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Abstract: Using matched employer-employee data from the state of Georgia, this paper investigates how differences in wage responsiveness contribute to the determination of observed wage differentials between documented and undocumented workers. Facing fewer employment opportunities, undocumented workers are found to be about 22 percent less sensitive than documented workers to employers' wage adjustments. In addition, this difference in wage responsiveness accounts for 27 percent of the observed within-firm wage differential between documented and undocumented workers. Implications of the results for recent state immigration legislation are discussed.

JEL classification: J42, J61, J2

Key words: labor demand, monopsony, illegal immigration, undocumented workers

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Employer Monopsony Power in the Labor Market for Undocumented Workers

I. Introduction and Background

Very little empirical investigation of the labor market experiences or impact of undocumented workers exists. DeFreitas (1988) and Hotchkiss and Quispe-Agnoli (2011) investigate the wage impact of the presence of undocumented workers, finding modest impacts that vary across worker skill level and across sectors. Brown et al. (2008) present evidence that employing undocumented workers gives some firms a fairly significant competitive advantage, suggesting that the lower wages paid to undocumented workers likely derives from a monopsonistic position of the employer, rather than reflecting merely lower productivity of the workers. This paper directly estimates labor supply elasticities for documented and undocumented workers, finding evidence that undocumented workers are less sensitive to wages than their documented co-workers--suggestive that employers do have monopsonistic power in the labor market for undocumented workers.

The paper also investigates the evidence for displacement of documented workers as more undocumented workers arrive. Consistent with previous literature, only evidence of displacement is found among earlier arriving undocumented workers. In addition, a decomposition of the wage differential between documented and undocumented workers indicates that, while there are clear differences in labor supply elasticities across documented status, the bulk of the observed wage differential derives from differences in marginal revenue product. These decomposition results are verified using cross-sectional data from the Individual Public Use Microsample (IPUMS).

A. Political Environment

According the National Conference of State Legislatures (NCSL), state legislative interest in immigration issues "spiked" in 2005.[1] During that year, 300 immigration bills were introduced into state legislatures, with 39 surviving to become law. 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 level through 2010. The NCSL attributes this level and 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 U.S. over the past 20 years. Between 1990 and 2010, it is estimated that the unauthorized population in the U.S. has grown at an average rate of nine percent per year (see INS 2003 and Passel and Cohn 2011).

This legislative activity has culminated in some high profile, very restrictive legislation passed in 2010 in Arizona and in 2011 in Georgia, Alabama, Indiana, and South Carolina, all of which are modeled after Arizona's legislation. Also notorious, and with some similarities, Utah took a slightly different track with a more comprehensive package including enforcement, integration, and a pilot temporary worker visa program, which is so far unique to Utah.[2] The results of the analysis in this paper will be interpreted in the context of this legislative environment, emphasizing the results' implications for how the different laws might be expected to affect the functioning of the labor market for undocumented and workers.

B. Theoretical Foundation

An 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

[1] Statistics contained in this paragraph were obtained from http://www.ncsl.org/default.aspx?tabid=19897 (accessed 10 October 2011).
[2] A variety of bills in Utah addressed each of these dimensions: HB116, HB466, HB469, and HB497.

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 source of the firm's monopsonistic power in the labor market derives from the behavior of workers, not from the degree of competition in the firm's product market. In other words, the presence of a large number of competitive firms does not preclude monopsonistic discrimination. In fact, a greater degree of product market competition will put additional pressures on an employer to take advantage of differential labor supply elasticities across workers (see Bhaskar et al. 2002: 167).

Using employer-employee matched data, this paper determines whether there is any empirical evidence that undocumented workers are less sensitive to wages than documented workers, providing an opportunity for employers to practice monopsonistic discrimination. Evidence for a lower labor supply elasticity among undocumented workers provides an explanation for why employers might be willing to undertake the risk of hiring undocumented workers. If employers are able to practice monopsonistic discrimination, it means that they are able to hire a worker at a wage less than the worker's marginal revenue product, which means the firm experiences a rent associated with the hire. The presence of this rent means that the employer is willing to pay a higher marginal cost hiring the worker, such as the risk of a fine if caught (see Manning 2011, 981). The highly restrictive employment legislation that has become law recently in several states has implications both for the cost of employment of all workers and the willingness of employers to continue incurring additional costs to hiring undocumented workers going forward. These implications will be discussed in detail in the concluding section to this paper.

The presence of monopsonistic employer power has been identified in a number of settings. Manning (2011)'s 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 U.S. and in other countries. Earlier evidence of monopsony power, and/or an environment ripe for monopsony power, has been found in labor markets for women (Ofek and Merrill 1997, Hirsch et al. 2006, and Barth and Dale-Olsen 2009), for blacks (Raphael and Riker 1999), and even in the world of sports (Scully 1989, Zimbalist 1992, and Scott et al. 1985).

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 U.S. 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 U.S. are undocumented.[3] In addition, DHS estimates for January 2008 that 61 percent of unauthorized

[3] The 2008 ACS estimates that 11.4 million people in the U.S. 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 U.S. in 2008 (http://www.dhs.gov/xlibrary/assets/statistics/publications/ois_ill_pe_2008.pdf).

immigrants come from Mexico (Hoefer et al. 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 et al. 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 which 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).[4] All of these factors reduce employment opportunities of undocumented workers, ceteris paribus, 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."

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

The purpose of this paper is to explore the evidence of the presence of monopsonistic discrimination in the labor market for undocumented workers by quantifying the degree to which undocumented workers are less sensitive to wages than documented workers. We also investigate the role that lower sensitivity plays in explaining the observed wage differential between documented and undocumented workers. The implications of the results in this paper are discussed in the context of recent state-level actions designed to reduce employment of undocumented workers.

II. 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).[5] 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 6-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.

[5] Certain jobs in agriculture, domestic services, and non-profit 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).

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).

A. Using SSNs to Identify Undocumented Workers

Details of how the SSN is used to identify undocumented workers are contained in Appendix A. The abbreviated version is that there are some easily identifiable ways in which a 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 SSN 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 or 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 was also identified nationally by Fortuny et al. (2007).[7] The pattern of growth is also consistent with Fortuny et al. who estimate that 72 percent of unauthorized immigrants in Georgia arrived in the last 10 years.

[Figure 1 here]

[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). Since seasonal undocumented workers are likely to be even less sensitive to wages than non-seasonal 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.

[7] Fortuny et al. (2007) estimate that nationally in 2004 the percent of workers in leisure and hospitality and construction that was undocumented was 10 percent each, nine percent of workers in agriculture, and six percent each in manufacturing, professional and business services, and other services. Also see Pena (2009).

Fortuny et al. (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 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 was 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.

B. 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 U.S. (Bovbjerg 2006).

Figure 2 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.

[Figure 2 here]

As mentioned earlier, data suggest that between 40 and 60 percent of Mexicans in the U.S. are undocumented, and that 61 percent of unauthorized immigrants come from Mexico (see footnote 3). 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 U.S. and in Georgia in order to compare growth rates to those in our sample. These results are reported in Table 1. The work force in GA grew faster over the period than the U.S. work force (2.9 percent vs. 1.5 percent, respectively). In addition, the number of foreign born, Hispanic workers in the U.S. grew faster (eight percent per year) than the overall work force; this phenomenon has been documented by others (Passel and 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 U.S. overall (also see Passel and 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%), among which we might expect a larger share of undocumented workers than among foreign born, Hispanics in general.

[Table 1 here]

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's 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.

Note that it is not essential for an employer to be able to distinguish between valid and invalid SSNs in order to practice monopsonistic discrimination. All that is necessary is that the employer can 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 sub-set 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 U.S. 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 U.S. Employers are instructed by the IRS to "not accept an ITIN in place of a 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."[8] ITIN numbers have a specific numbering scheme that makes them readily identifiable (see Appendix A). Figure 3 plots all workers identified as undocumented and the subset using ITIN numbers. The sample of workers with ITIN numbers is much smaller, and, thus, likely less representative, than all workers identified as undocumented. In addition, 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

[8] "Hiring Employees," <http://www.irs.gov/businesses/small/article/0,,id=98164,00.html>. Also see, "Individual Taxpayer Identification Number (ITIN)," <http://www.irs.gov/individuals/article/0,,id=96287,00.html>.

likely to use the same "SSN" across employers; this is necessary in order to control for individual worker fixed effects.

[Figure 3 here]

C. Sample Means

In order to be able to control for individual fixe effects, undocumented workers included in the analysis will be restricted to those using a ITIN as their SSN. Consequently, 1997 will be the first year of analysis. Table 2 presents some means for four groups of workers; (1) the full sample of documented workers, (2) a 3/1000 random sample of documented workers, (3) the full sample of undocumented workers, and (3) undocumented workers using a 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 3/1000 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.

[Table 2 here]

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 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 (defined as earning less than $3,000, in real terms, per quarter). As will be discussed in more detail below, a more relevant wage comparison will be one that is calculated within-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 percent (Kassoudji and Cobb-Clark 2002) to 42 percent (Rivera-Batiz 1999). A penalty here 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).[9] 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 (versus 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 a 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

[9] Churning is measured as the difference between worker flows and job flows divided by the average employment during the period. Worker flows is the sum of hires and separations and job flows is net employment change. $CHURN_{jt} = \frac{[Hires+Separations]-[|N_{jt}-N_{jt-1}|]}{[(N_{jt}+N_{jt-1})/2]}$, N_t is the number of workers in time *t* (Burgess et al. 2001).

intensity and NAICS classification.[10] Most notably, undocumented workers are more concentrated in agriculture, construction, and leisure and hospitality. In addition, while 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.

III. Theoretical and Empirical Framework

A. 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:

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

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:

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

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

Noting the formula for elasticity for worker of type *k*,

[10] Appendix B defines the sector classifications and Appendix C describes the construction of skill classifications.

$$\varepsilon_{Nw}^{k} = \frac{\partial N^k}{\partial w^k}\frac{w^k}{N^k} \Rightarrow \frac{\partial w^k}{\partial N^k} = \frac{w^k}{\varepsilon_{Nw}^{k} N^k}\,, \tag{4}$$

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

$$w^k = \frac{p\frac{\partial f}{\partial N^k}}{\left[\frac{1}{\varepsilon_{Nw}^{k}}+1\right]}\,, \tag{5}$$

where $\varepsilon_{Nw}^{k} > 0$.[11] Equation (5) illustrates that observed wage differences across groups of workers reflect productivity differences and/or differences in elasticities of labor supply. In a market absent of monopsony power, labor supply is perfectly elastic, $\varepsilon_{Nw}^{k} \to \infty$, 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 (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 (5) and differencing across worker types yields a decomposition of the percentage wage differential

[11] This result is analogous to what is referred to in the IO literature as third degree price discrimination, where prices are determined off of two separate demand curves, rather than one (see Schmalensee 1981). Here, wages are determined off two separate labor supply curves.

between those workers:

$$ln(w^d) - ln(w^u) = [ln(MRP^d) - ln(MRP^u)] + \left[ln\left(\frac{1}{\varepsilon_{Nw}^u} + 1\right) - ln\left(\frac{1}{\varepsilon_{Nw}^d} + 1\right)\right]. \quad (6)$$

The first term on the right hand side of equation (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 re-direct 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 workers 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.

B. 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 non-employment (Manning 2003: 98):

$$\varepsilon_{Nw,k} = \theta_R \varepsilon_{Rw,k}^e + (1 - \theta_R)\varepsilon_{Rw,k}^n - \theta_S \varepsilon_{Sw,k}^e - (1 - \theta_S)\varepsilon_{Sw,k}^n, \quad (7)$$

where θ_S is the share of a firm's separations which are a direct movement into another job (separation into employment), θ_R is the share of the firm's recruits that come directly from another job (recruits from employment), ε_{Rw}^e is the elasticity of recruits from employment, ε_{Rw}^n is the elasticity of recruits from non-employment, ε_{Sw}^{e} is the elasticity of separation to employment, and ε_{Sw}^{n} is the elasticity of separation to non-employment.

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 non-employment. 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 $\varepsilon_{Rw}^{e} = -\varepsilon_{Sw}^{e}$ (proposition 4.4, p. 99).[12] Second, the relationship between the recruitment elasticity from non-employment and the recruitment elasticity from employment can be expressed as (proposition 4.5, p. 100):

$$\varepsilon_{Rw}^{n}(w) = \varepsilon_{Rw}^{e} - \frac{w\theta_R'(w)}{\theta_R(w)[1-\theta_R(w)]} , \tag{8}$$

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). While 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 non-employment and calculate $\hat{\varepsilon}_{Sw}^{e}$ and $\hat{\varepsilon}_{Sw}^{n}$.

(2) Assume that the recruitment and separation elasticities into employment are constant and estimate $\hat{\varepsilon}_{Rw}^{e} = -\hat{\varepsilon}_{Sw}^{e}$.

[12] Work by 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 in order to control for dynamics of the economy, and we can see from the means in Table 2, that over the time period, separation rates (16.4% among documented workers and 24.1% among ITIN undocumented workers) and hiring rates (16.5% among documented workers and 28.6% among ITIN undocumented workers) are quite similar.

(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 things and calculate $\theta_R'(w)$ which is simply the derivative of the estimating equation with respect to the wage. Then calculate $\hat{\varepsilon}_{Rw}^{n} = \hat{\varepsilon}_{Rw}^{e} - \frac{w\theta_R'(w)}{\theta_R(w)[1-\theta_R(w)]}$.

(4) Use all the pieces above to calculate $\hat{\varepsilon}_{Nw} = \theta_R \hat{\varepsilon}_{Rw}^{e} + (1-\theta_R)\hat{\varepsilon}_{Rw}^{n} - \theta_S \hat{\varepsilon}_{Sw}^{e} - (1-\theta_S)\hat{\varepsilon}_{Sw}^{n}$.

The empirical problem, then, reduces to merely estimating separation equations for workers who separate into employment and workers who separate into non-employment. Of course, this estimation strategy is performed separately for documented and undocumented workers in order 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 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.

C. Empirical Specification of Worker Separations

Workers' separation elasticities are determined by estimating the following linear probability separation equation separately for documented workers (*k*=*d*) and for undocumented workers (*k*=*u*):

$$S_{injt} = \gamma_0^k + \gamma_1^k \ln\left(w_{injt}\right) + \gamma_2^k h_{nt-4} + \gamma_3^k X_{injt} + \delta_i + \varphi_n + \varepsilon_{injt} \tag{9}$$

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 non-employment. [13] 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 (9) are used to calculate the average separation elasticity with respect to wages for workers of type *k* as follows:

$$\bar{\varepsilon}_{Sw}^{k} = \frac{1}{N^k}\sum_{i=1}^{N^k}\frac{\partial S}{\partial w}\frac{w_i}{S_i} = \frac{1}{N^k}\hat{\gamma}_1^k\sum_{i=1}^{N^k}\frac{1}{S_i} \ , \quad (10)$$

where N^k is the total number of workers of type *k*.[14]

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

In order 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. In order to improve the chances that an undocumented worker is using the same identification ("SSN") number from one observation to the next, as mentioned earlier, we restrict the undocumented worker sample further 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

[13] Since the data are restricted to workers in Georgia, non-employment means not being observed in the data. Workers not observed in the data could have moved out of state for another job.

[14] Since the separation probability for each worker is not observed, the elasticities reported correspond to the elasticity for the average worker of each type.

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's 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 be using the ITIN disappears from the undocumented sample and the new documented "person" appears in the sample. Even though this is physically the same person and we cannot track a person's status change.[15] 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 U.S. 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, since 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/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.

[15] 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 order 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 and DiNardo 2000), the share of workers in the 6-digit NAICS industry that is undocumented is also included as a regressor. In addition, a sector-by-year fixed effect is included in order 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.

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 and 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 et al. 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.[16]

D. Estimating Displacement

In addition to the presence of substitute labor 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

[16] 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.

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 (9). The average separation elasticity with respect to the share of new hires (four quarters ago) that is undocumented is calculated as:

$$\bar{\varepsilon}_{Sh}^{k} = \frac{1}{N^k}\sum_{i=1}^{N^k}\frac{\partial S}{\partial h}\frac{h_i}{S_i} = \frac{1}{N^k}\hat{\gamma}_2^k\sum_{i=1}^{N^k}\frac{h_i}{S_i} \quad . \tag{11}$$

The average separation elasticity with respect to the hiring of undocumented workers gives us some indication of the degree of displacement taking place. 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 reason for displacement.

IV. Results

Appendix Table D1 contains the OLS linear probability estimates corresponding to equation (9) for both separation to employment and separation to non-employment. Estimation of multiple high-dimensional fixed effects models via probit or logit is not feasible.[17] Estimates from Table D1 are used to calculate the elasticities. Elasticities calculated from estimation 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.

As expected, higher paid workers have lower probabilities of separation and workers

[17] Estimation is performed using the Stata ado-file felsdvreg (see Cornelissen 2009). 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 and Zayats 2008). Also see Caudill (1988) for another advantage of linear probability models over probit or logit.

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 begin 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, *ceteris paribus*, 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, ceteris paribus.

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.

Regarding the regressor of interest for estimating displacement, a greater number of newly arriving undocumented workers at the firm (four quarters ago) increases separation to both employment and non-employment 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 non-employment (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 immigrants than on outcomes of natives (see Ottaviano and Peri 2006 and Lalonde and Topel 1991).

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.

A. Estimates of Overall Labor Supply Elasticities

One additional piece of information is needed beyond the elasticities of labor supply to employment and non-employment; that is the second term on the right hand side of equation (8) that allows us to estimate the recruitment labor supply elasticity from non-employment. Table D2 contains the linear probability estimates corresponding to the estimation that a new hire/recruit is from employment. 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.

Table 3 contains the estimated labor supply elasticities and separation elasticities with respect to new hires, 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.[18] For the full sample, a one percent decrease in the wage reduces the supply of undocumented workers by 1.85 percent, but reduces the supply of

[18] 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.

documented workers by 2.37 percent.[19] In other words, documented workers are more likely than undocumented workers to quit their jobs in response to a wage reduction.

[Table 3 here]

Although considerably larger than estimated elasticities surveyed by Manning (2011), the degree of monopsony power suggested by the elasticities reported in Table 3 is still likely overestimated.[20] 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.[21] Pertaining to estimates of labor supply elasticities using non-experimental 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

[19] 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 and Moore (2007). They are also larger than those estimated by Bhaskar et al. (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 one; and are similar to those estimated by Ransom and Oaxaca (2010), whose estimates were close to 2.0 for both men and women.
[20] 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 school teachers is considerably larger, it also suggests a significant amount of monopsony power.
[21] Rearrangements of the terms in equation (5), 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.

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 that include 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 in 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 the individual parts if the individual parts are similarly biased.

Labor supply elasticities estimated separately across wage groups and broad industry characteristics are also reported in Table 3 and they tell a remarkably robust story across sub-groups and across sectors. Across both documented and undocumented workers, the elasticity of labor supply increases in 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 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 exception 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 (*ceteris paribus*) 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 Liu 2009, Damm 2009, Munshi 2003, Aguilera and Massey 2003, and Bauer et al. 2002 for further evidence on the role of networks in generating better employment outcomes).[22]

B. Estimates of Displacement

Turning to the separation elasticities (found in the last two columns of Table 3), newly arriving undocumented workers appear to have no impact on displacing documented workers. In contrast, an increase in the share of new hires that is undocumented increases, overall, the percent of undocumented workers separating by 0.023 percent, and 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

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

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.

This displacement of existing undocumented workers by newly arriving undocumented workers is consistent with that found by Ottaviano and Peri (2006) and Lalonde and Topel (1991) who find that the arrival of immigrants negatively impacts the labor market outcomes of earlier arrivals more than those of natives.

C. Decomposition of the Wage Differential

Making use of equation (6), Table 4 presents the decomposition of the average within-firm log wage differential (or, roughly, the percentage wage differential) between documented and undocumented workers. It's important to remember that the elasticities of labor supply that are estimated here are firm-specific elasticities and, thus, contribute to the wage differentials observed within the firm.

[Table 4 here]

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 marginal revenue product. In general, lower wage workers appear to be more homogeneous in terms of productivity with 44 percent of the observed within-firm wage differential between documented and undocumented low wage workers being accounted for by differences in marginal revenue product. In contrast, 83 percent of the within-firm documented/undocumented wage differential among high wage earners results from productivity differentials, meaning that sensitivity to wages (elasticity of labor supply) is much more similar among documented and undocumented high wage earners.

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 difference in labor supply elasticities makes its largest contribution to explaining wage differentials in Agriculture, which makes sense as there is likely very little productivity differential among the very low-skilled workers found in this sector. And, the lack of contribution of differences in labor supply elasticities in those sectors with relatively highly developed networks (Construction, Professional & Business Services, and Leisure & Hospitality) in reflected in the decomposition, as well (with Financial Activities, again, being a bit of an anomaly). The thin numbers of undocumented workers in each of these individual sectors, however, suggest that these sector decompositions should be interpreted with caution.

Industries also vary be degree of unionization, although overall unionization rates in Georgia are lower than in other regions of the U.S. 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.[23]

D. Validity Check -- Wage Decomposition using IPUMS

The results in Table 4 suggest that roughly 70 percent of the observed firm-level wage differential between documented and undocumented workers arises from differences in productivity between the two types of workers. In order to determine whether this is reasonable, we perform a validity check using cross-sectional data from the Individual Public Use Microsample (IPUMS) from Census for census year 2000. This check involves performing a standard Oaxaca (1973)/Blinder (1973) decomposition of observed wage differentials between non-Hispanic natives vs. Mexican immigrants.[24] 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 U.S. are undocumented (see footnote 3). 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 U.S., for workers in Georgia, and for workers in the U.S. across sectors. 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

[23] 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.

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

differential Table D3 is roughly 40 percent, compared with a 30 percent observed firm-level wage differential in Table 4. We might expect the individual wage differential to be larger than the firm level wage differential because (1) since it is an average across firms in different sectors, and (2) because some of the documented workers in Table 4 are likely documented immigrants, whereas there are no immigrants in the non-Hispanic group in Table D3.[25]

In addition, differences in characteristics (i.e., productivity) account for the vast majority of the observed wage differentials in both Table 4 and Table D3. 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 4 and Table D3 is found in Agriculture, where, based on the results in Table 4, we would have expected much less of the wage differentials in agriculture to be accounted for by differences in productivity. While not perfect, the similarities in patterns found in these two tables indicate that the administrative data used for the analysis in this paper is fairly representative of what might expect in the population as a whole, or, at least, in Georgia more generally.

V. Conclusions and Policy Implications

The main finding from the analysis performed in this paper is that the majority (over 70 percent) of the observed within-firm wage differential between documented and undocumented workers is the result of differences in productivity across the two types of workers. That also means that nearly 30 percent of the wage differential is accounted for by differences in the workers' labor supply elasticities; undocumented workers are estimated to be less sensitive to wages (have lower labor supply elasticities) than documented workers. This means that there is

[25] This is consistent with Aydemir and Skuterud (2008) who find greater differentials between immigrants and natives in Canada across firms than within firms.

a larger gap between wages paid and productivity of undocumented workers, affording employers of undocumented workers a rent associated with their hiring.

An important question is what implication do these results have for the current state-level legislative environment of increasingly restrictive hiring regulation of undocumented workers. While the discussion here is far from a general equilibrium analysis of the impact of any specific policy (for example, see Eren et al. 2011 and Dixon and Rimmer 2009), it offers some informed conjecture in the context of the analysis and conclusions in this paper.

The states of Arizona, Utah, Georgia, Indiana, South Carolina, and Alabama all passed high-profile legislation in 2010 and 2011 targeted toward unauthorized immigrants and their employment.[26] Employers in each state (to varying degrees) are now required to verify that employees are authorized to work in the state. This requirement increases the cost to employers of hiring any worker. The simple relationship between hiring costs, recruitment elasticities, and labor supply elasticities presented by Manning (2011) gives us an idea of the potential impact of this sort of hiring cost increase. Manning derives the following simple relationship between hiring costs, the effectiveness of a dollar spent on hiring, and workers' elasticity of labor supply:

$$\frac{H}{wN} = \frac{\beta}{\varepsilon}, \tag{12}$$

where H is total hiring expenditure, w is the wage, N is total number of workers, so the left hand side reflects total hiring costs as a share of the wage bill; β is the elasticity of hiring expenditure, which reflects the percent increase in the number of hires from a one percent increase in hiring expenditure; and ε is the labor supply elasticity. One prediction from this simple relationship is that the lower the labor supply elasticity (such as is the case for undocumented workers), the greater share of the wage bill the employer is willing to pay to hire

[26] Lawsuits in each state, except South Carolina, have been filed and enjoined (NCSL 2011).

the worker. This is because the lower is the labor supply elasticity, the larger is the gap between the worker's productivity and the wage paid to the worker, thus the greater rents a firm gains from employing the worker. This would explain why firms are willing to undertake the risk (which increases the cost of hiring) of hiring undocumented workers in the first place.

The increased screening cost that employers face being required to use the Federal e-Verify (or similar) program is analogous to an increase in H with no accompanying increase in number of workers (β close to zero). To maintain the equality in equation (12), employers will endeavor to hire workers with smaller and smaller labor supply elasticities; suggesting even greater rents to hiring undocumented workers. In other words, since each worker costs more to hire, there is increased incentive to hire workers that are not as sensitive to wages (more restricted in their alternative opportunities).

Each law also provides for sanctions for employers who knowingly hire an undocumented worker. For example, employers with government contracts in Alabama who knowingly employ undocumented workers can have their business license suspended for up to 60 days for the first violation and have it revoked for a second violation. Increased fines and enforcement of regulations increase the cost of hiring undocumented workers only, which effectively eats away at the wedge between wages and productivity; large enough fines drive that difference to zero, eliminating any rents employers might enjoy from hiring undocumented workers.

Part of Utah's law, which is different from the other states, sets up a temporary guest worker program. 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/her Permit. The implication of a

Permit not tied to a single employer is to increase the employment opportunities of workers holding the Permit.[27] This is expected to increase those workers' labor supply elasticities, reducing the gap between their productivity and their wage; firms will not be willing to incur as great a cost to hire them.[28] The implication is that by raising the labor supply elasticity of "undocumented" workers, they now have to compete with documented workers more purely at a productivity level, which is likely to reduce their attractiveness to employers. 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).

Even if a Utah-type guest worker program is effective in increasing "undocumented" workers' labor supply elasticities, the amount by which they will rise is bounded from above by other limitations of opportunity experienced by all low-skilled immigrants. Evidence that immigrants in general have lower labor supply elasticities than native workers is found in research documenting that immigrants are likely to be found in riskier jobs than natives and not compensated for that additional risk (Hersch and Viscussi 2010 and Orrenius and Zavodny 2009). Further, Arbona et. al (2010) report that both documented and undocumented immigrants from Mexico and Latin America have similar levels of fear of deportation, suggesting that the labor supply elasticity will not be greatly affect by the legitimization of previously undocumented workers. Any policy that legitimizes the status of undocumented workers would, at best, mitigate any monopsony power employers are able to exercise over those workers.

[27] Workers must be living in the state of Utah when they apply for the permit, pay a fee, pass a health and criminal background check, and possess health insurance (see NCSL 2011).
[28] See Cobb-Clark et al. (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.

References

Aguilera, Michael b. and Douglas S. Massey. "Social Capital and the Wages of Mexican Migrants: New Hypotheses and Tests." *Social Forces* 82(2) (December 2003): 671-701.

Arbona, Consuelo; Norma Olvera; Nestor Rodriguez; Jacqueline Hagan; Adriana Linares; and Margit Wiesner. "Acculturative Stress Among Documented and Undocumented Latino Immigrants in the United States." *Hispanic Journal of Behavioral Sciences* 32(3) (2010): 362-84.

Aydemir, Abdurrahman and Mikal Skuterud. "The Immigrant Wage Differential Within and Across Establishments." *Industrial and Labor Relations Review* 61(3) (April 2008): 334-52.

Barth, Erling, and Harald Dale-Olsen, "Monopsonistic Discrmination, Worker Turnover, and the Gender-wage Gap," *IZA Discussion Paper No. 3930*, January 2009.

Bauer, Thomas; Gol Epstein; and Ira N. Gang. "Herd Effects or Migration networks? The Location Choice of Mexican Immigrants in the U.S." *IZA Discussion Paper No. 551* (August 2002).

Benjamin, J.D.; P. Chinloy; G.D. Jud; and D.T. Winkler. "Do Some People Work Harder than Others? Evidence from Real Estate Brokerage." *Journal of Real Estate Finance and Economics* 35(1) (July 2007): 95-110.

Bhaskar, V., Alan Manning, and Ted To, "Oligopsony and Monopsonistic Competition in Labor Markets," *Journal of Economic Perspectives*, 16(2), 155-74, Spring 2002.

Blinder, Alan S. "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources* 8 (Fall 1973): 436-55.

Boraas, Stephanie and William M. Rodgers III. "How Does Gender Play a Role in the Earnings Gap? An Update." *Monthly Labor Review* 126(3) (March 2003): 9-15.

Bovbjerg, Barbara D. 2006. *Social Security Numbers: Coordinated Approach to SSN Data Could Help Reduce Unauthorized Work*, Testimony before the Subcommittees on Social Security and on Oversight, Committee on Ways and Means, House of Representatives, GAO-06-458T, http://www.gao.gov/new.items/d06458t.pdf, (accessed 15 December 2008).

Brown, J. David; Julie L. Hotchkiss; and Myriam Quispe-Agnoli. "Undocumented Worker Employment and Firm Survival." *Federal Reserve Bank of Atlanta Working Paper #2008-28* (December 2008).

Burdett, Kenneth and Dale T. Mortensen. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review* 39(2) (1988): 257-73.

Burgess, Simon; Julie Lane; and David Stevens. "Churning Dynamics: An Analysis of Hires and Separations at the Employer Level." *Labour Economics* 8 (2001): 1-14.

Card, David and John DiNardo. "Do Immigrant Inflows Lead to Native Outflows?" *American Economic Review Papers and Proceedings* 90 (2) (May 2000), 360-7.

Caudill, Steven B. "An Advantage of the Linear Probability Model over Probit or Logit." *Oxford Bulletin of Economics & Statistics* 50(4) (November 1988): 425-7.

Cobb-Clark, Deborah A.; Clinton R. Shiells; and B. Lindsay Lowell. "Immigration Reform: The Effects of Employer Sanctions and Legalization on Wages." *Journal of Labor Economics* 13(3) (1995): 472-98.7

Committee on Ways and Means, House of Representatives. 2004. *Greenbook,* WMCP 108-6, Section 4, (April).

Cornelissen, Thomas. "The Stata Command felsdvreg to Fit a Linear with Two High-dimensional Fixed Effects." *The Stata Journal* 8(2) (accessed 12 November 2009): 170-98.

Cortes, Patricia. "The Effect of Low-skilled Immigration on U.S. Prices: Evidence from CPI Data." *Journal of Political Economy* 116(3) (2008): 381-22.

Costa, Dora L. "The Wage and the Length of the Work Day: From the 1890s to 1991." *Journal of Labor Economics* 18(1) (January 2000): 156-81.

Cuadros, Paul and Red Springs. "Should Illegal Workers be Unionized?" *TIME* 07 December 2006) <http://www.time.com/time/nation/article/0,8599,1567635,00.html> (accessed 21 October 2009).

Damm, Anna Piil. "Ethnic Enclaves and Immigrant Labor Market Outcomes: Quasi-Experimental Evidence." *Journal of Labor Economics* 27(2) (April 2009): 281-314.

Dardia, Michael; Tracey Grose; Hugh Roghmann; and Peggy O'Brian-Strein. "The High-tech Downturn in Silicon Valley: What Happened to all those Skilled Workers?" Bulingame, CA: The Sphere Institute, 2005.

Dávila, Alberto; Alok K. Bohara; and Rogelio Saenz. "Accent Penalties and the Earnings of Mexican Americans." *Social Science Quarterly* 74(4) (December 1993): 902-16.

DeFreitas, Gregory. "Hispanic Immigration and Labor Market Segmentation." *Industrial Relations* 27(2) (Spring 1988): 195-214.

Depew, Briggs and Todd A. Sørensen. "Monopsony Power and the Business Cycle: Prewar evidence from the Ford Motor Company." *Mimeo*, University of Arizona (20 June 2011).

Dixon, Peter B. and Maureen T. Rimmer. "Illegal Immigration: Restrict or Liberalize?" *Mimeo*, Centre of Policy Studies, Monash University (9 April 2009).

Eren, Selçuk; Hugo Benítez-Silva; and Eva Cárceles-Poveda. "Effects of Legal and Unauthorized Immigration on the US Social Security System." *Levy Economics Institute Working Paper #689* (October 2011).

Ethier, Wilfred J. "Illegal Immigration: The Host-country Problem." *American Economic Review* 76(1) (March 1986): 56-71.

Fortuny, Karina; Randy Capps; and Jeffrey S. Passel. "The Characteristics of Unauthorized Immigrants in California, Los Angeles County, and the United States." *Mimeo*. Washington, D.C.: The Urban Institute (March 2007).

Hall, Robert E. "Wages, Income, and Hours of Work in the U.S. Labor Force." In Glen G. Cain and Harold W. Watts, eds. *Income Maintenance and Labor Supply*, pp. 102-62. Madison, WI: Institute for Research on Poverty, 1973.

Hersch, Joni and W. Kip Viscusi. "Immigrant Status and the Value of Statistical Life." *Journal of Human Resources* 45(3) (Summer 2010): 749-71.

Hirsch, Barry T. and Edward J. Schumacher. "Classic or new Monopsony? Searching for Evidence in Nursing Labor Markets." *Journal of Health Economics* 24 (2005): 969-89.

Hirsch, Boris, Thorsten Schank, and Claus Schnabel, "Gender Differences in Labor Supply to Monopsonistic Firms: An Empirical Analysis Using Linked Employer-Employee Data from Germany," *Friedrich-alexander-Universitat Erlangen-Nurnberg Discussion Papers No. 47*, November 2006.

Hoefer, Michael; Nancy Rytina; and Christopher Campbell. "Estimates of the Unauthorized Immigrant Population Residing in the United States: January 2006." *Population Estimates*. Washington, D.C.: US Department of Homeland Security, Office of Immigration Statistics (August 2007).

Hoefer, Michael; Nancy Rytina; and Bryan C. Baker. "Estimates of the Unauthorized Immigrant Population Residing in the United States: January 2008." *Population Estimates*. Washington, D.C.: US Department of Homeland Security, Office of Immigration Statistics (February 2009).

Hotchkiss, Julie L. "Endogeneity of Tenure in the Determination of Quit Behaviour of Young Workers." *Applied Economics Letters* 9 (2002): 231-3.

Hotchkiss, Julie L. and Myriam Quispe-Agnoli. "The Impact of Undocumented Workers on Documented Worker Wages." *Federal Reserve Bank of Atlanta Working Paper #2011-XX* (forthcoming 2011).

Hotchkiss, Julie L.; M. Melinda Pitts; and John C. Robertson. "Earnings on the Information Technology Roller Coaster: Insight from Matched Employer-Employee Data." *Southern Economic Journal* 73(2) (2006): 342-61.

Hotchkiss, Julie L. and Robert E. Moore. "Assessing the Welfare Impact of the 2001 Tax Reform on Dual-Earner Families." *FRBA Working Paper 2007-27* (December 2007).

INS (U.S. Immigration and Naturalization Service, Office of Policy and Planning). "Estimates of the Unauthorized Immigrant Population Residing in the United States: 1990 to 2000," Report 1211 (January 2003). <http://www.dhs.gov/ximgtn/statistics/publications/archive.shtm>, accessed 17 October 2007.

Jasso, Guillermina. "Migration and Stratification." *Social Science Research* 40 (2011): 1292-1336.

Jasso, Guillermina; Douglas S. Massey; Mark R. Rosenzweig; and James P. Smith. "The New Immigrant Survey Pilot (NIS:P): Overview and New Findings about U.S. Legal Immigrants at Admission." *Demography* 37(1) (February 2000): -138.

Kossoudji, Sherrie A. and Deborah A. Cobb-Clark. "Coming out of the Shadows: Learning about Legal Status and Wages from the Legalized Population." *Journal of Labor Economics* 20(3) (2002): 598-628.

Kossoudji, Sherrie A. and Deborah A. Cobb-Clark. "IRCA's Impact on the Occupational Concentration and Mobility of Newly-legalized Mexican Men." *Journal of Population Economics* 13 (2000): 81-98.

Lalonde, Robert and Robert Topel. "Labor Market Adjustments to Increased Immigration." In J. Abowd and R. Freeman, eds. *Immigration, Trade, and the Labor Market*, 167-200. Chicago: University of Chicago Press, 1991.

Liu, Cathy Yang. "Ethnic Enclave Residence, Employment, and Commuting of Latino Workers." *Journal of Policy Analysis and Management* 28 (4) (2009): 600-25.

Machin, Stephen and Alan Manning. "Testing Dynamic Models of Worker Effort." *Journal of Labor Economics* 10(3) (July 1992): 288-305.

Manning, Alan. *Monopsony in Motion*. Princeton: Princeton University Press, 2003.

Manning, Alan. "Imperfect Competition in the Labor Market." In Orley Ashenfelter and David Card, eds., Handbook of Labor Economics, Vol. 4, pp. 973-1041, 2011.

Mincer, Jacob and Boyan Jovanovic. "Labor Mobility and Wages." In Sherwin Rosen, ed. *Studies in Labor Markets*, pp. 21-63. Chicago: University of Chicago Press, 1981.

Morales, Rebecca. “Transitional Labor: Undocumented Workers in the Los Angeles Automobile Industry,” *International Migration Review*, 17(4), (1983-1984): 570-596.

Mroz, Thomas A. and Yaraslau V. Zayats. "Arbitrarily Normalized coefficients, Information Sets, and False Reports of 'Biases' in Binary Outcome Models." *Review of Economics and Statistics* 90(3) (August 2008): 406-13.

Munshi, Kaivan. "Networks in the modern Economy: Mexican Migrants in the U.S. Labor Market." *Quarterly Journal of Economics* (May 2003): 549-98.

Naidu, Suresh. "Recruitment Restrictions and Labor Markets: Evidence from the Postbellum U.S. South." *Journal of Labor Economics* 28(2) (2010): 413-45.

NCSL (National Conference of State Legislatures). "State Omnibus Immigration Legislation and Legal Challenges." 30 September 2011. <http://www.ncsl.org/default.aspx?TabId=22529> (accessed 10 October 2011).

Oaxaca, Ronald. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14(3) (October 1973): 693-709.

Ofek, Haim and Yesook Merrill. "Labor Immobility and the Formation of Gender Wage Gaps in Local Markets." *Economic Inquiry* 35 (January 1997): 28-47.

Orrenius, Pia M. and Madeline Zavodny. "Do Immigrants Work in Risker Jobs?" *Demography* 46(3) (August 2009): 535-51.

Ottaviano, Gianmarco I.P. and Giovanni Peri. "Rethinking the Effects of Immigration on Wages." *NBER Working Paper #12497* (August 2006).

Passel, Jeffrey S. and D'Vera Cohn. "A Portrait of Unauthorized Immigrants in the United States." *Pew Hispanic Center Report* (14 April 2009).

Passel, Jeffery S. and D'vera Cohn. *Unauthorized Immigrant Population: National and State Trends 2010*. Washington, D.C.: Pew Hispanic Center, February 2011.

Pedace, Roberto. "Immigration, Labor Market Mobility and the Earnings of Native-born Workers: An Occupational Segmentation Approach." *American Journal of Economics and Sociology* 65(2) (April 2006): 313-45.

Pena, Anita Alves. "Legalization and Immigrants in U.S. Agriculture." *The B.E. Journal of Economic Analysis & Policy* 10(1), Article 7 (2010).

Peri, Giovanni and Chad Sparber. "Task Specialization, Immigration, and Wages." *American Economic Journal: Applied Economics* 1(3) (2009): 135-69.

Preston, Julie. "Utah G.O.P Adopts Immigration Alternative." *New York Times 11March 2011* <http://www.nytimes.com/2011/03/07/us/07utah.html?pagewanted=all> (accessed 10 October 2011).

Ransom, Michael R. and Ronald L. Oaxaca. "New Market Power Models and Sex Differences in Pay." *Journal of Labor Economics* 28(2) (april 2010): 267-89.

Ransom, Michael R. and David P.Sims. "Estimating the Firm's Labor Supply Curve in a 'New Monopsony' Framework: Schoolteachers in Missouri." *Journal of Labor Economics* 28(2) (April 2010): 331-56.

Raphael, Steven and David Riker. "Geographic Mobility, Race, and Wage Differentials." *Journal of Urban Economics* 45 (January 1999): 17-46.

Rivera-Batiz, Franciso. "Undocumented Workers in the Labor Market: An Analysis of the Earnings of Legal and Illegal Mexican Immigrants in the United States." *Journal of Population Economics* 12(1) (February 1999): 91-116.

Robinson, Joan, *The Economics of Imperfect Competition.* Macmillan: London, 1933.

Royalty, Anne Beeson. "Job-to-job and Job-to-nonemployment Turnover by Gender and Education Level." *Journal of Labor Economics* 16(2) (April 1998):392-443.

Scott, Frank A. Jr.; James E. Long; and ken Somppi. "Salary vs. Marginal Revenue Product under Monopsony and Competition: The Case of Professional Basketball." *Atlantic Economic Review* 13(3) (September 1985): 50-9.

Scully, Gerald W. *The Business of Major League Baseball*. Chicago: University of Chicago Press, 1989.

Semple, Kirk. 2008. "With Economy, Day Laborer Jobs Dwindle." *nytimes.com* (20 October), <http://www.nytimes.com/2008/10/20/nyregion/20laborers.html?partner=rssnyt>, (accessed 20 October 2008).

Schmalensee, Richard. "Output and Welfare Implications of Monopolistic Third-Degree Price Discrimination." *American Economic Review* 71 (March 1981): 242-7.

Stark, Oded. 2007. "Work Effort, Moderation in Expulsion, and Illegal Migration." *Review of Development Economics* 11 no. 4 (February): 585-90.

U.S. Department of Labor, Employment and Training Administration, "Comparison of State Unemployment Laws," <http://workforcesecurity.doleta.gov/unemploy/uilawcompar/2008/comparison2008.asp> (accessed 10 December 2008).

U.S. Department of Housing and Urban Development. "Disclosure and Verification of Social Security Numbers (SSNs) for the Section 235 Program." Mortgagee Letter 90-39 (9 November 1990). <http://209.85.165.104/search?q=cache:5VRIgv1oFQYJ:www.fha.gov/reference/ml1990/90-39ml.doc+pocketbook+social+security+numbers&hl=en&ct=clnk&cd=9&gl=us> (accessed 20 September 2007).

Walker, Devona. "Unions want to bring illegal immigrants into fold." *HeraldTribune.com* (19 July 2006) <http://www.heraldtribune.com/article/20060719/BUSINESS/607190541?Title=Unions-want-to-bring-illegal-immigrants-into-fold> (accessed 21 October 2009).

Yueh, Linda Y. "Do Social Networks Increase Labour Supply Elasticities." *Applied Economics Letters* 15 (2008): 5-10.

Zappone, Christian. "Unions Get Behind Illegal Workers: AFL-CIO lends hand to day laborers with offers of aid, advocacy." *CNNMoney.com* (17 August 2006) <http://www.time.com/time/nation/article/0,8599,1567635,00.html> (accessed 21 October 2009).

Zimbalist, Andrew. *Baseball and Billions*. New York: Basic Books, 1992.

Figure 1.

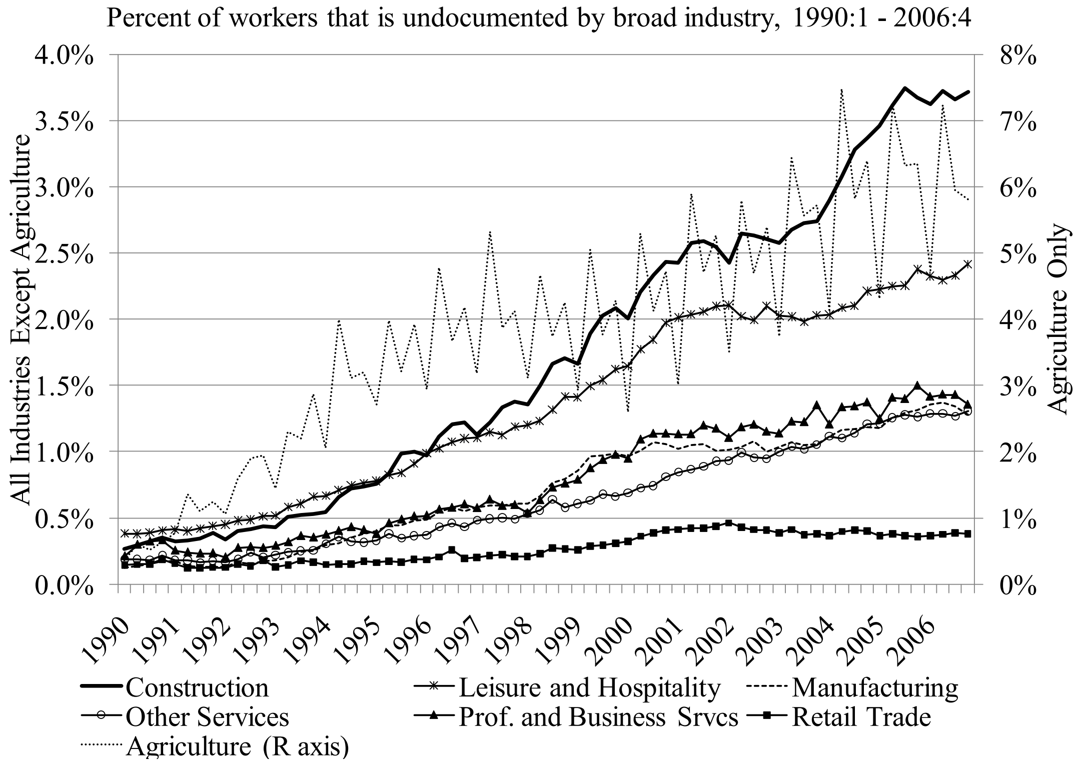
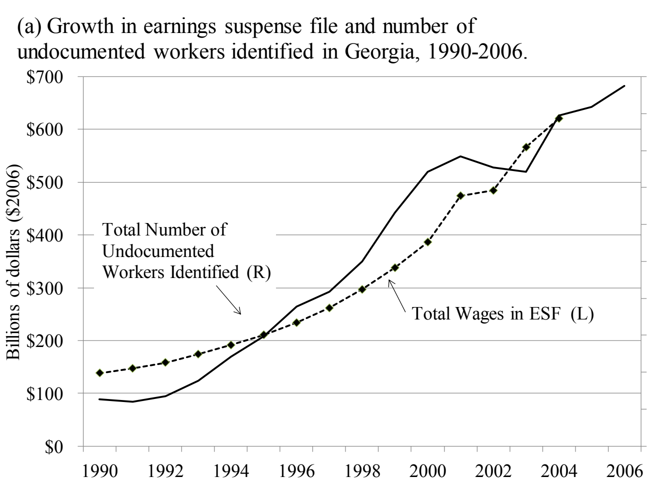
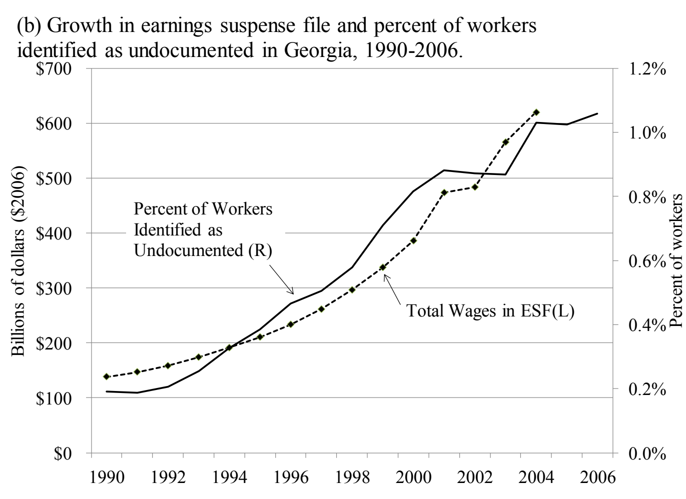


Figure 2. Growth in the earnings suspense file and the total number and percent of workers identified as undocumented in Georgia, 1990-2006.





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

Figure 3.

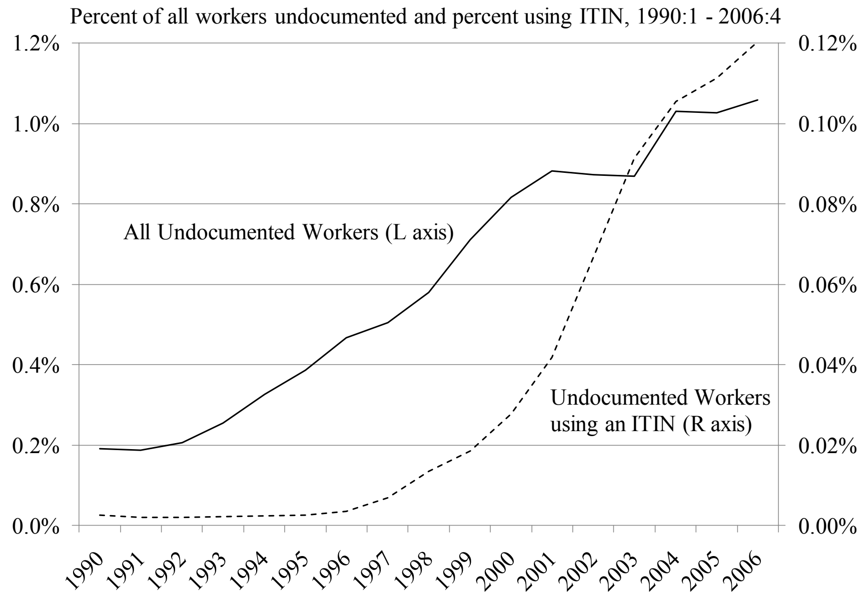


Table 1. Average annual growth, 1994-2006, in US and GA employment, Hispanic workers, and workers identified as undocumented.

Average Annual Growth Rate of:	
Total number of workers in the U.S.	1.48%
Total number of foreign born, Hispanic workers in the U.S.	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%*

Source: Current Population Survey, Basic Survey (March), 1994-2006; and authors' calculations.
Note: 1994 is used as starting year since is the first year the Current Population Survey has a reliable indicator of Hispanic ethnicity.

Table 2. Sample means, 1997-2006.

	Documented		Undocumented	
	Full Sample	3/1000 random sample	Full Sample	ITIN only
Wage (real quarterly earnings)	$8,514	$8,575	$4,190	$4,886
	(11974)	(11805)	(6112)	(4547)
Workers earning less than R$3,000/qtr	$1,202	$1,204	$1,140	$1,342
	(880)	(880)	(880)	(888)
Workers earning at least R$3,000/qtr	$11,878	$11,827	$6,836	$6,848
	(13156)	(12883)	(7351)	(4569)
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		9.0%	7.6%	3.7%
Separating to non-employment		7.5%	28.0%	20.4%
Percent of workers newly hired	17.2%	16.5%	37.3%	28.6%
Recruited from employment		9.0%	7.2%	3.7%
Recruited from non-employment		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 6-digit NAICS industry that is undoc.	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)	2796.9	2943.7	1287.4	330.7
	(6772)	(6915)	(4081)	(1636)
Worker churning among documented workers employed at the firm	26.5%	25.8%	46.2%	31.1%
Distribution by sector skill classification				
Low skill		12.9%	33.2%	27.8%

Medium skill High skill		58.2% 28.9%	62.4% 4.4%	68.2% 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 Srvcs (17%) (includes temporary services)	16%	16%	19%	15%
Education and Health Services (15%)	18%	19%	2%	2%
Leisure and Hospitality (10%)	11%	10%	23%	23%
Other Services (5%) (includes private household, laundry, and repair and maintenance services)	3%	3%	3%	7%
No. 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 \$2006Q4. Full-time status is defined as earning at least \$3,000 (real \$) per quarter (see Hotchkiss et al. 2006 and Dardia et al. 2005). Standard errors are in parentheses. Sample means correspond to workers observed from 1997-2000 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 et al. 2001).

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

Table 3. Overall elasticities of labor supply ($\hat{\varepsilon}_{Nw}$) and separation elasticities, to non-employment, with respect to undocumented new hires ($\hat{\varepsilon}_{Sh}^{n}$) by worker and firm groups.

	Overall Elasticities of Labor Supply ($\hat{\varepsilon}_{Nw}$)		Separation Elasticities to Nonemployment ($\hat{\varepsilon}_{Sh}^{n}$)	
	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/qtr	0.79*	0.73*	0.001	0.01
	(0.012)	(0.064)	(0.003)	(0.011)
≥ R$3,000/qtr	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				
Nat. Res. & Ag.	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)
Trans. & 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)
Fin. 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)
Prof. & Bus Srvcs	1.44*	3.17^	-0.001	0.066
	(0.026)	(1.361)	(0.003)	(0.059)
Ed. and Health	3.61*	1.84*	0.003	0.035
	(0.088)	(0.518)	(0.004)	(0.033)
Leisure & Hosp.	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)

See notes to Tables 2. Documented refer to the 3/1000 random sample of documented workers; Undocumented includes only those workers using a ITIN number as their SSN. *neo*=not enough observations. $^{*}\Rightarrow$ statistical significance at the 99 percent confidence level; $^{\wedge}\Rightarrow$ statistical significance at the 95 percent confidence level; $^{+}\Rightarrow$ statistical significance at the 90 percent confidence level. Also see notes to appendix table D1. 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.

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

Note: See derivation of equation (6) in the text. Also see notes to Table 3.

Appendix A: Using SSNs to Identify Undocumented Workers

A.1. 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/her social security number (SSN). There are a number of ways in which one can establish that a reported social security number 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.[29] In addition, there are several known limitations on what can be considered a valid social security number, so a simple algorithm is used to check whether each number conforms to the valid parameters.

There are three pieces to a SSN.[30] The first three numbers are referred to as the Area Number. This number is assigned based on the state in which the application for a 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 a SSN consists of the two-digit Group Number. The lowest group number is 01, and they are assigned in non-consecutive 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.

[29] See Social Security Number Verification Service <http://www.ssa.gov/employer/ssnv.htm>.
[30] 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 >.

The last four digits of a 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 U.S. 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 U.S. Employers are instructed by the IRS to "not accept an ITIN in place of a 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."[31] 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 one percent in 1997 to over 60 percent by the end of 2006.

A series of SSNs were de-commissioned by the Social Security Administration because they had been put on fake Social Security Cards used as props to sell wallets.[32] 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, 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 a 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.

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[31] "Hiring Employees," <http://www.irs.gov/businesses/small/article/0,,id=98164,00.html>. Also see, "Individual Taxpayer Identification Number (ITIN)," <http://www.irs.gov/individuals/article/0,,id=96287,00.html>.
[32] See U.S. Department of Housing and Urban Development (1990).

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.

A.2. Does "Invalid" mean "Undocumented?"

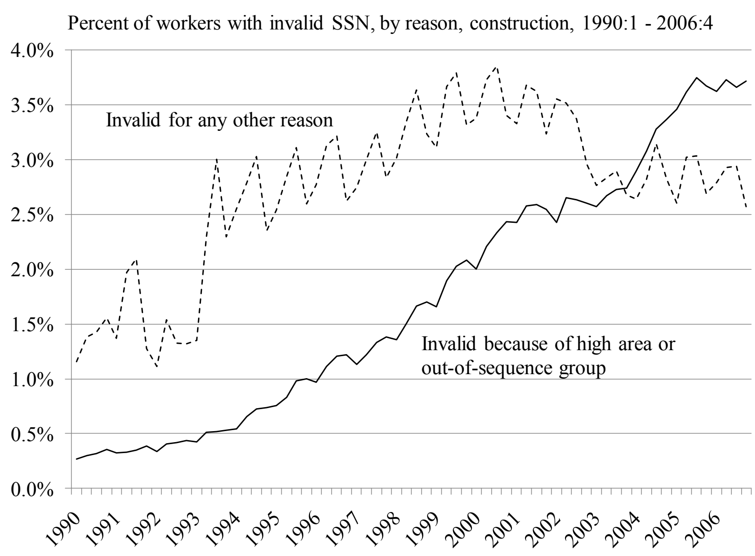
Not all invalid SSN are classified as undocumented workers; examining the patterns of incidence of different types of invalid SSNs suggests that some types are firm generated rather than worker generated. Figure A1 illustrates the incidence patterns across types of invalid SSNs in construction. The percent of workers with SSNs having a high area number or out-of-sequence group number displays the expected growth in undocumented workers (see Hoefer et al. 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 a SSN for workers who will only be employed a very short time.[33] The high degree of churning observed among workers with invalid SSNs for these other reasons is consistent with either of these practices.

[Figure A1 here]

[33] 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.

Since 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 <u>area number that is too high or a group number assigned out of sequence</u>; 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 Individual Tax Identification Number (ITIN) as their SSN. This is discussed further in the text.

Figure A1.



Appendix B: Definition of Sectors

Table B1: Definitions of sectors based on 2-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

Appendix C: Skill Intensity Categories

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 since 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. 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 D: Additional Tables.

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

	Separate to Employment = 1		Separate to Non-employment = 1	
Variable	Documented (3/1000)	Undoc. (ITIN only)	Documented (3/1000)	Undoc. (ITIN only)
Ln(w)	-0.114* (0.001)	-0.046* (0.003)	-0.084* (0.001)	-0.124* (0.004)
Firm Age	-0.007* (0.002)	-0.004 (0.005)	-0.011* (0.002)	-0.028^ (0.011)
Firm Size (#wrkrs/10000)	-0.021* (0.006)	0.022 (0.181)	-0.012^ (0.005)	0.571^ (0.224)
Worker Churning	0.079* (0.006)	0.008 (0.006)	0.057* (0.006)	-0.005 (0.011)
% Wrkrs in Industry that is Undocumented	0.0003 (0.001)	0.002 (0.001)	0.003^ (0.001)	0.0000 (0.003)
Share of New Hires Undocumented (lagged 4 quarters)	-0.003 (0.011)	0.007+ (0.004)	-0.007 (0.011)	0.022^ (0.010)
County Unemployment Rate (lagged 1 quarter)	-0.0002 (0.001)	-0.002 (0.004)	0.0001 (0.001)	-0.006 (0.008)
Worker Labor Market Experience	0.012* (0.001)	0.015* (0.002)	0.026* (0.001)	0.084* (0.005)
Labor Market Experience Squared	-0.0001* (0.000003)	-0.0004* (0.00004)	-0.0001* (0.000003)	-0.0023* (0.0001)
Elasticity of labor supply to employment ($\hat{\varepsilon}^e_{Sw}$)	-1.175* (0.0149)	-0.975* (0.0686)		
Elasticity of labor supply to non-employment ($\hat{\varepsilon}^n_{Sw}$)			-1.143* (0.0176)	-0.776* (0.0250)
Separation elasticity wrt share of new hires that is undocumented ($\hat{\varepsilon}_{Sh}$)	-0.0003 (0.0011)	0.027+ (0.0157)	-0.001 (0.0014)	0.023^ (0.0110)
Specification Including Tenure:				
Elasticity of labor supply to employment ($\hat{\varepsilon}^e_{Sw}$)	-1.190* (0.0153)	-1.047* (0.0136)		
Elasticity of labor supply to non-employment ($\hat{\varepsilon}^n_{Sw}$)			-1.152* (0.0178)	-0.61* (0.0065)
Separation elasticity wrt 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/she does not appear on the firm's payroll for four consecutive quarters. A worker has separated into employment is 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 1997-2006 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.

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

Variable	New Hire from Employment = 1	
	Documented (3/1000)	Undoc. (ITIN only)
Ln(w)	-0.004* (0.0014)	-0.003+ (0.0017)
Firm Age	-0.0001 (0.0001)	-4E-07 (0.0001)
Firm Size (#workers/10000)	-0.008 (0.0032)	0.012 (0.0086)
Worker Churning	0.037* (0.0070)	0.059* (0.0068)
% 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)
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 in order 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 (% of Differential)	Unexplained Portion of Differential (% 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 U.S.)			
Nat. Res. & Ag.	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%)
Trans. & 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%)
Fin. Activities	0.36	0.29 (80.5%)	0.07 (19.5%)
Information	0.36	0.25 (68.7%)	0.11 (31.3%)
Prof. & Bus Srvcs	0.58	0.53 (90.6%)	0.06 (9.4%)
Ed. and Health	0.34	0.29 (86.1%)	0.05 (13.9%)
Leisure & Hosp.	0.12	0.15 (>100%)	-0.03 (--)
Other Services	0.27	0.19 (69.3%)	0.08 (30.7%)

Note: 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.