes from the estimation of workers' separation elasticities.[11] These are obtained by estimating the following linear probability separation equation separately for documented workers ($k = d$) and for undocumented workers ($k = u$):

$$S_{injt} = \gamma_0^k + \gamma_1^k \ln(w_{injt}) + \gamma_2^k h_{nt-4} + \gamma_3^k X_{injt} + \delta_i + \varphi_n + \varepsilon_{injt} \tag{1}$$

where S_{injt} is the probability that worker i separates from employer n (in industry j) in quarter t.

Separate equations are estimated for workers who separate into employment (are employed by a different firm in the following quarter) and for workers who separate into nonemployment.[12] w_{injt} is the real quarterly wage observed for worker i in quarter t; h_{nt-4} is the percent of new hires in firm n that are undocumented (lagged four quarters); and X_{injt} are other characteristics of the worker, firm, industry at time t that might affect the rate of separation. The estimation will also include a set of quarter-by-year fixed effects. δ_i is the individual fixed effect defined as the worker's reported SSN and φ_n is a fixed effect for the firm in which the worker is employed.

The estimated parameter coefficients from equation (1) are used to calculate the average separation elasticity with respect to wages for workers of type k as follows:

$$\bar{\varepsilon}_{Sw}^k = \frac{1}{N^k} \sum_{i=1}^{N^k} \frac{\partial S}{\partial w} \frac{w_i}{S_i} = \frac{1}{N^k} \hat{\gamma}_1^k \sum_{i=1}^{N^k} \frac{1}{S_i} \tag{2}$$

where N^k is the total number of workers of type k.[13] The key determinant of this elasticity, thus the estimate of a worker's sensitivity to the wage, is the coefficient on the wage regressor, $\hat{\gamma}_1^k$. The closer this (negative) coefficient is to zero, the less sensitive the workers are to changes in the wage.

[11] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.
[12] Because the data are restricted to workers in Georgia, nonemployment means not being observed in the data. Workers not observed in the data could have moved out of state for another job.
[13] Because the separation probability for each worker is not observed, the elasticities reported correspond to the elasticity for the average worker of each type.

The percent of new hires in firm n at time t that are undocumented is calculated as $h_{nt} = H^u_{nt}/\left(H^u_{nt} + H^d_{nt}\right)$, where H^k is the number of undocumented ($k = u$) and documented ($k = d$) workers hired by the firm during the previous four quarters.

To be able to include an individual fixed effect, we need to be confident that the worker is using the same SSN from one quarter or employer to the next. We expect this to be the case for documented workers, but could prove to be a problematic assumption for undocumented workers. To improve the chances that an undocumented worker is using the same identification number from one observation to the next, as mentioned earlier, we restrict the undocumented worker sample by keeping only those workers with invalid SSNs that conform to the ITIN numbering scheme. We expect that undocumented workers who are using ITINs are more likely to be using the same number from one employer to the next. This restriction is why the period of analysis begins in 1997 (the year of first ITIN issuance), and the undocumented sample is restricted to workers using their ITIN as a SSN.

It is also worth pointing out that if an undocumented worker using an ITIN becomes documented (attains legal status) and obtains a valid SSN, that person's status in our data changes as well; the "person" that used to use the ITIN disappears from the undocumented sample and the newly documented person appears in the sample. Even though this is physically the same person, we cannot track a person's status change.[14] For our purposes, and as it relates to the inclusion of a fixed effect, the data coding correctly places the person into the undocumented sample and then into the documented sample. Using the New Immigrant Survey, Jasso (2011) reports that roughly 40 percent of new legal immigrants in 2003 had some experience of being in the United States illegally at some time before attaining legal status. The percentage whose spell of illegality is most likely to have more immediately preceded legalization is about 12 percent (Jasso, 2011, Table 6). This does not mean that 12 (or even 40) percent of the undocumented workers in this paper eventually become documented, however, because those who obtain legal status are going to be a very select group of those who initially entered illegally (Jasso et al., 2000, p. 136).

Whether w_{injt} should be treated as endogenous to the worker's separation decision is a natural question (see Hotchkiss, 2002). However, besides the fact that limited data preclude simultaneous estimation of wages and separation, the real issue is how a worker's wage compares to his or her alternative wage. We expect that individual fixed effects (capturing all time-invariant determinants of a worker's human capital) and firm fixed effects (capturing whether the firm is a high- or low-wage firm) should minimize concerns regarding potential endogeneity bias.

To control for the possibility that undocumented workers are drawn to industries experiencing a rising relative demand for their skills or to industries that have a history of hiring undocumented workers (see Card & DiNardo, 2000), the share of workers in the six-digit NAICS industry that is undocumented is also included as a regressor. In addition, a sector-by-year fixed effect is included to control for industry specific time trends.

A worker is considered separated if the worker's SSN disappears from the employer's files for at least four consecutive quarters; shorter periods of separation were also estimated with no appreciable difference in results.

[14] We do not have any demographic information on individual workers that might allow us to identify (and exclude) those who are most likely to have changed their status from undocumented to documented. We would suspect that if a person is able to make such a change, they would also likely change employers.

In addition to the regressors of particular interest, worker tenure and labor market experience are included and are expected to be negatively related to worker separation (Mincer & Jovanovic, 1981). Again, because of concerns about potential endogeneity of tenure in the determination of separation, results excluding tenure are the ones presented, but are not appreciably different than those when tenure is included (elasticities from this later specification are included in tables for comparison). The age and size of the worker's firm and the churning of workers by the firm are expected to affect observed individual separations (Burgess, Lane, & Stevens, 2001); both older and larger firms are expected to have hiring mechanisms in place to generate more successful hires, thus less separation. County level unemployment rate (lagged by one quarter) is also included to control for general local labor market conditions.[15]

Estimating Displacement

In addition to the potential of undocumented workers willing to take a lower wage putting downward pressure on documented worker wages, arrival of undocumented workers impacting the outflow of documented workers could also have considerable social welfare impacts if documented workers were flowing into unemployment (rather than to merely another job). The impact of undocumented worker inflow on displacement (to either another job, or to non-employment) can also be investigated using the specification in equation (1). The average separation elasticity with respect to the share of new hires (four quarters ago) that is undocumented is calculated as the following:

$$\bar{\varepsilon}^k_{Sh} = \frac{1}{N^k}\sum_{i=1}^{N^k}\frac{\partial S}{\partial h}\frac{h_i}{S_i} = \frac{1}{N^k}\hat{\gamma}_2^k\sum_{i=1}^{N^k}\frac{h_i}{S_i} \tag{3}$$

The average separation elasticity with respect to the hiring of undocumented workers gives us some indication of the degree of displacement taking place. The key determinant of the degree of displacement is the coefficient ($\hat{\gamma}_2^k$) on the regressor that measures the share of new hires that is undocumented (h_{nt-4}). The further this (positive) coefficient is from zero, the more likely a worker is to separate as the share of new hires within the firm that is undocumented increases. Documented workers may voluntarily separate from their employers as wages are driven lower or in anticipation of losing their jobs down the road. Involuntary displacement would be the direct replacement of documented workers with undocumented workers. The analysis, however, will not be able to distinguish between the reasons for displacement.

RESULTS

Appendix D, Table D1, contains the OLS linear probability estimates corresponding to equation (1) for both separation to employment and separation to nonemployment.[16] Estimation of multiple high-dimensional fixed effects models via probit or

[15] Additional regressors were investigated, such as county-level firm birth and death rates and a measure of market competitiveness; their inclusion did not appreciably affect the estimated regressors of interest or the conclusions.
[16] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

logit is not feasible.[17] Estimates from Table D1 are used to calculate the elasticities. Elasticities calculated from the specification including tenure are reported at the bottom of Table D1; there is no appreciable difference in estimated coefficients or in estimated elasticities. The coefficient that is the most changed when tenure is excluded is that related to total labor market experience.

Impact of Control Variables on Separation

As expected, higher paid workers have lower probabilities of separation and workers employed at older firms are less likely to separate. Employer size has a differential impact across workers status, with documented workers less likely to separate from larger firms and undocumented workers neither more nor less likely to separate. Larger firms may have mechanisms in place to more efficiently make use of a temporary workforce that might often be satisfied by undocumented workers.

Documented workers with greater labor market experience have higher rates of separation, suggesting that workers with more experience may be more aware of better job opportunities and more likely to take advantage of them. This result could also be a function of the fact that very long tenures are truncated as a result of the calculation of tenure and experience beginning with the data in 1990. Furthermore, in general, one might expect that the greater number of employers undocumented workers are exposed to, the greater the likelihood of detection, and thus the less willing, everything else held constant, for undocumented workers to job hop. However, the greater the experience an undocumented worker has, the more knowledge of who is a safe employer increases, thus increasing separations to job, everything else held constant.

The share of workers in the industry that is undocumented does not significantly impact the probability of separation among either documented or undocumented workers. This may be because any affect is soaked up by the additional inclusion of the sector-by-year fixed effect.

The (lagged) county-level unemployment rate appears to have no impact on separations beyond the quarter-by-year fixed effects. Worker churning has a differential impact on separation rates among the types of workers, with a high-churn production process meaning greater separation among documented workers, but no significant separation behavior among the undocumented.

Evidence on Documented Worker Displacement

Regarding the regressor of interest for estimating displacement of currently employed documented workers, a greater number of newly arriving undocumented workers at the firm (four quarters ago) increase separation to both employment and nonemployment among earlier arriving undocumented workers. At the same time, a greater share of hires that is undocumented does not appear to significantly affect the separation of documented workers to nonemployment (or employment). This outcome is consistent with others' findings that the arrival of new immigrants has a greater negative impact on labor market outcomes among earlier arriving

[17] Estimation is performed using the Stata ado-file felsdvreg (see Cornelissen, 2008). Avoidance of common interpretation bias in heterogeneity corrected logit or probit estimations makes the linear probability model even that much more appealing, particularly in the implementation of various robustness checks (see Mroz & Zayats, 2008). Also see Caudill (1988) for another advantage of linear probability models over probit or logit.

immigrants than on outcomes of natives (see Lalonde & Topel, 1991; Ottaviano & Peri, 2006).

The separation elasticities, found in the last two columns of Table 2, indicate that a 10 percent increase in the share of new hires that is undocumented increases the chance of an existing undocumented worker separating by 0.23 percent. This result is of similar magnitude and significance across different groups of undocumented workers. Interestingly, the magnitude of displacement is larger among higher paid undocumented workers than among lower paid undocumented workers, and greater in sectors with a greater share of higher skilled workers than in sectors with fewer highly skilled workers. This could be because there are fewer undocumented workers in those sectors (and at that pay level) to begin with—the number displaced represents a larger share.

The conclusion from the estimation of these separation elasticities is that because there does not appear to be a direct displacement of currently employed documented workers when a firm employs undocumented workers, removing undocumented workers is not likely to appreciably increase employment of documented workers.

Estimation of Labor Supply Elasticities

The estimation of labor supply elasticities is what allows us to investigate the degree to which undocumented workers' willingness to accept lower wages puts downward pressure on documented worker wages; this will be done in the next section. But first, as described in the Appendix C, one additional piece of information is needed to estimate the overall labor supply elasticities of workers: the recruitment labor supply elasticity from nonemployment.[18] Appendix Table D2 contains the linear probability estimates corresponding to the estimation that a new hire/recruit is from employment.[18] A higher degree of churning in the firm, a lower wage, and greater labor market experience all increase the chances that a firm's new hire (both documented and undocumented) comes from employment.

In addition to the displacement separation elasticities, Table 2 also contains the estimated labor supply elasticities, for the full samples as well as for different groups of workers. As hypothesized, undocumented workers are less sensitive (about 22 percent less sensitive) to wage changes than documented workers, overall.[19] For the full sample, a 1 percent decrease in the wage reduces the supply of undocumented workers by 1.85 percent, but reduces the supply of documented workers by 2.37 percent.[20] In other words, documented workers are more likely than undocumented workers to quit their jobs in response to a wage reduction. This implies that undocumented workers are indeed limited in their labor market opportunities, willing to take lower wages, everything else held constant, and, thus, their presence does put some additional downward pressure on wages of substitute workers.

[18] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.
[19] As pointed out earlier, restrictions to the undocumented worker sample (e.g., exclusion of seasonal and non-ITIN workers) likely means this is a lower bound estimate of the difference in labor supply elasticities between documented and undocumented workers. We are grateful to an anonymous referee for pointing this out.
[20] As expected, these labor supply elasticities are larger than those estimated for workers on the hours margin (labor force participation or hours of work). For example, see Hall (1973), Costa (2000), Benjamin et al. (2007), and Hotchkiss, Moore, and Rios-Avila (2012). They are also larger than those estimated by Bhaskar, Manning, and To (2002), who reported elasticities in the range of 0.7 and 1.2; larger than those estimated by Manning (2003), who reported elasticities roughly equal to 1; and are similar to those estimated by Ransom and Oaxaca (2010), whose estimates were close to 2.0 for both men and women.

Table 2. Overall elasticities of labor supply ($\hat{\varepsilon}_{Nw}$) and separation elasticities, to nonemployment, with respect to undocumented new hires ($\hat{\varepsilon}^{n}_{Sh}$) by worker and firm groups.

	Overall elasticities of labor supply ($\hat{\varepsilon}_{Nw}$)		Separation elasticities to nonemployment ($\hat{\varepsilon}^{n}_{Sh}$)	
	Documented	Undocumented	Documented	Undocumented
Full sample	2.37*	1.85*	–0.001	0.023^
	(0.018)	(0.064)	(0.001)	(0.011)
Earnings level				
<R$3,000/quarter	0.79*	0.73*	0.001	0.01
	(0.012)	(0.064)	(0.003)	(0.011)
≥R$3,000/quarter	6.09*	4.39*	–0.005+	0.034^
	(0.111)	(0.276)	(0.003)	(0.014)
Sector skill classification				
Low skill	1.74*	1.75*	–0.009	0.0298+
	(0.033)	(0.121)	(0.006)	(0.017)
Medium skill	2.19*	1.99*	–0.001	0.019
	(0.022)	(0.083)	(0.002)	(0.015)
High skill	3.61*	2.60*	0.0003	0.069^
	(0.069)	(0.519)	(0.002)	(0.035)
NAICS sector				
Natural Resources & Agriculture	1.73*	0.66*	–0.036	0.02
	(0.203)	(0.222)	(0.025)	(0.045)
Construction	2.19*	2.21*	–0.006	0.029
	(0.083)	(0.168)	(0.008)	(0.038)
Manufacturing	4.24*	2.72*	–0.002	0.047
	(0.159)	(0.396)	(0.006)	(0.037)
Transportation & Utilities	3.51*	3.35^	0.001	–0.035
	(0.193)	(1.520)	(0.006)	(0.060)
Retail Trade	2.30*	2.06*	–0.003	–0.01
	(0.043)	(0.278)	(0.002)	(0.027)
Financial Activities	3.49*	3.52*	–0.005	0.005
	(0.128)	(1.334)	(0.004)	(0.054)
Information	3.96*	1.57*	–0.004	0.019
	(0.191)	(0.132)	(0.004)	(0.023)
Professional & Business Services	1.44*	3.17^	–0.001	0.066
	(0.026)	(1.361)	(0.003)	(0.059)
Education and Health	3.61*	1.84*	0.003	0.035
	(0.088)	(0.518)	(0.004)	(0.033)
Leisure & Hospitality	1.40*	2.21*	–0.002	0.023
	(0.029)	(0.139)	(0.006)	(0.017)
Other Services	2.39*	2.17*	0.005	0.007
	(0.125)	(0.247)	(0.007)	(0.032)

Notes: See notes to Table 1. "Documented" refers to the three of 1,000 random sample of documented workers; undocumented includes only those workers using an ITIN number as their SSN. *Statistical significance at the 99 percent confidence level; ^Statistical significance at the 95 percent confidence level; +Statistical significance at the 90 percent confidence level. Also see notes to Appendix Table D1. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787. Results are not reported for the Wholesale Trade sector because there were not enough observations for the first-stage estimation of the probability that a new hire comes from employment (vs. non-employment); this sector did not provide rich enough data to perform this estimation.

Although considerably larger than estimated elasticities surveyed by Manning (2011), the degree of monopsony power suggested by the elasticities reported in Table 2 is still likely overestimated.[21] The results suggest that in the absence of monopsony power, documented workers would be earning wages that are 42 percent higher than they are and undocumented workers would be earning 54 percent higher wages.[22] Pertaining to estimates of labor supply elasticities using nonexperimental data, Manning (2011) discusses several reasons why labor supply elasticity estimates might be biased downward. One contributing factor to downward biased elasticities is a failure to control for the worker's alternative wage. The ability to include individual fixed effects and the ability to control for seasonal and cyclical wage determining factors through year-by-quarter fixed effects is one advantage the analysis in this paper has over others.

Manning (2011) also identifies the inclusion of controls that are correlated with a worker's permanent wage as another reason for downward bias elasticities. Although the inclusion of individual fixed effects helps us in one dimension, it is also likely highly correlated with a worker's permanent wage. This is probably more of an issue for documented workers so may be a source for underestimating the *gap* between documented and undocumented elasticities.

Manning (2011) also points out that models including worker tenure as a regressor will always result in lower labor supply elasticities; this is one reason why results excluding tenure are reported in this paper, although the conclusions are not appreciably different when tenure is included. The quality/accuracy of administrative data (especially the reporting of wages) over self-reported data is likely the single most important reason why the labor supply elasticities estimated here are larger than those surveyed by Manning.

In spite of the fact that the labor supply elasticities in this paper are still likely to be biased downward, we must emphasize that the purpose of this analysis is to estimate the *relative* magnitude of the elasticities between documented and undocumented workers. Even if both elasticities are biased downward, their *relative comparison* is likely to be more accurate than each of the individual estimates, if the individual estimates are similarly biased.

Labor supply elasticities estimated separately across wage groups and broad industry characteristics are also reported in Table 2, and they tell a remarkably robust story across subgroups and across sectors. Across both documented and undocumented workers, the elasticity of labor supply increases with the wage level, with higher wage workers more sensitive to wage changes than lower wage workers; and across skill classification of the firm's sector, with both documented and undocumented workers employed in higher skilled sectors being more sensitive to wage changes than workers employed in lower skilled sectors. This increasing sensitivity to wages in earnings and skill level is consistent with other estimates in the literature; for example, see Royalty (1998) who finds that labor supply elasticities

[21] Labor supply elasticities surveyed by Manning (2011) range from a low of 0.2 to a high of 1.9. Even though Ransom and Sims' (2010) 3.7 estimate of a labor supply elasticity among schoolteachers is considerably larger, it also suggests a significant amount of monopsony power.

[22] Rearranging the terms in equation (C.5), in Appendix C, the degree to which workers are paid less than their marginal revenue product is found: $\frac{MRP-w}{w} = \frac{1}{\varepsilon_{nw}}$. Although Hirsch and Schumacher (2005) point out that the presence of an upward sloping supply curve is not sufficient evidence to establish the presence of monopsony power, this combined with easily identifiable characteristics and limited employment opportunities of undocumented workers is highly suggestive that firms are enjoying monospony power in their employment of at least undocumented workers. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

for those with less than a high school degree are lower than for those with at least a high school degree, among both men and women.

A few exceptions arise to undocumented workers being less sensitive to wage changes more narrowly in Professional & Business Services and Leisure & Hospitality, and marginally in Construction and Financial Activities. This is not entirely unexpected given the evidence that Yueh (2008) presents indicating that workers with larger social networks will exhibit greater labor supply elasticities (everything else held constant) than those with smaller social networks. Even though Yueh estimates individual own-wage elasticities, we would expect social networks to influence a worker's willingness to supply labor to a specific firm in much the same way as it affects their willingness to supply more hours to the labor market; "Social networks can offer flexibility and options through conveying information about the labor market and job prospects" (p. 10). In addition, we would expect this *social network* effect to be strongest in sectors with a larger concentration of undocumented workers, which include Construction, Professional & Business Services, and Leisure & Hospitality (also see Aguilera & Massey, 2003; Bauer, Epstein, & Gang, 2002; Damm, 2009; Liu, 2009; Munshi, 2003, for further evidence on the role of networks in generating better employment outcomes).[23]

DECOMPOSING THE WAGE DIFFERENTIAL

As detailed in Appendix C, the wage differential between documented and undocumented workers can be decomposed into differences in productivity between the two types of workers and differences in wage sensitivity.[24] The greater the contribution of wage sensitivity to the observed wage differential, the greater potential for additional downward pressure on wages resulting from the presence of undocumented workers.[25] Table 3 presents the decomposition of the average within-firm log wage differential (or, roughly, the percentage wage differential) between documented and undocumented workers. It is important to remember that the elasticities of labor supply presented in Table 2 are firm-specific elasticities and, thus, contribute to the wage differentials observed within the firm.

Overall, 27 percent of the observed wage differential between documented and undocumented workers is the result of differences in their elasticities of labor supply and the remaining 73 percent is the result of differences in their productivity. The implication is that nearly three-quarters of the overall wage differential results from differences in productivity between documented and undocumented workers. Thus, undocumented workers' willingness to accept lower wages is not a very large source of downward pressure on documented worker wages. This does not mean there is no downward wage pressure from the presence of undocumented workers. It simply means that the ability of employers to exploit their monopsony power is not contributing very much additional wage pressure overall.

Looking across firm and worker characteristics, lower wage workers appear to be more similar in terms of productivity with 44 percent of the observed within-firm wage differential between documented and undocumented low-wage workers

[23] The relative similarities in estimated labor supply elasticities in the Financial Activities sector is harder to explain.

[24] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[25] Differences in productivity may also reflect differences in fixed costs of hiring each worker type, such as penalties associated with hiring undocumented workers (see Ethier, 1986), or differences in match-specific human capital across types of worker.

Table 3. Log wage differentials between documented and undocumented workers decomposed into differences between marginal revenue product and differences in workers' labor supply elasticities.

	Average within-firm log wage differential $ln(w^d) - ln(w^u)$	Difference in workers' MRPs $[ln(MRP^d) - ln(MRP^u)]$ (Percentage of differential)	Difference in workers' elasticities of labor supply $[ln(\frac{1}{\varepsilon_{nw}^u}+1) - ln(\frac{1}{\varepsilon_{nw}^d}+1)]$ (Percentage of differential)
Full sample	0.30	0.22	0.08
(including tenure)		(73%)	(27%)
Full sample	0.30	0.22	0.08
(excluding tenure)		(74%)	(26%)
Earnings level			
< R$3,000/quarter	0.08	0.03	0.04
		(44%)	(56%)
≥ R$3,000/quarter	0.31	0.26	0.05
		(83%)	(17%)
Sector skill classification			
Low skill	0.23	0.24	–0.003
		(>100%)	–
Medium skill	0.33	0.30	0.03
		(90%)	(10%)
High skill	0.27	0.19	0.08
		(70%)	(30%)
NAICS sector			
Nat. Res. & Ag.	0.29	–0.18	0.47
		–	(>100%)
Construction	0.35	0.36	–0.003
		(>100%)	–
Manufacturing	0.35	0.25	0.10
		(71%)	(29%)
Trans. & Utilities	0.27	0.26	0.01
		(96%)	(4%)
Retail Trade	0.37	0.33	0.04
		(90%)	(10%)
Financial Activities	0.28	0.28	–0.002
		(>100%)	–
Information	0.33	0.07	0.27
		(20%)	(80%)
Prof. & Bus. Services	0.26	0.52	–0.25
		(>100%)	–
Ed. and Health	0.28	0.09	0.19
		(33%)	(67%)
Leisure & Hosp.	0.22	0.38	–0.17
		(>100%)	–
Other Services	0.25	0.22	0.03
		(88%)	(12%)

Notes: The formula for decomposing the observed, within-firm wage differentials between documented and undocumented workers is given by the following equation:

$$ln(w^d) - ln(w^u) = [ln(MRP^d) - ln(MRP^u)] + \left[ln\left(\frac{1}{\varepsilon_{Nw}^u}+1\right) - ln\left(\frac{1}{\varepsilon_{Nw}^d}+1\right)\right].$$

See the derivation of this equation in Appendix C. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787. Also see notes to Table 2.

being accounted for by differences in productivity. In contrast, 83 percent of the within-firm documented/undocumented wage differential among high-wage earners results from differences in productivity, suggesting even less substitutability among high-wage earners than among low-wage earners. These two results suggest that downward wage pressures are likely to be greater among lower wage workers than among higher wage workers, as we might expect, although even among low-wage workers, the contribution of productivity differences accounts for nearly half of the observed wage differential.

Grouping firms by skill level (share of workers in the sector with at least some college), we see that the share of the observed within-firm wage differential between documented and undocumented workers accounted for by differences in productivity declines as the firm's sector increases in skill designation. This may be because undocumented workers employed in higher skilled sectors such as Education & Health, Financial Services, and Information are quite different, and more specialized, hence more similar to documented workers, than undocumented workers employed in lower skilled sectors such as Agriculture, Construction, and Leisure & Hospitality.

The decomposition within each more narrowly defined sector grouping shows that the removal of undocumented workers is likely to have greatest potential for wage relief (as measured by a larger contribution of estimated labor supply elasticities to the observed wage gap) in Agriculture, which makes sense as there is likely very little productivity differential among the very low-skilled workers found in this sector. However, there is likely to be less wage relief resulting from the loss of employers to exploit their monopsony power with the removal of undocumented workers in sectors with relatively highly developed worker networks (Construction, Professional & Business Services, and Leisure & Hospitality). A more established worker network would increase the information flow about jobs and opportunities (see Liu, 2009; Yueh, 2008), thus limiting an employer's ability to exploit their monopsony power. Again, this does not mean there is no downward wage pressure in these sectors from the presence of undocumented workers. It simply means that the ability of employers to exploit their monopsony power is not contributing additional pressures in these sectors.

Industries also vary by degree of unionization, although overall unionization rates in Georgia are lower than in other regions of the United States. Nonetheless, the presence of union representation at the firm would likely restrict the degree to which the firm can exploit their monopsony power in setting wages across groups of workers. A simple correlation between unionization rates and the share of the wage differential accounted for by differences in labor supply elasticities provides some weak support for this notion. The correlation is –0.43, meaning that the greater the percent of workers covered by (or members of) a union contract, the lower will be the share of the wage differential accounted for by elasticity differences.[26]

Validity Check—Wage Decomposition Using IPUMS

The results in Table 3 suggest that roughly 70 percent of the observed firm-level wage differential between documented and undocumented workers arises from

[26] Rates of union coverage and membership for 2000 were obtained from http://www.unionstats.com. Recruiting efforts on the part of some unions indicate that they recognize an opportunity to boost their ranks by offering protection to undocumented workers by mitigating firms' ability to engage in monopsonistic discrimination. See Zappone (2006), Walker (2006), and Cuadros and Springs (2006) for descriptions of those union efforts.

differences in productivity between the two types of workers. To determine whether this is reasonable, we perform a validity check using cross-sectional data from the Individual Public Use Microsample (IPUMS) from the Census for census year 2000. This check involves performing a standard Oaxaca (1973) and Blinder (1973) decomposition of observed wage differentials between non-Hispanic natives vs. Mexican immigrants.[27] Of course, not all Mexican immigrants are undocumented, and vice versa, but data from the ACS and DHS suggest that between 40 and 60 percent of Mexicans in the United States are undocumented (see footnote 2). The idea with this validity check is that the portion of the wage differential explained by differences in worker characteristics roughly corresponds to differences in productivity across workers.

Appendix Table D3 summarizes the results from this decomposition performed for all workers in the United States, for workers in Georgia, and for workers in the United States across sectors.[28] These wage differentials are not firm-level wage differentials, and we are not able to control for firm or individual fixed effects, but the exercise will give us some idea whether our estimate of the relative contribution of the differences in labor supply elasticities (and resulting differences in marginal revenue product) are in the ball park of what we should expect. The overall wage differential Table D3 is roughly 40 percent, compared with a 30 percent firm-level wage differential in Table 3. We might expect the individual wage differential to be larger than the firm-level wage differential because (1) it is an average across firms in different sectors and (2) some of the documented workers in Table 3 are likely documented immigrants, whereas there are no immigrants in the non-Hispanic group in Appendix Table D3.[29]

In addition, differences in characteristics (i.e., productivity) account for the vast majority of the observed wage differentials in both Table 3 and Appendix Table D3.[28] The portion of the wage differential explained by productivity differentials (or by observed characteristics, in the case of the CPS) is largest in Professional & Business Services and in Leisure & Hospitality across both analyses. The most glaring differences between the decompositions in Table 3 and Appendix Table D3 is found in Agriculture, where based on the results in Table 3, we would have expected much less of the wage differentials in agriculture to be accounted for by differences in productivity.[28] Although not perfect, the similarities in patterns found in these two tables indicate that the administrative data used for the analysis in this paper are fairly representative of what might be expected in the population as a whole, or at least, in Georgia more generally.

CONCLUSIONS AND POLICY IMPLICATIONS

Proponents of recent state-level immigration reform laws often use language suggesting an expectation that many of their states' economic and criminal woes will

[27] We also performed the analysis comparing non-Hispanic natives and Hispanic immigrants. Observed wage differentials were slightly smaller, but the decompositions were very similar.

[28] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[29] This is consistent with Aydemir and Skuterud (2008) who find greater differentials between immigrants and natives in Canada across firms than within firms. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

be greatly diminished with the removal of unauthorized immigrants. Appendix E contains a summary of state-level omnibus immigration legislation between 2005 and 2011 illustrating the extent to which legislatures have tried to make life difficult for unauthorized immigrants overall, and more specifically in the labor market.[30] The purpose of this paper was to investigate one dimension of those omnibus laws—the expected improvement in employment and wage outcomes among documented workers if undocumented workers were removed from the labor market. The analysis contained here estimates the degree to which documented workers compete with undocumented workers based on productivity vs. a willingness to accept low wages, and whether there is any evidence of direct displacement of documented workers by the employment of undocumented workers.[31]

First of all, there is no evidence from the analysis here that currently employed documented workers are displaced when their employers hire undocumented workers. The only ones who experience any higher rates of separation when their employers hire new undocumented workers are earlier arriving undocumented workers. This result suggests that there is less substitutability between documented workers and undocumented workers than legislators fear, and it is consistent with other results found in the literature (e.g., see Lalonde & Topel, 1991; Ottaviano & Peri, 2006).

Second, although there is some variation across worker and firm characteristics, the overall difference in wages paid to documented and undocumented workers are more reflective of the differences in their productivity, rather than differences in their sensitivity to wages, also suggesting less substitutabilty between documented and undocumented workers than apparently presumed. In other words, undocumented workers are paid less than documented workers not because they are willing to take a lower wage, everything else held constant, but mostly because they are less productive. The implication of these two results is that the removal of undocumented workers from the labor market will not likely increase employment levels of documented workers, nor raise wages as much as expected. This does not mean there will be no effect on wages if the supply of undocumented labor in certain sectors, particularly sectors employing low-paid, low-skill workers, is removed. It simply means there is not as much wage difference to gain from the removal of employers' ability to exploit a certain class of worker.

One state stands out as an exception to the typical state-level approach to immigration reform. In 2011, Utah's legislature passed a number of laws under an omnibus umbrella that was guided by the principles of the *Utah Compact* (http://www.theutahcompact.com/about-the-compact). Providing a frame for the employment piece of the legislation, the Compact states

> Utah is best served by a free market philosophy that maximizes individual freedom and opportunity. We acknowledge the economic role immigrants play as workers and taxpayers. Utah's immigration policies must reaffirm our global reputation as a welcoming and business friendly state.

If effective, the law would provide for legitimization of workers through a formal guest worker/permit, state visa, and resident immigrant programs for workers who

[30] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787.

[31] For examples of a general equilibrium treatment of this issue, see Eren, Benítez-Silva, and Cárceles-Poveda 2011 and Dixon and Rimmer 2010.

entered the United States (and Utah) illegally.[32] Unlike the federal temporary or seasonal non-immigrant work visas, H-2A and H-2B, the Utah Work Permit would be applied for by the worker, not the employer, which means the worker is not tied to a specific employer through his or her permit. This feature would increase workers' employment opportunities and reduce even further the role of employer monopsony power plays in contributing to wage differentials between documented and permitted (formerly undocumented) workers.[33] Anything that reduces employers' ability to exercise monopsony power over permitted workers increases the advantage documented workers have in terms of being able to compete for jobs based entirely on productivity contributions—in the absence of monopsony power, permitted workers' wages will rise, making documented workers more competitive as an employment alternative. However, even if permitted workers have higher labor supply elasticities than they did as undocumented workers (because their employment opportunities have increased), they may continue to face other limitations of opportunity experienced by all low-skilled immigrants (e.g., see Arbona et al., 2010; Hersch & Viscussi, 2010; Orrenius & Zavodny, 2009b).

While the legal battle over state immigration legislation has only begun (see NCSL, 2012), the legal challenge in Utah targets the law enforcement aspect of the omnibus bill, rather than the temporary guest worker program. Although the state has to be granted a waiver to implement its program, many are anxious to see whether it can provide a model for the nation as a whole (see Preston, 2011).

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[32] See Hanson (2007) for the logic behind establishing a global, worker-based guest worker program.
[33] See Appendix E, Table E1 , for requirements workers must meet to obtain a permit. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's Web site and use the search engine to locate the article at http://www3.interscience.wiley.com/cgi-bin/jhome/34787. See Cobb-Clark, Shiells, and Lowell (1995) for evidence that legitimizing undocumented workers might be expected to raise their wages by increasing their employment opportunities, but more costly sanctions are likely to lower their wages.

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APPENDIX A: USING SSNs TO IDENTIFY UNDOCUMENTED WORKERS

Identifying Invalid Social Security Numbers

Every quarter employers must file a report with their state's Department of Labor detailing all wages paid to workers who are covered under the Social Security Act of 1935. Each worker on this report is identified by his or her Social Security number (SSN). There are a number of ways in which one can establish that a reported SSN is invalid. The Social Security Administration provides a service by which an employer can upload a file of SSNs for checking, but one must register as an employer to obtain this service.[34] In addition, there are several known limitations on what can be considered a valid SSN, so a simple algorithm is used to check whether each number conforms to the valid parameters.

There are three pieces to an SSN.[35] The first three numbers are referred to as the Area Number. This number is assigned based on the state in which the application for an SSN was made; it does not necessarily reflect the state of residence. The lowest Area Number possible is 001 and the highest Area Number ever issued, as of December 2006, is 772. Using information provided by the SSA, the dates at which area numbers between 691 and 772 are first assigned can be determined. Any SSN with an Area Number equal to 000, greater than 772, or which shows up before the officially assigned date, will be considered invalid.

The second piece of an SSN consists of the two-digit Group Number. The lowest group number is 01, and they are assigned in nonconsecutive order. Any SSN with a Group Number equal to 00 or with a Group Number that appears in the data out of sequence with the Area Number will be considered invalid.

The last four digits of an SSN are referred to as the Serial Number. These are assigned consecutively from 0001 to 9999. Any SSN with a Serial Number equal to 0000 is invalid.

In 1996 the Internal Revenue Service (IRS) introduced the Individual Tax Identification Number (ITIN) to allow individuals who had income from the United States to file a tax return (the first ITIN was issued in 1997). It is simply a *tax processing number*, and does not authorize an individual to work in the United States. Employers are instructed by the IRS to "not accept an ITIN in place of an SSN for employee identification for work. An ITIN is only available to resident and nonresident aliens who are not eligible for U.S. employment and need identification for other tax purposes."[36] ITIN numbers have a 9 in the first digit of the Area Number and a 7 or 8 in the first digit of the Group Number. Anyone with this numbering scheme will be identified as having an invalid Area Number; the percent of SSNs with high area numbers that also match the ITIN numbering scheme has risen from about 1 percent in 1997 to over 60 percent by the end of 2006.

A series of SSNs were decommissioned by the Social Security Administration because they had been put on fake Social Security Cards used as props to sell wallets.[37] Apparently, some people who purchased the wallets thought the fake Social Security Cards were real and started using them as their own. If any of these 21 *pocketbook* SSNs appear in the data, they are considered invalid,

[34] See Social Security Number Verification Service <http://www.ssa.gov/employer/ssnv.htm>.
[35] Historical information and information about valid SSNs can be found at the Social Security Administration's Web sites: <http://www.ssa.gov/history/ssn/geocard.html>, <http://www.xocialsecurity.gov/employer/stateweb.htm>, and <http://www.socialsecurity.gov/employer/ssnvhighgroup.htm>.
[36] See Internal Revenue Service (2011) and Internal Revenue Service (2012).
[37] See U.S. Department of Housing and Urban Development (1990).

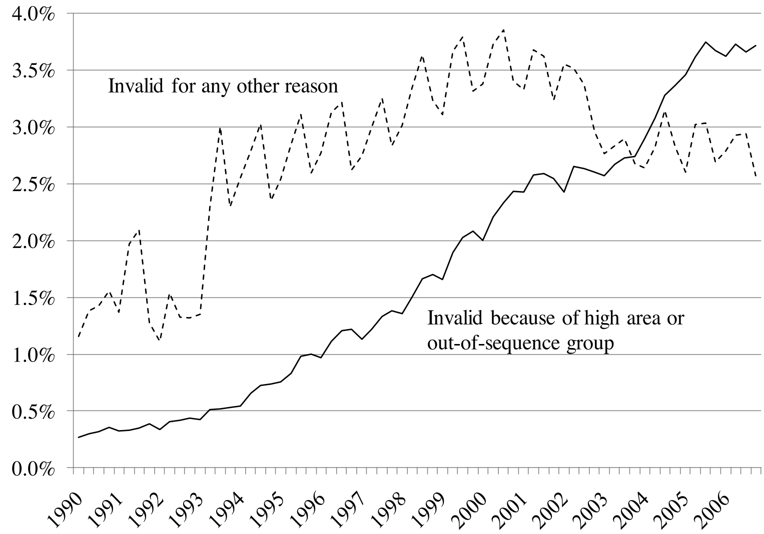


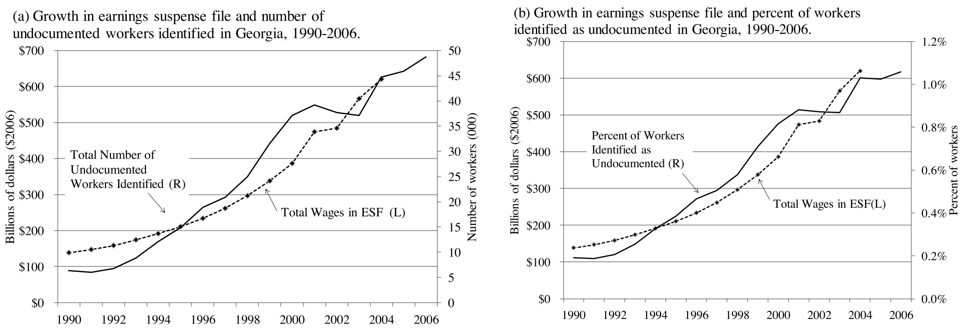
Figure A1. Percent of Workers with Invalid SSN, by Reason, Construction, 1990:1 to 2006:4.

although their frequency is so low as to be inconsequential. In addition, a number of SSNs are exactly equal to the employer identification number. These are invalid, primarily because they have too few digits. In any instance where an SSN is used for more than one person on a firm's UI wage report or does not have the required number of digits (including zeros), the SSN is considered invalid.

The possibility that someone fraudulently uses a valid SSN assigned to someone else poses a special problem. First of all, the SSN will show up multiple times across firms in one quarter for workers with different surnames (the wage report includes the first three characters of the workers' surnames). With this information alone, it is not possible to know which worker is using the SSN fraudulently and who the valid owner of the number is. If one of the SSN/surname pairs shows up in the data initially in a quarter by itself, this is the pair that is considered valid and all other duplicates (with different surnames) are considered invalid.

Does Invalid Mean Undocumented?

Not all invalid SSN are classified as undocumented workers; examining the patterns of incidence of different types of invalid SSNs suggests that some types are firm generated rather than worker generated. Figure A1 illustrates the incidence patterns across types of invalid SSNs in construction. The percent of workers with SSNs having a high area number or out-of-sequence group number displays the expected growth in undocumented workers (see Hoefer, Rytina, & Campbell, 2007), whereas the incidence of SSNs for other reasons exhibits a flat to declining, highly seasonal pattern (this seasonality appears in all other sectors, as well). The strong seasonal nature of the other invalid reasons suggests that firms are temporarily assigning invalid SSN numbers to workers before having time to gather the information for the purpose of record keeping/reporting. Or, firms may decide to not bother obtaining an SSN for workers who will only be employed a very short



Source: Huse (2002) for estimates 1990 to 2000, Johnson (2007) for estimates 2001 to 2004, and authors' calculations. Dollar estimates reflect 2006 values, using the PCE chain-weighted deflator.

Figure A2. Growth in the Earnings Suspense File and the Total Number and Percent of Workers Identified as Undocumented in Georgia, 1990 to 2006.

time.[38] The high degree of churning observed among workers with invalid SSNs for these other reasons is consistent with either of these practices.

Because there is no way to know whether a temporary assignment by the firm of an invalid SSN is to merely cover for temporary employment of an undocumented worker or to allow the firm to file its wage report before having had a chance to record the worker's valid SSN, a worker is only classified as undocumented if the SSN reported has an area number that is too high or a group number assigned out of sequence; workers with invalid SSNs for any other reason are considered neither undocumented nor documented and, thus, are excluded from the analysis. This will clearly undercount the actual number of undocumented workers. However, all workers, regardless of SSN classification, are included in counts of aggregate firm employment. The sample of undocumented workers, for the purpose of estimating labor supply elasticities, is narrowed further to only include those who report an ITIN as their SSN. This is discussed further in the text.

Are Undocumented Workers Correctly Identified?

There are several reasons we are confident that the sample of undocumented workers is representative. First of all, the rate of growth seen in both the number and percent of undocumented workers identified in Georgia matches closely the rate of growth in the Social Security Administration's (SSA) earnings suspense file (ESF). The ESF is a repository of Social Security taxes paid by employers that cannot be matched to a valid name or SSN. It is widely believed that this growth in the ESF reflects growing incidence of unauthorized work in the United States (Bovbjerg, 2006).

Figure A2 plots the number of workers (panel a) and the percent of workers (panel b) identified as undocumented along with the size of the ESF. This figure shows a remarkable consistency between the growth seen in workers identified as undocumented and the ESF.

As mentioned earlier, data suggest that between 40 and 60 percent of Mexicans in the United States are undocumented, and that 61 percent of unauthorized

[38] Indeed, a worker has 90 days to resolve a discrepancy that results in the receipt of a no-match letter from the Social Security Administration. The employee may be long gone before such a letter is even received.

Table A1. Average annual growth, 1994 to 2006, in U.S. and GA employment, Hispanic workers, and workers identified as undocumented.

Average annual growth rate of:	
Total number of workers in the United States	1.48%
Total number of foreign-born, Hispanic workers in the United States	8.03%
Total number of foreign-born, Hispanic workers with less than a high school degree in Georgia	7.28%
Total number of workers in Georgia	2.92%
Total number of foreign-born, Hispanic workers in Georgia	26.82%
Total number of foreign-born, Hispanic workers with less than a high school degree in Georgia	21.48%
Total number of workers in GA identified as undocumented	25.29%

Note: 1994 is used as starting year because it is the first year the Current Population Survey has a reliable indicator of Hispanic ethnicity.

Source: Current Population Survey, Basic Survey (March), 1994 to 2006; and authors' calculations.

immigrants come from Mexico (see footnote 2). Clearly not all Hispanics are undocumented, or vice versa; however, using weighted data from the Current Population Survey (CPS), we calculate the average annual growth in total workers and total number of foreign-born, Hispanic workers in the United States and in Georgia to compare growth rates to those in our sample. These results are reported in Table A1. The work force in GA grew faster over the period than the U.S. work force (2.9 vs. 1.5 percent, respectively). In addition, the number of foreign-born, Hispanic workers in the United States grew faster (8 percent per year) than the overall work force; this phenomenon has been documented by others (Passel & Cohn, 2009). But most importantly for our purposes is that the growth rate of foreign-born, Hispanic workers in GA (roughly 27 percent per year), which is much larger than in the United States overall (also see Passel & Cohn, 2009), is similar to the growth in the number of workers in GA classified here as undocumented. We also observe a similarly large growth rate in the number of foreign-born, Hispanic workers with less than a high school degree (21 percent), among which we might expect a larger share of undocumented workers than among foreign-born, Hispanics in general.

The close match in growth rates in the number of workers classified as undocumented with that of the SSA ESF and with the number of foreign-born, Hispanic workers in Georgia as measured by the CPS, suggests that the mechanism employed in this paper to identify undocumented workers is accurate; it is clear that not all undocumented workers are being captured in the data, but likely those identified as undocumented are undocumented. Any remaining mis-classifications will show up in the error term and limit the estimation in its ability to identify any systematic relationships between wages and characteristics of documented workers and their employers.

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APPENDIX B: ADDITIONAL DATA DETAILS

Based on its two-digit NAIC, each firm is placed into a broad industry sector. These sectors and their corresponding NAIC are detailed in Table B1.

Each industry is assigned a skill intensity based on the weighted average of educational attainment of workers in that industry, using the Current Population Survey for 1994. This year was chosen because this is the first year in which the nativity (place of birth) of respondents is reported. For each industry, the percent of workers with less than a high school education (LTHS), a high school education (HS), some college (SCOLL), college degree (COLL), and graduate education (GRAD) is calculated. Skill intensity categories was assigned as follows:

$$Low\,Skill = \begin{cases} 1 \; if \; LTHS > HS + COLL \\ 0 \; otherwise \end{cases}$$

$$High\,Skill = \begin{cases} 1 \; if \; SCOLL + COLL + GRAD > HS + SCOLL \\ 0 \; otherwise \end{cases}$$

$$Medium\,Skill = \begin{cases} 1 \; if \; High\,Skill = 0 \, and \, Low\,Skill = 0 \\ 0 \; otherwise \end{cases}$$

About 23 percent of the industries are classified as high skill, 15 percent at low skill, and 62 percent at medium skill. Some examples of low-skill industries include agriculture, some manufacturing, and accommodation and food services.

Table B1. Definitions of sectors based on two-digit NAIC classifications.

Sector	Included 2-digit NAIC
Construction	23
Manufacturing	31–33
Transportation and Utilities	22, 48–49
Wholesale Trade	42
Retail Trade	44–45
Financial Activities	52–53
Information	51
Professional and Business Services (includes temporary services)	54–56
Education and Health Services	61–62
Leisure and Hospitality	71–72
Other Services (includes private household, laundry, and repair and maintenance services)	81

Medium-skill industries include construction, retail trade, some manufacturing, some education and health, and arts and entertainment. High-skill industries include the information sector, electronic computer manufacturing, the financial sector, and some education and health.

APPENDIX C: THEORETICAL FRAMEWORK AND EMPIRICAL DETAILS

The Firm's Optimal Wage Policy

A profit-maximizing firm facing two distinguishable and separable types of workers will decide how many workers to hire of each type available based on the marginal revenue product of each type of worker and on the wage paid to each type of worker. This optimization problem leads to the standard result showing that the wage each worker type is paid is an increasing function of the worker's marginal revenue product and the worker's elasticity of labor supply.

Suppose the firm has two types of workers, documented (d) and undocumented (u). It is assumed that the firm can distinguish between these two workers and that the workers cannot collude. The firm solves the following optimization problem:

$$\max_{N^d, N^u} \pi = pf(N^d, N^u, C) - w^d(N^d)N^d - w^u(N^u)N^u \tag{C.1}$$

where N^k and w^k reflect the number of workers and wages, which are a function of type $k = (d,u)$; C is amount of capital input; and p is the product price. The two first-order conditions, then, are the following:

$$p\frac{\partial f}{\partial N^d} - \frac{\partial w^d}{\partial N^d}N^d - w^d(N^d) = 0, \text{ and} \tag{C.2}$$

$$p\frac{\partial f}{\partial N^u} - \frac{\partial w^u}{\partial N^u}N^u - w^u(N^u) = 0 \tag{C.3}$$

Noting the formula for elasticity for worker of type k,

$$\varepsilon^k_{Nw} = \frac{\partial N^k}{\partial w^k}\frac{w^k}{N^k} \Rightarrow \frac{\partial w^k}{\partial N^k} = \frac{w^k}{\varepsilon^k_{Nw} N^k} \tag{C.4}$$

and using the second part of equation (C.4) to replace that term in equations (C.2) and (C.3), and solving the first-order conditions for workers' wages, yields

$$w^k = \frac{p\frac{\partial f}{\partial N^k}}{\left[\frac{1}{\varepsilon^k_{Nw}} + 1\right]} \tag{C.5}$$

where $\varepsilon^k_{Nw} > 0$.[39] Equation (C.5) illustrates that observed wage differences across groups of workers reflect productivity differences and differences in elasticities of

[39] This result is analogous to what is referred to in the Input-Output literature as third degree price discrimination, where prices are determined based on two separate demand curves, rather than on one (see Schmalensee, 1981). Here, wages are determined from two separate labor supply curves.

labor supply. In a market absent of monopsony power, labor supply is perfectly elastic, $\varepsilon^k_{Nw} \to \infty$, and $w^k = p\frac{\partial f}{\partial N^k}$.

The elasticity of labor supply reflected here is not the one commonly estimated in the labor supply literature, which would reflect an individual's willingness to supply their labor to the market, typically estimated as a labor force participation or hours-of-work decision. The labor supply elasticity in equation (C.5) reflects the willingness of workers to supply their labor to a specific firm. One would expect this elasticity to be larger, meaning that workers would be more sensitive to wage changes at a specific firm than to changes in a workers' overall market wage. The reason, of course, is the greater number of employment alternatives when considering wages at a specific firm.

Estimation of the labor supply elasticities across documented and undocumented workers will allow us to estimate how much of the observed wage differential between these groups of workers can be accounted for by differences in estimated labor supply elasticities and how much can be accounted for by differences in productivity. Taking the log of equation (C.5) and differencing across worker types yields a decomposition of the percentage wage differential between those workers:

$$ln(w^d) - ln(w^u) = [ln(MRP^d) - ln(MRP^u)] + \left[ln\left(\frac{1}{\varepsilon^u_{Nw}} + 1\right) - ln\left(\frac{1}{\varepsilon^d_{Nw}} + 1\right)\right] \tag{C.6}$$

The first term on the right-hand side of equation (C.6) not only reflects differences in productivity levels of workers performing the same job, or task, but also differences in tasks being performed by the two groups of workers that contribute to total output. Peri and Sparber (2009) present evidence that with the arrival of immigrants with a specific set of skills, natives will redirect their human capital toward a different task group, so that differences in observed wages not only reflect potential differences in raw productivity levels, but also differences in tasks across workers. Differences in productivity may also reflect differences in fixed costs of hiring each worker type, such as penalties associated with hiring undocumented workers (see Ethier, 1986), or differences in match-specific human capital across types of worker. The empirical problem becomes the estimation of the elasticity of labor supply for the two groups of workers.

Estimating the Elasticity of Labor Supply

We apply the strategy outlined by Manning (2003, Ch. 4) to obtain an estimate of the average elasticities of labor supply to the firm for documented and undocumented workers. Manning points out that the overall elasticity of labor supply with respect to the wage for worker of type $k = (d, u)$, $\varepsilon_{Nw,k}$ is a weighted average of the responsiveness of recruits and those separating from and to employment or nonemployment (Manning, 2003, p. 98):

$$\varepsilon_{Nw,k} = \theta_R\varepsilon^e_{Rw,k} + (1-\theta_R)\,\varepsilon^n_{Rw,k} - \theta_S\varepsilon^e_{Sw,k} - (1-\theta_S)\varepsilon^n_{Sw,k} \tag{C.7}$$

where θ_S is the share of a firm's separations that directly move to another job, θ_R is the share of the firm's recruits that come directly from another job (recruits from employment), ε^e_{Rw} is the elasticity of recruits from employment, ε^n_{Rw} is the elasticity of recruits from nonemployment, ε^{e}_{Sw} is the elasticity of separation to employment, and ε^{n}_{Sw} is the elasticity of separation to nonemployment.

The data available allow us to directly estimate both separation elasticities, but, like Manning (2003), we do not observe all recruits to the firm, only the newly hired and whether they come from employment or nonemployment. Thus, we appeal to the same assumptions applied by Manning to obtain elasticities of recruitment. First, if both separation and recruitment elasticities to employment are constant, then $\varepsilon^{e}_{Rw} = -\varepsilon^{e}_{Sw}$ (proposition 4.4, p. 99).[40] Second, the relationship between the recruitment elasticity from nonemployment and the recruitment elasticity from employment can be expressed as (proposition 4.5, p. 100):

$$\varepsilon^{n}_{Rw}(w) = \varepsilon^{e}_{Rw} - \frac{w\theta'_R(w)}{\theta_R(w)\left[1-\theta_R(w)\right]} \tag{C.8}$$

where the share of recruits from employment (θ_R) can be expressed as a probability that a new recruit came from employment, which will be a function of the wage offer (among other things). Although we are not comfortable assuming the *number* of new hires (say, from employment) necessarily accurately reflects the number of recruits (or, rather, job applicants, from employment) to a firm, we assume, again like Manning, that the *share* of new hires from employment accurately reflects the share of recruits from employment.

The complete estimation strategy is as follows:

1. Estimate separation equations for separations to employment and to nonemployment and calculate $\hat{\varepsilon}^{e}_{Sw}$ and $\hat{\varepsilon}^{n}_{Sw}$.
2. Assume that the recruitment and separation elasticities into employment are constant and estimate $\hat{\varepsilon}^{e}_{Rw} = -\hat{\varepsilon}^{e}_{Sw}$.
3. Estimate a linear probability model (or limited dependent variable model) of the probability that a new-hire (recruit) comes from employment as a function of the wage (and other variables), and calculate $\theta'_R(w)$, which is simply the derivative of the estimating equation with respect to the wage. Then calculate $\hat{\varepsilon}^{n}_{Rw} = \hat{\varepsilon}^{e}_{Rw} - \frac{w\theta'_R(w)}{\theta_R(w)[1-\theta_R(w)]}$.
4. Use all the pieces above to calculate $\hat{\varepsilon}_{Nw} = \theta_R\hat{\varepsilon}^{e}_{Rw} + (1-\theta_R)\,\hat{\varepsilon}^{n}_{Rw} - \theta_S\hat{\varepsilon}^{e}_{Sw} - (1-\theta_S)\hat{\varepsilon}^{n}_{Sw}$.

The empirical problem, then, reduces to merely estimating separation equations for workers who separate into employment and workers who separate into nonemployment. Of course, this estimation strategy is performed separately for documented and undocumented workers to obtain different elasticities of labor supply for the two groups of workers. To be clear, there is nothing about the estimation strategy described above, or the empirical specification described below that assumes anything about the presence of firm monopsony power. The question is whether differential elasticities of labor supply provides an environment in which

[40] Depew and Sørensen (2011) relax this assumption of constant separation and recruitment elasticities, but are not able to allow for different types of separation. Another assumption of this model is that firms are in a steady state, meaning one firm's separation is another firm's hire. This is not likely to be the case in each time period over the entire time period used for estimation, but each estimation controls for quarter-by-year fixed effects to control for dynamics of the economy, and this can be seen from the means in Table 1, that over the time period, separation rates (16.4 percent among documented workers and 24.1 percent among ITIN undocumented workers) and hiring rates (16.5 percent among documented workers and 28.6 percent among ITIN undocumented workers) are quite similar.

firms can exercise monopsony power and how much of the observed wage differential might be explained by those differences.It is an empirical question, not an assumed outcome.

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APPENDIX D: ADDITIONAL TABLES

Table D1. Linear probability estimates of separation equations, excluding tenure.

Variable	Separate to employment = 1		Separate to nonemployment = 1	
	Documented Three of 1,000 random sample	Undocumented (ITIN only)	Documented Three of 1,000 random sample	Documented (ITIN only)
Ln(w)	–0.114*	–0.046*	–0.084*	–0.124*
	(0.001)	(0.003)	(0.001)	(0.004)
Firm age	–0.007*	–0.004	–0.011*	–0.028^
	(0.002)	(0.005)	(0.002)	(0.011)
Firm size (number of workers/10,000)	–0.021*	0.022	–0.012^	0.571^
	(0.006)	(0.181)	(0.005)	(0.224)
Worker churning	0.079*	0.008	0.057*	–0.005
	(0.006)	(0.006)	(0.006)	(0.011)
Percent of workers in industry that is undocumented	0.0003	0.002	0.003^	0.0000
	(0.001)	(0.001)	(0.001)	(0.003)
Share of new hires undocumented (lagged 4 quarters)	–0.003	0.007+	–0.007	0.022^
	(0.011)	(0.004)	(0.011)	(0.010)
County unemployment rate (lagged 1 quarter)	–0.0002	–0.002	0.0001	–0.006
	(0.001)	(0.004)	(0.001)	(0.008)
Worker labor market experience	0.012*	0.015*	0.026*	0.084*
	(0.001)	(0.002)	(0.001)	(0.005)
Labor market experience squared	–0.0001*	–0.0004*	–0.0001*	–0.0023*
	(0.000003)	(0.00004)	(0.000003)	(0.0001)
Elasticity of labor supply to employment ($\hat{\varepsilon}^{e}_{Sw}$)	–1.175*	–0.975*		
	(0.0149)	(0.0686)		
Elasticity of labor supply to nonemployment ($\hat{\varepsilon}^{n}_{Sw}$)			–1.143*	–0.776*
			(0.0176)	(0.0250)
Separation elasticity with respect to the share of new hires that is undocumented ($\hat{\varepsilon}_{Sh}$)	–0.0003	0.027+	–0.001	0.023^
	(0.0011)	(0.0157)	(0.0014)	(0.0110)
Specification including tenure:				
Elasticity of labor supply to employment ($\hat{\varepsilon}^{e}_{Sw}$)	–1.190*	–1.047*		
	(0.0153)	(0.0136)		
Elasticity of labor supply to nonemployment ($\hat{\varepsilon}^{n}_{Sw}$)			–1.152*	–0.61*
			(0.0178)	(0.0065)

Table D1. Continued.

Variable	Separate to employment = 1		Separate to nonemployment = 1	
	Documented Three of 1,000 random sample	Undocumented (ITIN only)	Documented Three of 1,000 random sample	Undocumented (ITIN only)
Separation elasticity with respect to the share of new hires that is undocumented ($\hat{\varepsilon}_{Sh}$)	–0.0003 (0.0011)	0.009* (0.0029)	–0.001 (0.0014)	0.023* (0.0025)
Number of observations	371,787	50,240	362,705	57,093

Notes: A worker is declared separated from a firm if he or she does not appear on the firm's payroll for four consecutive quarters. A worker has separated into employment if he appears on a new firm's payroll the quarter following separation; otherwise, the worker has separated into non-employment. Analysis includes workers employed in Georgia 1997 to 2006 inclusive. The undocumented sample is restricted to those using an ITIN number. Model also includes individual- and firm-level fixed effects, quarter-by-year fixed effects, and sector-by-year fixed effects. Worker labor market experience and firm age are only since 1990, the first year of available data. Robust standard errors, clustered at the firm level, are in parentheses. *Statistical significance at the 99 percent confidence level; ^Statistical significance at the 95 percent confidence level; +Statistical significance at the 90 percent confidence level. Also see notes to Table 2 in the paper.

Table D2. Linear probability estimates of the probability that a new hire (recruit) comes from employment.

Variable	New hire from employment = 1	
	Documented Three of 1,000 random sample	Undocumented (ITIN only)
Ln(w)	–0.004* (0.0014)	–0.003+ (0.0017)
Firm age	–0.0001 (0.0001)	–4E-07 (0.0001)
Firm size (number of workers/10,000)	–0.008 (0.0032)	0.012 (0.0086)
Worker churning	0.037* (0.0070)	0.059* (0.0068)
Percent of workers in industry that are undocumented	–0.005* (0.0017)	–0.004* (0.0008)
Share of new hires undocumented (lagged 4 quarters)	0.006 (0.0424)	0.007^ (0.0107)
County unemployment rate (lagged 1 quarter)	–0.014* (0.0018)	–0.0002 (0.0026)
Worker labor market experience	0.030* (0.0004)	0.153* (0.0066)
Labor market experience squared	–0.0004* (0.00001)	–0.006* (0.00054)

Table D2. Continued.

	New hire from employment = 1	
Variable	Documented Three of 1,000 random sample	Undocumented (ITIN only)
Number of observations	59,466	17,258
$\theta_R =$	0.548	0.203
$\frac{w\theta'_R(w)}{\theta_R(w)[1-\theta_R(w)]} =$	–0.018	–0.054

Notes: See notes to Table D1. Estimation of a limited dependent variable model with fixed effects requires a lot from the data in terms of multiple individual observations across multiple outcomes. The undocumented worker sample size is too small to provide for inclusion of fixed effects in this first-stage analysis. Fixed effects are excluded from both the documented and undocumented worker analyses at this stage to preserve consistency of analysis across worker types. Estimation including fixed effects (for the full sample and larger sectors) produces final elasticity estimates and conclusions consistent with those reported in the paper.

Table D3. Decomposition of log wage differential between non-Hispanic (NH) and Mexican (M) workers, estimated using the Public Use Micro Sample for 2000.

	Average log wage differential	Explained portion of differential (Percentage of differential)	Unexplained portion of differential (Percentage of differential)
All U.S. workers	0.40	0.35 (88.6%)	0.05 (11.4%)
Workers in Georgia	0.44	0.38 (85.8%)	0.06 (14.2%)
NAICS sector (workers in United States)			
Natural Resources & Agriculture	0.43	0.40 (92.9%)	0.03 (7.1%)
Construction	0.33	0.27 (80.8%)	0.06 (19.2%)
Manufacturing	0.45	0.39 (86.8%)	0.06 (13.2%)
Transportation & Utilities	0.31	0.23 (72.9%)	0.08 (27.1%)
Wholesale Trade	0.47	0.42 (89.0%)	0.05 (11.0%)
Retail Trade	0.18	0.14 (75.5%)	0.04 (24.5%)
Financial Activities	0.36	0.29 (80.5%)	0.07 (19.5%)
Information	0.36	0.25 (68.7%)	0.11 (31.3%)
Professional & Business Services	0.58	0.53 (90.6%)	0.06 (9.4%)
Education and Health	0.34	0.29 (86.1%)	0.05 (13.9%)

Table D3. Continued.

	Average log wage differential	Explained portion of differential (Percentage of differential)	Unexplained portion of differential (Percentage of differential)
Leisure & Hospitality	0.12	0.15 (>100%)	–0.03 (–)
Other Services	0.27	0.19 (69.3%)	0.08 (30.7%)

Notes: Decompositions resulting from OLS estimation of log hourly wage equations with regressors age and age squared; female, married, education, mobility, and English proficiency dummies; as well as measures of computer use at work and at home.

APPENDIX E: STATE-LEVEL OMNIBUS IMMIGRATION REFORM LEGISLATION THROUGH 2011

Table E1. Summary of law enforcement and employment details contained in state omnibus immigration legislation in 2010 and 2011.

	Law enforcement	Employment
Arizona (2010) SB 1070 HB 2162	Requires state and local officers to determine immigration status of a person involved in a lawful stop, detention, or arrest, or in the enforcement of any other ordinance if there is reason to suspect the person is an illegal alien.	It is illegal for a vehicle's occupant to hire (or enter a vehicle to be hired) on a street if it blocks or impedes traffic.
	Must verify legal status with federal government of anyone arrested.	Unlawful for illegal alien to apply for, solicit, or perform work.
	Indemnifies officers from legal action unless he or she acted unlawfully.	Employers are required to keep a record of employment verification for three years or the duration of the employee's employment, whichever is longer.
	"Every alien, 18 years of age and over, shall at all time carry with him and have in his personal possession any certificate of alien registration or alien registration receipt card issue to him;" not doing so, the person is guilty of a misdemeanor.	
	It is a crime to knowingly conceal, harbor, or conceal an illegal alien from detection, or to induce an illegal alien to enter the state.	
Alabama (2011) HB 56	State and local law enforcement are required to reasonably attempt to determine the immigration status of an individual otherwise having an encounter with law enforcement.	Unlawful for illegal alien to apply for, solicit, or perform work.
		Public contractors and subcontractors are required to use E-Verify.
		Business license can be suspended or revoked if owner knowingly hires illegal aliens.
		It is illegal for a vehicle's occupant to hire (or enter a vehicle to be hired) on a street if it blocks or impedes traffic.

Table E1. Continued.

	Law enforcement	Employment
Georgia (2011) HB 87	With probable cause that a crime has been committed (including any traffic offense), an officer is authorized to verify immigration status. Exempts people acting as a witness to a crime, reporting a crime, or seeking assistance as a victim of a crime.	Public employers are required to obtain an affidavit from all subcontractors attesting that the subcontractor uses E-Verify (or doesn't have any employees).
	All foreign nationals confined for any period of time in a county or municipal jail will be questioned regarding lawful presence in the state.	Wages paid to an employee in excess of $600 cannot be deducted as a business expense unless the employee has been verified using E-Verify.
	It is a crime to knowingly conceal, harbor, or conceal an illegal alien from detection, or to induce an illegal alien to enter the state.	
Indiana (2011) SB 590	It is a crime to knowingly conceal, harbor, or conceal an illegal alien from detection.	State agencies, political subdivisions, and contractors with the state or political subdivisions must use E-Verify.
	Status of a foreign national must be considered when setting bail or bond requirements.	Employers are prohibited from taking certain tax credits and deductions for workers hired illegally unless the employer participated in the E-Verify program.
South Carolina (2011) S 20	State and local law enforcement are required to reasonably attempt to determine the immigration status of an individual otherwise having an encounter with law enforcement. The officer must then contact federal authorities to determine if the person must be arrested on immigration charges.	Unlawful for illegal alien to apply for, solicit, or perform work.
	It is a crime to knowingly conceal, harbor, or conceal an illegal alien from detection, or to induce an illegal alien to enter the state.	All public contractors and subcontractors must use E-Verify. An employer has three days to check immigration status using E-Verify.

Table E1. Continued.

	Law enforcement	Employment
		Business license can be suspended or revoked if owner knowingly hires illegal aliens.
Utah (2011) H 116 H 466 H 469 H 497	Law enforcement officers will request verification status while enforcing state law or local ordinance, and it is illegal to not have or provide documentation.	Establishes a temporary guest worker program; eligibility requires evidence of residence in the state before May 10, 2011, regularly provided contact information, no criminal record, good health, proof of work within 30 days of application, health insurance, and a “driving privilege card.” Work permit is good for two years and applicant must pay a fine for being in Utah illegally in the first place.
	Requires that immigration status be verified of anyone arrested for serious crimes. Passengers of a vehicle that has been detained may also be questioned about their immigration status.	Employers are prohibited from knowingly hiring an undocumented worker without a permit.
		Employers with 15 or more workers must use E-Verify or similar program to verify employment.
		Establishes a worker visa program and a state commission will collaborate with Nuevo Leon, Mexico to fill jobs in Utah.
		Allows for U.S. citizens and Utah residents to sponsor a *resident immigrant* who will be allowed to live, work, and study in Utah.

Sources: “State Omnibus Immigration Legislation and Legal Challenges” National Conference of State Legislatures (18 April 2012). Access May 1, 2012 (http://www.ncsl.org/issues-research/immig/omnibus-immigration-legislation.aspx). “Arizona’s Immigration Enforcement Laws” National Conference of State Legislatures (28 July 2011). Accessed May 1, 2012 (http://www.ncsl.org/issues-research/immig/analysis-of-arizonas-immigration-law.aspx). Note that Lawsuits in each state, except South Carolina, have been filed and enjoined (see http://www.ncsl.org/issues-research/immig/omnibus-immigration-legislation.aspx).