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Abstract: Using matched employer-employee data from the state of Georgia, this paper investigates the potential for employer monopsony power in the labor market for undocumented workers. Undocumented workers are found to be about 40 percent less sensitive as documented workers to their employers' wage adjustments. This difference in labor supply elasticities accounts for about 30 percent of the observed within-firm wage differential between documented and undocumented workers. There is no statistically significant evidence of displacement of documented workers as more undocumented workers are hired.

JEL classification: J42, J61, J2

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

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I. Introduction and Background

The model of monopsonistic discrimination was developed by Robinson (1933) to describe a labor market in which two groups of equally productive workers (men and women) are paid different wages because they differ in their elasticities of labor supply. 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. 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 of employers practicing monopsonistic discrimination against undocumented workers. If so, this has important implications for tighter restrictions on illegal immigration. If wages for both documented and undocumented workers are being determined in a competitive labor market, then greater restrictions of unauthorized immigration will unambiguously lead to higher wages, increased production costs, and likely higher prices paid by consumers. In the presence of monopsony employer power, the implication of tighter immigration policy would depend on the form that policy takes.

If the policy involved rounding up all the undocumented workers, sending them home, then shutting down the border to prevent others from entering, the impact would be the same as under perfect competition -- higher production costs and consumer prices. However, the more restrictive policy could take the form of legitimizing current undocumented workers through, say, a guest worker program, and tightly controlling the flow of workers across the border in response to changes in domestic demand. This would have the effect of removing the employer's monopsony power and would result in higher wages and employment among those previously unauthorized (rents formerly accruing to firms will now go to the workers). The impact on production costs in this case is unclear as the impact of both rising wages and employment on average wages is ambiguous.[1]

The presence of monopsonistic employer power has been identified in a number of settings. Evidence of potential monopsonistic discrimination against women as a result of lower labor supply elasticities (relative to men) is provided by Hirsch et al. (2006) and Barth and Dale-Olsen (2009). Geographic mobility, by limiting employment choices, of women (Ofek and Merrill 1997) and of blacks (Raphael and Riker 1999) has also been identified as a source of monopsonistic discrimination. Scully (1989) and Zimbalist (1992) provide evidence of monopsonistic discrimination (at least through the 1980s) in baseball for players that are contractually limited in their employment options by being tied to one team before achieving free-agent status. Scott et al. (1985) offer similar evidence for basketball players.

In the case where workers are divided and one group is paid less than an equally productive different group, Lang et al. (2005) present a theoretical model in which monopsonistic labor market outcomes can arise in equilibrium and does not necessarily require firms to overtly discriminate against the lower-paid group. It only requires that the disadvantaged group *think* employers are discriminatory. They offer this model as explanation for the persistent wage gap between black and white workers.

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[1] See Dixon and Rimmer 2009 for results from a general equilibrium simulation exercise of the welfare effects of a myriad of different U.S. immigration reform policies.

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.[2] In addition, DHS estimates for January 2008 that 61 percent of unauthorized 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 employment 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. All of these factors reduce employment opportunities of undocumented workers, ceteris paribus. Stark (2007) presents a compelling theoretical mechanism through

[2] 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).

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."

Very little empirical investigation of the labor market experiences of undocumented workers exists. DeFreitas (1988) and Hotchkiss and Quispe-Agnoli (2009) 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) presents evidence that employing undocumented workers gives 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 making up for lower productivity of the workers. This paper estimates labor supply elasticities for documented and undocumented workers, finding evidence that undocumented workers are less sensitive to wages than their documented co-workers. The paper also investigates the evidence for displacement of documented workers as more undocumented workers arrive; no evidence of displacement is found. 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.

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).[3] 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.

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, immigration status).

A. 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

[3] 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).

checking, but one must register as an employer to obtain this service.[4] 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.[5] 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.

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

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

[5] 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 >.

nonresident aliens who are not eligible for U.S. employment and need identification for other tax purposes."[6] 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. Identifying undocumented workers with ITIN numbers will be important in the fixed-effects estimation described below.

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.[7] 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.

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

[6] "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>.
[7] See U.S. Department of Housing and Urban Development (1990).

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.

B. 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 1 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.[8] The high degree of churning observed among workers with invalid SSNs for these other reasons is consistent with either of these practices.[9]

[Figure 1 here]

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, the analysis below takes the conservative tack by considering as undocumented only those workers whose SSNs are classified as invalid because the <u>area number is too high or the group number is</u>

[8] 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.

[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).

assigned out of sequence; workers with invalid SSNs for any other reason are considered neither undocumented nor documented and, thus, are excluded from the analysis. This will clearly undercount the actual number of undocumented workers. However, all workers, regardless of SSN classification, are included in counts of aggregate firm employment.

Figure 2 plots the prevalence of undocumented workers in the seven broadly defined sectors with the highest incidences, excluding agriculture. The concentration of workers in these sectors was also identified nationally by Fortuny et al. (2007).[10] 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 2 here]

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.

[10] 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).

C. Are Undocumented Workers Correctly Identified?

There are several reasons we are confident that the sample of undocumented workers is representative. The DHS estimates for January 2008 that 61 percent of unauthorized immigrants come from Mexico (Hoefer et al. 2009). One test of the accuracy of identifying undocumented workers, then, might be to compare the geographic distribution of those identified as undocumented for the purposes of analysis in this paper and the geographic distribution of various ethnic and racial groups across counties in the state. Table 1 presents these correlation coefficients for 2005.

[Table 1 here]

The correlation between the percent of the county population that is Hispanic and the percent of workers in the county identified as undocumented is 0.18 (of course, some individuals may live and work in different counties). The correlations with the percent that is Asian and the percent that is African American in the counties are both negative. The correlation of the percent of firms in the county employing undocumented workers with ethnicity is also positive and highest as it relates the percent of the county population that is Hispanic (0.38). The correlation of the presence of these firms with percent of the county population that is Asian is also positive, but smaller at 0.27; the correlation with the percent of the population that is African American is again negative.

Additionally, 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.; about 43 percent of employers associated with wage payments that end up in the ESF come from only five of 83 broad industry classifications, with eating and drinking establishments (leisure and hospitality, 17 percent) and construction (10 percent) being the largest contributors (Bovbjerg 2006).

Figure 3 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. The average annual growth rate since 1990 in the number and percent of workers identified as undocumented and in the ESF are each about 14 percent, whereas the average annual growth rate of the entire labor force in Georgia is only two percent.

[Figure 3 here]

The positive correlation between the Hispanic population across counties in Georgia and the percent of workers identified as undocumented for this analysis, as well as closely matching growth in undocumented workers identified in Georgia and growth in the SSA ESF independently suggest 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.

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.

D. Sample Means

For reasons discussed below, the analysis is constrained to include workers only between 1997 and 2000 inclusive. Table 2 presents some means for this sample of workers. In addition, the table contains means for an even smaller sub-set of undocumented workers whose SSN numbers follow the number scheme of ITIN numbers, and for a 1/100 random sample of documented workers. The full sample of documented workers of over 62 million observations is too large for estimation, so a 1/100 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 could be 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 "part-time" 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 $5,984 and the average undocumented worker earnings at the same firms is $4,345, putting the within-firm undocumented worker wage penalty at just under 30 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).

Undocumented workers are likely to have been on their current job a shorter amount of time, have less labor market experience , and reflect greater separation behavior (not holding anything else constant). Undocumented workers appear to be concentrated among smaller employers who experience a greater degree of churning among its documented workforce, suggesting a need for workforce flexibility, as has been documented among firms that employ undocumented workers (Morales 1983-1984). The smaller firm size could be reflecting the typical size of firms in industries more likely to hire undocumented workers. The larger share of new hires that is undocumented among the undocumented sample suggests that undocumented workers are concentrated in certain industries.

There are some notable differences in the distribution of workers across industry skill intensity and NAICS classification.[11] 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 monopsonist 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

[11] Appendix A defines the sector classifications and Appendix B describes the construction of skill classifications.

and the worker's elasticity of labor supply.

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

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

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:

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

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

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

$$\varepsilon_{nw}^k = \frac{\partial n^k}{\partial w^k}\frac{w^k}{n^k} \Rightarrow \frac{\partial w^k}{\partial n^k} = \frac{w^k}{\varepsilon_{nw}^k n^k} \ , \tag{4}$$

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 $\varepsilon_{nw}^k > 0$.[12] 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 that commonly estimated in the labor supply literature, which would reflect an individual's willingness to supply their labor to the

[12] 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.

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 number of employment alternative 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 between those workers:

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

The empirical problem becomes the estimation of the elasticity of labor supply for the two groups of workers. Comparing the marginal revenue product across groups of workers will not only reflect differences in productivity levels of workers performing the same job, or task, but also differences in tasks being performed 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).

B. Estimating the Elasticity of Labor Supply

Estimates of labor supply elasticities are obtained by exploiting a relationship identified by others between workers' elasticity of labor supply (ε_{nw}) and elasticity of separation (ε_{sw}):

$$\varepsilon_{nw} = -2\varepsilon_{sw} > 0 \ . \tag{7}$$

Ransom and Oaxaca (2009) appeal to this relationship to estimate the role monopsony power plays in gender pay differences at a regional grocery store chain. Bhaskar et al. (2002) make use of estimated separation elasticities to make inferences about employer monopsony power, emphasizing that the focus on separation elasticities is not a focus on the level of turnover, but on the sensitivity of those separations to the wage. Also, Barth and Dale-Olsen (2009) exploit the same relationship in a firm-level analysis of labor supply elasticity differences between men and women. As all of these earlier studies point out, it is much easier to estimate the elasticity of separation than it is to estimation the elasticity of labor supply (or elasticity of recruitment).

The relationship in equation (7) relies on two assumptions. First, it requires that the flow of recruits (or new hires) equals the flow of separations; that one employer's separation is another employer's recruitment. To improve the chances of this condition being met, we restrict the sample to individuals who separated into another job (see Manning 2003: 99). Note from Table 2 that the percent of workers in the separating is fairly close to the percent of workers that are newly hired. The much smaller percent of workers separating into employment reflects that fact that employers are hiring from non-employment as well as employment and our requirement that a worker be observed in a new job the quarter immediately following the quarter of separation. Since the hire rates slightly exceed the separation rates during this particularly strong labor market, we would expect the labor supply elasticity estimated for this subset of workers to be overestimated.

A second assumption is required as a result of how undocumented workers are identified. Since undocumented workers are defined as those using certain types of invalid SSNs, it is not reasonable to expect that an undocumented worker would use the same SSN when moving from one employer to another. However, if a worker is using an ITIN, they are probably more likely to use that same number across employers. This is why the period of analysis is restricted to the years 1997 (the year of first ITIN issuance) through 2000, and the undocumented sample is restricted to workers using their ITIN as a SSN. Figure 4 plots the percent of workers identified as undocumented and the percent of workers using an ITIN. The growth in the share of workers identified using ITINs understandably increased tremendously after 1997. This figure also illustrates how the ITIN restriction reduces the sample of undocumented workers substantially.

[Figure 4 here]

C. Empirical Specification of Worker Separations

The relationship between wages and worker separations derives from a simple version of the standard search problem. The details of this model, and a discussion of how separation elasticities might be expected to differ across documented worker status, are found in Appendix C. The main point from the derivation is that while one might be able to compare separation rates between documented and undocumented workers, based on the fact that undocumented workers earn a lower wage on average, one cannot determine analytically how the two groups of workers will respond to changes in those wages. In other words, the way in which separation (thus labor supply) elasticities will compare across the two groups cannot be determined theoretically.

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*):

$$S_{injt} = \gamma_0^k + \gamma_1^k \ln(w_{injt}) + \gamma_2^k h_{nt} + \gamma_3^k X_{injt} + \delta_i + \theta_n + \varepsilon_{injt} \quad (8)$$

where S_{injt} is the probability that worker *i* separates from employer *n* (in industry *j*) in quarter *t* and is employed by a different firm the following quarter (workers who separate into non-employment are excluded from the estimation); w_{injt} is the real quarterly wage observed for worker *i* in quarter *t*; h_{nt} is the percent of new hires in firm *n* that are undocumented; 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 year and quarter fixed effects. δ_i is the individual fixed effect defined as the worker's reported SSN and θ_n is a fixed effect for the firm in which the worker is employed. The percent of new hires in firm *n* at time *t* that are undocumented is calculated as $h_{nt} = H_{nt}^u / (H_{nt}^u + H_{nt}^d)$, where H^k is the number of undocumented (*k*=*u*) and documented (*k*=*d*) workers hired by the firm during the previous four quarters.

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.

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. 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 (Jovanovic 1979). Again, because of concerns about potential endogeneity of tenure in the determination of separation (Hotchkiss 2002), a specification excluding tenure is estimated with no appreciable change in results (see Appendix D). 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.[13]

Given the estimation results from equation (8), the average separation elasticity with respect to wages for workers of type *k* can be calculated as follows:

$$\bar{\varepsilon}_{sw}^{k} = \frac{1}{N^k}\sum_{i=1}^{N^k}\frac{\partial s}{\partial w}\frac{w_i}{s_i} = \frac{1}{N^k}\hat{\gamma}_1^k\sum_{i=1}^{N^k}\frac{1}{s_i} \ , \tag{9}$$

where N^k is the total number of workers of type *k*. The average labor supply elasticity for workers of type *k*, then, from equation (7), is $\bar{\varepsilon}_{nw}^{k} = -2\bar{\varepsilon}_{sw}^{k}$.[14]

D. Estimating Displacement

To the extent that the arrival of undocumented workers depresses wages in a labor market or results in employers substituting documented workers with undocumented workers, an outflow of documented workers is expected. This potential outflow could not only affect estimates of the wage impact, but could also have considerable social welfare impacts if

[13] 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.
[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.

documented workers were flowing into unemployment (rather than to merely another job). The impact of undocumented worker inflow on displacement can also be investigated using the specification in equation (8). The dependent variable in this case, however, is not separation into another job, but, rather, separation into non-employment.[15] The average separation elasticity with respect to the share of new hires that is undocumented is calculated as:

$$\bar{\varepsilon}_{sh}^{k} = \frac{1}{N^k}\sum_{i=1}^{N^k}\frac{\partial s}{\partial h}\frac{h_i}{s_i} = \frac{1}{N^k}\hat{\gamma}_2^k\sum_{i=1}^{N^k}\frac{h_i}{s_i}\,. \tag{10}$$

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 types of displacement.

IV. Results

Appendix Table D1 contains the OLS linear probability estimates corresponding to equation (8) 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.[16] Table D2 contains the linear probability estimates for the specification excluding worker tenure; there is no appreciable change in estimated coefficients or in estimated elasticities. The coefficient that is the most changed across specifications is that related to total labor market experience.

[15] 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.

[16] 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.

As expected, higher paid workers have lower probabilities of separation and workers employed at older firms are less likely to separate. Employer size has a differential impact across workers status, with documented workers less likely to separate from larger firms and undocumented workers more 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.

Unexpectedly, documented workers with longer tenure and experience have higher rates of separation, perhaps reflecting high rewards during this period of rapid economic growth to changing employers and to labor market experience in general. 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. While undocumented workers with more experience are also more likely to separate, separation to another job is reduced the longer an undocumented worker has been employed by a specific firm. In general, one would expect that the more 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.

The share of workers in the industry that is undocumented only increases documented workers' separations to another job. If firms that employ undocumented workers pay lower wages overall, this could reflect the ability of documented workers to chase the higher-paying jobs at firms not hiring undocumented workers.

Regarding the regressor of interest for estimating displacement from the separation to non-employment, a greater number of newly arriving undocumented workers *decreases* separation among earlier arriving undocumented workers. This outcome is consistent with a growing share of the workforce overall being undocumented. 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, for that matter).

The greater the (lagged) county level unemployment rate, the less likely an undocumented worker is to separate, which is consistent with worker effort models (for example, see Machin and Manning 1992). However, higher unemployment rates during this time period do not appear to affect the separation rates among documented workers. Worker churning also 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 Labor Supply Elasticities

Table 3 contains the estimated labor supply elasticities and separation elasticities with respect to new hires. As hypothesized, documented workers are more sensitive (about 62 percent more sensitive) to wage changes than undocumented workers, overall. For the full sample, a one percent decrease in the wage reduces the supply of undocumented workers by 1.28 percent, but reduces the supply of documented workers by 2.07 percent.[17] In other words, documented workers are more likely than undocumented workers to quit their jobs in response to a wage reduction.

[Table 3 here]

Similar to the analysis of Ransom and Oaxaca (2009) this analysis yields estimates of monopsony power that is likely overestimated. The results suggest that in the absence of monopsony power, documented workers would be earnings wages that are 48 percent higher

[17] 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 Costa (2000), Benjamin et al. (2007), and Hotchkiss and Moore (2007). They are in the ball park to firm-level elasticities of labor supply estimated by Bhaskar et al. (2002), who reported elasticities in the range of 0.7 and 1.2; and by Ransom and Oaxaca (2009), whose estimates were close to 2.0 for both men and women.

than they are and undocumented workers would be earning 78 percent higher wages.[18] In spite of the level estimates of monopsony power, the *relative* magnitude of the elasticities are likely still relevant. Labor supply elasticities estimated separately across wage groups and broad industry characteristics are also reported in Table 3 and they tell a remarkably consistent 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 paid workers more sensitive to wage changes than lower paid workers, then decreases at the highest wage level. This change in elasticities across wage groups is indicative of a labor supply curve that starts out concave then has a transition point between the third and fourth quartile. This pattern of estimates is consistent with those found by other across varying income levels (e.g., Hall 1973 and Hotchkiss and Moore 2007).

Across broad sector classifications and grouping workers by their industry's skill level, undocumented workers are less sensitive to wage changes than documented workers. Exceptions are found in Construction, Retail Trade, and Leisure & Hospitality; undocumented workers in these sectors are *more* sensitive to wage changes than documented workers. 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, and we would expect this "social network" effect to be strongest in sectors with a larger concentration of undocumented workers (also see Damm 2009, Munshi 2003, and Aguilera and Massey 2003 for further evidence on the role of networks in generating better employment outcomes).

[18] Rearrangements of the terms in equation (5), the degree to which workers are paid less than their marginal revenue product is found: $\frac{MRP-w}{w} = \frac{1}{\varepsilon_{nw}}$. As pointed out by Hirsch and Schumacher (2005), the presence of an upward sloping supply curve is not sufficient evidence to establish the presence of monopsony power. However, differing labor supply elasticities across two groups of workers presents a firm the opportunity to differentiate wage payments along a dimension additional to productivity.

Both documented and undocumented workers become more sensitive to wage changes as the skill intensity of their employer's sector increases, although the number of undocumented workers employed by firms in the highest skill sector is too small to yield a precise estimate.

B. 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 (identified in the table as "part-time") and workers in lower-skill sectors exhibit much lower wage differences between documented and undocumented workers and a greater share of the differential is explained by differences in labor supply elasticities. In other words, lower wage and lower skill documented and undocumented workers are much more similar in their productivity levels than are higher paid and higher skill documented and undocumented workers.

The differences across broad sectors are consistent with this conclusion. The Agriculture sector stands out with more than 100 percent of the within-firm wage differential being contributed by differences in elasticities of labor supply across worker types. This sector is likely the one with the most homogenous of worker skills, and thus it makes sense that very little of the observed wage differential would be the result of differences in marginal revenue products across worker status.

Three other sectors stand out for the relatively *small* contributions that labor supply elasticity differences make. Differences across worker status in labor supply elasticities in Construction, Retail Trade, and Leisure & Hospitality contribute nothing to the wage differentials observed in those sectors. As mentioned previously, Yueh (2008) has shown that the presence of networks increases workers' labor supply elasticities. It would make sense that these networks would be greatest in the industries in which there is a relatively large representation of undocumented workers.

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 -0.38, 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.[19]

C. Estimates of Displacement

Turning to the separation elasticities (found in Table 3), newly arriving undocumented workers appear to have no impact on displacing documented workers. At worst, the point estimate would suggest that four documented workers are displaced for every 1,000

[19] 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.

undocumented workers hired. The only elasticity estimated to be significantly different from zero (at the 95% confidence level) is among workers employed in medium skill firms; seven documented workers are displaced as a result of 1,000 additional undocumented workers hired. Although not significantly different from zero, there may be a scale effect at work in Agriculture, Construction, Leisure & Hospitality, and high skill employers with fewer documented workers separating as more undocumented workers are hired by firms in those sectors.

In contrast to the displacement evidence among documented workers, an increase in the share of new hires that is undocumented decreases, overall, the percent of undocumented workers separating by 0.078 percent. However, the impact varies across skill and sector of employer. Although not significantly different from zero, earlier arriving undocumented workers might suffer some displacement with newly arriving undocumented workers in low skill sectors, particularly Agriculture, Retail Trade, and Leisure & Hospitality. This displacement would be consistent with that of 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. One might expect that in these sectors the level of undocumented workers has reached a saturation point such that newly arriving undocumented workers are in direct competition with those who arrived earlier.

The relatively large and significantly negative separation elasticities among undocumented workers in Construction, Manufacturing, Professional & Business Services, and Other Services, might indicate that the production processes in these sectors is flexible enough to absorb continued arrival of undocumented workers without displacing earlier arriving ones.

V. Implications and Conclusions

The analysis in this paper presents evidence that firms are exploiting the limited employment and grievance opportunities of undocumented workers to pay them lower wages than documented workers. Approximately 30 percent of the observed within-firm pay differential between documented and undocumented workers is the result in differences in labor supply elasticities of these workers. The remainder (70 percent of the pay differential) is the result of differences in marginal revenue product between documented and undocumented workers. The role that differences in labor supply elasticities play in wage differentials across documented status, however, does vary across sectors.

Firms who enjoy a monopsony position in the labor market typically enjoy greater profits from being able to pay at least some of its workers a wage lower than their marginal revenue product. These firms may not take kindly to efforts to limit their supply of inexpensive labor through stricter immigration policies. In addition, if those policies were successful in limiting the supply of undocumented workers, resulting in higher production costs; consumers may see the effect in the form of higher product prices (see Cortes 2008).

Alternatively, if immigration reform policies were focused on eliminating the monopsony position of employers, and employers paid all workers a wage equal to their marginal revenue product, they would be indifferent between hiring documented and undocumented workers (with the same productivity levels). While this may not seem like a boon to documented workers, they would now be competing with undocumented workers on skill and human capital rather than on a willingness to be paid less than their actual contribution to the firm's output.

Eliminating the firm's monopsony power would require legitimizing the presence of workers who are now considered undocumented. One way to do this would be to create a permeable border, allowing the flow of workers to be dictated by the demands of employers through something like a guest-worker program. Facilitating an employers' ability to draw workers from a larger pool when needed would likely have to be accompanied by strictly enforced penalties for hiring workers outside of the guest-worker program. Of course, policy makers may have other goals in mind, such as ensuring the highest wage possible for U.S. citizens. If this is the case, the implications for immigration policy would look very different.

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.

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

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.

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.

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.

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

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.

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 #2010-XX* (forthcoming 2010).

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).

Jovanovic, Boyan. "Job Matching and the Theory of Turnover." *The Journal of Political Economy* 87(5, part 1) (October 1979): 972-90.

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.

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.

Lang, Kevin; Michael Manove; and William R. Dickens. "Racial Discrimination in Labor Markets with Posted Wage Offers." *American Economic Review* 95(4) (September 1327-40).

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.

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.

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

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

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." *Mimeo*, Colorado State University (10 March 2009).

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

Ransom, Michael R. and Ronald L. Oaxaca. "New Market Power Models and Sex Differences in Pay." Working Paper #540, Industrial Relations Section, Princeton University (January 2009).

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.

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.

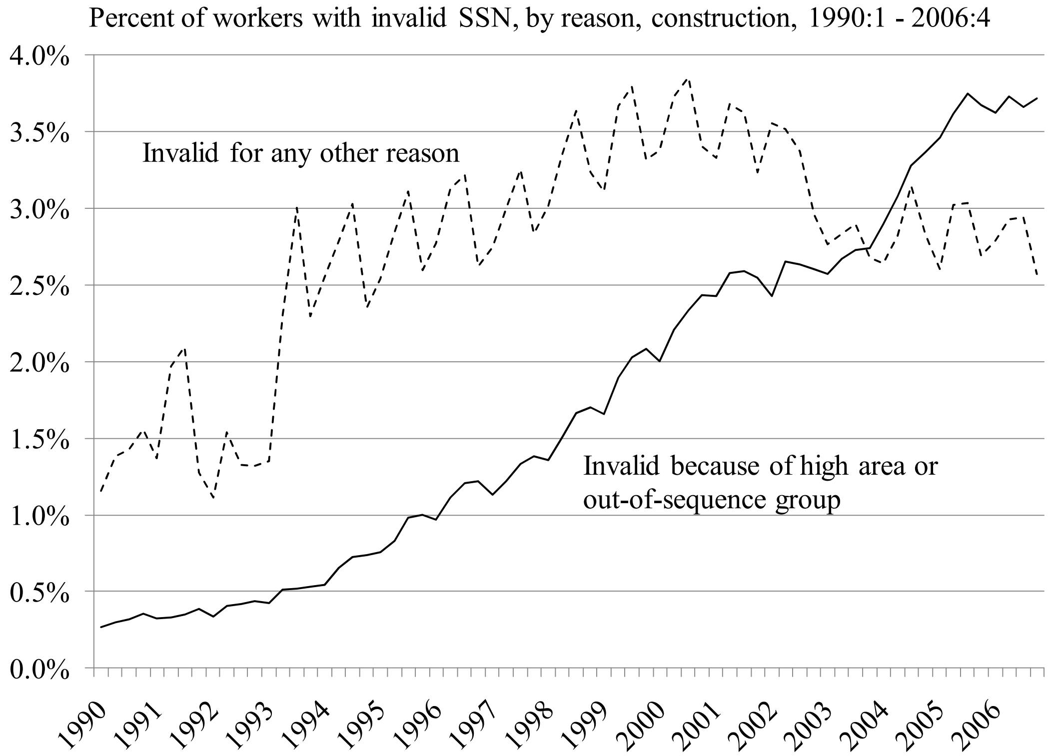


Figure 2.

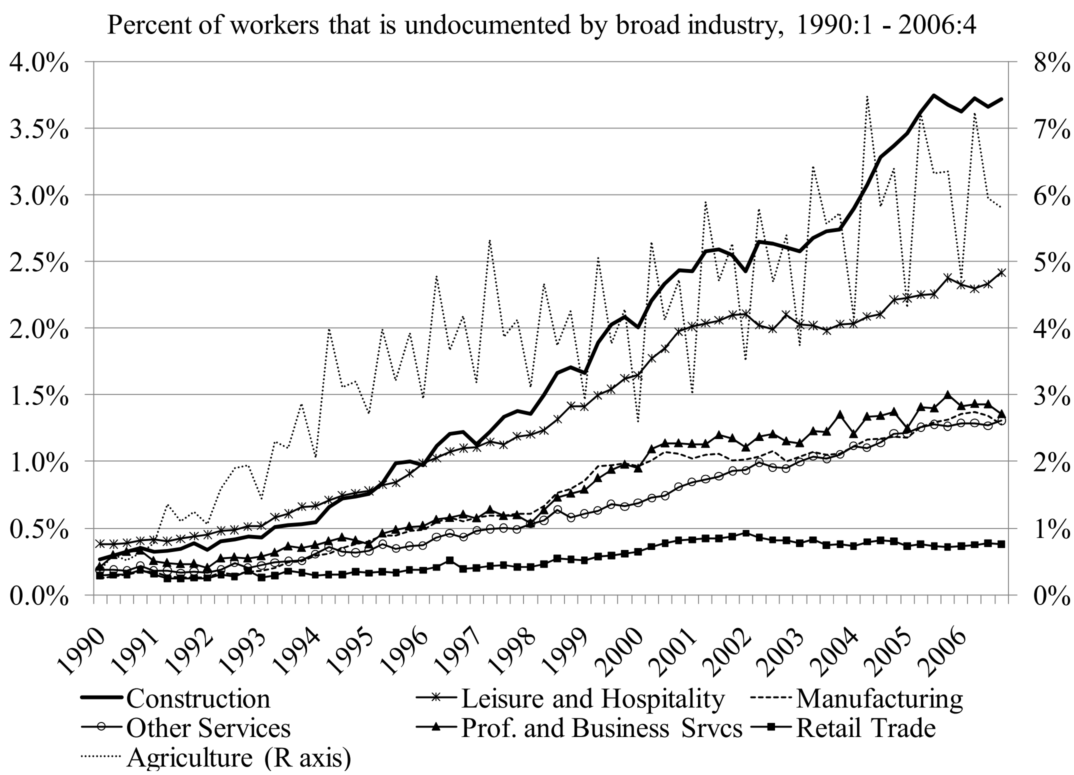
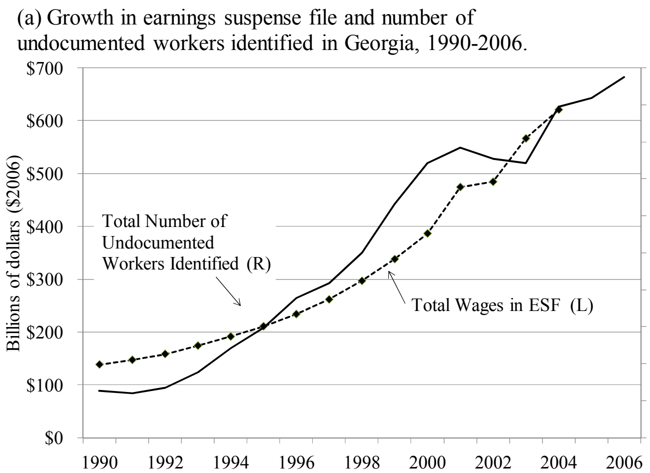
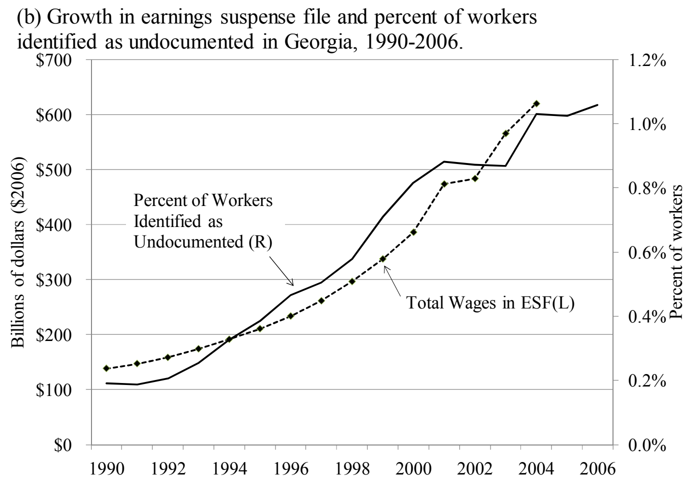


Figure 3. Growth in the earnings suspense file and the total number and percent of workers identified as undocumented in Georgia, 1990-2006.





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 4.

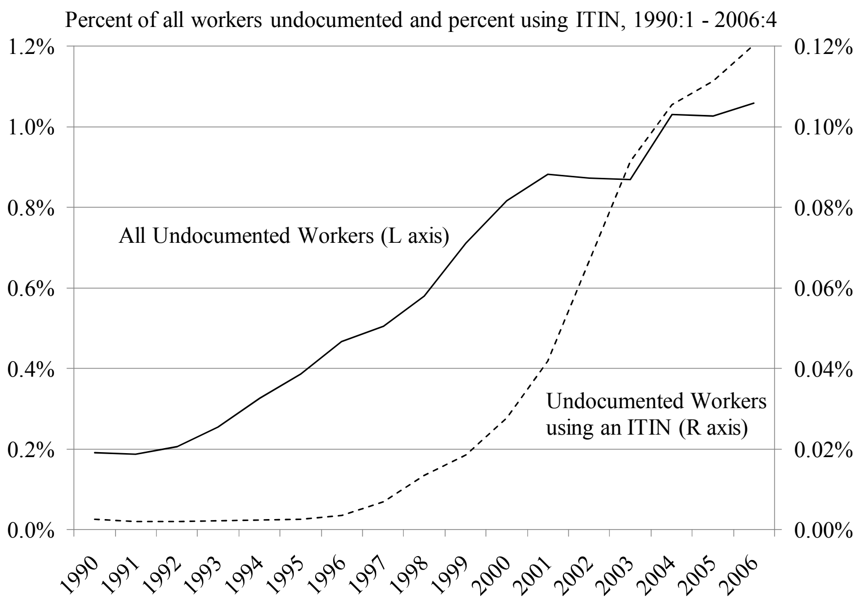


Table 1. Correlation between percent of workers identified as undocumented by county and the percent of firms that employ them, with the percent of the population in each county that is Hispanic, African American, and Asian.

Percent of Population that is:	Percent of Undocumented Workers in County	Percent of Firms Employing Undocumented Workers in County
Hispanic	0.18	0.38
Asian	-0.02	0.27
African American	-0.19	-0.13

Table 2. Sample means, 1997-2000.

	Documented		Undocumented	
	Full Sample	1/100 random sample	Full Sample	ITIN only
Wage (real quarterly earnings)	$8,053 (11684)	$8,105 (11795)	$3,820 (5934)	$4,237 (4815)
Part-time workers	$1,181 (878)	$1,184 (875)	$1,097 (866)	$1,188 (884)
Full-time workers	$11,495 (13001)	$11,539 (13122)	$6,657 (7439)	$6,904 (5249)
Worker tenure (number of quarters)	11.29 (12.10)	11.41 (12.17)	3.42 (4.22)	2.69 (2.33)
Worker labor market experience (number of quarters since 1990)	22.59 (12.68)	22.66 (12.72)	5.50 (6.07)	3.31 (2.91)
Percent of workers separating	18.4%	16%	36%	24%
Separating to employment	*na*	9%	8%	4%
Separating to non-employment	*na*	7%	28%	20%
Percent of workers newly hired	18.6%	17%	37%	29%
Share of firms' new hires that is undocumented	0.9%	1.0%	10.5%	16.19%
Percent of workers in firm's 6-digit NAICS industry that is undoc.	0.65%	0.65%	2.48%	2.53%
Age of employer (number of quarters since 1990)	30.6 (11.0)	30.7 (11.0)	27.32 (12.64)	25.51 (13.87)
Employer size (number of workers)	2,738 (6125)	2,664 (6081)	1,138 (2989)	883 (2978)
Wrkr churning among documented workers employed at the firm	30 %	29%	50%	44%
Distribution by skill intensity				
Low skill	14%	14%	34%	31%
Medium skill	59%	59%	60%	64%
High skill	27%	27%	6%	5%
NAICS Sector Shares (U.S. share)[a]				
Natural Resources and Agriculture (1%)	1%	1%	7%	5%
Construction (6%)	5%	5%	14%	22%
Manufacturing (15%)	15%	15%	18%	11%
Transportation and Utilities (4%)	5%	5%	1%	<1%
Wholesale Trade (5%)	5%	5%	4%	4%
Retail Trade (13%)	14%	14%	6%	7%

Financial Activities (7%)	5%	5%	2%	2%
Information (3%)	4%	4%	<1%	<1%
Professional and Business Srvcs (17%) (includes temporary services)	16%	16%	19%	17%
Education and Health Services (15%)	17%	16%	3%	2%
Leisure and Hospitality (10%)	11%	11%	23%	23%
Other Services (5%) (includes private household, laundry, and repair and maintenance services)	3%	3%	2%	5%
No. of observations	62,876,329	62,544	390,433	9,237

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. Labor supply elasticities (ε_{nw}) and separation elasticities with respect to undocumented new hires (ε_{sh}) by wage quartiles and industry groups, base model with both individual and firm fixed effects.

	Labor Supply Elasticities (ε_{nw})		Separation Elasticities (ε_{sh})	
	Documented	Undocumented	Documented	Undocumented
Full Sample	2.07* (0.029)	1.28* (0.096)	0.004 (0.003)	-0.078* (0.017)
PT/FT Status				
Part-time	0.71* (0.028)	0.50* (0.111)	-0.002 (0.007)	-0.039 (0.029)
Full-time	5.78* (0.177)	1.81$^{\wedge}$ (0.77)	0.007 (0.007)	-0.102* (0.034)
Wage Quartiles				
Quartile 1	0.60* (0.029)	0.38$^{\wedge}$ (0.148)	-0.007 (0.008)	-0.086^{+} (0.047)
Quartile 2	5.36* (0.280)	1.80^{+} (0.958)	0.014 (0.010)	-0.090^{+} (0.051)
Quartile 3	12.33* (0.886)	3.14 (3.45)	0.008 (0.015)	-0.034 (0.058)
Quartile 4	3.03* (0.534)	-1.21 (1.604)	0.007 (0.015)	-0.238* (0.061)
Skill Intensity				
Low skill	1.51* (0.069)	1.18* (0.202)	-0.006 (0.015)	0.031 (0.034)
Medium skill	1.86* (0.035)	1.62* (0.125)	0.007^{+} (0.004)	-0.117* (0.022)
High skill	3.18* (0.098)	-0.65 (0.828)	-0.002 (0.007)	-0.178$^{\wedge}$ (0.070)
NAICS Sector				
Nat. Res. & Ag.	1.59* (0.443)	0.20 (0.418)	-0.041 (0.073)	0.071 (0.099)
Construction	1.64* (0.144)	2.35* (0.27)	-0.025 (0.019)	-0.192* (0.055)
Manufacturing	3.61* (0.14)	1.98* (0.449)	0.037 (0.016)	-0.153$^{\wedge}$ (0.068)
Trans. & Utilities	3.87* (0.294)	*neo*	-0.053$^{\wedge}$ (0.022)	*neo*
Wholesale Trade	3.93* (0.255)	1.77^{+} (0.916)	0.050 (0.015)	-0.059 (0.102)
Retail Trade	1.83* (0.068)	2.54* (0.496)	0.010 (0.008)	0.058 (0.045)
Fin. Activities	2.41* (0.225)	*neo*	-0.010 (0.016)	*neo*

Information	2.20* (0.22)	*neo*	-0.010 (0.020)	*neo*
Prof. & Bus Srvcs	1.34* (0.056)	1.00* (0.210)	0.003 (0.008)	-0.090^ (0.036)
Ed. and Health	3.30* (0.12)	1.32 (1.294)	-0.020 (0.015)	-0.284* (0.093)
Leisure & Hosp.	1.25* (0.067)	1.43* (0.222)	-0.005 (0.014)	0.027 (0.038)
Other Services	2.29* (0.24)	1.76^ (0.625)	0.011 (0.013)	-0.200* (0.073)

See notes to Tables 2. Documented refer to the 1/100 random sample of documented workers; Undocumented includes only those workers using a ITIN number as their SSN. *neo*=not enough observations. * ⇒ statistical significance at the 99 percent confidence level; ^ ⇒ statistical significance at the 95 percent confidence level; + ⇒ statistical significance at the 90 percent confidence level.

Table 4. Log wage differentials between documented and undocumented workers decomposed into differences between marginal revenue product and differences in firms' potential monopsony power.

	Average within-firm Log Wage Differential $\ln(w^d)$-$\ln(w^u)$	Difference in workers' MRPs $[\ln(MRP^d)$-$\ln(MRP^u)]$ (% of Differential)	Difference in workers' elasticities of labor supply $\left[\ln\left(\frac{1}{\varepsilon^u_{nw}}+1\right)-\ln\left(\frac{1}{\varepsilon^d_{nw}}+1\right)\right]$ (% of Differential)
Full Sample	0.29	0.21 (73%)	0.08 (27%)
PT/FT Status			
Part-time	0.04	-0.05 (--)	0.09 (> 100%)
Full-time	0.31	0.19 (61%)	0.12 (39%)
Skill Intensity			
Low skill	0.17	0.12 (73%)	0.05 (27%)
Medium skill	0.32	0.30 (93%)	0.02 (7%)
High skill	0.53	--	--
NAICS Sector			
Nat. Res. & Ag.	0.24	-0.32 (--)	0.56 (> 100%)
Construction	0.34	0.39 (> 100%)	-0.05 (--)
Manufacturing	0.36	0.29 (80%)	0.07 (20%)
Trans. & Utilities	0.21	--	--
Wholesale Trade	0.41	0.31 (77%)	0.10 (23%)
Retail Trade	0.42	0.46 (> 100%)	-0.04 (--)
Fin. Activities	0.29	--	--
Information	0.54	--	--
Prof. & Bus Srvcs	0.26	0.20 (78%)	0.06 (22%)
Ed. and Health	0.45	0.32 (71%)	0.13 (29%)
Leisure & Hosp.	0.14	0.16 (> 100%)	-0.02 (--)
Other Services	0.23	0.19 (84%)	0.04 (16%)

Note: See derivation of equation (6) in the text.

Appendix A: Definition of Sectors

Table A1: 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 B: 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.

<u>Appendix C: Separation Elasticity</u>

The purpose of this appendix is to illustrate how a worker's separation rate is related to the worker's wage distribution and how that translates into the worker's separation elasticity. It is the separation elasticity, under a strong assumption of steady state, that allows us to estimate a worker's elasticity of labor supply.

Appealing to a simple version of the standard search problem and assuming that workers are more willing to work for firms paying higher wages, the following separation rates for documented and undocumented workers can be derived:[1]

$$S^d(w; F^d[w]) = \delta + \lambda^d(1 - F^d[w]) \text{ and } S^u(w; F^u[w]) = \delta + \lambda^u(1 - F^u[w]) \qquad \text{(C.1)}$$

where S^k is the separation rate of documented (k=d) and undocumented (k=u) workers; δ is the job destruction rate, assumed to be the same for documented and undocumented workers;[2] and λ^k is the job offer arrival rate for documented and undocumented workers. The mere presence of some firms that will not hire undocumented workers means the offer arrival rate is lower for undocumented workers than for documented workers, $\lambda^u \leq \lambda^d$.

Based on the assumptions leading to equation (1) and the additional labor market constraints that undocumented workers face, undocumented workers are expected to draw wage offers from a distribution ($F^u[w]$) that is stochastically dominated by the wage offer distribution that documented workers face ($F^d[w]$), implying that at any given wage, $\tilde{w}$, $F^d[\tilde{w}] \leq F^u[\tilde{w}]$, or $\Pr[W^d \leq \tilde{w}] \leq \Pr[W^u \leq \tilde{w}]$. The lower offer arrival rate and stochastically

[1] See Burdett and Mortensen (1988) and Manning (2003, sections 2.2 and 4.4). The basic assumptions of the model are that firms have identical constant returns to scale, workers are identical, each worker has the same value of leisure, some workers are employed and others are unemployed, and workers can search while employed. The main relevant implication from the equilibrium search model is that the firm has to offer a higher wage to attract more workers. Also see Jovanovic (1979) whose job matching model also predicts that workers paid a higher wage are less likely to separate from their employers.

[2] δ is assumed to be the rate at which a job for which both types of workers would qualify is destroyed and is, thus, affected by the general strength of the labor market. If the job destruction rate among undocumented workers exceeds that among documented workers, their separation rates cannot be compared analytically.

inferior wage distribution lead to the result that for any given wage, $\tilde{w}$, the separation rate among undocumented workers is lower than among documented workers:[3]

$$S^u(\tilde{w};F^u[\tilde{w}]) \le S^d(\tilde{w};F^d[\tilde{w}]). \tag{C.2}$$

This result is consistent with DeFreitas (1988) who finds that Hispanic immigrants (although not necessarily undocumented) do not exhibit higher turnover tendencies than documented workers when comparing equally skilled workers in the same sectors. The ability of firms to exploit their monospony power is predicated not on how often workers separate, but on how sensitive that separation behavior is to changes in the wage. Constructing the elasticity of separation allows a comparison of workers' sensitivity to wage changes abstracting from expected wage level of the workers.

From equation (A.2), the elasticity of separation with respect to the wage for worker of type *k*, evaluated at the expected wage for that worker type ($\overline{w}^k$) is:

$$\varepsilon_{Sw}^k\Big|_{w=\overline{w}^k} = \left\{\frac{\partial S^k[w;F^k(w)]}{\partial w}\frac{w}{S^k(w)}\right\}\Bigg|_{w=\overline{w}^k} = \frac{-\lambda^k f^k[w]w}{S^k(w)}\Bigg|_{w=\overline{w}^k} < 0 . \tag{C.3}$$

In general, for which group of workers the elasticity is larger cannot be determined analytically; the shape of the wage offer density function relative to the expected wage for each group will ultimately determine the relative sizes of the elasticity. The point is, knowing that the wage offer distribution of documented workers stochastically dominates the wage offer distribution of undocumented workers indicates that the separation rate of documented workers exceeds that of undocumented workers (within the framework of this simple search model and at a given wage). However, it does not tell us how sensitive the workers will be to wage changes, relative to one another.

[3] This result only requires one of the two conditions--lower offer arrival rate or stochastically inferior wage offer distribution--but it is not unreasonable to expect both of these conditions to be satisfied.

Appendix D: Linear Probability Parameter Estimates and Robustness Checks.

Table D1. Linear probability estimates of separation equations.

	Separate to Employment = 1		Separate to Non-employment = 1	
Variable	Documented (1/100)	Undoc. (ITIN)	Documented (1/100)	Undoc. (ITIN)
Ln(w)	-0.116* (0.002)	-0.0596* (0.0044)	-0.075* (0.001)	-0.108* (0.006)
Worker Tenure	0.005* (0.0005)	-0.016^ (0.007)	0.003* (0.005)	0.007 (0.012)
Firm Age	-0.092* (0.008)	-0.015 (0.020)	-0.060* (0.007)	-0.088* (0.025)
Firm Size (#wrkrs/10000)	-0.093* (0.017)	0.461* (0.170)	-0.037* (0.014)	0.571^ (0.224)
Worker Churning	0.070* (0.011)	0.019 (0.016)	0.043* (0.009)	-0.011 (0.023)
% Wrkrs in Ind. Undoc.	0.023* (0.005)	0.004 (0.007)	0.012 (0.004)	-0.005 (0.010)
Share of New Hires Undoc	0.016 (0.032)	-0.038^ (0.015)	0.034 (0.026)	-0.101* (0.022)
Lagged County Unemployment Rate	-0.001 (0.002)	-0.016^ (0.008)	0.0005 (0.001)	-0.020+ (0.011)
Worker LM Experience	0.023* (0.003)	0.067* (0.014)	0.046 (0.002)	0.137* (0.020)
LM Experience Squared	-0.0003* (0.00002)	-0.001* (0.0003)	-0.0004* (0.00001)	-0.005* (0.0004)
Number of Observations	57,791	6,125	57,468	7,469
Labor supply elasticity (ε_{nw})	2.07* (0.029)	1.28* (0.096)	--	--
Separation elasticity wrt share of new hires that is undocumented (ε_{sh})	--	--	0.004 (0.003)	-0.078* (0.017)

Notes: A worker is declared separated from he 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 1997-2000 inclusive. The undocumented sample is restricted to those whose SSN corresponds to the ITIN numbering scheme. Model also includes individual and firm level fixed effects and year and quarter dummies. Worker labor market experience and firm age are only since 1990, the first year of available data. * $\Rightarrow$ statistical significance at the 99 percent confidence level; ^ $\Rightarrow$ statistical significance at the 95 percent confidence level; + $\Rightarrow$ statistical significance at the 90 percent confidence level. Also see notes to Table 2.

Table D2. Linear probability estimates of separation equations, excluding worker tenure.

	Separate to Employment = 1		Separate to Non-employment = 1	
Variable	Documented (1/100)	Undoc. (ITIN)	Documented (1/100)	Undoc. (ITIN)
Ln(w)	-0.114* (0.002)	-0.0604* (0.0045)	-0.075* (0.001)	-0.108* (0.006)
Worker Tenure	--	--	--	--
Firm Age	-0.093* (0.008)	-0.017 (0.020)	-0.061* (0.007)	-0.087* (0.025)
Firm Size (#wrkrs/10000)	-0.097* (0.017)	0.450* (0.170)	-0.039* (0.014)	0.578^ (0.224)
Worker Churning	0.068* (0.011)	0.021 (0.016)	0.042* (0.009)	-0.011 (0.023)
% Wrkrs in Ind. Undoc.	0.022* (0.005)	0.004 (0.007)	0.011 (0.004)	-0.005 (0.010)
Share of New Hires Undoc	0.017 (0.032)	-0.037^ (0.015)	0.034 (0.026)	-0.101* (0.022)
Lagged County Unemployment Rate	-0.001 (0.002)	-0.017^ (0.008)	0.0005 (0.001)	-0.019+ (0.011)
Worker LM Experience	0.031* (0.003)	0.046* (0.010)	0.050 (0.002)	0.145* (0.013)
LM Experience Squared	-0.0003* (0.00002)	-0.001* (0.0003)	-0.0004* (0.00001)	-0.005* (0.0004)
Number of Observations	57,791	6,125	57,468	7,469
Labor supply elasticity (ε_{nw})	2.04* (0.029)	1.30* (0.096)	--	--
Separation elasticity wrt share of new hires that is undocumented (ε_{sh})	--	--	0.004 (0.003)	-0.078* (0.017)

Notes: See notes to Table D1.