Flight of the H-1B: Inter-Firm Mobility and Return Migration Patterns for Skilled Guest Workers

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Abstract

We study the job mobility of highly-skilled Indian IT guest workers and provide new evidence on their inter-firm mobility and return migration patterns. We use a unique dataset to show that these workers are mobile and that lower paid guest workers are more likely than higher paid guest workers to separate to another firm in the U.S. This may be surprising given concerns about the H-1B program's restrictions on immigrant job mobility. We also analyze return migration decisions and find that low wage workers repatriate more than high wage workers, and that this relationship intensifies during the Great Recession. This partially mitigates concerns that guest worker visa programs do not adjust to supply and demand. Following this finding, we show that the employment to population ratio (EPOP) for highly-skilled male workers has fallen at a much steeper rate since 2008 than is typically recognized, once we account for the phenomenon of *discouraged immigrants*.

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1 Introduction

One of the main conduits for skilled migration, the H-1B visa program, admits up to 85,000 new skilled immigrant workers annually to the U.S.[1] Comprehensive immigration reform proposals would increase the number of H-1B visas, make it easier to transfer visas between employers, and further penalize firms that are heavy visa-users (MacDonald, Lopez, Decker and Valerio 2013). Proponents of an expanded program argue that higher levels of skilled immigration will lead to higher growth rates through more innovation, consistent with the work of Kerr and Lincoln (2010) and Hunt and Gauthier-Loiselle (2010). Concerns about an expanded program relate to both high-skilled immigration as a whole, and issues related to the particular institutional features of the H-1B labor market. The work of Borjas (2009) and Borjas and Doran (2012) argues that there are negative consequences of high-skill immigration on native workers' labor market outcomes. Our analysis is better suited to address existing concerns about the H-1B visa program itself, in particular that: 1) that workers on this visa are in a condition of "indentured servitude" due to frictions in the labor market, 2) that firms pay workers on these visas below-market wages, and 3) that the program has no labor market test to ensure that immigrants do not crowd out citizens during periods of heightened unemployment (Hira 2010).[2] In this paper, we provide rigorous evidence to aid in the assessment these three concerns.

We submit that answers to the above claims may lie in the study of inter-firm mobility and return migration patterns. Accordingly, we present new evidence using unique job mobility data for over 70,000 Indian workers on temporary visas who worked at six large Indian information technology firms in the U.S. from 2003-2011. Our results cast doubt on the claim that these workers labor in indentured servitude. They reveal that inter-firm mobility of these workers is actually quite similar to other estimates in the literature obtained from presumably more mobile workers in other labor markets, suggesting that market forces prevent firms from dramatically underpaying these workers. We also find that these workers return to India at higher rates during weak labor markets, at least partially mitigating any concerns of excess supply of immigrant workers during a recession.

The present paper stands at the intersection of research on skilled immigration and labor market frictions. Typically, if firms take advantage of workers, then workers' primary recourse should be to freely quit their jobs and find better employers. However, guest worker programs impose frictions that inhibit inter-firm mobility. For example, the explicit cost of transferring an H-1B visa between employers ranges between $2000 and $5225, while workers on an L1 visa are entirely prohibited from switching employers. Job mobility in a market with this type of friction has yet to be empirically addressed in the literature, but intuition would strongly suggest that workers laboring in such an institutional setting would be

[1] See http://www.uscis.gov for detailed statistics on visas granted.

[2] Further information suggesting that workers on these visas may be vulnerable to exploitation includes the following EPI report Hira (2010), AFL-CIO report (Dorning and Fanning 2012), and research by Matloff (2002) and Chakravartty (2006).

less mobile. In the framework of Manning (2003), the degree of inter-firm mobility of workers directly affects firms' ability to pay workers less than their marginal product.[3] This suggests a labor market that is ripe for exploitation.

Our analysis suggests that the degree of inter-firm mobility as measured by quits with respect to wages is similar to other studies of mobility for workers not facing these government imposed frictions. We also find that the elasticity does drop significantly with the start of the Great Recession, consistent with Depew and Sorensen (2012). If anything, our results for H-1B visa holders are likely to be biased downward (towards higher levels of exploitation) for two reasons: in addition to the standard omitted variable bias (discussed in detail later), our dataset includes an unknown number of workers on L1 visas who are completely immobile.

Current reforms proposed in Congress would adjust the number of visas to business cycle fluctuations in order to ensure that the program does not harm citizens during especially high bouts of unemployment. We present estimates of rates of return migration to India, and find that lower paid workers are more likely to return than higher paid workers, consistent with earlier research (Abramitzky, Boustan and Eriksson 2012). We expand on this, finding for the first time that the sensitivity of return with respect to wage increases during economic downturns as does the overall probability of return migration. This should partially alleviate some concerns of opponents of the program. Additionally, we note the importance of return migration in measuring the general health of labor markets. Specifically, the employment to population ratio for prime-aged skilled male workers in 2011 would be even worse in a counterfactual scenario in which migration patterns did not fluctuate during the Great Recession. We find that recalculating the ratio by adding back in people we term *discouraged immigrants* (based on deviations from the 2000-2008 trend growth rate in the immigration population) reveals nearly twice as large a decline in the employment to population (EPOP) ratio.

2 Background

The Immigration Act of 1990 created the H-1B and L1 visa categories. The H-1B visa program is intended to enable organizations to bring workers into the U.S. in certain skilled occupations experiencing labor shortages. The L1 visa is meant for multinational firms that need to transfer overseas workers to their U.S. operations. Both are considered "non-immigrant" visas, meaning that guest workers on these

[3] A small but growing body of recent work has found evidence across a variety of settings that interfirm mobility with respect to wages is relatively low when compared to the assumption of perfect competition (most estimates of quit elasticities range between -.5 and -2.5), suggesting that some firm wage setting power may exist. Examples include Boal (1995), Ransom and Oaxaca (2005), Ransom and Oaxaca (2010), Hirsch, Shank and Schnabel (2006), Hirsch (2007), Hotchkiss and Quispe-Agnoli (2009), Ransom and Sims (2010), Hirsch, Shank and Schnabel (2010), Falch (2010), Ransom and Lambson (2011), Falch (2011), Dube, Lester and Reich (2011), Depew and Sorensen (2012) and Webber (2011).

visas are expected to return to their home country when their visa expires. The visas do have a "dual intent," however, and it is possible to apply for permanent residency while on a H-1B or L1 visa. Individuals who receive H-1B visas are required to be of "distinguished merit or ability" while holders of L1 visas are expected to possess "specialized knowledge." Both the H-1B and L1 visas are issued to individuals for initial periods of 3 years and may be renewed once for a total of 6 years, after which the temporary worker must either return home or apply for permanent residency.[4]

Tight labor markets and the "Dot-Com" boom of the late 1990s created a perception of labor shortages in the IT Industry. Even today, despite elevated unemployment rates, companies continue to report severe difficulty finding skilled workers in the Science, Technology, Engineering and Mathematics (STEM) occupations. One response to these shortages has been calls for more immigration of skilled workers. Skilled immigration reform proposals center around the H-1B and L1 visas that are the most frequently used by computer professionals: in fiscal year 2010, 47% of H-1B recipients were in computer-related occupations (Wasem 2012).

In its last major revision of the H-1B visa program, The American Competitiveness and Worker Investment Act for the 21st Century (AC21), Congress addressed some concerns about the "portability" of the H-1B visa and enacted reforms aimed at preventing worker exploitation. Prior to AC21, H-1B workers had been able to switch employers only after the approval of a new petition, which could take in excess of six months to obtain. With the AC21 revision, workers who were already on an H-1B visa could now switch employers immediately upon the initiation of a sponsorship petition by their new employer. As the Congressional Record indicates, Congress felt that a competitive and properly functioning labor market was critical in order to insure that H-1B workers were not exploited. As the legislative committee report declared, "the market would not tolerate exploitation, especially given the fierce competition for skilled workers. An H-1B employee who is not being treated fairly can easily be petitioned by another employer and switch to work for that employer(Hatch 2000)".

Despite these reforms, there is reason to believe that frictions in this labor market are still being created by government regulations. A skilled worker who meets the eligibility criteria for a H-1B or L1 visa cannot find employment in the U.S. without also finding an employer willing to undergo a time-consuming visa application and sponsorship process. To transfer a worker who already holds an H-1B visa from their current employer, the hiring employer must initiate a visa application in a regulatory system that requires application and legal fees.[5] Excluding legal and

[4]An annual cap of 65,000 was initially placed on the number of H-1B visas available. The American Competitiveness and Workforce Improvement Act of 1998 increased the H-1B visa cap to 115,000 for 1999 and 107,500 for 2000. The American Competitiveness and Worker Investment Act for the 21st Century of 2000 (AC21) increased the cap to 195,000 through 2003, after which the number of visas reverted to 65,000. Additional changes allowed another 20,000 recipients of post graduate degrees obtained in the U.S. to receive these visas.

[5]A brief history of the fees includes a $1,000 fee on large employers that sunset on October 1, 2003; but after December 8, 2004, this fee was restored and increased to

administrative costs (approximately \$2,000), the fees are \$2,000 for all employers, an additional \$2,000 for large employers of H-1B visas, and an additional \$1,225 for expedited processing. Would-be employers must also provide evidence regarding the non-displacement and notification of incumbent workers. These regulations generate significant paperwork for the employer (the forms required have an estimated paperwork burden of 3 hours and 45 minutes), and should theoretically limit the number of employers willing to hire H-1B workers, decreasing outside options for these workers. Meanwhile, regulations for workers on L1 visas explicitly prohibit them from switching jobs.

Several case studies have uncovered worker testimony regarding the implications of employer unwillingness to sponsor H-1B workers. Compared to having a green card (which allows workers to obtain another job without employer sponsorship), H-1B workers reported feeling “bound” and “tied down” to their employers (Banerjee 2006, Banerjee 2009). Banerjee also reported that workers employed by Indian IT contractors found it difficult to obtain work directly from American firms, which preferred to maintain flexibility by outsourcing labor to Indian IT and other subcontractor firms, and that workers felt that their inability to switch employers meant that they weren’t treated as equal members of the labor market, leading to lower wages, longer working hours, and decreased opportunities. As a worker in another study put it, “It’s not as free of a market. Maybe not deliberately, but companies take them (H-1B workers) for granted...The pay is lower, \$20,000 at my level, because we are less mobile. They take advantage of the situation.”(Chakravartty 2006). The actual degree of immobility of these workers is an important empirical question which our unique dataset will allow us to rigorously assess.

Wage differentials between workers on H-1B visas and U.S. nationals are a matter of some contention. The most convincing evidence of a negative effect of costly job mobility on wages comes from studies of what happens to workers on temporary visas after they obtain a green card. Two studies using data from the New Immigrant Survey show that temporary workers receive a 20-25% wage boost once they receive a green card (Mukhopadhyay and Oxborrow 2012, Kandilov 2007). Another study that examines the difference between citizens, green card holders and temporary workers finds that IT workers with a green card earn only 6.1% more than IT workers without a green card (Mithas and Lucas 2010).

The Immigration and Nationality Act requires employers of H-1B visa workers to them the prevailing wage and prohibits discrimination against these workers with respect to pay and benefits. Studies using prevailing wage documentation filed by firms find that H-1B workers earn less (Miano 2005), and a review of studies released by think tanks finds that H-1B workers are paid 15-33% less than comparable

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\$1,500; after March 8, 2005, firms had to pay an additional \$500 fraud prevention fee; from February 17, 2009 to February 17, 2011, the Employ American Workers Act imposed additional restrictions on banks receiving bailout funds hiring workers on H-1B visas, and after August 14, 2011, an additional \$2,000 fee was imposed on each petition for a H-1B worker for certain employers. This information is available at the USCIS website.

workers (Matloff 2006). These studies, as Mithas and Lucas (2010) note, suffer various flaws, stemming from the inability to account for experience and education and the unreliability of data.[6] Mithas and Lucas (2010) find that workers on H-1B visas earn more than citizens after conditioning on age, education, and experience. But weaknesses in Mithas and Lucas' (2010) study warrant further examination. First, their data comes from a non-random internet survey of 50,000 IT professionals by InformationWeek magazine, raising questions about the representativeness of the sample. Second, the data does not contain information on detailed occupation or tasks performed by the worker. Thus it is hard to directly compare immigrant and citizens wages in their data. Lofstrom and Hayes (2011) finds that the earnings gap between H-1B workers and naturalized citizens was 13.6% in 2009 while the gap between H-1B workers and all U.S. citizens was 3.1 percent.[7] Again, an empirical assessment of how much inter-firm mobility workers may exhibit (and the likely corresponding firm wage setting power) will allow us to provide more evidence on the likelihood that these workers are severely underpaid as compared to citizens.

3 Data and Empirical Strategy

3.1 Data

The companies in our dataset belong to the Indian IT industry, which is a large employer of H-1B and L1 workers. Companies in this industry are the largest users of these visa programs; these "offshore outsourcing" companies contract with major corporations in the U.S. and elsewhere to act as intermediaries in the supply of IT services (Hira 2010). Our dataset includes records from 6 Indian IT firms and 72,606 employees for the years 2003-2011. Given estimates that only 270,000 H-1B workers are in the country at a given time, our sample is a sizable portion of the stock of H-1B workers (Lowell 2000). As is typical in the Indian IT industry, the employees are a mix of H-1B, L1, and U.S. citizens and permanent residents, although the visa holders are the vast majority of these workers (Hira 2010). We do not capture the individual's visa status. This means we have an unknown number of L1 holders in our dataset, as well as permanent resident and citizens. Because L1 workers cannot change employers we will not observe any quits to competing firms for them. To sharpen the focus on workers holding visas, we eliminate from our dataset workers who earn less than $30,000 and more than $130,000, creating

[6]Employers applying for H-1B visas must file a Labor Condition Application (LCA) with the Labor Department declaring the number of foreign workers, workers in each occupation, and wages at a particular work establishment. A frequent data source used by firms when filing LCAs is the Occupational Employment Statistics data provided by the BLS, which provides wage data by occupation and geographical region. One of the key problems with using this data, however, is that LCAs are attached to work locations and not to workers and thus aren't necessarily a reflection of actual wages paid.

[7]Lofstrom's sample of all H-1Bs from 2009 had a mean age of 30.6 in Information Technology, and annual earnings averaging $76,698. This is comparable to our sample's average age of 29.5 and earnings of $72,184.25.

a window that should capture most of those in the dataset who are on visas, rather than high paid American executives at the company, or low paid American staff, such as clerical and custodial workers.

Information in the dataset includes a U.S. employment start date and an exit date. The exit date takes two forms: it either notes the date on which a worker returned to India, or notes the date on which a worker otherwise separates from employment (legally, these workers would have to have gained employment at another firm in the U.S. in order to remain in the country). Because the workers would have to quickly find new employment, we believe that the vast majority of separations (other than returns to India) observed are voluntary separations. We therefore refer to these exits as "quits". In contrast, some returns to India may involve the worker's choice to return migrate for personal reasons, while some others clearly are involuntary separations: when work is finished on a software development project or training is complete, an employee leaves the U.S., and therefore a return to India is observed.

Other observable characteristics in the data include the base annual salary as well as the age, gender, and the state in which the employee worked. Each of these variables are observed on the last date available (i.e. the data are not time-varying). We believe that we have the most relevant salary information, as it is the salary effective at the time a worker made the decision to quit or a return decision was made. We do not capture hours worked.

We now turn to the summary statistics of our dataset. In Table 1, we present the mean and standard deviations of key variables in our sample. The mean salary in our dataset is $72,184 with a standard deviation of $15,415. Note that the range of salaries in our sample is restricted to $30,000 - $130,000 for reasons discussed earlier in this section. Twenty-two percent of our observations quit during our entire period of study, and twenty-nine percent return to India during this time. Our summary statistics also show that married individuals are a majority of our observations, and that our sample is overwhelmingly young and male.

Figure 1 shows the density of quits to another firm and returns to India for the entire sample by days of tenure. The density increases for approximately the first year of employment, and then declines for the remainder of the period. This suggests that any analysis which assumes a monotonic relationship between the hazard of separating and time will be incorrectly specified. We do not observe spikes in returns around 3 or 6 years, which is when visa authorizations end. This suggests that the workers' separations and returns are driven by decisions not directly related to visa regulations.

Figure 2 shows changes in quit and return rates over time. We see the return rate spike in 2008, which would suggest that fears that guest workers adversely impact citizens especially during economic downturns are at least partially mitigated by their increased propensity to return to their home country during bad labor markets. In contrast, the quit rate decreases during hard economic times, suggesting that interfirm job mobility may be hampered during recessions, and that these workers have a smaller quit elasticity with respect to wage in times of higher unemployment. The actual cyclicality of these elasticities are presented in the following section.

3.2 Empirical Strategy

Here we describe our empirical strategy for estimating the elasticity of separations with respect to earnings for Indian IT workers who are in the U.S. on temporary visas. We choose to study separations to other firms and returns to India by estimating "quit elasticities" and "return elasticities", respectively. We begin with a discussion of our econometric model. This is followed by a description of how the model identifies the key empirical parameters of our study. Finally, we discuss threats to identification.

We estimate the two elasticities discussed above using duration analysis. The use of a duration model is a logical fit for modeling the length of an employment spell, as it allows us to exploit the time dependence of duration data in order to estimate the effects of various regressors on the length of an employment spell. Recent work studying the relationship between compensation and employee separation has used single risk duration models. Webber (2011) estimates the elasticity of separation for US workers, Hirsch et al. (2010) estimates the elasticity of separation by gender and Hirsch and Jahn (2012) estimates the elasticity of separation by nativity. Other notable papers studying other aspects of job mobility have also used hazard models (Booth, Francesconi and Garcia-Serrano 1999, Farber 1994).

Our preferred duration model is the competing risk hazard model (Fine and Gray 1999). To our knowledge, we are the first to apply a competing risk model in this setting. Because individuals exit the firm through both separation to another firm as well as through returns to India, a competing risk model is more appropriate than a single risk hazard model, such as the commonly used Cox proportional hazard model. The competing risk hazard model that we employ here is similar to the Cox model in that it also non-parametrically estimates the baseline hazard. The fact that the model makes no assumptions about the shape of the baseline hazard is advantageous because Figure 1 shows that a non-monotonic relationship between the hazard of separation and time at the firm exists in our data.

Below we show the hazard of separation (either quit or return) given by the competing risk hazard function. The instantaneous hazard of separation is

$$\lambda_{i,j}(t) = \lambda_{0,j}(t) \exp\{\beta^j w_i + \delta^j X_i + \gamma^j V_{it}\}, \tag{1}$$

for each individual i and risk j (j=quit,return). t is the duration of employment at the firm. $\lambda_{0,j}(t)$ is the non-parametric baseline hazard that is constant for all individuals, but varies over time and between risks. The main regressor of interest, $w_i = ln(salary_i)$, is the log annual salary of the worker. X_i is a vector of observable characteristics that affect the duration of employment and are constant over time.[8] Included in X_i are sex, marital status, start age, start age squared and firm specific indicators. V_{it} is a vector of observable characteristics that vary over time for each

[8]Although some of these characteristics are likely to change over time, they are constant in the data.

individual in the study. Included in V_{it} is the level and square of the local area unemployment rate that individual i faces at duration time t.

To obtain the quit elasticity, we estimate equation 1 specifying the main risk as employment ending by the worker exiting the firm to employment at another firm in the US. We refer to this elasticity as the quit elasticity, because it is unlikely that many of the workers who were laid off or fired by their firm ended up employed at other U.S. firms, as discussed above. Through the hazard model we count as right censored observations of workers who remained in employment throughout our study, and we specify returns to India as a competing risk. For this specified treatment of the data, β in equation 1 represents the quit elasticity. A simple wage posting search model suggests that β is less than zero because workers who are receiving a lower wage, holding all else constant, are more likely to receive an outside wage offer that dominates their current wage. If Indian guest workers are immobile, as others have suggested, than β should be zero. A quit elasticity of zero suggests that wages play no role in the mobility of these workers and therefore firms are able to pay these workers their reservation salary.[9] To our knowledge, the estimation of equation 1 will provide the first empirical evidence of the role of wages in the separation decisions of H-1B and L-1 workers.

We similarly estimate the return elasticity by estimating the effect of log salary on the likelihood that an employment spell ends through return to India. We treat all other exits from the firm as competing risks in this analysis. Using this specification of the separation decision, β in equation 1 is the return elasticity. Workers may return to India after being fired or laid off, or after voluntary quitting. It is unclear if firms are more likely to terminate the employment of higher or lower wage workers. However, just as lower wage workers are more likely to find better outside options within the U.S., we also believe that they may be more likely to return to India as well. Thus we expect this estimate of β to be negative as well.

To further shed light on the workings of the H-1B Indian IT labor market in the U.S., we estimate how the elasticities of separation change over the business cycle. We do this by using variation in state level unemployment rates to proxy for tightness of labor markets. Depew and Sorensen (2012) show that the Burdett-Moretensen search model in the framework of Manning (2003) implies that the elasticity of separation is likely to be more elastic during economic expansions than recessions. Using employee records from two manufacturing firms from the inter-war period, they were able to confirm this finding with empirical evidence. However, they do so using only variation over time between expansions and recession, while here we are able to exploit both across time and across state variation in the unemployment rate.

Understanding how the elasticity of quits varies over the business cycle is of

[9] By law, H1B workers are required to receive the prevailing wage and this limits the ability of firms to markdown wages beyond a certain point. However, a profit maximizing firm may be able to hire workers who are more productive than natives in unobserved dimensions and then pay them the prevailing wage, which in effect would be a form of discrimination.

particular interest because it would demonstrate whether or not the labor market of H-1B Indian IT workers is similar to other labor markets that become more competitive during expansions as inter-firm mobility increases and less competitive during recessions as this mobility slows down. Additionally, understanding the cyclicality of the elasticity of returns informs us as to how the selection of these migrants and the level of return migration may change over the business cycle. Understanding this process is of importance to opponents of the program who fear that the presence of these workers during economic downturns may harm natives.

Our work is not unique in studying wages and mobility over the business cycle; this question has been examined in previous studies such as Solon, Whately and Stevens (1997) and Devereux and Hart (2006). However, neither of these previous works estimates elasticities of separation nor do they study the mobility behavior of immigrants. We study changes in the elasticity of separation over the business cycle by adding interactions of log salary (w_i) and the unemployment rate in the hazard function in equation 1. We choose to interact both the level and square of the unemployment rate with log salary because it is likely that there exists a non-linear relationship between the elasticity of separation and the unemployment rate. Therefore, the competing risk model of interest takes the form

$$\lambda_{i,j}(t) = \lambda_{0,j}(t) \exp\{\beta^j w_i + \alpha_1^j w_i UR_{it} + \alpha_2^j w_i UR_{it}^2 + \delta^j X_i + \gamma^j W_{it}\}. \qquad (2)$$

Under this specification, the elasticity of separation can be calculated as $\beta+\alpha_1 UR+\alpha_2 UR^2$.

Finally, we turn our attention to threats to identification. Consistent estimates of our parameters of interest hinge on the assumption that the included regressors are exogenously determined. The problematic regressor in this context is the log of salary, which my be correlated with unobserved factors such as productivity of the worker. In this instance, highly productive workers are more likely to receive a higher salary and, holding all else constant, are more likely to be more mobile. Therefore, estimates of the quit elasticity may be biased upwards towards zero, suggesting that workers are less mobile than they actually are. Ransom and Sims (2010) is able to instrument for salary and shows that this intuition holds true as the OLS estimates on wage are larger than the IV estimates.[10] Therefore, our results will likely underestimate the role of compensation in a worker's decision to quit. We believe that the return elasticity will be biased in the opposite direction. This stems from the fact that we believe firms will choose layoff and fire less productive workers who likewise have lower wages.

Our data contain a mixture of workers on L1 and H-1B visas. Some analysis of visas grated to large firms in this industry suggests that the visas may be evenly split between the two categories. We believe that H-1B workers and L1 workers are likely are paid similar wages. Accordingly, as L1 workers are explicitly prohibited from inter firm mobility, and should therefore not respond to lower wages with

[10]Ransom and Sims (2010) does not use a hazard model to study the separation, however, the intuition on the direction of the bias is consistent across the competing risk hazard model and a linear model.

increased movement, we believe that their inclusion in our data will result in an attenuation bias in our findings. If it were the case that L1 workers were paid significantly higher wages than H-1B visa workers, we would be confounding their higher wages and decreased propensity to quit with a causal effect of the higher wages and possibly be overstating the quit elasticity of these workers. However, our analysis of USCIS data shows that there exists variation across firms in relative prevalence of the two types of visas across firms in this industry. Our inclusion of firm indicator variables (we do not know the actual firm, but we have been given an anonymized firm indicators) should partially alleviate this concern. Again, our prior is that the H-1B and L-1 workers are paid similar wages, thus the effect of their inclusion in our estimation should be to attenuate our elasticity estimates.

4 Results

Tables 2 and 3 report the quit and return elasticities obtained using our preferred set of controls[11]. Table 2 includes all observations, with quits being considered the event and treating returns as a competing risk to the event. Table 3 considers the event to be a return to Indian and treats quits as a competing risk. Each table presents parameter estimates for five different groups of workers: all observations, male, female, married and single.

Table 2 shows a coefficient on log salary of -0.467. As we discussed in the Model section, this can be interpreted as a quit elasticity. This is slightly smaller than previous results in the literature that study other groups of workers (Webber 2011), as we will show in detail below. This elasticity implies that a 10% increase in salary yields a 4.67% decrease in the probability of quitting. Given that these results are not zero suggests that these workers are mobile and that low earning workers are able to relocate to other employment. These results are surprising given the costly legal nature of mobility for H-1B workers and perceptions that they are immobile. Also note that an unknown portion of workers are on L1 visas and are therefore completely immobile. Thus, we are underestimating the responsiveness of H-1B workers to changes in their salary at the end of the period of observation. In summary, we see that lower paid workers in our market are more likely to quit (presumably to find better jobs) than are higher paid workers in our market, just as is the case with citizens. Table 2 shows that men have a more elastic separation elasticity than women, consistent with Ransom and Sims (2010) and Hirsch et al. (2006), and that married workers more elastic than single workers.

Table 3 reports the elasticity of return to India with respect to the salary for our full sample of workers, as well as the four subgroups of workers discussed above. The estimates for the full sample show that workers are 15% less likely to return to India for each additional 10% increase in salaries. The point estimate of the return elasticity is similar across the four heterogenous groups. Males and single

[11] Additional specifications and results appear robust and are available from the authors upon request

individuals are slightly less responsive to lower wages in their decision of returning to India.

In addition to the return and the quit elasticities, Tables 2 and 3 also provide estimates of the relationship between the unemployment rate and quit and return rates. The estimated coefficients on the unemployment rate and its square in Table 2 are jointly significant at the .1% level, and show a surprising positive marginal association of the unemployment rate on the quit rate. However, note that we are not yet measuring the effect of unemployment on separations through the elasticity, which we will turn our attention to in the next set of tables. Like Figure 2, which shows a dramatic increase in return rates during years of high unemployment, the coefficients on the unemployment rate and unemployment rate squared terms suggest a positive marginal effect of unemployment on return hazards over most unemployment rates observed in our data.

To assess how the quit and return elasticity vary with the unemployment rate, we run an additional set of hazards that include an interaction between wage and the unemployment rate. We discuss the estimation results from these hazard models in more detail below. To begin, we present Figures 3 and 4, which are scatterplots of state and year level unemployment rates and the corresponding average quit and return rates. Quit rates decrease and return rates increase as the unemployment rate increases. These results measure quit and return rates instead of quit and return elasticities and do not include state and year controls. However, they are suggestive of cyclicality of worker mobility and provide a motivation for formal testing of the cyclicality of the quit and return elasticity.

Tables 4 and 5 repeat the analyses reported in Tables 2 and 3 with an additional set of terms that allow us to estimate the cyclicality of the elasticities. Each table presents two chi-squared test statistics on a null hypothesis of joint insignificance of a set of parameters. The first chi-square statistic tests for the joint insignificance of log wage interacted with unemployment and the unemployment rate squared. We always reject the null of joint insignificance in Table 4, and reject for our pooled sample and the two larger groups in Table 5. This strongly suggests that there is a relationship between the quit and return elasticities and the business cycle, as captured by the unemployment rate. The second chi-squared test rejects a null of perfectly inelastic labor supply to the firm, which some critiques of the H-1B program suggest may exist.

At the bottom of Tables 4 and 5, we report quit and return elasticities at unemployment rates of 4%, 7%, and 10%. In Table 4, we see that the quit elasticity becomes more inelastic as the unemployment rate increases. When the unemployment rate is 4%, then a 10% increase in the wage is associated with a 15.9% decrease in the quit rate. When unemployment is 7% the 10% increase in wage corresponds to a 3.6% decrease in quits. Finally when the unemployment rate is 10%, a 10% increase in wage actually yields an estimated increase in the quit rate. The results show that an unemployment rate of 8.1% yields an estimate of perfectly inelastic labor supply to the firm. These results show that, after unemployment becomes very high, labor market churn breaks down for these workers.

In the bottom panel of Table 5, we see that lower wage workers become more likely to return to India as the unemployment rate increases. At an unemployment rate of 4%, a 10% increase in the wage is associated with a 11.1% decrease in the return rate. For an unemployment rate of 7%, the 10% increase in wage results in a 16.1% decrease in returns to India. Finally, when the unemployment rate is 10%, the 10% increase in wage results in a 16.6% decrease in the return rate.

Figures 5 and 6 graphically display the marginal effect of unemployment on the quit elasticities. Figure 5 displays the marginal effect of unemployment on the quit elasticity. In the figure, we see the positive relationship between the elasticity and the unemployment rate that we had previously described: the elasticity is below -1 at full employment, but begins to approach zero as the unemployment rate increases. Figure 6 explores heterogeneity in this relationship across our different observable groups. It appears that the relatively inelastic estimates for females are less sensitive to fluctuations in the business cycle. Similarly, single workers appear to also have somewhat less variability in their quit elasticities over the business cycle.

Figures 7 and 8 repeat the exercise for return elasticities. Figure 7 shows a negative relationship between the return elasticity and the unemployment rate for a large majority of levels of unemployment observed in our period of study, though there does appear to be a positive relationship at very high levels of unemployment. Again, this suggests that the decision to return to India is more sensitive to wages at higher levels of unemployment. Figure 8 shows that this basic pattern holds for each of our subgroups.

Finally, in Table 7 we explore the effects of including additional controls as well as the difference in the estimated elasticities between the competing risk model that we employ and the standard Cox proportional hazard model. Our first specification includes only unemployment, its square, and the log of wage. The second specification also includes the individual characteristics previously mentioned, and the third specification adds firm indicators. We see that the Cox proportional hazard model generally yields more elastic estimates than the competing risk model. Also, we see that results stabilize from the inclusion of the second set of controls. The 4th specification, which includes month and year indicators, does not change the Cox estimates substantially, nor does the 5th specification, which includes state indicators as well. Unfortunately, at the time of this writing, after close to 10 days of computational time on a UNIX server with Stata-MP, these results are not yet available for the competing risk hazard model. We hope to include these in a future draft, however we believe that this table provides some evidence that our current results in the competing risk model should be robust to the inclusion of these additional controls.

In summary, our duration analysis has illustrated three important points: 1) there are finite but not perfectly inelastic quit and return elasticities, 2) the quit elasticity is countercyclical (becoming more inelastic during periods of high unemployment) and 3) the return elasticity is pro-cyclical (generally becoming more elastic during periods of high unemployment).

5 Discussion of the Results

In this section, we relate the above results to models of frictions in labor markets, claims made about the exploitation of H-1B workers, and broader implications for the labor market. We first show how our results compare to the literature. Then we discuss Manning's (2003) wage setting model. Following this, we discuss evidence that his model may apply in our setting. We then assess how our findings shed light on questions about guest worker pay, mobility, and attachment to the U.S. labor market in recessions. Finally, inspired by our observation of increased return migration during the Great Recession, we explore how changes in migration patters during an economic downturn may create *discouraged immigrants* and thereby lead to hard to interpret changes in EPOP.

5.1 Our Results Relative to the Literature

Table 4 provides strong evidence that our estimates are similar to the literature. We show this in Figure 9, which shows where our own estimate of the quit elasticity (at an unemployment rate of 7%) falls in the distribution of previous estimates, as reported by (Manning 2011).[12] We see that our results are near the mode of the distribution of previously estimated elasticities in this literature. This suggests that the exogenously imposed switching cost of the visa program may be trumped by the thickness of this labor market and the prevalence of information regarding job opportunities. As we have noted, if there exists bias in our results, it is likely attenuates our estimates, suggesting that without the omitted variables bias issue and attenuation effects of including L-1 visa workers, H-1B workers may be even more responsive to lower wages in their quit decisions than our results state here.

5.2 Wage Setting with Finite Quit Elasticities

Robinson (1933) shows that a profit maximizing firm that is the sole employer in the labor market will set wages as a fraction of marginal revenue product.

$$w = MPR_L \frac{\epsilon_{Lw}}{1+\epsilon_{Lw}} \tag{3}$$

The term ϵ_{Lw} is the elasticity of labor supply to the firm. This is similar to a standard IO price setting model under monopoly or monopolistic competition where firms have some power to set price above marginal cost (Berry, Levinsohn and Pakes 1995).

[12]We use 25 estimated quit elasticities reported by Manning (2011) in Tables 6 and 7 of his book chapter. When multiple groups were reported, we took raw average of the reported estimates. When ranges were given, we took the midpoint. For one paper reporting one sided bounds, we used the bound itself as the estimate. All reported elasticities in these tables were from estimates of the effect of wages on separations. Rather than report the implied supply elasticities, as Manning did, we instead report minus one half of his numbers, i.e. the raw separation elasticity results that would have been used to generate the implied supply elasticity numbers.

Robinson developed her model to explain discrimination against workers with identical marginal revenue products. She shows that workers belonging to observably different groups with different ϵ_{Lw} terms would be paid different wages. We later show evidence of the presence of this form of discrimination in our data. We argue that this supports the general applicability to our data of the wage setting model given in Equation 3.

There has been increased interest in *monopsonistic* models of the labor market over the last decade, following Manning's (2003) model where search frictions lead to firm wage setting power, even when there are many employers in the market. Manning and earlier work by Card and Krueger (1995) show that the supply elasticity (ϵ_{Lw}) is equal to twice the absolute value of the quit elasticity (ϵ_{qw}).[13] Thus we may infer what percent of their marginal revenue product workers earn as a function of the quit elasticity. We do this to evaluate firms' potential to exploit these guest workers.

We now to our attention to arguments about why the separation elasticity might indeed be finite. In short, the perfectly elastic labor supply curve to the firm, indicative of perfect competition, can only exist in a frictionless market in which workers may costlessly and instantaneously move to a new job. In the real world, a small decrease in the wage for a given firm will likely not cause all workers to quit this firm. This is due to the presence of frictions. Commonly pointed to frictions are: 1) imperfect information, which prevents workers from having knowledge of all possible competing job offers (i.e. other words, the arrival rate of job offers is finite) and, 2) frictions reducing mobility may be imposed upon the individual or market from the outside. For example a government regulation which imposes fees on mobility between jobs would be an exogenous friction.[14]

5.3 Implications for Pay of H-1B Workers

The Manning wage-setting model implies that discrimination along non-productivity related characteristics is associated with the quit elasticity. If the Manning model applies in this setting, we would expect to find relatively lower wages for groups with relatively lower elasticities. In Table 6, the left column presents the familiar male-female decomposition while the right presents the married-single decomposition. The top row shows the average log earnings for the higher paid group (males and married individuals) and the bottom row shows the same for the lower paid group (females and single individuals). We see a gender wage gap of 7.44 log points and a marital status wage gap of 12.15 log points. The next row reports the explained portion of the gap as given by the Oaxaca (1973) decomposition. In each

[13]Card and Krueger (1995) shows that the supply elasticity is equal to the sum of absolute values of the quit elasticity and the recruitment elasticity. Manning (2003) argues that the quit and recruitment elasticities are equal to one another in absolute value, yielding the expression above.

[14]This is similar to work in Industrial Organization by Gowrisankaran, Shcherbakov, and Nosal, who empirically show that the existence of switching costs for consumers allows firms greater liberty in setting prices.

regression we include as explanatory variables the unemployment rate faced by the worker, age and age-squared, gender and marital status indicator variables, and fixed effects for the state, firm, month, and year of the observation. We find that almost exactly half of a 7.44 log point difference in male and female earnings is explained by our control variables, leaving a 3.72 log point gap that cannot be explained by the observed characteristics.[15] We also find that around 1.85 log points of the married to single pay difference remains unexplained. Both unexplained portions are significantly different from zero at the 99.9% level.

In the bottom panel of the table we report the implied amount of *third-degree factor price discrimination* (at different levels of unemployment). We define *third-degree factor price discrimination* as the predicted difference in wages resulting from differences in ϵ_{Lw}. We focus first on the implied amount of this discrimination at an unemployment rate of 7%. Note that by examining this measure for different levels of unemployment, one can see that the implied amount of discrimination varies over the business cycle as the elasticities themselves vary over the business cycle. At the 7% level, we see that a profit maximizing firm would indeed pay men 66.7 log points more than women and married workers 67.8 log points more than single workers, on account of different levels of wage setting power between these different sets of workers. The model predicts much wider pay gaps than we actually observe, consistent with there being more constraints to wage setting than the simple model would suggest. Nevertheless, this exercise does suggest that different estimated elasticities in our data are indeed correlated with pay gaps in the direction predicted by the model.

This suggests that firms may indeed be able to pay guest workers less than citizens or green card holders, if they were to possess lower elasticities. While we are not able to estimate the elasticity for citizens and green card holders, the relatively large elasticity estimates for the guest workers suggest that any pay differences, while they may exist, are likely to be relatively modest.

5.4 Claims Regarding the H-1B Program

We now take the evidence presented earlier and summarize how it relates to some of the central contentions surrounding guest worker visa programs. One premise of opponents of guest worker programs is that workers on these visas are unable to freely move between employers once they arrive in the U.S. The data that we have presented here contradicts this assertion. Our summary data shows that around 22% quit their jobs and remain in the U.S. As these workers cannot separate to unemployment and remain in compliance with U.S. immigration law, presumably they have found work at another employer. Further, we find that the lowest paid among these workers are the most likely to quit their job, consistent with workers moving in the labor market to escape bad or low paying employers. Specifically, we find that a 10% decrease in wages is associated with a 4.7% increase in the quit rate.

[15] While we do not observe the typically important control variable of years of education, we believe there to be vary little variation in this variable among these workers.

Considering that our data include an unknown number of L-1 visa holders, who are explicitly prohibited from separating from employment, this strongly suggests that H-1B visa workers who are employed by large Indian IT firms (who are the largest users of the H-1B and L-1 visa programs) are in fact quite mobile. While it is difficult to assess the subjective claim of indentured servitude, these results do not strike us as being compelling enough to assert that the working conditions for the guest workers do not meet this condition.

The Oaxaca decompositions presented above relate to a second claim made regarding the H-1B visa program: that workers on these visas are dramatically underpaid. The evidence provided above suggests that the Manning wage setting model has some predictive power in our data. The evidence also suggests that a wedge exists between what workers are paid and their marginal revenue product. However, the higher than expected degree of mobility of these workers translates into limited wage setting power for the employers in this dataset. As with the above estimates of implied gaps between groups, the finite mobility of the workers likely overstates the size of the wedge as firms are constrained by factors not captured by the model. While this is a deviation from a perfectly competitive model, it may not be very different from the labor market at large.

A third concern of opponents of the H-1B program is that it does not adjust the number of visas available over the business cycle. Our data show that the absolute number of return migrants and the rate of return migration increases during the years of the Great Recession. Further, as shown in Figure 4, the rate of return also increases across states and years as the unemployment rate increases. These pieces of evidence suggest that return migration during recessions should at least partially mitigate concerns that the program does not adjust to labor market conditions.

5.5 *Discouraged Immigrants* and EPOP

Our estimates show that there are generally both higher return rates and a higher return elasticities during periods of high unemployment. This brings our attention to a potential issue of not accounting for cyclical return migration. Here we explore the consequences of this phenomenon on measurement of EPOP.

We use the American Community Survey (ACS), conducted in April of each survey year, to construct the trend growth rates (from 2000 through 2008) in the population of male immigrants with a Bachelor's degree who are older than 25 and younger than 50. We first consider Indian born workers. Indian workers, while a significant part of this labor market, are a minority of all foreign born workers who fit the criteria above. We then turn attention to all foreign born workers. In Figures 10 and 11, we show the break from trend migration starting in 2008 for Indian workers and all foreign born workers, respectively. We see that the Great Recession has created around 40 thousand fewer Indian immigrants and 290 thousand fewer immigrants from all source countries than the trend growth would have suggested. This may stem from either higher rates of outmigration, as seen in our data, or lower rates of immigration.

The clear advantage of EPOP over the unemployment rate is that it is not biased by discouraged workers, who self-select out of both the numerator and denominator of the unemployment rate in response to tough labor markets. However, the EPOP will not be robust to *discouraged immigrants*: if the size of the potential labor force in a given market has been affected by labor market conditions, then the standard measure of the EPOP might mis-state the true health of the labor market by not correcting for immigrants who disappear from the sample.

In Figure 12, we show how the EPOP for the demographic groups in question has changed since the onset of the Great Recession. The ratio has declined by 2.28 percentage points: from 93.98% to 91.70% from 2008 through 2011. However, we see that this decline would have been much larger were we to include the discouraged immigrants among the workers not employed in this market. Specifically, we see that the inclusion of the missing Indian immigrants would have led to an extra quarter of a percentage point decline in EPOP of 2.53 percentage points (as EPOP would have declined to 91.45%). When assessing the impact for all immigrants, we find that EPOP would have declined by 4.09 percentage points to 89.89%.

In summary, discouraged immigrants are in part a byproduct of the type of the return migration that we observe in our data. The standard measure of the EPOP does not consider these immigrants. By including them, we conclude that the employment to population ratio has suffered a larger decline during the Great Recession than standard analysis would suggest. Specifically, we find that in the labor market in question, the decline in the EPOP is between 11% (when considering only Indian immigrants) and 79% (when considering all immigrants) larger than when conventional measured.

6 Conclusions

One major criticism of the H-1B visa program is that it limits the mobility of visa holders by imposing costs on prospective employers, placing them in a situation of indentured servitude. Search models show that labor markets cease to yield perfectly competitive outcomes when significant levels of frictions exist. Typically, we think of these frictions as coming from shortcomings in the market, such as imperfect information about available jobs or the quality of a potential match. In the case of the labor market for H-1B workers, frictions are imposed from outside the labor market by government regulations: there are explicit costs to changing the sponsoring employer of a visa. General regulatory costs may dissuade some firms from hiring these workers at all, thus thinning the labor market. It is not surprising that the popular consensus about this labor market is that it is plagued by immobility resulting in the exploitation of workers.

However, our empirical analysis finds high levels of worker mobility: lower paid workers are more likely to quit their current job than are higher paid workers, consistent with a well functioning labor market where churn moves workers to better employers. The degree of mobility that we observe is comparable to findings in other markets not affected by government imposed frictions. After further consideration, this may not be so surprising given that the labor market for these workers was "hot" due to a boom in this labor market during the period we observe. An additional factor is that these workers, who after all migrate to the U.S., may be particularly mobile in terms of willingness to search and move within the U.S., have more industry than firm specific human capital, or have particularly thick networks (Yueh 2008). At the same time, our empirical analysis clearly deviates from the standard competitive model of a frictionless labor market. While our results reject comparisons of this market to indentured servitude, they also reject the conclusion that this labor market is perfectly competitive.

Several caveats color our conclusions related to the H-1B program. First, our data come from six large Indian IT firms. While they are a substantial part of the market – and much of the controversy over the use of these visas centers around them – we do not claim that these results are true for the market as a whole. Second, we do not speak to the situation of L1 workers directly. While they are in our dataset, we cannot distinguish between H-1B and L-1 workers, and they are likely to be more vulnerable given that they cannot terminate employment without giving up their legal status in the U.S. As discussed previously, the restrictions on L1s imply that H-1B workers are even more mobile than our results suggest, as the unidentifiable L-1 workers are legally prohibited from moving between employers.

This research also contributes three findings related to return migration over the business cycle. First, we find that lower paid workers are more likely to return to India than are higher paid workers, consistent with Abramitzky et al. (2012). Second, we find that the relationship between salary and return probability becomes tighter during economic downturns. Finally, we demonstrate that the phenomenon of countercyclical migration may lead to underestimates of declines in the employment to population ratio during recessions. Essentially, were it not for return migration, concerns regarding immigration during periods of recession would be aggravated and the employment to population ratio would be significantly lower.

Beyond the H-1B program, the present study adds to the literature on frictions in the labor market. We are the first study to examine quit elasticities as a function of unemployment, and we further the evidence in an earlier study showing that firm market power increases during economic downturns (Depew and Sorensen 2012). These findings may shed light on "jobless recoveries" and the role that market power plays in macroeconomic downturns (Erickson and Mitchell 2007). The relationship between the business cycle and the quit elasticity is an area that is ripe for future research.

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Table 1: Summary Statistics

	Mean	St. Dev.	N
Salary	72184.25	15415.57	72606
Quit	0.22	0.41	72606
Return	0.29	0.46	72606
Start Age	29.50	5.28	72606
Female	0.18	0.39	72606
Married	0.62	0.49	72606

Table 2: Competing Risk Regression Results: Quit to another Firm

	All	**Male**	**Female**	**Married**	**Single**
ln(Salary)	-0.4677***	-0.5035***	-0.2322*	-0.6034***	-0.1009
	(0.0870)	(0.0968)	(0.1261)	(0.0952)	(0.1249)
Unemp. Rate	0.1327	0.1224	0.1670	0.3105***	-0.1146
	(0.0938)	(0.0917)	(0.1084)	(0.1118)	(0.0822)
Unemp. Rate-Sq.	-0.0052	-0.0049	-0.0061	-0.0145**	0.0073
	(0.0053)	(0.0051)	(0.0065)	(0.0063)	(0.0048)
Female	-0.0145			0.1673***	-0.2598***
	(0.0296)			(0.0413)	(0.0398)
Married	-0.0220	-0.0940***	0.3016***		
	(0.0239)	(0.0231)	(0.0620)		
Start Age	0.0248*	0.0200	0.0901***	-0.0225	0.0408***
	(0.0131)	(0.0148)	(0.0215)	(0.0168)	(0.0139)
Start Age-Sq.	0.0003*	0.0003*	-0.0005**	0.0009***	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
N	1667335	1387393	279942	1125742	541593

[a] Included fixed effects: Firm.

[b] Standard errors clustered on the state are presented in parentheses.

[c] * 0.10, ** 0.05 and ***0.01 denote significance levels.

Table 3: Cox Proportional Hazard Regression Results: Return to India

	All	**Male**	**Female**	**Married**	**Single**
ln(Salary)	-1.5067***	-1.5609***	-1.7916***	-1.6573***	-1.3692***
	(0.0926)	(0.0718)	(0.1880)	(0.0885)	(0.1307)
Unemp. Rate	0.5809***	0.5651***	0.6631***	0.5402***	0.6193***
	(0.0831)	(0.0848)	(0.0822)	(0.0954)	(0.0752)
Unemp. Rate-Sq.	-0.0294***	-0.0279***	-0.0357***	-0.0265***	-0.0323***
	(0.0053)	(0.0054)	(0.0053)	(0.0060)	(0.0048)
Female	0.2105***			0.0593	0.3519***
	(0.0424)			(0.0537)	(0.0439)
Married	-0.4509***	-0.4900***	-0.4878***		
	(0.0236)	(0.0254)	(0.0370)		
Start Age	0.1644***	0.2400***	0.0273	0.1997***	0.2089***
	(0.0281)	(0.0309)	(0.0322)	(0.0326)	(0.0336)
Start Age-Sq.	-0.0024***	-0.0033***	-0.0015***	-0.0027***	-0.0036***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
N	1667335	1387393	279942	1125742	541593

[a] Included fixed effects: Firm.

[b] Standard errors clustered on the state are presented in parentheses.

[c] * 0.10, ** 0.05 and ***0.01 denote significance levels.

Table 4: Competing Risk Regression Results: Quit to another Firm

	All	**Male**	**Female**	**Married**	**Single**
ln(Salary)	-3.8391***	-4.1905***	-2.7722**	-5.6028***	-0.0791
	(0.7603)	(0.7370)	(1.3466)	(0.8162)	(1.5868)
ln(Salary)×UR	0.6484***	0.6953***	0.5288	0.9871***	-0.2054
	(0.2202)	(0.2163)	(0.3835)	(0.2275)	(0.4497)
ln(Salary)×UR-Sq.	-0.0217	-0.0220	-0.0220	-0.0385***	0.0271
	(0.0138)	(0.0139)	(0.0234)	(0.0144)	(0.0267)
Unemp. Rate	-7.0467***	-7.5791***	-5.6749	-10.6561***	2.2016
	(2.4943)	(2.4484)	(4.2825)	(2.5389)	(5.0287)
Unemp. Rate-Sq.	0.2330	0.2366	0.2361	0.4115**	-0.2967
	(0.1560)	(0.1568)	(0.2603)	(0.1607)	(0.2988)
Female	-0.0161			0.1724***	-0.2650***
	(0.0279)			(0.0394)	(0.0406)
Married	-0.0359	-0.1091***	0.2989***		
	(0.0238)	(0.0228)	(0.0622)		
Start Age	0.0184	0.0127	0.0861***	-0.0345**	0.0380***
	(0.0127)	(0.0143)	(0.0219)	(0.0154)	(0.0140)
Start Age-Sq.	0.0003**	0.0004**	-0.0005*	0.0010***	0.0001
	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0001)
N	1667335	1387393	279942	1125742	541593
Chi-Sq.†	118.83	122.56	22.67	112.27	36.42
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Chi-Sq.‡	147.73	158.32	23.37	127.77	45.49
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Quit Elasticity:					
Unemp. Rate=4	-1.5924	-1.7615	-1.0088	-2.2705	-0.4665
	(0.0254)	(0.0258)	(0.0721)	(0.0457)	(0.0550)
Unemp. Rate=7	-0.3628	-0.4018	-0.1482	-0.5801	-0.1874
	(0.0298)	(0.0299)	(0.0721)	(0.0315)	(0.0795)
Unemp. Rate=10	0.4764	0.5618	0.3164	0.4170	0.5801
	(0.0283)	(0.0299)	(0.0439)	(0.0250)	(0.1007)

[a] Included fixed effects: Firm.

[b] Standard errors clustered on the state are presented in parentheses. P-values are in brackets.

[c] * 0.10, ** 0.05 and ***0.01 denote significance levels.

† Chi squared statistic for the joint test of cyclicality (two interactions terms equal zero: ln(Salary)×UR and ln(Salary)×UR-squared).

‡ Chi squared statistic for the joint test of non-zero elasticities (three log salary terms equal zero: ln(Salary), ln(Salary)×UR and ln(Salary)×UR-squared).

Table 5: Competing Risk Regression Results: Return to India

	All	**Male**	**Female**	**Married**	**Single**
ln(Salary)	0.2752	0.4906	0.3683	0.3583	0.4914
	(0.5932)	(0.5973)	(1.2864)	(0.7149)	(1.0415)
ln(Salary)×UR	-0.4484***	-0.5066***	-0.4751	-0.5044**	-0.3979
	(0.1649)	(0.1673)	(0.3165)	(0.2034)	(0.2724)
ln(Salary)×UR-Sq.	0.0255**	0.0282***	0.0230	0.0285**	0.0186
	(0.0102)	(0.0108)	(0.0177)	(0.0131)	(0.0154)
Unemp. Rate	5.5606***	6.1980***	5.8996*	6.1733***	4.9997*
	(1.8645)	(1.9045)	(3.4968)	(2.3163)	(3.0261)
Unemp. Rate-Sq.	-0.3130***	-0.3412***	-0.2895	-0.3452**	-0.2371
	(0.1163)	(0.1234)	(0.1967)	(0.1498)	(0.1718)
Female	0.2095***			0.0574	0.3517***
	(0.0422)			(0.0535)	(0.0435)
Married	-0.4506***	-0.4893***	-0.4876***		
	(0.0238)	(0.0256)	(0.0369)		
Start Age	0.1655***	0.2420***	0.0273	0.2023***	0.2102***
	(0.0280)	(0.0306)	(0.0316)	(0.0326)	(0.0339)
Start Age-Sq.	-0.0024***	-0.0033***	-0.0015***	-0.0027***	-0.0036***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
N	1667335	1387393	279942	1125742	541593
Chi-Sq.†	8.02	15.43	2.55	10.69	4.31
	[0.0181]	[0.0004]	[0.2800]	[0.0048]	[0.1158]
Chi-Sq.‡	273.10	427.54	89.48	332.11	125.21
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Return Elasticity:					
Unemp. Rate=4	-1.1099	-1.0849	-1.1635	-1.2029	-0.8023
	(0.0195)	(0.0192)	(0.1554)	(0.0253)	(0.0516)
Unemp. Rate=7	-1.6125	-1.6749	-1.8285	-1.7743	-1.3817
	(0.0152)	(0.0106)	(0.0648)	(0.0170)	(0.0289)
Unemp. Rate=10	-1.6556	-1.7578	-2.0789	-1.8320	-1.6261
	(0.0218)	(0.0099)	(0.1042)	(0.0125)	(0.0572)

[a] Included fixed effects: Firm.

[b] Standard errors clustered on the state are presented in parentheses. P-values are in brackets.

[c] * 0.10, ** 0.05 and ***0.01 denote significance levels.

† Chi squared statistic for the joint test of cyclicality (two interactions terms equal zero: ln(Salary)×UR and ln(Salary)×UR-squared).

‡ Chi squared statistic for the joint test of non-zero elasticities (three log salary terms equal zero: ln(Salary), ln(Salary)×UR and ln(Salary)×UR-squared).

Table 6: Oaxaca Decompositions by Gender and Marital Status

	Male-Female	**Married-Single**
Male/Married	11.1796***	11.2125***
	(0.0101)	(0.0102)
Female/Single	11.1052***	11.0909***
	(0.0105)	(0.0095)
Difference	0.0744***	0.1215***
	(0.0030)	(0.0026)
Explained	0.0372***	0.1030***
	(0.0030)	(0.0030)
Unexplained	0.0372***	0.0185***
	(0.0038)	(0.0032)
N	72606	72606
Implied Monopsony:		
Gap UR=4	0.1527	0.5293
Gap UR=7	0.6670	0.6781

[a] Included fixed effects: State, Firm, Month and Year.

[b] Included regressors: Unemp. Rate, Male, Married, Age, and Age-Sq.

[c] Standard errors clustered on the state are presented in parentheses.

[d] * 0.10, ** 0.05 and ***0.01 denote significance levels.

[e] The implied monopsony gap is derived from equation ref# in section ref# by using the point estimates from Table ref#.

Table 7: Elasticity Estimates: Competing Risk Robustness Check

	Quit Elasticity		**Return Elasticity**	
	Cox PH	**Comp. Risk**	**Cox PH**	**Comp. Risk**
No BC 1	-0.9362	-0.0216	-2.2667	-1.6369
	(0.1610)	(0.1527)	(0.1030)	(0.0837)
No BC 2	-1.5792	-0.5331	-2.5166	-1.6176
	(0.1700)	(0.1575)	(0.1309)	(0.0956)
No BC 3	-1.5411	-0.4677	-2.7254	-1.5067
	(0.1181)	(0.0870)	(0.2274)	(0.0926)
No BC 4	-1.4862	-0.3317	-2.7926	-1.5177
	(0.1285)	(0.0834)	(0.2408)	(0.0987)
No BC 5	-1.5490	X	-2.8285	X
	(0.1268)		(0.2596)	
BC 1	-1.0528	-0.0125	-2.6499	-1.9451
	(0.0900)	(0.0764)	(0.0144)	(0.0134)
BC 2	-1.6375	-0.5015	-2.7474	-1.7484
	(0.0706)	(0.0569)	(0.0203)	(0.0151)
BC 3	-1.5590	-0.3628	-2.9819	-1.6125
	(0.0440)	(0.0298)	(0.0587)	(0.0152)
BC 4	-1.5486	X	-3.0400	-1.6351
	(0.0531)		(0.0667)	(0.0154)
BC 5	-1.5887	X	-3.0678	X
	(0.0514)		(0.0742)	

[a] Standard errors clustered on the state are presented in parentheses.

[b] * 0.10, ** 0.05 and ***0.01 denote significance levels.

Figure 1: Distribution of Tenure

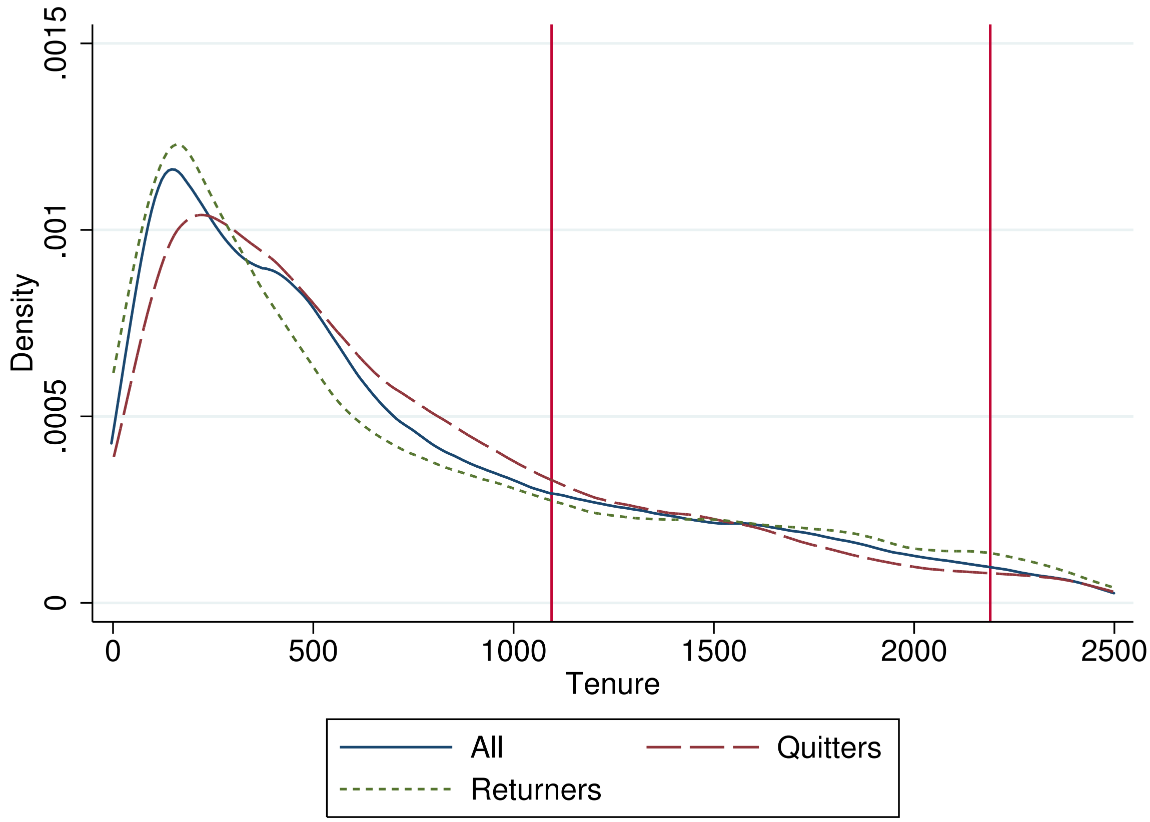
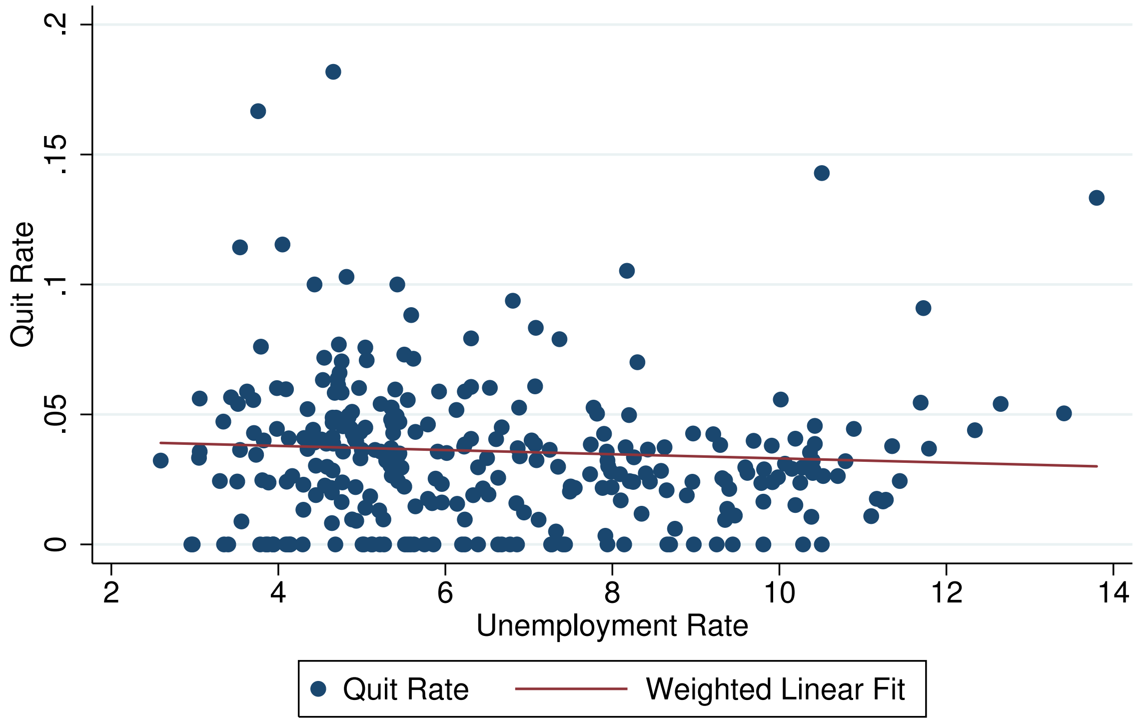


Figure 2: Quit and Return Rates

Figure 3: Quit Rate by State and Year



The weighted linear fit line uses all state by year quit rates and is weighted by the number of observations within a state and year. The scatter plot is limited to state by year of observations that have at least ten observations.

Figure 4: Return Rate by State and Year

The weighted linear fit line uses all state by year return rates and is weighted by the number of observations within a state and year. The scatter plot is limited to state by year of observations that have at least ten observations.

Figure 5: Quit Elasticities for All Employees

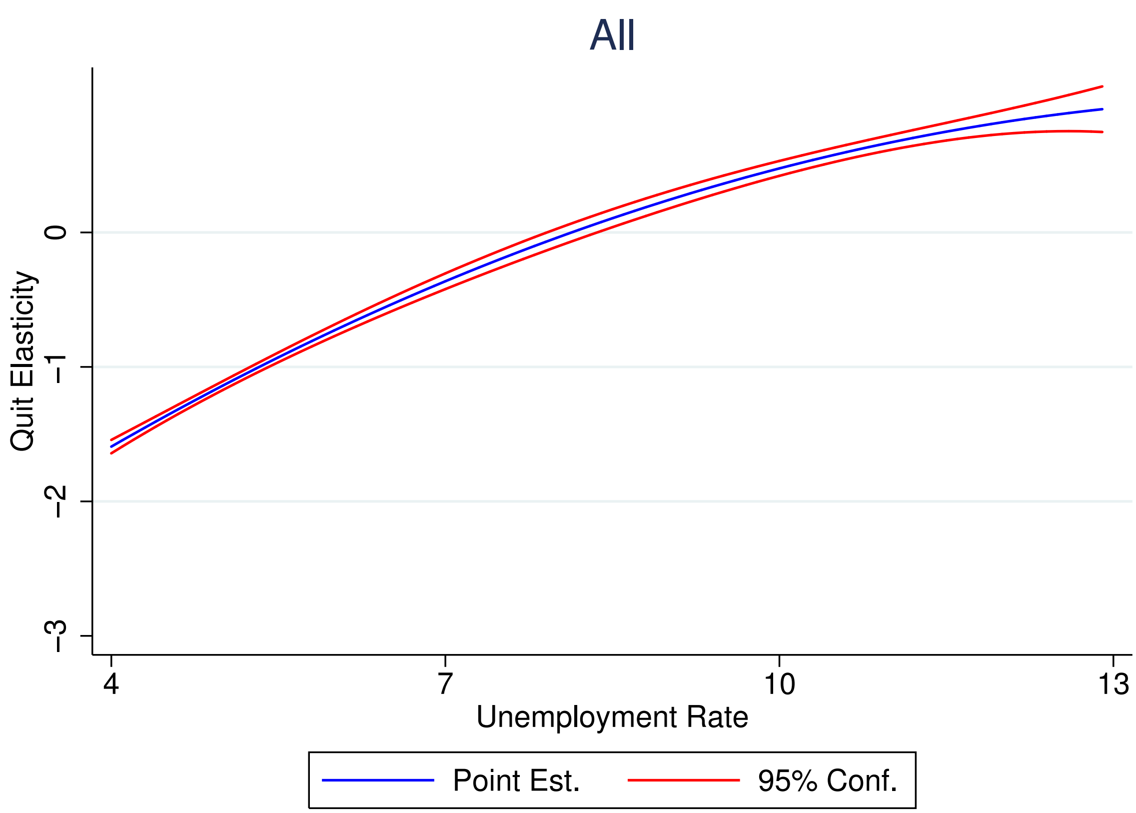


Figure 6: Quit Elasticities by Hetergenous Groups

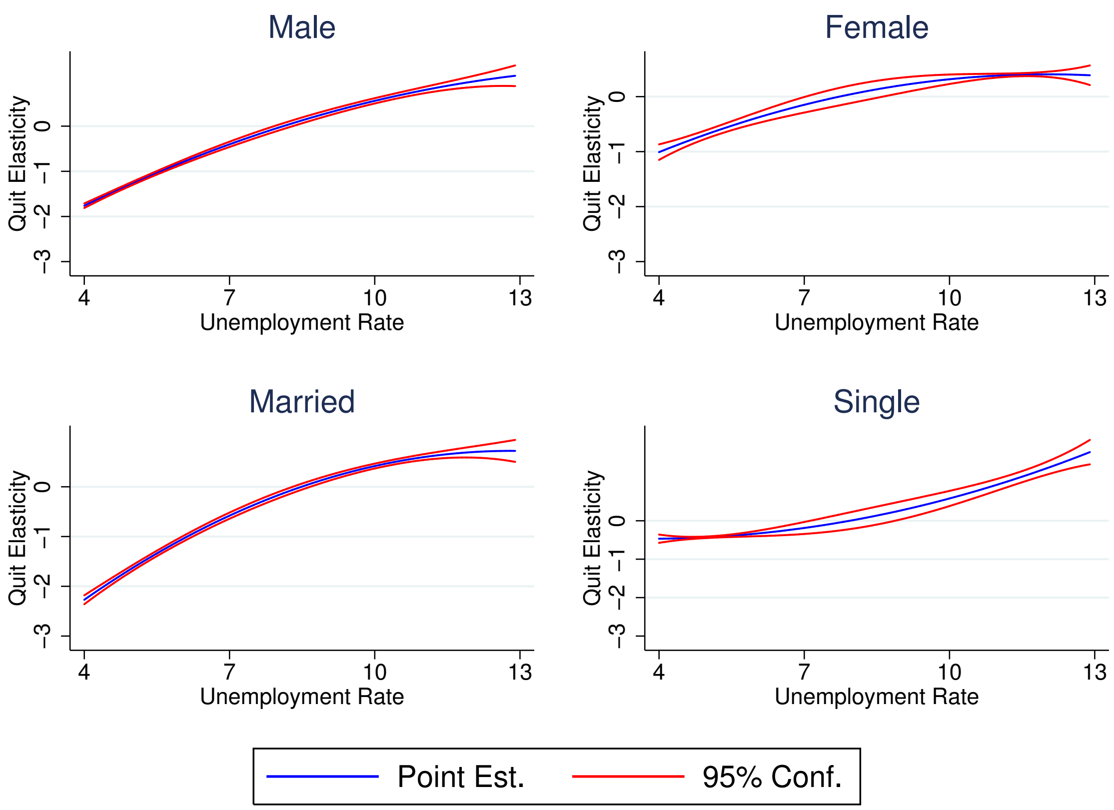


Figure 7: Return Elasticities for All Employees

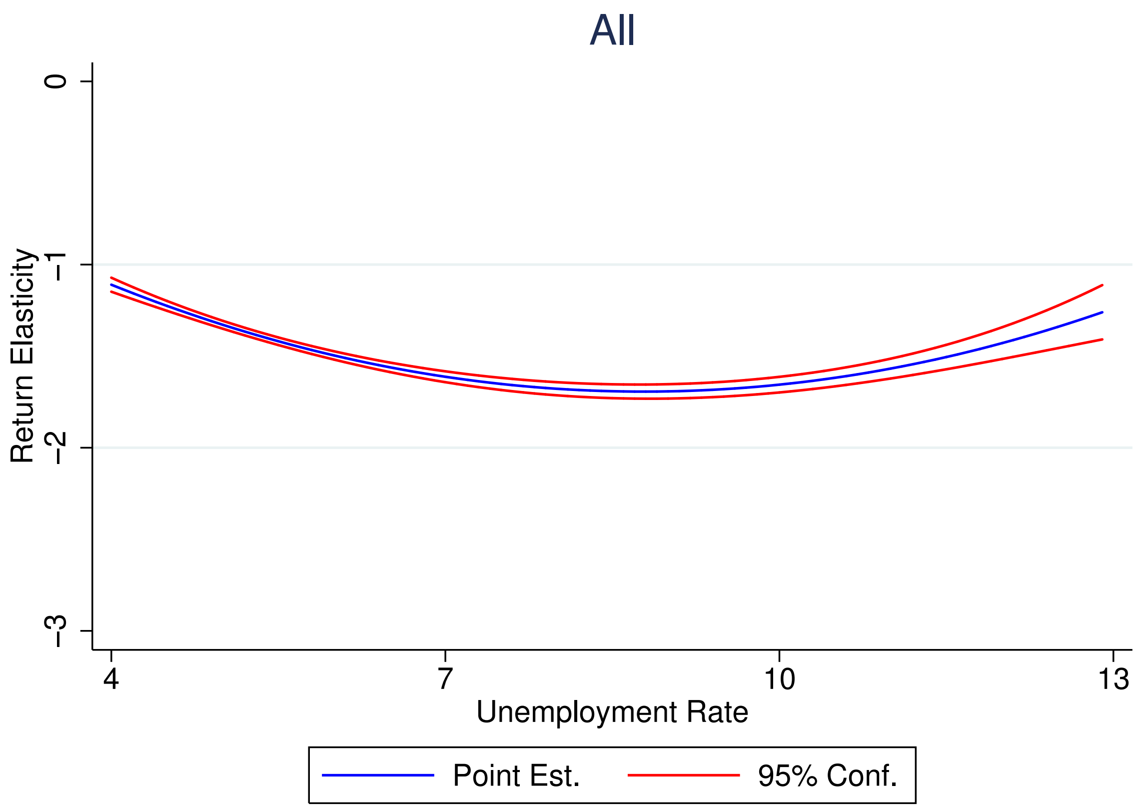


Figure 8: Return Elasticities by Heterogenous Groups

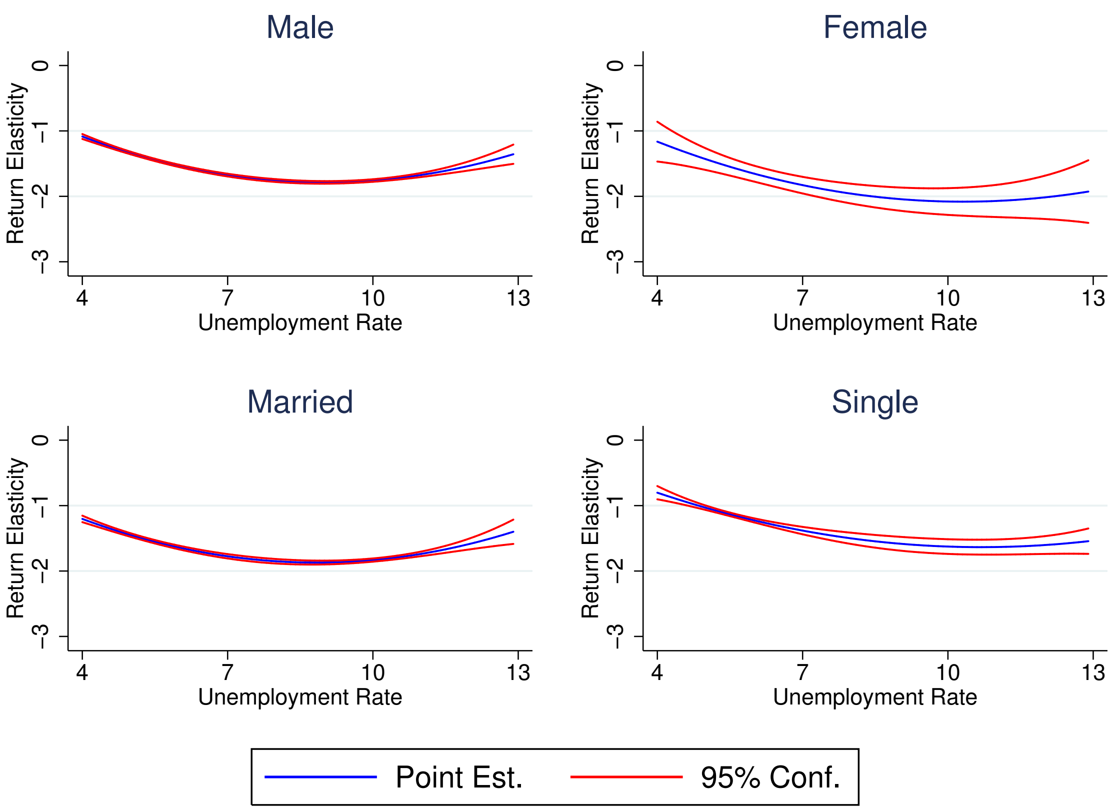


Figure 9: Previous Estimates of Elasticities

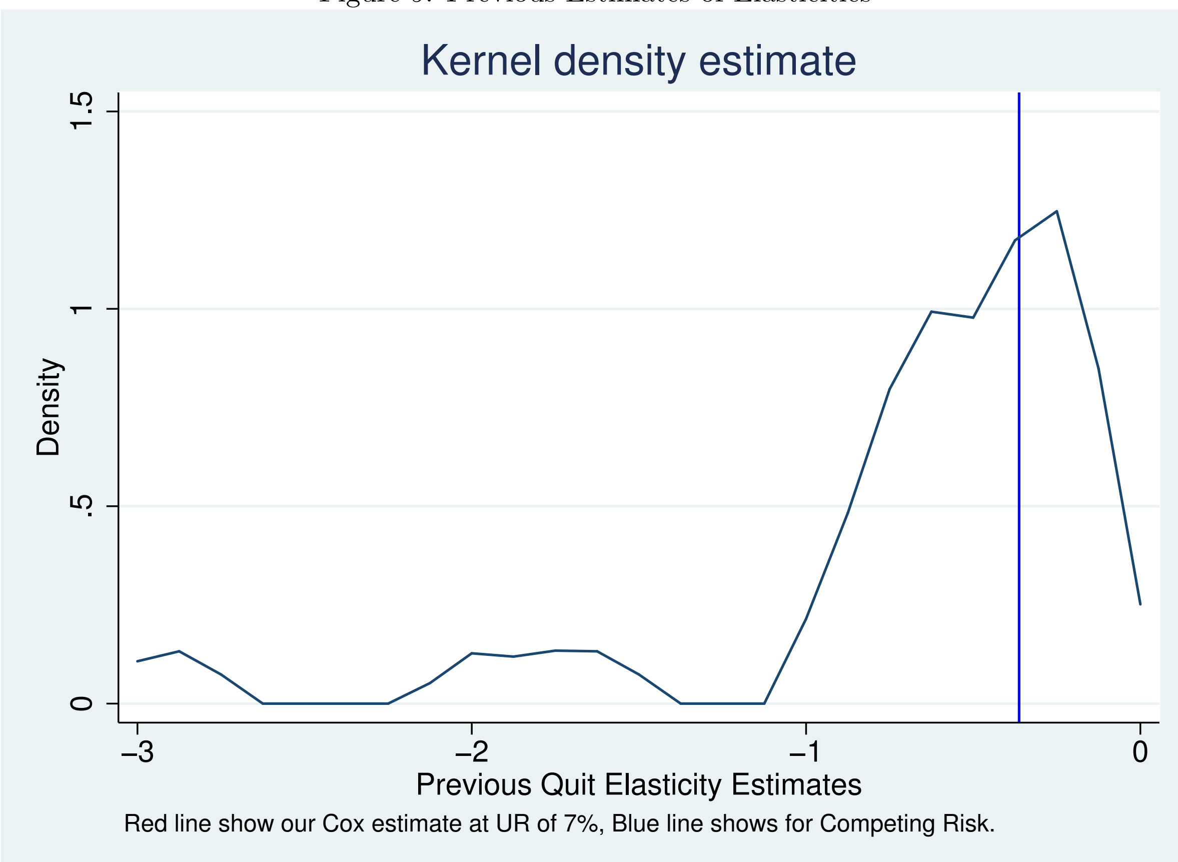


Figure 10: Indian Migration After the Great Recession

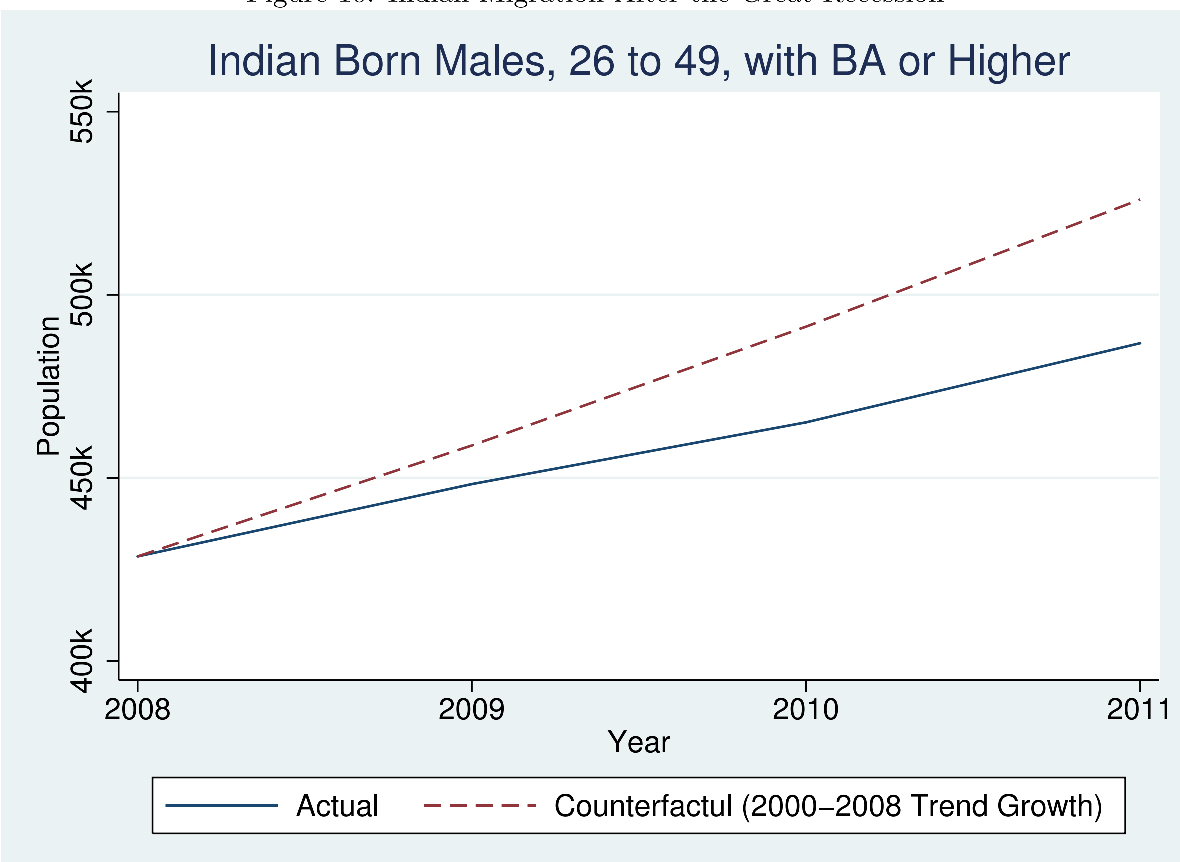


Figure 11: Foreign Born Migration After the Great Recession

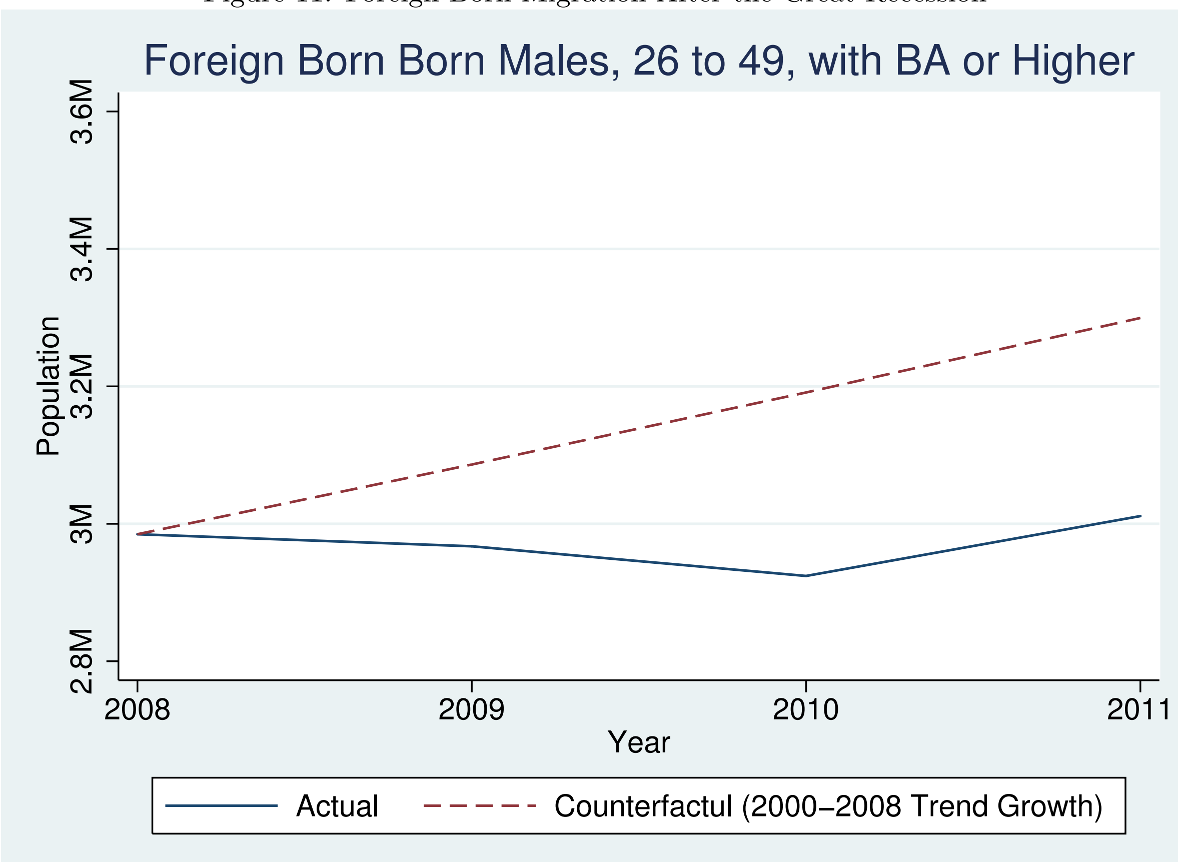
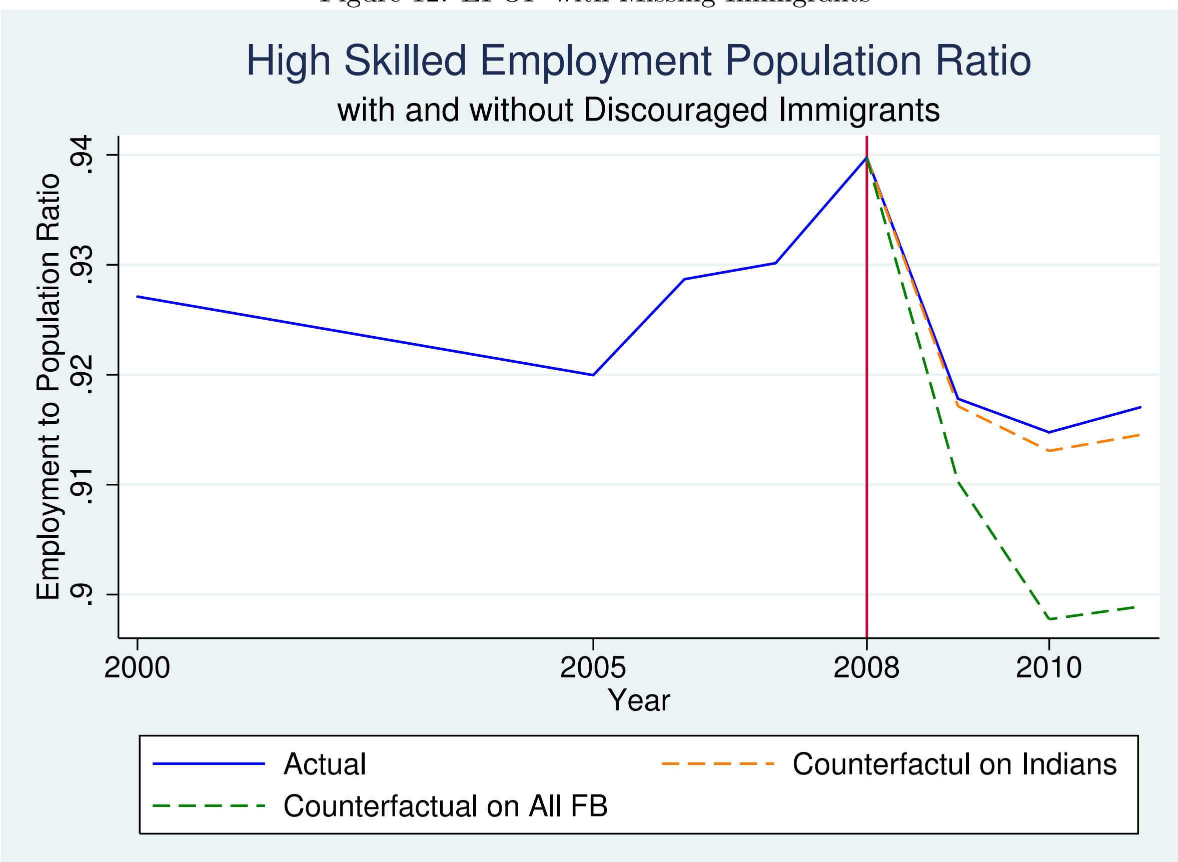


Figure 12: EPOP with Missing Immigrants



A Wage Posting Model and Monopsonistic Competitioni

Here we detail the relationship between search models and quit elasticity. Manning bases his model on the Burdett and Mortensen (1998) search model. Their model of the separation rate is defined below

$$s(w) = \delta + \lambda(1 - F(w)) \tag{4}$$

The separation equation can be thought of in terms of both voluntary separations and involuntary separations. The term δ captures involuntary separations through exogenous job destruction. The second half of the equation gives the quit rate. Here, λ is the job offer arrival rate, and $F(w)$ is the cumulative distribution of wage offers. Under this wage posting model, an individual separates from the firm when she receives an outside wage offer that dominates her current wage. The elasticity of quits with respect to the wage is then

$$\epsilon_{qw} = \frac{\partial s}{\partial w}\frac{w}{s(w)} = \frac{-\lambda f(w)}{\delta + \lambda(1 - F(w))}. \tag{5}$$

This expression is finite if λ is finite, meaning that there are search frictions which prevent workers from instantaneously and simultaneously receiving offers for all available jobs, and if F(w) is non-degenerate. The latter will happen if there are costs to filling vacancies, as these costs will generate an indeterminacy where there are many ways for firms to arrive at a zero profit condition. Firms may either take a "high road" where they pay a high wage and face a few recruiting costs, or firms can take a "low road" where they pay a low wage but have high turnover costs.

In the context of this labor market, we can conceptualize the effect of H-1B visa costs as affecting workers by lowering λ. If it is costly to hire these workers then fewer firms may be willing to do so and thus fewer job offers will arrive to workers. It can be shown that the derivative of the elasticities with respect to λ is negative. As λ increases and frictions in the labor market decrease, workers will quit at higher rates in response to lower wages (Depew and Sorensen 2012).