Immigrant Wages and Recessions: Evidence from Undocumented Mexicans

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Abstract

We study the impact of recessions on the real wages of undocumented immigrants in the US using data from the Mexican Migration Project. Empirical evidence shows that undocumented immigrants experience larger wage drops during recessions than legal immigrants, suggesting that the frequent renegotiation of contracts leads to greater wage flexibility. Because migration decisions also adjust to these wage changes, the observed equilibrium wages are capturing both lowered aggregate productivity and a smaller supply of migrant workers. To separate these effects, we analyze an equilibrium migration model where native wages are rigid while immigrant wages are flexible. In a counterfactual experiment with a fixed supply of immigrant workers, we see a stronger relationship between aggregate negative productivity shocks and immigrant wages. We also find that the flexibility of immigrant wages could reduce the volatility of high-skilled native employment over the business cycles, but magnifies the volatility of low-skilled native employment.

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1. Introduction

Immigration reform is perennially a topic of debate in the US. Anti-immigrant rhetoric can get stronger during downturns, when there are heightened fears about job security and the wages of native workers. In this paper, we study how the wages of undocumented workers change over the business cycle. If immigrant wages are more flexible than those of natives, then perhaps heightened concerns about immigration during downturns are justified because firms could shift towards immigrant workers to adjust to changes in the economy. On the other hand, if immigrant wages are flexible, we could see fewer migrants in the US during downturns in response to the lower wage opportunities.[1]

Past work has documented that immigrants experience larger employment and wage drops during recessions than natives (Bratsberg et al. (2006), Orrenius and Zavodny (2010), and Chiswick et al. (1997)). However, these existing studies do not distinguish between documented and undocumented immigrants. Analyzing the impact separately for undocumented immigrants is important because (i) undocumented immigrants typically generate the strongest concerns over the negative impacts on low-skilled native workers, and (ii) we may see varying wage flexibility for documented versus undocumented immigrants due to the short-term nature of the latter's wage contracts. By using the data from the Mexican Migration Project (MMP), which reports both legal status and wages, we are able to isolate the effect to the undocumented immigrant population.

We find that undocumented immigrants wages decrease as the US unemployment rate increases, and the magnitude is larger than for legal immigrants. Because migration is endogeneous, it could be that the observed negative relationship is driven by compositional changes in the ability or skill of immigrants over the business cycle. We control for selection by looking at the wage growth of undocumented immigrants over repeated trips to the US, and again find a negative correlation between wages and the unemployment rate. We argue that one potential cause of this wage flexibility is the short-term nature of contracts for undocumented immigrants. We run the same analysis with legal immigrants in the MMP, and indeed find smaller effects for legal immigrants who are more likely to have longer-term labor contracts. Supporting our findings, we repeat our analysis using CPS data, separating likely legal and likely undocumented Mexicans, and find similar results.

As wages decrease, fewer immigrants will move to the US (Hanson and Spilimbergo (1999), Lessem (2018), Nakajima (2019)). This could drive up equilibrium wages in down-

[1] Past empirical work finds that immigration rates are affected by changes in US wages. See Hanson and Spilimbergo (1999), Lessem (2018), and Nakajima (2019).

turns. In the second part of the paper, we build a model to decompose the changes in the equilibrium wage, aiming to understand the contributions of productivity shocks and the migration response. In the model, Mexicans migrate between the two countries, making decisions on where to live by comparing their wage options in the two countries. After seeing an aggregate productivity shock, a representative firm hires native and undocumented immigrant workers. Native wages are fixed, and undocumented immigrant wages are determined through firm demand in response to the productivity shock and undocumented immigrant labor supply. We calibrate the parameters of the model so as to replicate the patterns in migration rates and native employment levels between 1980 and 2011. We decompose the decrease in undocumented immigrant wages during a downturn into two factors: a negative aggregate productivity shock and the supply response of undocumented immigrants. In a counterfactual experiment, we shut down the migration channel and show a stronger relationship between aggregate shocks and undocumented immigrant wages. We also show that the flexible wage setting of undocumented immigrants could mitigate high-skilled native employment fluctuations over the business cycles, but magnifies low-skilled native employment fluctuations.

There is an extensive literature on wage cyclicality, not specific to immigrants. Some papers include Solon et al. (1994), who find evidence of wage cyclicality, claiming that previous work which did not find this effect did not account for composition effects that gave more weight to low-skill workers in expansions than in recessions. Eslby et al. (2016) also find that real wages are procyclical, although they do report that real wages for men in the Great Recession adjust slower.

Bratsberg et al. (2006) studied wage cyclicality specifically for immigrants, finding that immigrants experience larger wage drops in recessions than natives. We take this a step further in this paper by comparing undocumented and documented immigrants. One key difference between these groups is that undocumented immigrants are likely to work under short-term or fixed-term contracts where wages are negotiated more frequently. Existing studies show that undocumented immigrants' labor contracts tend to be less formal, and undocumented immigrants are employed "without a legal contract that defines the terms and conditions for their jobs" and "typically contracted on an at-will basis" (Hanson (2007)).

Previous literature has shown that workers under short-term contracts experience larger cyclicality in wages and employment, supporting our theory that we should see greater wage flexibility for undocumented versus documented immigrants. This work has mostly been done in the context of the European labor market. Babecky et al. (2010) show that downward nominal wage rigidity is more prevalent among workers with permanent contracts and collective bargaining coverage. Card et al. (1999) compare the wage adjustments from demand shocks in countries with different institutions that affect wage flexibility, and find that wages in the US are more flexible than in France, where labor institutions make employment transitions harder.[2] Lastly, there is empirical evidence that, when faced with a negative demand shock, wages for fixed term contracts receive a larger impact than wages for permanent contracts. Edo (2016) analyzes how immigration shocks affect the wages of fixed versus indefinite contracts in France, and finds that wages of fixed term workers change more in response to these shocks. Related, Oreopoulos et al. (2012) find significant costs to graduating in a recession, meaning that workers who are just starting their career will earn lower wages during downturns. This suggests that newly negotiated contracts will more easily adjust to the state of the economy, suggesting that undocumented immigrant wages would be affected by economic conditions more than legal immigrants, since their wages are frequently negotiated due to the absence of long-run contracts.

The paper is organized as follows. Section 2 explains the data, and the empirical analysis is shown in Section 3. The equilibrium analysis is explained in Section 4. Section 5 concludes the paper.

2. Data

We use data from the MMP to estimate the relationship between undocumented immigrant wages and US economic conditions. The MMP is a repeated cross-sectional survey that started in 1987 and is still ongoing. Most respondents were surveyed in Mexico, and asked about prior moves to the US.[3] Detailed information is collected about each person's first and last move to the US, including these people's wages and legal status, enabling us to study how wages change over the business cycle.[4] The MMP also gathers a retrospective migration history from household heads and spouses, enabling us to create a panel dataset with each person's location at each point in time. This will allow us to examine changes in undocumented immigrant flows over the business cycle. The panel dataset also reports each person's occupation at each point in time.[5]

[2]Several papers study how this affects employment rates. Blanchard and Landier (2002) study the effect of a reform that triggered a widespread diffusion of fixed term contracts and found that the reform substantially increased turnover. Goux et al. (2001) support the view that it is less costly to adjust the number of fixed term contracts than to adjust the number of permanent term contracts.

[3]There is also limited sampling in the US, but these sample sizes are small.

[4]Unfortunately, there is only information on one wage for each trip. When the duration of a trip spans multiple years, we do not know which job on the trip the data refer to.

[5]The MMP reports occupations according to the Clasificacion Mexicana de Ocupaciones, which was created by the Mexican National Institute of Statistics and Geography (INEGI).

We use demographic information such as age and years of education. Wages are converted to 2012 US dollars using the CPI index from the Bureau of Labor Statistics. Since workers only report one wage for the first and last trip, we use the average inflation rate over the duration of each trip.

Four main data restrictions are made. First, we focus on men, since female labor force participation rates are low, making their migration decisions less influenced by the state of the economy. Second, we restrict the sample to migrants who claimed their first and last trip to be on undocumented status. We include legal immigrants in a separate specification where we compare the wage flexibility of documented and undocumented immigrants. Third, we focus on undocumented immigrants who first visited the US after the Bracero program (1942–1964). During this period, the US government aggressively encouraged temporary laborers to fill the shortage in the agricultural labor force after World War II. Legal workers under the program were protected, through, for example, the minimum wage. We omit these observations from our sample because of the different selection into undocumented migration in this period. In addition, since we are interested in how wages correlate with the state of the economy, we need to pinpoint each wage with a given point in time. However, the MMP reports only one wage for each trip, which means that for people with long durations of stay in the US, we do not know what point in time the wage is referring to. Therefore, we restrict the sample to those who stayed for less than 15 months. This means that the sample average of the unemployment rate over the visit duration is calculated using at most two years. Since the duration of stay correlates with wage, eliminating workers who stayed longer potentially leads to some biased results.[6] Also, this restriction results in the loss of 39% of the data. In Section A, we perform robustness checks using the full sample, to make sure that this data restriction is not affecting our findings.

The MMP data allow us to study how undocumented wages change over the business cycle. In particular, it is a unique dataset because it provides information on undocumented immigrant wages, which is not possible to precisely pin down in other surveys.[7] However, there are some weaknesses of the data. In each round of the survey, households are randomly selected from a given set of communities to be included in the survey. The communities chosen, especially in the early years of the survey, were mostly from areas where migration to the US was prevalent. Over time, the survey has expanded into areas with lower migration rates. Nonetheless, the communities are not selected randomly. Since there are booms and recessions repeatedly throughout the years we use,

[6]The direction is ambiguous. A higher wage gives an incentive to stay longer and earn more, but also allows one to accumulate savings faster and return to Mexico.

[7]The Los Angeles Family and Neighborhood Survey gives information on wages and legal status, but the samples are limited to poor neighborhoods in the Los Angeles area.

we believe that this non-randomness of sampled communities is not driving our results. Furthermore, most of the sampling is done in Mexico and covers past migration histories. Because of this data collection method, households who have entirely moved to the US or households from communities with low migration rates are not included in the sample. Thus, our results only capture the characteristics of temporary migrants from communities with high migration rates.

2.1 Summary statistics

Table 1 presents summary statistics on the sample of undocumented immigrants that is used in the paper. The first column looks at the full sample of men used in this paper. First, looking at demographics, we see that the sample is dominated by individuals with relatively low educational attainment, as 90% of the sample has fewer than 12 years of education. Next, we look at some summary statistics on migration behavior. The mean age of a person's first trip to the US is around 26. The average migrant has made approximately 2.6 trips to the US, and around 44% of migrants moved to the US just once. On average, each trip to the US lasts for around 40 months. Looking at wages, we find that average hourly wages are around \$11.[8] Undocumented immigrants work in mainly agricultural, manufacturing, and service sectors. The second column restricts the sample to those we use in the main specification, which is people with migration durations less than 15 months. This results in a loss of a large share of the data, and we see much shorter durations based on this sample selection.

2.2 Measuring recessions

To study how undocumented immigrant wages change over the business cycle, we need a measure of the variation in economic conditions. To do this, we use the US unemployment rate at each point in time. Figure 1 shows variations in the unemployment rate over time for the total population and Mexican immigrants, using data on people aged 16 and over from the CPS. Since both unemployment rates track each other closely, we use the unemployment rate for all individuals to measure the state of the economy. In the estimation, we use the unemployment rate in the state where a person is living to allow for variations across locations. Because of potential selection into low unemployment states, we repeat our analysis using national unemployment rates as a robustness check in Section A.

[8] For the first trip to the US, wages can be reported at the hourly, weekly, or monthly level. We convert all wages to hourly wages, assuming each worker works 8 hours per day, 5 days a week, $\frac{30.5}{7}$ weeks per month, and every month of the year. For the last trip to the US, wages are reported at the hourly level.

3. Empirical evidence

In this section, we study how undocumented immigrant wages change over the business cycle. We first do this using OLS, and find that wages decrease as the unemployment rate increases. However, there are potential selection issues, given that the quality of undocumented immigrants could change over the business cycle. Since the MMP data provide wages for a person's first and last trip to the US, we have two data points for people who have moved more than once. We use this to analyze how an individual's wages change with the business cycle.[9]

One potential cause of this flexibility is the short-term nature of labor contracts in this population. If undocumented immigrants are more likely to change jobs than legal immigrants, we should see less wage flexibility in our sample of legal immigrants. We compare the wage flexibility of documented and undocumented immigrants in the MMP. In the last part of this section, we use data from the CPS to again compare these two groups. Unlike the MMP, in the CPS we cannot precisely identify the legal status of each worker, but we instead use demographic characteristics to "guess" the legal status of each respondent.

3.1 Wages and unemployment in the MMP

We use OLS to estimate the effect of economic conditions on undocumented immigrant wages. To do this, we test how wages vary with the unemployment rate, while controlling for relevant demographic characteristics. We estimate the following wage regression:

$$\log(w_{ijt}) = \alpha_0 + \alpha_1 X_{it} + \alpha_2 u_{jt} + \gamma_j + \eta_t + \epsilon_{ijt} \ , \tag{1}$$

where w_{ijt} is wages, and the vector X_{it} contains individual characteristics, such as age, education, and occupation. The term u_t is the state unemployment rate at time t, which is the average unemployment rate during the time an immigrant was in the US. We include both state and year fixed effects (γ_j and ν_t, respectively), and ϵ_{ijt} is an independent and identically distributed (i.i.d.) error.

The first two columns of Table 2 show the results. In column (1), we use the full sample and find that a one percentage point increase in the unemployment rate lowers hourly wages by 1.4%. One concern about these results is recall bias, since the MMP surveys are conducted after migrants return to Mexico. In column (2) we only include

[9] This is done to attempt to control for selection. However, this is a biased sample, since we only have two observations for people who chose to move to the US more than once.

people whose migration was within five years of the survey, to reduce recall bias, and we see even larger effects of the unemployment rate on wages in this sample.

So far, we have shown that the hourly wages of undocumented immigrants decrease as the unemployment rate increases. However, as wages decrease, people become less likely to migrate, changing the composition of the undocumented immigrant population.[10] For example, if an unobservable factor (i.e., skill) affects wage outcomes in the US, it will also affect migration decisions. As wages in the US decrease, the composition of the undocumented immigrant population would change. In this setting, looking at just the average wages of those who chose to move will give biased results. We next use data on repeat migrants to estimate the relationship between the unemployment rate and wages while controlling for selection.

We use data from undocumented immigrants who made multiple trips to analyze the relationship between wage growth and economic conditions. Because we are looking at the same individual over time, individual fixed effects cancel out and we can address this type of selection.

Consider a modification of equation (1) that includes an individual fixed effect:

$$\log(w_{ijt}) = \alpha_0 + \alpha_1 X_{it} + \alpha_2 u_{jt} + \gamma_j + \eta_t + \nu_i + \epsilon_{ijt} \;, \tag{2}$$

where ν_i is an individual fixed effect that will be differenced out when we look at wage growth. Consider the changes between the first and last trip, denoted by F and L, respectively:

$$\Delta \log(w_{ijt}) = \alpha_0 + \alpha_1 \Delta X_{it} + \alpha_2 \Delta u_{jt} + \gamma_j + \eta_t + \Delta\epsilon_{ijt}, \tag{3}$$

where $\Delta \log(w_{ijt}) = \log(w_{iF}) - \log(w_{iL})$ As in the analysis for the wage levels, we control for the state of the economy using the unemployment rate u in the state where a person is living, so Δu_{jt} is the change in the unemployment rate between the first and last trip. For the other explanatory variables (X_i), we use the change in age between the first and the last trip, the year of the first US migration, and the total number of trips. We also continue to include state, year, and occupation fixed effects.

Columns (3) and (4) of Table 2 show the results. In column (3), we see a negative and statistically significant coefficient on the unemployment rate on wages, indicating that people earn lower wages in a recession. To interpret this, consider two workers with the

[10] There is empirical evidence supporting the view that migrants who arrive to the US during recessions could be different from those who arrive in other times. For example, Chiswick et al. (1997) documents that immigrants who enter the US during recessions have higher employment rates, suggesting that those who enter the US during recession have better work-related characteristics.

same characteristics. Suppose worker A did not experience any economic change (i.e., $\Delta u = 0$) and worker B experienced a unit increase in the unemployment rate between the first and last trip (i.e., $\Delta u = 1$). Then worker B's wage on the last trip will be 2.8% lower than worker A's. In column (4), we attempt to address recall bias by using only people who had moved within five years of the survey. This substantially reduces the sample size because, for this analysis, we need two observations for each person, and there are not many respondents with both their first and last US migration within five years of the survey. In this case, the coefficient on the unemployment rate is still negative and statistically significant (at the 10% level).

In the previous specifications, we included occupation fixed effects, showing that even if we control for occupation choice, wages decrease with the unemployment rate. It is also possible that workers switch occupations with the state of the economy. We estimate the probability that a person works in a given occupation (agriculture, skilled manufacturing, unskilled manufacturing, transportation, services, and sales) using a multinomial logit regression.[11] We control for demographic factors, primary occupation in Mexico, and their occupation in the previous year. We also include state and year fixed effects.[12] The results, reported as marginal effects in Table 3, demonstrate that, as the unemployment rate increases, people are more likely to work in agriculture and sales, and less likely to work in skilled manufacturing. This suggests that people change occupations over the business cycle. This is another potential avenue by which wages could change over the business cycle.

3.2 Legal status and wage flexibility in the MMP

One potential explanation for the wage flexibility of undocumented immigrants is short term labor contracts. If these workers are constantly renegotiating wages as they acquire new jobs, then we should expect wages to adjust to the state of the economy. We examine this mechanism in this section. We first compare the likelihood of changing jobs each year for documented and undocumented immigrants, using a variable in the MMP that

[11] We recognize that these do not sound like typical notions of occupations, and instead are a mix of industry and occupation. We occupations in the MMP are coded following the occupation classifications created by the Mexican statistical agency INEGI.

[12] The MMP reports a worker's occupation for each year of US stay, so for this analysis, we also include undocumented immigrants who stayed for more than 15 months. In the wage analysis, we had to drop immigrants who stayed for more than 15 months, since only one wage is reported for the first and last trip, so we do not know the year of each wage for immigrants who stayed in the US for more than a year. In contrast, in the occupation analysis, we can include immigrants who stayed for more than 15 months since we have occupation reported for each year. We find a similar result when we restrict to those who stayed in the US for less than 15 months.

reports whether a person has changed jobs. Table 4 shows the results from a probit regression, where the dependent variable is whether not a person changed jobs in a given year. In column (1), we use all observations, and in column (2) we just use observations within 5 years of the survey to reduce recall bias. In both specifications, we see that legal immigrants are less likely to change jobs than undocumented immigrants.

If these short term contracts are a source of the wage flexibility, we should see that legal immigrant wages are less flexible than those of undocumented immigrants. We next make this comparison, again using the MMP data, but now including both documented and undocumented immigrants in our analysis. The results of our baseline wage regression are shown in Table 5. In the first column, we show the full sample. The second column shows just undocumented workers (which is the same as the baseline results in Table 2), and the third column shows just the sample of documented workers. In the full sample, there is no statistically significant effect of the unemployment rate on wages, although the sign of the coefficient is negative. When we restrict the sample to just undocumented workers, we see our result that increases in the unemployment rate lower wages. When we look at just legal immigrants, we no longer see a statistically significant effect of the unemployment rate on wages, and the magnitude of the coefficient decreased. Therefore, these results show that, in the MMP, we see a stronger negative relationship between wages and the unemployment rate for the population of undocumented immigrants.

3.3 Robustness checks

3.3.1 Strength of community networks

Local networks have been shown to be an important determinant of migration decisions. Mckenzie and Rapoport (2010) show that migrants with weak networks in the destination are selected positively or in an education-neutral fashion, whereas migrants with stronger networks are negatively selected. This could make an average migrant from weak network communities lower-skilled than an average migrant from strong network communities. In addition, it could be that, during a recession, networks become more important in finding a well-paying job and, therefore, only migrants with a strong community network migrate to the US. If this is the case, the observed drop in undocumented immigrant wages during a recession could be driven by the change in the composition of migrants in the US.[13] As a robustness check, we run the wage-unemployment regression separately for undocumented immigrants from communities with strong and weak migrant networks. We define the strength of the network using a community level variable

[13] Networks also affect the wealth impact on migration. Mckenzie and Rapoport (2007) show that as networks grow, wealth is less of a constraint on migration, and the poor are more likely to migrate.

in the MMP which reports the migration rate in that community.[14] Table 6 shows that the magnitude of the coefficient on the unemployment rate is remarkably similar for low- and high- migration home communities. However, it is only statistically significant (at the 10% level) for the low-migration home communities. In the third column of Table 6, we use the full sample, to increase the sample size used in the regression, but interact the unemployment rate with a dummy variable for being in a low migration community. This allows for the relationship between the unemployment rate and wages to vary for people from low and high migration communities. Using this specification, we see a negative effect of the unemployment rate on wages, and this effect is larger in low migration communities.

3.3.2 Keeping respondents who stayed in the US for more than 15 months

In the baseline specification, our sample only included respondents who stayed in the US for less than 15 months. We made this restriction because we only see one wage per trip, so it is hard to pin a time-specific unemployment rate to each trip. This is a strong restriction that results in a loss of almost 40% of the data. As another robustness check, we relax this assumption and include all respondents. Since only one wage is reported for each trip, it is unclear how to calculate the unemployment rate, since averaging the unemployment rate over many years can cause us to miss the effect of a downturn. We use the last year the person was in the US as the unemployment rate for each observation. We chose this instead of the first year of each trip because certain time-varying regressors have a stronger relationship with wages when they were measured at the end of the trip instead of the start of the trip. We repeat the analysis for wage levels and growth, as in Section 3.1, and the results are in Appendix A. In columns (1) and (2) of Table A.1, we look at the wage-level regressions. The sign of the coefficient on the unemployment rate stays the same, although it decreases in magnitude and is only statistically significant in one specification. Columns (3) and (4) show the wage growth regressions. In these specifications, we see that an increase in the unemployment rate lowers wages, although it is not statistically significant.

We next use a Heckman selection model to correct for any bias that was introduced by our sample restrictions. In our baseline results, we focus on a sample of people with durations in the US of less than 15 months, which is an endogenously selected sample. The selection may be correlated with the US unemployment rate. For example, suppose migrants who are successful in the US labor market are more likely to stay for longer

[14]To do this, we take the mratio variable from the MMP, which gives the migration rate in a person's community. We find the median of this variable and use this to split the sample into those from high and low migration communities.

durations, and US business cycles are positively correlated with those in Mexico. Then, it could be that during US recessions, even unsuccessful migrants choose to stay in the US longer because their wages in Mexico are also going down. If this is the case, then the relationship between US unemployment and US wages will be biased upward. We control for this selection using a Heckman selection model. We use rainfall in the origin Mexican state as an instrument, following Munshi (2003) who uses rainfall in the origin community in Mexico as an instrument for the size of network at the destination. This is correlated with the length of stay in the US, but uncorrelated with US wages and the US unemployment rate. These results are shown in Table A.2 in Appendix A. After we control for selection, we see that increases in the unemployment rate lower wages.[15] The results under OLS and the Heckman model are similar, which suggests that the observed negative relationship between undocumented immigrant wages and the US unemployment rate cannot be explained by compositional changes due to selection.

3.3.3 National unemployment rate

The baseline results use the unemployment rate in the state where a person is living. This leads to endogeneity concerns since people can select into low unemployment states. In Appendix A, we use national unemployment rates as an additional robustness check.[16] To calculate the national unemployment rate, we take the average over the state unemployment rates where undocumented immigrants live, weighting the average by the fraction of the MMP sample living in a given place. Columns (1) and (2) of Table A.3 shows the wage-level regressions, and Columns (3) and (4) show the results for wage growth. In all of these specifications, we see a negative and statistically significant effect of the unemployment rate on wages.[17]

3.3.4 GDP per capita

Another possible concern is that the unemployment rate is determined endogenously with wages. For example, states could implement policies that both increase wages and reduce unemployment. If this is true, then there could be a bias in our results. On the one hand, we do not think this should cause too much concern, given that we are focusing on a small group in our analysis, undocumented immigrants, who are unlikely to be the

[15]The coefficient on the inverse Mills ratio is negative, implying that there is negative selection from this sample restriction.

[16]Data on state unemployment rates are from the Local Area Unemployment Statistics from the Bureau of Labor Statistics. These are seasonally adjusted values.

[17]Because the national unemployment rate varies only with time, we cannot use year fixed effects in these specifications.

focus of policies aiming to boost wages or lower unemployment. However, as a robustness check, we repeated our baseline specifications, using state per capita GDP as our independent variable instead of the unemployment rate. These results are in Appendix A as Table A.4. The first 2 columns show wages in levels, and we see a positive and statistically significant relationship between GDP per capita and undocumented immigrant wages. In the last 2 columns, we look at wage growth. We see a positive relationship between wages and GDP per capita, but it is not statistically significant. However, we suspect that some of this effect is driven by migration into areas with better job opportunities, as research has shown that migrants move in response to economic shocks (Cadena and Kovak (2016)). To investigate this, we reran the analysis only looking at people who did not switch locations, and see a positive and statistically significant relationship between GDP per capita and the wage growth of undocumented workers.[18][19]

3.4 CPS data

So far, we have seen that increases in the unemployment rate lowers wages for undocumented immigrants in the US using data from the MMP. We also compared legal and undocumented immigrant wages and saw greater flexibility in the latter group. In this section, we repeat this analysis using data from the CPS. The CPS has more reliable wage information than the MMP, but unfortunately does not report the legal status of each respondent. We follow the methodology used in Borjas (2017) to separate likely legal from undocumented immigrants in the CPS (focusing on a sample of Mexican-born individuals).

To use the CPS data, we first have to "guess" the legal status of each immigrant. Borjas (2017) develops a methodology using the ASEC files in the CPS to try to identify undocumented immigrants. He defines a person as a legal immigrant if one of the following conditions holds: that person was born before 1980, is a citizen, receives government benefits[20], is a veteran or is in the military, works in the government sector, resides in public housing or receives rental subsidies (or that person's spouse does), was born in Cuba, works in an occupation that requires licensing, or is married to a legal immigrant or citizen. We use this methodology to separate legal and undocumented immigrants in

[18] These results are not reported in the paper, but are available upon request.

[19] An alternate way to address the selection issue, as we did with the unemployment rate, would be to use national per capita GDP. This, however, would only provide variation over time, and we would lose the cross-sectional variation. Because per capita GDP mostly increases over time, we lose the variation that we need for identification.

[20] Specifically, benefits considered are Social Security benefits, SSI, Medicaid, Medicare, and military insurance.

the ASEC data.[21,22]

We analyze how wages respond to the unemployment rate, separating the analysis for our suspected legal and undocumented immigrants. The sample contains men aged 25–55 from 1994–2012.[23] We only use data on high school dropouts. This is because undocumented immigrants typically have lower levels of education, and we do not want our results to be driven by sample composition. This is particularly relevant because past work such as Hoynes et al. (2012) finds that recessions hit the lower-skilled workers hardest. We control for age, education, and number of years in the US, and also include state, year, and occupation fixed effects. The results are in Table 7. Column (1) shows the whole sample of Mexican-born individuals in the ASEC, column (2) restricts to those who we identify as undocumented immigrants, and column (3) restricts to those who we identify as legal immigrants. We only see a negative and statistically significant effect of the unemployment rate on wages in the undocumented immigrant group.

Similarly, when we look at wage growth in the ASEC in Table 8, we see that an increase in the unemployment rate lowers wages for the full sample of documented and undocumented immigrants in column (1). Column (2) only looks at undocumented immigrants; in this case, the magnitude of the coefficient increases, although it is not statistically significant. In column (3), which only includes legal immigrants, the magnitude of the coefficient decreases as compared to columns (1) and (2), yet it is also not statistically significant. These results support our hypothesis that the wage impact is larger in a segment of the population more likely to work under short-term contracts.

3.5 Migration responses to recessions

The empirical evidence shows that wages of undocumented immigrants drop during recessions. We find a smaller effect in samples that include legal immigrants, suggesting that the effect is due to short-term contracts. These results demonstrate changes in the equilibrium wage, which reflects both aggregate demand and the supply of immigrant workers. In this section, we show that migration rates respond to these lower wages in downturns, hence lowering the supply of undocumented immigrants. This could poten-

[21] Most of these classifications are straightforward. Occupational licensing is done at the state level. We define an occupation as needing licensing if more than half of the states require licensing for that job. The licensing data were collected from the O*NET database.

[22] We can compare the characteristics of the undocumented immigrants in the MMP and those we identify as undocumented in the CPS to see the degree of selection in the MMP. The average age is 34.7 in the MMP and 36.6 in the CPS. Comparing education levels, 67% of the MMP respondents have 6 or fewer years of education. This number is 57% in the MMP. These comparisons show that the ages seem similar, but the MMP sample has lower levels of education.

[23] We cannot use earlier data because information on country of birth is only available starting in 1994.

tially raise immigrant wages. We then analyze an equilibrium model to account for this mechanism in the next section of the paper.

We run a probit regression, testing whether a person who is living in Mexico chooses to move to the US during that year. We control for both the US and the Mexican unemployment rate,[24] as well as age, education, marital status, whether or not a person is from a high migration state in Mexico,[25] and US border enforcement. The first column of Table 9 shows the results. The negative coefficient on the US unemployment rate implies that when the US is in a recession, fewer workers migrate to the US.

We also did the same exercise looking at return migration rates, where the dependent variable equals 1 if a migrant living in the US returns to Mexico. These results are shown in column (2) of Table 9. Although the estimated coefficient on the US unemployment rate is not statistically significant, it is positive, suggesting that more workers return to Mexico when the US is in a recession.

4. Equilibrium analysis

The previous section suggests that undocumented Mexican workers experience larger wage drops during recessions than legal immigrants. Since migration patterns change over the business cycle, the supply of undocumented immigrant labor in the US fluctuates. The observed equilibrium wages are capturing both the effects of the productivity shocks as well as the supply adjustments. In this section, we build and calibrate a model to decompose these different effects. We also use the model to study how the flexibility of undocumented immigrant wages affects native employment fluctuations over the business cycle.

4.1 Model

We use a static equilibrium model to highlight how migration decisions and the flexible wage setting of undocumented immigrants affect their wages and natives' employment fluctuations over the business cycle. We consider a representative firm who hires high-skilled native workers, low-skilled native workers and undocumented immigrant workers to produce output. In the model, Mexicans decide which country to reside in based on relative wages and the cost of crossing the border. Throughout this section, only undocu-

[24] The Mexican unemployment rates are taken from the MMP for 1973–2010 and from the OECD for 2011.

[25] These are the states with the highest migration rates, where migrant networks are strong and hence people may be more likely to migrate. These states are Aguascalientes, Durango, Guanajuato, Hidalgo, Jalisco, Michoacan, Morelos, Nayarit, San Luis Potosi, and Zacatecas.

mented immigrants are considered, due to data limitation on documented immigrants to quantify their migration behavior and wage patterns.

We assume that high-skilled and low-skilled native wages are exogenous to the model and denote them as w^H_{Nt} and w^L_{Nt} at period t. This assumes a perfectly elastic labor supply curve, and captures the empirical trend that native wages are less flexible than undocumented immigrant wages. Wages for undocumented immigrants in the US w_{It} are determined endogenously through the supply and demand for undocumented immigrants in the US. We assume that wages in Mexico are exogenous and denote them as w_{Mt}.

4.1.1 Firm side

A firm's output in period t depends on aggregate productivity z_t and the quantity of high-skilled and low-skilled workers, L^H_t and L^L_t, respectively. The first-level labor aggregate combines high- and low-skilled labor as follows:

$$L_t = [\theta(L^H_t)^\gamma + (1-\theta)(L^L_t)^\gamma]^{1/\gamma}. \tag{4}$$

The second-level labor aggregate combines low-skilled native (N^L_t) and undocumented immigrant labor (I_t) as follows:[26]

$$L^L_t = [\phi(N^L_t)^\rho + (1-\phi)(I_t)^\rho]^{1/\rho}. \tag{5}$$

High-skilled labor is produced only high-skilled natives labor: [27]

$$L^H_t = N^H_t. \tag{6}$$

The elasticity of substitution between high- and low-skilled labor is $\frac{1}{1-\gamma}$, and the elasticity of substitution between low-skilled natives and undocumented immigrants as $\frac{1}{1-\rho}$.

We write the firm's output as $z_t(L_t)^\psi$. We use a Cobb-Douglas function with parameter ψ, where we assume decreasing returns to scale in labor so $0 < \psi < 1$. The two inputs into the Cobb-Douglas function are capital (which we assume to be fixed) and labor, which is the CES aggregation of different types of labor given in equation (4). Given wages w^H_{Nt}, w^L_{Nt}, and w_{It}, the firm solves the following profit maximization problem:

$$\max_{N^H_t, N^L_t, I_t} \quad z_t(L_t)^\psi - w^H_{Nt}N^H_t - w^L_{Nt}N^L_t - w_{It}I_t \,, \tag{7}$$

[26]For simplicity, we assume that all undocumented immigrants produce low-skilled labor, as a vast majority of undocumented Mexican immigrants have less than 12 years of education.

[27] One interpretation of this model setup is that firm hires skilled native labor and purchases an intermediate input, which is produced by unskilled native and undocumented immigrant labor. This intermediate good setup can be explained by immigrants working in, for example, the construction sector, where they do the basic tasks and then native workers do the more complicated tasks, as in the framework in Djajic (1997).

where equations (4), (5), and (6) hold. Because the model is static, the firm only considers current-period profits when making hiring decisions.

The first-order conditions are

$$\begin{aligned} w_{Nt}^{H} &= z_t\psi[\theta(N_t^H)^\gamma + (1-\theta)(L_t^L)^\gamma]^{\frac{\psi}{\gamma}-1}\theta(N_t^H)^{\gamma-1} && (8)\\ w_{Nt}^{L} &= z_t\psi[\theta(N_t^H)^\gamma + (1-\theta)(L_t^L)^\gamma]^{\frac{\psi}{\gamma}-1}(1-\theta)(L_t^L)^{\gamma-1} \\ &\qquad [\phi(N_t^L)^\rho + (1-\phi)(I_t)^\rho]^{1/\rho-1}\phi(N_t^L)^{\rho-1} && (9)\\ w_{It} &= z_t\psi[\theta(N_t^H)^\gamma + (1-\theta)(L_t^L)^\gamma]^{\frac{\psi}{\gamma}-1}(1-\theta)(L_t^L)^{\gamma-1} \\ &\qquad [\phi(N_t^L)^\rho + (1-\phi)(I_t)^\rho]^{1/\rho-1}(1-\phi)(I_t)^{\rho-1}, && (10) \end{aligned}$$

which implies

$$I_t = \underbrace{\left(\frac{\phi}{1-\phi}\frac{w_{It}}{w_{Nt}^L}\right)^{\frac{1}{\rho-1}}}_{\equiv X} N_t^L, \tag{11}$$

$$N_t^H = \left(\frac{1-\theta}{\theta}\frac{w_{Nt}^H}{w_{Nt}^L}(\phi + (1-\phi)X^\rho)^{\gamma/\rho-1}\phi\right)^{\frac{1}{\gamma-1}} N_t^L. \tag{12}$$

Because undocumented immigrant wages are flexible, there is no unemployment for undocumented immigrants. Let $I_t^D(w_{It}, w_{Nt}^H, w_{Nt}^L)$ denote the firm's demand for undocumented immigrant workers. We assume that native labor is abundant and that the wage for natives is sufficiently high so that the number of natives hired by the firm is always given by the first-order conditions.

When solving the model, we also assume that $\bar{N}$ high-skilled natives are always hired at a different firm, and we calibrate its value. This reflects the reality that not all high-skilled natives work at firms that hire undocumented immigrants.[28] This model setup allows us to match a situation where undocumented immigrants wages are more flexible than high-skilled native wages, while at the same time undocumented immigrant employment is more volatile than high-skilled natives.

[28]We impose this assumption to make the model more flexible. Since I and N^H and move in one-to-one (in log-terms) in the CES production function, the volatility of native employment must equal that of the undocumented immigrant labor in the model. However, in the data, the volatility of high-skilled native employment is lower than that of the undocumented immigrants over the business cycle. Therefore, in order to accommodate these differences, we assume that there is some proportion of natives who are always hired at a different firm and calibrate this proportion. We did not include analogous parameter for the low-skilled natives because the moments matched reasonably well without it.

4.1.2 Worker side

We assume that a worker's location at the start of the period ℓ_t is exogenous to the model. He can be living in the US or Mexico, and then decides which of the two countries to live in for the next period by comparing the value of living in each location. These values have three components: the wages in each country, the cost of moving, and the payoff shocks.

Wages vary between the US and Mexico, and the wage function is written as:

$$w_t(\hat{\ell}) = \begin{cases} w_{Mt} & \text{if } \hat{\ell} = MEX \\ w_{It} & \text{if } \hat{\ell} = US. \end{cases} \tag{13}$$

The cost of moving from ℓ_t to $\hat{\ell}$ is denoted by $c(\ell_t, \hat{\ell})$, and is defined as follows:

$$c(\ell_t, \hat{\ell}) = \begin{cases} c_1 & \text{if } \ell_t = MEX \text{ and } \hat{\ell} = US \\ c_2 & \text{if } \ell_t = US \text{ and } \hat{\ell} = MEX \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

Moving to a new location has a constant cost, which varies for Mexico to US migration and return migration. The cost of moving to the US is given by c_1, and the cost of returning to Mexico is given by c_2. If a worker stays in the same location, the cost is 0.

We assume that utility is linear in wages with coefficient α. Denote the set of payoff shocks as $\eta = \{\eta_{US}, \eta_{MEX}\}$, and we assume these are distributed with an extreme value type I distribution. Because the model is static, individuals pick the location with the highest per-period valuation. Then the value function is given by

$$V_t(\ell_t) = \max_{\hat{\ell} \in \{US, MEX\}} \left\{ \alpha(w_t(\hat{\ell}) - c(\ell_t, \hat{\ell})) + \eta_{\hat{\ell}} \right\}. \tag{15}$$

We use the model to calculate the probability that a person lives in the US in each period, conditional on his location at the start of the period. Following McFadden (1973) and Rust (1987), these probabilities $p_t(\ell_t)$ are given by

$$p_t(MEX) = \frac{\exp(\alpha(w_{It} - c_1))}{\exp(\alpha(w_{It} - c_1)) + \exp(\alpha w_{Mt})} \tag{16}$$

$$p_t(US) = \frac{\exp(\alpha w_{It})}{\exp(\alpha w_{It}) + \exp(\alpha(w_{Mt} - c_2))}. \tag{17}$$

Equation (16) gives the probability that someone who is in Mexico moves to the US, and equation (17) gives the probability that someone who already lives in the US stays there. Assume there are I_{1t}^0 people in Mexico at the start of period t and I_{2t}^0 people in the US at the start of period t. Then the total supply of undocumented immigrants in the US after workers make their migration decisions is

$$I^S_{US,t}(w_{It}) = p_t(MEX)I^0_{1t} + p_t(US)I^0_{2t}. \tag{18}$$

We can then equate labor supply and demand to get the equilibrium condition for undocumented immigrant wages w_{It}:

$$I^D_t(w_{It}, w^H_{Nt}, w^L_{Nt}) = I^S_{US,t}(w_{It}) \ , \tag{19}$$

where $I^D_t(w_{It}, w^H_{Nt}, w^L_{Nt})$ comes from the firm's first-order conditions in equations (11) and (12).

To summarize, the variables determined in equilibrium are the undocumented immigrant wage w_{It}, undocumented immigrant labor in the US $I^S_{US,t}(w_{It})$, high-skilled native employment N^H_t and low-skilled native employment N^L_t. These are solved using the firm's first order conditions and the labor market clearing condition.[29]

The effect of the flexibility of undocumented immigrant wages on high-skilled and low-skilled native employment is ambiguous. If low-skilled native and undocumented immigrant labor are complements (resp. substitutes), then the flexible wage setting of undocumented immigrants mitigates (resp. accelerates) native labor demand fluctuations over the business cycle. Similarly, if high-skilled native and low-skilled labor are complements (resp. substitutes), then the flexible wage setting of undocumented immigrants mitigates (resp. accelerates) high-skilled native labor demand fluctuations over the business cycle. In the next section, we will calibrate the model parameters, and then be able to understand how this undocumented immigrant wage flexibility impacts natives.

We end this section with an explanation of our choice of the firm's maximization problem. It is natural to think that the native-immigrant wage gap comes from a "penalty" that a firm faces when hiring undocumented immigrants. This "penalty" potentially takes many forms. For example, IRCA (1986) prohibits firms from knowingly hiring undocumented workers, creating a cost in expectation from hiring undocumented workers. Also, undocumented immigrants may be less productive compared to the natives due to lower English skills. Moreover, undocumented immigrant workers may be more likely to quit a job because return migration is relatively common and because migrants are more mobile than natives within the US.[30] However, it is impossible to separately identify lower

[29]We confirm using numerical simulation that the equilibrium wage exists and is unique, under the calibrated parameters. If w_I=0, then $I^D > I^S$. If w_I is very large, then $I^D < I^S$. Because the demand for undocumented immigrant labor is decreasing with respect to w_I and the supply of undocumented immigrants I^S_{US} is increasing with respect to w_I, there is a unique equilibrium wage for undocumented immigrant w^*_I.

[30]See Cadena and Kovak (2016).

productivity and an additional hiring cost in the MMP data. Therefore, instead of considering an additional hiring cost for each undocumented immigrant worker, we assume that all costs associated with hiring an undocumented immigrant are captured through the substitutability of undocumented immigrant and low-skilled natives in the production function.

4.2 Calibration procedure

This section explains how the time-invariant model parameters $\Theta \equiv (\alpha, \rho, c_1, c_2, \bar{N})$, endogenous variables (natives' labor N_t^H and N_t^L, undocumented immigrant stock in the US I_t), and TFP z_t are solved for.[31] We assume $\psi = 0.67$, which is the labor share of output used in the macroeconomics literature. We assume $\theta = 0.5$ and $\phi = 0.5$. For the elasticity of substitution between high- and low-skilled labor ($\frac{1}{1-\gamma}$), we calibrate the model using two different values that lie between the range of estimates attained by existing literature (Katz and Murphy (1992), Card (2009), Diamond (2016), Piyapromdee (2014)). Specifically, we set the elasticity of substitution between high- and low-skilled workers as 1.1 and 3.0, and show the results in both cases.[32] We calibrate the remaining parameters of the model using a procedure similar to indirect inference.

We take the following values from the data: wages in Mexico w_{Mt}, high-skilled native wages w_{Nt}^H, low-skilled native wages w_{Nt}^L, undocumented immigrant wages w_{It}, and the stock of Mexicans in the US and in Mexico at the start of the period, I_{1t}^0 and I_{2t}^0, respectively. For a given set of parameters Θ, we solve for the Mexico to US migration rate $p_t(MEX)$ and the rate of staying in the US $p_t(US)$ using equations (16) and (17). Using equation (18), we can then solve for the supply of undocumented immigrants in the US in a period (again conditional on our parameter guess Θ). We then solve for N_t^L using the firm's first-order condition in equation (11), assuming that the supply of undocumented immigrants equals the demand for undocumented immigrant workers under the given wages $(w_{Nt}^H, w_{Nt}^L, w_{It})$. Once we know N_t^L, we can solve for N_t^H using equation (12). Once we know N_t^H, N_t^L and I_t, we can calculate TFP z_t using equation (8). This allows us to get year-by-year model predictions for migration rates, return migration rates, native employment, and stock of undocumented immigrants in the US $(p_t(MEX), p_t(US), N_t^H, N_t^L, I_t)$. We can repeat this procedure for any set of parameters Θ.

We find the values for $(\alpha, \rho, c_1, c_2, \bar{N})$ so that the model predictions replicate the migration levels and key data patterns over the business cycle. The former is done by matching

[31] For simplicity, we assume that the capital is constant over time.

[32] While we cannot match the data moments under $\bar{N} = 0$, there are multiple combinations of γ and $\bar{N}$ that match the data moments. Therefore, we try multiple values consistent with the literature and show that the counterfactual results are robust.

the average migration rate $E[p_t(MEX)]$ and the rate of staying in the US $E[p_t(US)]$. The latter is done by picking the values that replicate the extent to which native employment, the migration rate from Mexico to the US, and the stock of undocumented immigrants drop during recessions.[33] We capture the elasticities using the coefficient on the unemployment rate in the following regressions:

$$\log(p_t(MEX)) = \kappa_0^p + \kappa_1^p u_t + \varepsilon_t^p \quad (20)$$

$$\log(I_t) = \kappa_0^I + \kappa_1^I u_t + \kappa_2^I[\text{calendar year dummies}] + \varepsilon_t^I \quad (21)$$

$$\log(N_t^H + \bar{N}) = \kappa_0^{NH} + \kappa_1^{NH} u_t + \kappa_2^{NH}[\text{calendar year dummies}] + \varepsilon_t^{NH} \quad (22)$$

$$\log(N_t^L) = \kappa_0^{NL} + \kappa_1^{NL} u_t + \kappa_2^{NL}[\text{calendar year dummies}] + \varepsilon_t^{NL}, \quad (23)$$

where $\varepsilon_t^p, \varepsilon_t^I, \varepsilon_t^{NH}$ and ε_t^{NL} are i.i.d. errors. We use the above regressions to compute the model moments.[34] For the data moments, we run the same regressions with additional controls. We do so because in reality other factors, such as demographic factors, affect the migration behavior and the distributions of such factors change over time in the MMP. Table 10 shows the regression results for the data moments.

The elasticity of substitution between low-skilled natives and immigrants (i.e., $\frac{1}{1-\rho}$) is pinned down by the employment fluctuations among low-skilled labor. In particular, all else equal, as we increase the elasticity of substitution between low-skilled natives and immigrants, the relationship between the US unemployment rate and low-skilled native employment becomes steeper in the model. See Appendix B for details on how this is identified.

4.3 Data

We use various data sources to calibrate the model. The year-by-year migration rates are calculated using the MMP data. We can only use data from household heads and spouses in the MMP, since they are the only workers for whom we have lifetime migration histories, which is the data necessary for this exercise. The supply of undocumented immigrant workers also comes from the MMP, weighted so that the sample matches the

[33] We also consider a version where we match how the net flow of undocumented immigrants – inflow to the US minus outflow to Mexico – varies over the business cycle. We obtain similar results for the counterfactual experiments.

[34] Since the model does not contain any demographic features that affect the migration rate or the number of undocumented immigrants in the US in each year, the regressors in the above equations are sufficient for capturing the relationship between the volatilities of migration rates and number of undocumented immigrants over the business cycle.

size of the Mexican population in each year.[35,36]

The information on average wages of undocumented immigrants in the US comes from the MMP. For native hourly wages and employment, we use data from the CPS for full-time employed and non-self-employed men aged 22–25. We classify high-skilled natives as those with 12 or more years of education, and low-skilled natives as those with fewer than 12 years of education.[37] For Mexican wages, we use data from the Encuesta Nacional de Empleo (ENE) from 1995 to 2004 and from the Encuesta Nacional de Ocupación y Empleo (ENOE) for 1995 to 2010. For the remaining years, we use the data from the Mexican Census.[38] Because the census data are only available every 10 years, we smooth out the year-to-year fluctuations using GDP growth in Mexico in each year.[39] We use PPP adjusted exchange rates from the OECD and then convert to 2012 US dollars. Thus, the Mexican wages are given in terms of the level of consumption good that can be purchased using a dollar in the US in 2012. Figure 2 illustrates the hourly wages of natives and Mexican immigrants in the CPS data.[40] We also show hourly wages of undocumented Mexican immigrants from the MMP for comparison. Native wages are much higher than the wages of Mexicans living in the US surveyed in the CPS. The wages for undocumented immigrants surveyed in the MMP are even lower, which makes sense since the CPS sample is likely biased towards legal immigrants.

4.4 Results

Table 11 shows the parameter values, under the two assumed levels of the elasticity of substitution between high- and low-skilled workers. In the remainder of this section, we will refer to Case 1 as the case where the elasticity of substitution between high and low skill workers is 1.1, and Case 2 as the case where the elasticity is 3. We show the results in both cases, given that this represents a reasonable range of estimates for this elasticity as found in previous work. We will show that the qualitative results are fairly robust to the

[35] The MMP sample sizes are scaled up each year to match the actual population of Mexican males aged 15–64, which we obtained from the World Bank.

[36] Rigorously speaking, since the MMP surveys communities where migration is prevalent, these surveys overestimate of the number of undocumented workers in the US. However, the MMP's sampling method also fails to survey migrants whose entire family moved to the US, so the direction of the bias is unclear.

[37] We conducted sensitivity checks where we group high school dropouts and high school graduates as low-skilled labor. The results of the first counterfactual are qualitatively similar; however, this does change the results of the second counterfactual. We explain more in that section. The results are qualitatively similar when we omit high school graduates from both low- and high- skilled groups.

[38] Downloaded from IPUMS.

[39] Data from the World Bank.

[40] We eliminate the top and bottom 1% of wage observations.

value of this parameter. We find that low-skilled native and undocumented immigrant workers are more substitutable than high- and low-skilled workers, which is consistent with some previous research that finds that natives and immigrants of the same skill and experience levels are perfect or imperfect substitutes (Borjas et al. (2012), Ottaviano and Peri (2012), Piyapromdee (2014)).

The calibrated parameters show that utility increases in wages. The return migration cost is much lower than the cost of moving from Mexico to the US, and is actually negative. Migration models typically include a home premium and a moving cost that make people likely to stay in their home location.[41] In this context, because the model only has two locations and is static, the home premium is not separately identified from the moving cost. This explains the high Mexico to US moving costs and low return migration costs. The differences in average moving costs reflect a preference for living in Mexico, all things otherwise equal.

Table 12 presents the moments, both in the model and in the data. We look at the average US to Mexico migration rate, the average rate at which migrants stay in the US, and the elasticities of migration rates, undocumented immigrant stock, and native employment with respect to the unemployment rate. We see that the model moments match the data moments very closely.

4.5 Counterfactual 1: constant immigrant stock

The reduced-form evidence shows that undocumented migrant wages decrease during downturns. However, we also know that as US wages decrease, fewer people will move to the US, driving up the equilibrium wage. In the first counterfactual, we aim to understand the contribution of this migration response to economic conditions on the equilibrium outcome. To do this, we hold the undocumented immigrant stock constant at the predicted value under the calendar year trend, and calculate the resulting undocumented immigrant wages that make the firm optimally hire that level of undocumented immigrants. In doing this exercise, we take native wages and employment level to be equal to the baseline values, and solve for the counterfactual undocumented immigrant wage w_I using equation (11).

When undocumented immigrant stocks do not adjust to economic fluctuations, there will be a steeper relationship between the state of the economy and undocumented immigrant wages. Figure 3 shows the relationship between TFP and hourly wages in the baseline and the counterfactual. The left panel shows Case 1 and the right panel shows Case 2. We plot the data points on the TFP estimates, the hourly wages of undocumented

[41]See Kennan and Walker (2011) and Lessem (2018).

immigrants, and the regression line between those points. The line is steeper in the counterfactual case. To assess the magnitude of this difference, we regress undocumented immigrant wages against TFP:

$$w_{It} = \kappa_0^{wI} + \kappa_1^{wI} \log(z_t) + \epsilon_t^{w_I} , \tag{24}$$

where $\epsilon_t^{w_I}$ is an i.i.d. error. We run this regression in the baseline and counterfactual scenarios to compare the results. The results are in Table 13, where columns (1) and (2) show Case 1, and columns (3) and (4) show Case 2. In Case 1, the coefficient on z_t for undocumented immigrant wages is 0.30 in the baseline and 0.37 in the counterfactual.[42] Using the estimated relationship between TFP and unemployment (shown in Table 14), we find that when unemployment goes up by 1 percentage point, undocumented immigrant wages drop by 1.4% in the baseline and by 1.7% in the counterfactual.[43] This shows that the lowered supply of undocumented immigrants in a recession helps to mitigate the negative wage impact of the productivity shock. The results are very similar in Case 2, where we assumed more substitutability between low and high skilled workers.

4.6 Counterfactual 2: constant immigrants' wages

In the next counterfactual, we study how the flexible wage setting of undocumented immigrants affects the firm's demand for native and undocumented immigrant labor. To do this, we set native wages as in the data and fix undocumented immigrant wages at the average wage. We calculate the firm's demand for native workers and the firm's demand for undocumented immigrant workers the using equilibrium conditions. Figures 4-6 illustrate the relationship between employment and TFP for different types of labor.

Figure 4 shows that the relationship between labor demand and TFP for low-skilled natives flattens when undocumented immigrant wages are fixed, for both levels of elasticity of substitution between high- and low-skilled workers (which we called Case 1 and Case 2). This implies that if undocumented immigrant wages were rigid, the firm would demand fewer low-skilled natives during booms and more low-skilled natives during recessions.

On the other hand, for high-skilled natives, the relationship between TFP and labor demand becomes slightly steeper (in Case 1) or shows almost no change (in Case 2) when undocumented immigrant wages are fixed. This is shown in Figure 5. This implies that if

[42] We find similar results replacing TFP with unemployment rate, but the coefficients are not statistically different at the 10% level of significance.

[43] In the baseline, a unit increase in unemployment rate corresponds to a 4.7% decrease in TFP (Table 14), and a 1% decrease in TFP corresponds to a 0.3% decrease in the wages. The counterfactual numbers are calculated analogously.

undocumented immigrant wages were rigid, the firm would demand slightly more high-skilled natives during booms and slightly fewer high-skilled natives during recessions.

Lastly, when immigrant wages are fixed, the firm would demand more immigrants during booms and fewer undocumented immigrants during recessions. This is shown in Figure 6 for both cases.

In order to calculate the magnitude of these differences, we regress the demand for all three types of labor against TFP and calendar year dummy variables:

$$
\begin{aligned}
\log(N_t^H) &= \kappa_0^{NH} + \kappa_1^{NH}\log(z_t) + \kappa_2^{NH}[\text{calendar year dummies}] + \varepsilon_t^{NH} && (25)\\
\log(N_t^L) &= \kappa_0^{NL} + \kappa_1^{NL}\log(z_t) + \kappa_2^{NL}[\text{calendar year dummies}] + \varepsilon_t^{NL} && (26)\\
\log(I_t) &= \kappa_0^{I} + \kappa_1^{I}\log(z_t) + \kappa_2^{I}[\text{calendar year dummies}] + \varepsilon_t^{I}, && (27)
\end{aligned}
$$

where $\varepsilon_t^{NH}, \varepsilon_t^{NL}$ and ε_t^{I} are an i.i.d. errors. We run these regressions in the baseline and counterfactual case to compare the results.

Table 15 shows the results of these regressions when the elasticity of substitution between high and low skilled workers is 1.1 (Case 1), and Table 16 shows the results when the elasticity is 3.0 (Case 2). Columns (1) and (2) of both tables show the results for high-skilled natives. In Case 1, where high- and low-skilled workers are more complementary to each other, the coefficient on z_t increases when undocumented immigrant wages are fixed. When the unemployment rate goes up by 1 percentage point, the firm's demand for high-skilled native workers drops by 11.3% in the baseline and by 13.8% in the counterfactual. When high- and low-skilled workers are more substitutable to each other (Case 2), there is almost no impact.

Columns (3) and (4) show the results for low-skilled natives. In Case 1, the coefficient on z_t decreases when undocumented immigrant wages are fixed (4.03 in the baseline and 2.81 in the counterfactual). Using the estimated relationship between TFP and unemployment (shown in Table 14), we find that when the unemployment rate goes up by 1 percentage point, the firm's demand for low-skilled native workers drops by 18.9% in the baseline and by 13.2% in the counterfactual.[44] This indicates that there would be lower employment fluctuations for low-skilled natives in response to aggregate productivity shocks if undocumented immigrant wages were fixed. These results are qualitatively similar under Case 2, where we assumed higher substitutability between high- and low-skilled workers.[45]

The results for immigrants are in columns (5) and (6) of Table 15 and 16. In Case 1, we find that the coefficient on z_t for undocumented immigrant labor becomes larger when

[44] These numbers are not unrealistically high given that we focus on a special firm that hires both high-skilled native, low-skilled natives, and undocumented immigrant workers.

[45] We find similar results replacing TFP with unemployment rate, but the coefficients are not statistically different at the 10% level of significance.

undocumented immigrant wages are fixed (1.37 in the baseline and 3.00 in the counterfactual). When the unemployment rate goes up by 1 percentage point, the firm's demand for undocumented immigrant workers drops by 6.4% in the baseline and by 14.1% in the counterfactual. This indicates that there would be higher employment fluctuations for undocumented immigrants in response to aggregate productivity shocks if undocumented immigrant wages were fixed. These results are qualitatively similar in Case 2, where we assumed greater substitutability between high- and low-skilled workers.

Intuitively, since undocumented immigrant wages are fixed in the counterfactual, the firm will hire more undocumented immigrants during the good times (i.e., high aggregate productivity shock) and fewer during the recessions (i.e., low aggregate productivity shock). Since undocumented immigrant labor and low-skilled native labor are more substitutable, the demand for low-skilled native moves in the opposite direction as undocumented immigrant labor. This creates a flatter relationship between TFP shocks and low-skilled labor when undocumented immigrant wages are rigid. In contrast, since undocumented immigrant labor and high-skilled native labor are complements, the demand for native labor moves in the same direction as undocumented immigrant labor. This creates a steeper relationship between TFP shocks and high-skilled native labor demand when undocumented immigrant wages are rigid. This experiment implies that the flexible wage setting of undocumented immigrants mitigates the impact on high-skilled native employment over the business cycle, but it magnifies the impact for low-skilled natives.

4.7 Robustness

The model has two groups of native workers: high and low skilled. In the results presented above, we put high school graduates in the high skill group (hereafter called the "baseline grouping"). We conducted sensitivity checks where we group high school dropouts and high school graduates as low-skilled labor (which we call the "alternative grouping"). In this section, we explain our results when we use the alternative grouping. The tables and figures in this case are shown in Appendix C.[46]

A 1 percentage point increase in the US unemployment rate decreases low-skilled native employment by 5.2% under the baseline grouping and by 3.2% under the alternative grouping. As we explain in Appendix B, this implies a lower elasticity of substitution between low-skilled natives and immigrants in the alternative grouping, and indeed, we find an elasticity of substitution of 0.4 when using the alternative grouping. Table C.1 in

[46]We show the results assuming an elasticity of substitution between high and low skilled native labor of 1.1.

Appendix C shows the parameter results in this case. Table C.2 shows the moments.

Given this change in the elasticity of substitution, the counterfactual employment patterns under fixed immigrant wages (counterfactual 2) are different when we use the alternative and baseline groupings. In the alternative grouping, when immigrant wages are fixed, the firm hires more immigrants and more low-skilled natives in good times (since they are complements). Meanwhile, during recessions, the firm hires fewer immigrants and fewer low-skilled natives. Combining these two together, the counterfactual fluctuations become steeper, as opposed to flatter. Figure C.1 in Appendix C shows these results. Therefore, the implications of this counterfactual are different under the two groupings: in the alternative grouping, the flexible wage setting of immigrants reduces the volatility of low-skilled natives employment over the business cycle. The results of the first counterfactual are qualitatively similar regardless of which educational grouping we use.

5. Conclusion

Undocumented immigration from Mexico decreases during downturns in the US economy. This implies a weaker job market for this population in these times, but little is known about how wages adjust. In this paper, we study how Mexican undocumented immigrant wages respond to economic downturns. Because these wages are negotiated frequently due to the short-term nature of employment contracts in this population, we expect larger effects than for legal immigrants. Consistent with this theory, reduced-form evidence shows that undocumented immigrant wages decrease with the US unemployment rate. We run the same analysis using data on legal Mexican immigrants, and see smaller effects of the unemployment rate on wages. This supports our theory that the short-term nature of contracts drives wage flexibility, since legal immigrants will be more likely to work under long-term contracts.

As the unemployment rate increases and undocumented immigrant wages decrease, fewer people will choose to move to the US. In the second part of the paper, we analyze a model that captures the equilibrium effects resulting from changes in undocumented migrant flows over the business cycle. Counterfactuals show that, were the undocumented immigrant stock to be held constant during recessions, we would see larger drops in undocumented immigrant wages. We also show that the flexible wage setting of undocumented immigrants mitigates or shows no impact on high-skilled native employment fluctuations over the business cycle, but magnifies those for the low-skilled natives.

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Tables and figures

Table 1: Summary statistics

	(1)	(2)
Duration of a trip in the US (months)	Any	less than 15
Education distribution		
-6 or fewer years	63%	70%
-7 to 11 years	27%	22%
-12 years	6%	4%
-13 or more years	3%	3%
Mean age at first trip	25.85	27.04
Number of trips to US among migrants	2.59	3.21
Percentage of migrants that take only one trip	44%	31%
Mean duration of a single US trip (months)	39.57	7.44
Mean hourly wage (2012 US$)	10.81	10.06
Percent working in each occupation		
-Agriculture	27%	37%
-Skilled manufacturing	21%	15%
-Unskilled manufacturing	22%	21%
-Services	18%	16%
Number of people	6,938	3,055

Sample consists of men surveyed in the MMP. We drop people who moved to the US legally as well as people whose first trip to the US was before 1965.

Table 2: Relationship between wages and unemployment

	Log wages		Change in log wages	
	(1)	(2)	(3)	(4)
Unemployment rate	-0.014**	-0.041***	-0.028***	-0.021*
	(0.006)	(0.012)	(0.010)	(0.011)
Age	0.008***	0.012***	-0.005	0.051
	(0.002)	(0.003)	(0.011)	(0.048)
Age squared	-0.011***	-0.018***	-0.051	-0.213
	(0.002)	(0.004)	(0.059)	(0.731)
7-12 years education	0.012	0.007	-0.005	0.017
	(0.016)	(0.025)	(0.013)	(0.041)
13+ years education	0.111***	0.127**	-0.025	0.060
	(0.033)	(0.053)	(0.103)	(0.075)
Year of first US migration			0.006**	0.006***
			(0.003)	(0.002)
Conducted more than two trips			0.007	-0.030
			(0.028)	(0.031)
Constant	2.469***	2.632***	-11.730**	-12.700***
	(0.276)	(0.300)	(5.572)	(4.099)
Observations	2699	1399	420	144

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state, year, and occupation fixed effects. These regressions use data from the MMP, including only people who stay in the US for less than 15 months. We drop the top and bottom 2% of wage observations and use the MMP sample weights. We use state unemployment rates. For education variables, the excluded group is people with fewer than seven years of education. In columns (1) and (2), the dependent variable is log hourly wages, and in columns (3) and (4) we use the growth in log hourly wages for each person. Columns (1) and (3) use all men. Columns (2) and (4) use all male wages within five years of the survey. In columns (3) and (4), the age and age-squared variables record the change in age between the two wage observations.

Table 3: Multinomial logit regressions of working in different occupations

	Dependent variable=1 if work in a given sector					
	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture	Skilled Manufacturing	Unskilled Manufacturing	Transportation	Services	Sales
US unemployment	0.014***	-0.021***	-0.004	-0.000	0.003	0.008***
	(0.004)	(0.008)	(0.006)	(0.002)	(0.007)	(0.003)
Age	-0.009**	0.014**	0.005	0.004***	-0.012**	-0.001
	(0.003)	(0.006)	(0.005)	(0.001)	(0.005)	(0.002)
Age squared	0.015***	-0.021***	-0.002	-0.005**	0.013*	-0.000
	(0.004)	(0.008)	(0.007)	(0.002)	(0.007)	(0.003)
7-12 years education	-0.096***	0.014	0.067***	0.022***	-0.015	0.009**
	(0.010)	(0.015)	(0.012)	(0.003)	(0.012)	(0.004)
13+ years education	-0.156***	0.010	-0.025	-0.019	0.163***	0.028**
	(0.033)	(0.030)	(0.030)	(0.017)	(0.028)	(0.011)
Dummy for Primary	0.027***	0.040***	-0.042***	0.010***	-0.039***	0.004
	(0.007)	(0.013)	(0.011)	(0.003)	(0.012)	(0.004)
Dummy for Previous	0.037***	0.003	-0.013	-0.004	0.001	-0.023***
	(0.014)	(0.023)	(0.020)	(0.005)	(0.020)	(0.006)
Observations	11,412	11,412	11,412	11,412	11,412	11,412

Table reports marginal effects. Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state and year fixed effects. The sample is all men in the MMP, and we use the provided sample weights. We use state unemployment rates. For education variables, excluded group is those with fewer than seven years of education. The variable "Dummy for Primary" equals 1 if a respondent's primary occupation is the same as in the dependent variable and 0 otherwise. The variable "Dummy for Previous" equals 1 if the respondent was in the US the previous year and his occupation was the same as the the dependent variable and 0 otherwise.

Table 4: Job changes and legal status

	Dependent variable =1 if changed job	
	(1)	(2)
Legal	-0.079***	-0.037***
	(0.009)	(0.014)
US unemployment rate	0.055	0.046
	(0.137)	(0.136)
Age	-0.011***	-0.018***
	(0.004)	(0.004)
Age squared	0.006	0.014***
	(0.005)	(0.005)
7-12 years education	-0.050***	-0.066***
	(0.010)	(0.016)
13+ years education	-0.065***	-0.071***
	(0.018)	(0.024)
Observations	35369	12213

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We use data from the MMP and use the provided sample weights. US unemployment is the unemployment rate in a state a person is living in. Regressions include state and year fixed effects. We report marginal effects from a probit regression. The dependent variable equals 1 if a person changes jobs in a given year. Column (1) uses all observations, and column (2) only includes observations within 5 years of the survey year to reduce recall bias.

Table 5: Comparison of wages for legal and undocumented immigrants in the MMP

	Dependent variable = log hourly wages		
	(1)	(2)	(3)
	All	Undocumented	Legal
Unemployment rate	-0.010	-0.014**	-0.004
	(0.007)	(0.006)	(0.015)
Age	0.009***	0.008***	0.017***
	(0.002)	(0.002)	(0.004)
Age squared	-0.012***	-0.011***	-0.022***
	(0.002)	(0.002)	(0.005)
7-12 years education	0.004	0.011	-0.009
	(0.010)	(0.016)	(0.048)
13+ years education	0.053***	0.108***	-0.024
	(0.018)	(0.034)	(0.042)
Constant	2.286***	2.505***	1.963***
	(0.223)	(0.241)	(0.187)
Observations	3690	2699	991

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state, year, and occupation fixed effects. These regressions use data from the MMP, using the provided sample weights. We eliminate the top and bottom 2% of the wage observations. We use state unemployment rates. For education variables, the excluded group is those with fewer than seven years of education.

Table 6: Wage regressions by network status

	Dependent variable = log wages		
	(1)	(2)	(3)
	Low migration	High migration	All
Unemployment rate	-0.016*	-0.014	-0.013**
	(0.010)	(0.009)	(0.006)
Unemployment rate x low migration community			-0.003**
			(0.001)
Age	0.013***	0.013***	0.008***
	(0.003)	(0.002)	(0.002)
Age squared	-0.014***	-0.020***	-0.011***
	(0.004)	(0.004)	(0.002)
7-12 years education	0.033	0.000	0.014
	(0.022)	(0.009)	(0.016)
13+ years education	0.073	0.157***	0.112***
	(0.045)	(0.054)	(0.035)
Constant	2.395***	2.310***	2.475***
	(0.300)	(0.049)	(0.279)
Observations	1335	1364	2699

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions include state, year and occupation fixed effects. We use the MMP data, including only people who stay in the US for less than 15 months. We drop the top and bottom 2% of wage observations and use the MMP sample weights. We use state unemployment rates. For education variables, the excluded group is people with fewer than seven years of education. Column (1) uses people from communities with less than the median migration rates, and column (2) uses people from communities with greater than the median migration rates.

Table 7: Earnings regressions for documented and undocumented immigrants in the CPS

	Dependent variable=log earnings		
	(1)	(2)	(3)
	All	Undocumented	Documented
Unemployment rate	-0.010	-0.017**	-0.002
	(0.006)	(0.007)	(0.007)
Age	0.035***	0.040***	0.031***
	(0.008)	(0.012)	(0.008)
Age squared	-0.048***	-0.052***	-0.045***
	(0.010)	(0.015)	(0.009)
7-12 years education	0.039*	0.041*	0.038
	(0.022)	(0.023)	(0.030)
Years in US	0.012***	0.010***	0.012***
	(0.001)	(0.002)	(0.002)
Constant	4.727***	5.750***	4.686***
	(0.152)	(0.264)	(0.254)
Observations	2044	961	1083

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table uses the ASEC files in the CPS. We use the provided sample weights. Documented immigrants are identified using the criteria in Borjas (2017). We only use data on high school dropouts. We include state, year, and occupation fixed effects. We use the state unemployment rate. For education, the excluded group is those with fewer than seven years of education.

Table 8: Earnings growth regressions for documented and undocumented immigrants in the CPS

	Dependent variable = log earnings growth		
	(1)	(2)	(3)
	All	Undocumented	Documented
Change in unemployment rate	-0.028*	-0.035	-0.022
	(0.015)	(0.029)	(0.013)
Change in age	0.040	0.090	-0.015
	(0.065)	(0.128)	(0.088)
Change in age-squared	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
7-12 years education	0.015	0.002	0.032*
	(0.018)	(0.034)	(0.018)
Years in US	-0.002	-0.004**	-0.000
	(0.002)	(0.002)	(0.002)
Constant	-0.573***	-0.452**	-0.464***
	(0.109)	(0.173)	(0.141)
Observations	1608	739	869

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table uses the ASEC files in the CPS. We use the provided sample weights. Documented immigrants are identified using the criteria in Borjas (2017). We use state unemployment rates. For education variables, the excluded group is those with fewer than seven years of education. We only include data on high school graduates. We include state, year, and occupation fixed effects.

Table 9: Probit of migration decisions

	Dependent variable=1 if move	
	(1)	(2)
	Mexico to US	US to Mexico
US unemployment	-0.001**	0.002
	(0.000)	(0.006)
Unemployment in Mexico	-0.000	0.003
	(0.000)	(0.005)
Age	-0.000*	-0.008
	(0.000)	(0.006)
Age squared	-0.001***	0.004
	(0.000)	(0.007)
7-12 years education	-0.004***	-0.090***
	(0.001)	(0.014)
13+ years education	-0.013***	-0.117**
	(0.002)	(0.049)
Married	0.001**	0.088***
	(0.001)	(0.012)
Border enforcement	0.010***	0.068**
	(0.003)	(0.030)
High migration state	0.010***	
	(0.001)	

Table reports marginal effects from a probit regression using MMP data on undocumented immigrants. We use the MMP sample weights. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We included state fixed effects. We use national unemployment rates. For education variables, the excluded group is those with fewer than seven years of education. The variable "Border enforcement" is hours (in millions) spent patrolling the border.

Table 10: Elasticities in the data

	Dependent variable=log(X)			
	X=migration rate	X=immigrant stock	X=high-skilled native employment	X=low-skilled native employment
	(1)	(2)	(3)	(4)
US unemployment	-0.087**	-0.026*	-0.015**	-0.052***
	(0.040)	(0.013)	(0.006)	(0.014)
Share with 6 or fewer years education	-12.759	-0.357		
	(14.615)	(4.476)		
Share with 7 to 11 years education	0.502	4.342		
	(17.508)	(5.453)		
Share with 12 years education	-72.023**	-27.853***		
	(29.267)	(9.471)		
Average age	-0.022	0.176***		
	(0.166)	(0.054)		
Share married	3.677	0.067		
	(3.922)	(1.222)		
Share from migration prevalent community	-1.040	-0.720**		
	(0.989)	(0.336)		
Year 1980 to 198	-0.656	-0.294	0.315***	1.765***
	(0.620)	(0.201)	(0.022)	(0.071)
Year 1985 to 1989	-0.622	-0.212	0.309***	1.438***
	(0.514)	(0.165)	(0.015)	(0.0490)
Year 1990 to 1994	-0.506	-0.024	0.286***	1.113***
	(0.409)	(0.130)	(0.053)	(0.151)
Year 1995 to 1999	-0.163	0.056	-0.0041	0.297***
	(0.281)	(0.089)	(0.032)	(0.061)
Year 2000 to 2004	0.102	0.074	0.0503	0.174***
	(0.213)	(0.066)	(0.030)	(0.047)
Constant	8.343	2.608	10.11***	7.259***
	(13.903)	(4.303)	(0.042)	(0.102)
Observations	32	32	32	32
Adjusted R^2	0.898	0.971	0.840	0.945

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is the aggregate statistics for each calendar year. For calendar year dummies, the excluded group is 2005 to 2011.

Table 11: Parameter values

Case 1- Elasticity of substitution $1/(1-\gamma) = 1.1$	Notation	Value
Scaling parameter	α	0.30
Elasticity of substitution between low-skilled natives and immigrants	$1/(1-\rho)$	4.35
Moving cost from Mexico to the US	c_1	20.24
Moving cost from the US to Mexico	c_2	-2.00
Fixed number of natives hired under a different firm	$\bar{N}$	2.71
Case 2- Elasticity of substitution $1/(1-\gamma) = 3.0$	**Notation**	**Value**
Scaling parameter	α	0.30
Elasticity of substitution between low-skilled natives and immigrants	$1/(1-\rho)$	4.35
Moving cost from Mexico to the US	c_1	20.24
Moving cost from the US to Mexico	c_2	-2.00
Fixed number of natives hired under a different firm	$\bar{N}$	4.57

The table shows calibrated parameters attained via implementing the calibration strategy explained in Section 4.2. The top part of the table is the results when we set the elasticity of substitution between high and low skilled labor at 1.1. The bottom part of the table is when we set this elasticity to 3.0.

Table 12: Moments

Case 1- elasticity of substitution $1/(1-\gamma) = 1.1$	Notation	Model	Data
Average migration rate from Mexico to the US	$\mathbb{E}[p_t(MX)]$	0.013	0.013
Average rate of staying in the US	$\mathbb{E}[p_t(US)]$	0.740	0.717
Elasticity of migration rate from Mexico to the US	κ_1^p	-0.070	-0.087
Elasticity of immigrants' stock in the US	κ_1^I	-0.031	-0.026
Elasticity of high-skilled natives' employment	κ_1^{NH}	-0.015	-0.015
Elasticity of low-skilled natives' employment	κ_1^{NL}	-0.057	-0.052
Case 2- elasticity of substitution $1/(1-\gamma) = 3.0$	Notation	Model	Data
Average migration rate from Mexico to the US	$\mathbb{E}[p_t(MX)]$	0.013	0.013
Average rate of staying in the US	$\mathbb{E}[p_t(US)]$	0.740	0.717
Elasticity of migration rate from Mexico to the US	κ_1^p	-0.070	-0.087
Elasticity of immigrants' stock in the US	κ_1^I	-0.031	-0.026
Elasticity of high-skilled natives' employment	κ_1^{NH}	-0.015	-0.015
Elasticity of low-skilled natives' employment	κ_1^{NL}	-0.057	-0.052

The table shows the six moments we used to pin down parameters of the model. The first moment is the average migration rate from Mexico to the US between 1980 to 2011. The second moment is the proportion of Mexican immigrants in the US who choose to remain in the US in that year, which is averaged across years between 1980 to 2011. The third moment is the estimated coefficient on US unemployment rate attained by regressing the simulated likelihood of Mexicans migrating to the US against US unemployment rate. The fourth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated immigrant stock in the US against US unemployment rate and calendar year dummies. The fifth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated high-skilled natives' total employment against US unemployment rate and calendar year dummies. Lastly, the sixth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated low-skilled natives' total employment against US unemployment rate and calendar year dummies. The top part of the table is the results when we set the elasticity of substitution between high and low skilled labor at 1.1. The bottom part of the table is when we set this elasticity to 3.0.

Table 13: Counterfactual 1: fixed immigrant stock

	Dependent variable = immigrant wages			
	(1)	(2)	(3)	(4)
	Case 1		Case 2	
	Elasticity of substitution of 1.1		Elasticity of substitution of 3	
	Baseline	Counterfactual	Baseline	Counterfactual
Log(TFP)	0.304***	0.366***	0.307***	0.373***
	(0.047)	(0.064)	(0.042)	(0.058)
Constant	1.045***	0.780***	1.035***	0.754***
	(0.196)	(0.271)	(0.175)	(0.243)
Observations	32	32	32	32
Adjusted R^2	0.572	0.504	0.632	0.568

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In columns (1) and (2), we assume an elasticity of substitution between high and low skilled labor of 1.1. In columns (3) and (4), we assume the elasticity is equal to 3. Columns (1) and (3) show the baseline case, and columns (2) and (4) show the counterfactual scenarios.

Table 14: Relationship between estimated TFP and US unemployment rate

	Dependent variable = Estimated TFP	
	(1)	(2)
	Case 1	Case 2
	Elasticity of substitution of 1.1	Elasticity of substitution of 3
US unemployment rate	-0.047**	-0.049**
	(0.019)	(0.020)
Constant	4.514***	4.519***
	(0.125)	(0.129)
Observations	32	32
Adjusted R^2	0.145	0.147

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (1), we assume an elasticity of substitution between high and low skilled labor of 1.1. In column (3), we assume the elasticity is equal to 3.

Table 15: Counterfactual 2: fixed immigrants' wages in Case 1 (elasticity of substitution between high- and low-skilled workers of $\frac{1}{1-\gamma} = 1.1$)

	Dependent variable = labor demand					
	(1)	(2)	(3)	(4)	(5)	(6)
	High-skilled natives		Low-skilled natives		Immigrants	
	Baseline	Counterfactual	Baseline	Counterfactual	Baseline	Counterfactual
Log(TFP)	2.410***	2.927***	4.030***	2.807***	1.366***	3.004***
	(0.072)	(0.071)	(0.202)	(0.188)	(0.094)	(0.033)
Year 1980 to 1984	-0.076**	0.089**	0.003	-0.388***	-0.430***	0.090***
	(0.036)	(0.036)	(0.101)	(0.094)	(0.047)	(0.016)
Year 1985 to 1989	-0.083**	0.022	0.044	-0.204**	-0.298***	0.036**
	(0.031)	(0.031)	(0.088)	(0.082)	(0.041)	(0.014)
Year 1990 to 1994	0.111***	0.169***	0.308***	0.170**	-0.118***	0.065***
	(0.030)	(0.029)	(0.084)	(0.078)	(0.039)	(0.014)
Year 1995 to 1999	0.156***	0.163***	0.170**	0.152**	0.044	0.065***
	(0.023)	(0.022)	(0.063)	(0.059)	(0.029)	(0.010)
Year 2000 to 2004	0.040*	0.031	-0.049	-0.028	0.050*	0.020**
	(0.020)	(0.020)	(0.057)	(0.053)	(0.027)	(0.009)
Constant	-10.374***	-12.604***	-18.591***	-13.312***	-5.161***	-12.224***
	(0.317)	(0.312)	(0.889)	(0.827)	(0.414)	(0.143)
Observations	32	32	32	32	32	32
Adjusted R^2	0.995	0.996	0.983	0.980	0.988	0.999

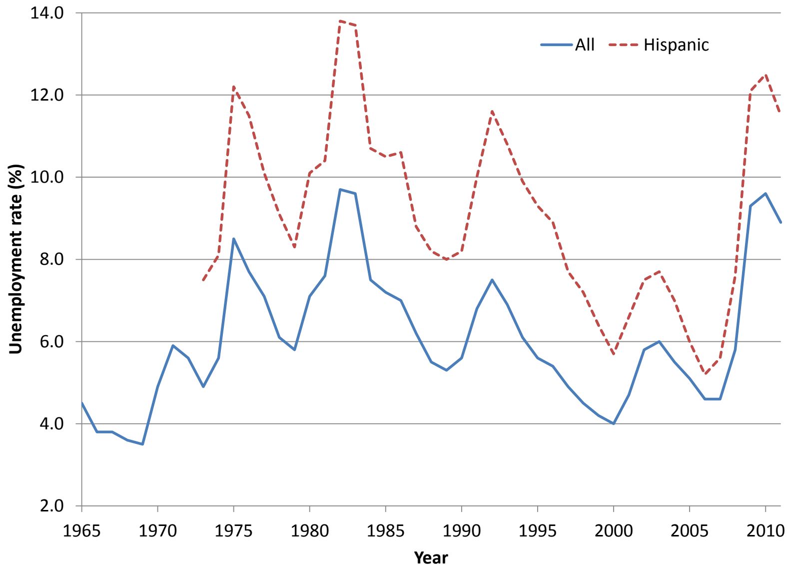
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For calendar year dummies, the excluded group is 2005 to 2011.

Table 16: Counterfactual 2: fixed immigrants' wages in Case 2 (elasticity of substitution between high- and low-skilled workers of $\frac{1}{1-\gamma} = 3.0$)

	Dependent variable = labor demand					
	(1)	(2)	(3)	(4)	(5)	(6)
	High-skilled natives		Low-skilled natives		Immigrants	
	Baseline	Counterfactual	Baseline	Counterfactual	Baseline	Counterfactual
Log(TFP)	2.924***	2.932***	3.495***	2.867***	1.162***	3.039***
	(0.088)	(0.088)	(0.163)	(0.161)	(0.091)	(0.009)
Year 1980 to 1984	0.170***	0.173***	-0.256***	-0.442***	-0.527***	0.024***
	(0.045)	(0.046)	(0.085)	(0.083)	(0.047)	(0.005)
Year 1985 to 1989	0.057	0.058	-0.099	-0.221***	-0.354***	0.013***
	(0.041)	(0.041)	(0.077)	(0.076)	(0.043)	(0.004)
Year 1990 to 1994	0.251***	0.251***	0.163**	0.106	-0.174***	-0.006
	(0.039)	(0.039)	(0.073)	(0.072)	(0.041)	(0.004)
Year 1995 to 1999	0.239***	0.238***	0.083	0.087	0.011	-0.004
	(0.031)	(0.031)	(0.057)	(0.056)	(0.032)	(0.003)
Year 2000 to 2004	0.049	0.048	-0.059	-0.044	0.047	0.003
	(0.029)	(0.029)	(0.053)	(0.053)	(0.030)	(0.003)
Constant	-12.662***	-12.694***	-16.205***	-13.511***	-4.256***	-12.311***
	(0.385)	(0.385)	(0.715)	(0.705)	(0.398)	(0.040)
Observations	32	32	32	32	32	32
Adjusted R^2	0.992	0.992	0.985	0.983	0.985	1.000

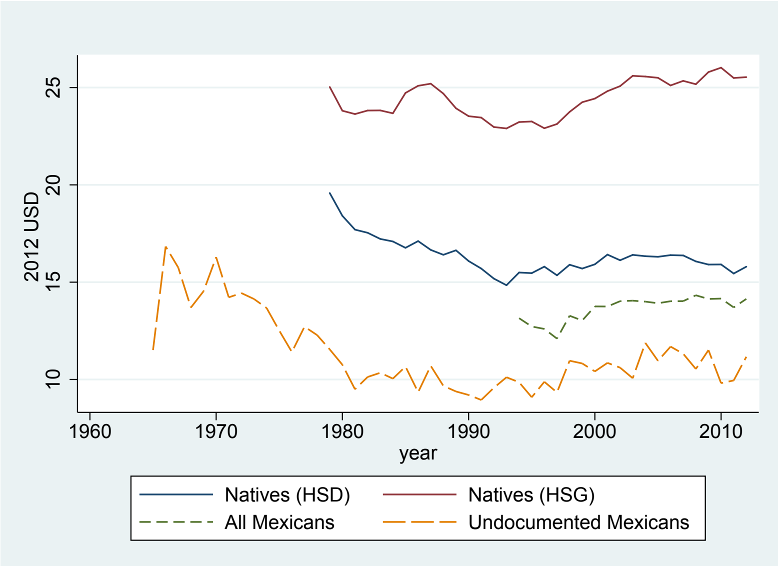
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For calendar year dummies, the excluded group is 2005 to 2011.

Figure 1: US unemployment rate



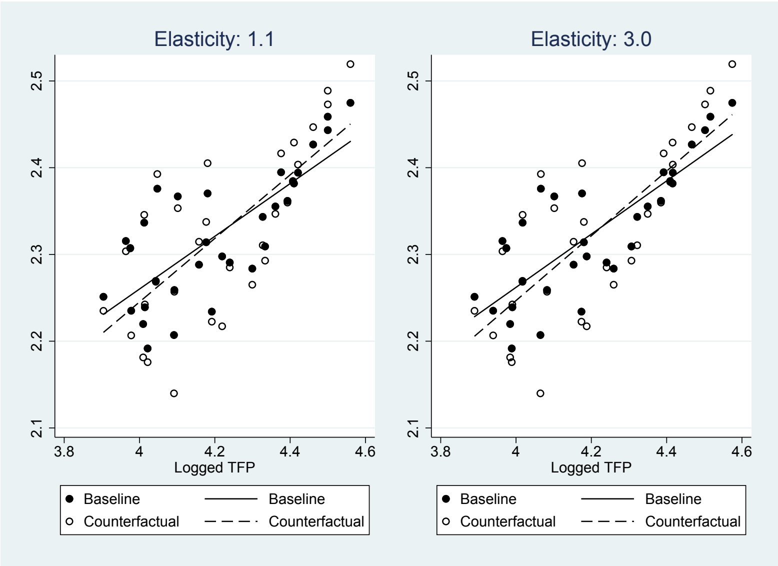
To create this figure, we used data on people aged 16 and over from the CPS.

Figure 2: Hourly wages in the US



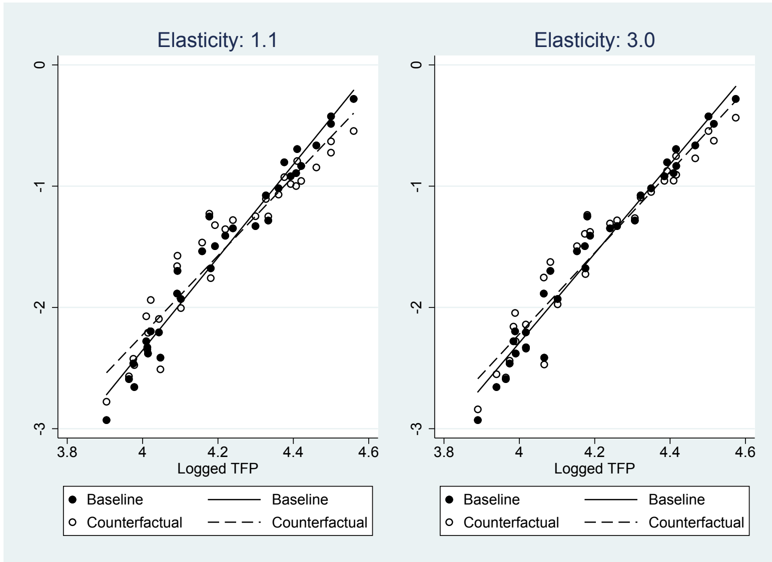
Native and all Mexicans wages are from the CPS. Undocumented Mexican wages are from the MMP.

Figure 3: Counterfactual 1: immigrants' hourly wages and TFP



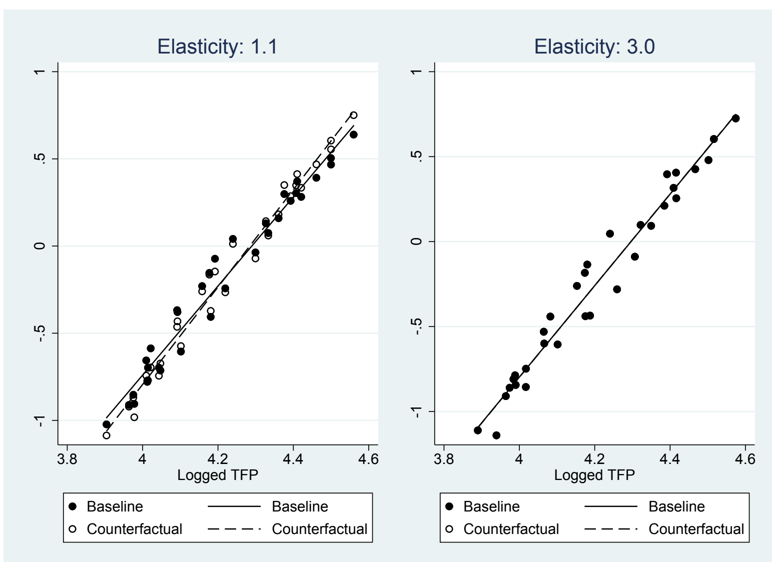
The plot on the left assumes an elasticity of substitution between high and low skilled labor of 1.1. The panel on the right assumes the elasticity is equal to 3.

Figure 4: Counterfactual 2: firm's labor demand for low-skilled natives and TFP



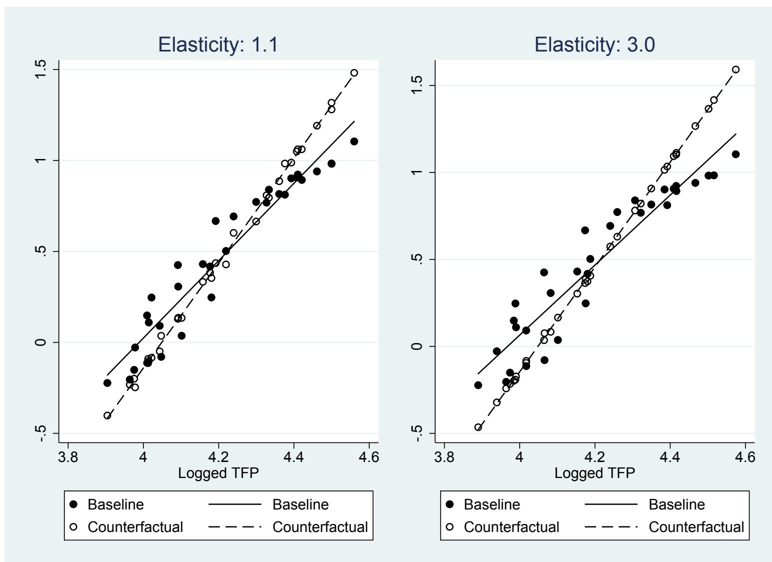
The plot on the left assumes an elasticity of substitution between high and low skilled labor of 1.1. The panel on the right assumes the elasticity is equal to 3.

Figure 5: Counterfactual 2: firm's labor demand for high-skilled natives and TFP



The plot on the left assumes an elasticity of substitution between high and low skilled labor of 1.1. The panel on the right assumes the elasticity is equal to 3.

Figure 6: Counterfactual 2: firm's labor demand for immigrants and TFP



The plot on the left assumes an elasticity of substitution between high and low skilled labor of 1.1. The panel on the right assumes the elasticity is equal to 3.

Appendix A Robustness checks

Keeping respondents who stayed in the US for more than 15 months

Table A.1: Relationship between wages and the unemployment rate

	Log wages		Change in log wages	
	(1)	(2)	(3)	(4)
Unemployment rate	-0.008	-0.020*	-0.008	-0.003
	(0.008)	(0.011)	(0.007)	(0.011)
Age	0.010***	0.007*	0.017	0.029
	(0.003)	(0.004)	(0.011)	(0.036)
Age squared	-0.012***	-0.009	-0.117***	0.143
	(0.003)	(0.005)	(0.042)	(0.623)
7-12 years education	0.053***	0.032**	0.050*	0.035
	(0.010)	(0.012)	(0.027)	(0.030)
13+ years education	0.118***	0.151**	0.121**	0.031
	(0.024)	(0.059)	(0.053)	(0.048)
Year of first US migration			0.009***	0.013***
			(0.002)	(0.002)
Conducted more than two trips			-0.047	-0.031
			(0.030)	(0.032)
Constant	2.366***	2.481***	-16.857***	-26.520***
	(0.243)	(0.223)	(4.470)	(2.970)
Observations	5078	2418	886	249

Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state, year and occupation fixed effects. These regressions use the MMP data, using the provided sample weights. We drop the top and bottom 2% of wage observations. We use state unemployment rates. For education variables, the excluded group is people with fewer than seven years of education. In columns (1) and (2), the dependent variable is log wages, and in columns (3) and (4) we use the growth in log wages for each person. Columns (1) and (3) use all men. Columns (2) and (4) use all male wages within 5 years of each survey.

Table A.2: Wage regressions controlling for selection

	(1) Migration	(2) Log Wages	(3) Migration	(4) Log Wages
Unemployment	-0.039*	-0.015**	-0.092**	-0.033***
	(0.021)	(0.007)	(0.042)	(0.009)
Age	0.014	0.003	0.054*	0.007**
	(0.009)	(0.002)	(0.033)	(0.003)
Age-squared	-0.018	-0.003	-0.051	-0.010**
	(0.012)	(0.003)	(0.049)	(0.005)
7-12 years education	-0.161***	0.025*	-0.129**	-0.003
	(0.027)	(0.014)	(0.054)	(0.016)
13+ years education	0.166*	0.061***	0.283**	0.087*
	(0.097)	(0.020)	(0.140)	(0.048)
Log rainfall	-0.165		-0.287***	
	(0.103)		(0.092)	
Constant	0.211	2.552***	0.126	2.439***
	(0.948)	(0.115)	(0.950)	(0.122)
Inverse Mills ratio		-0.164		-0.025
		(0.086)		(0.035)
Observations	5,123	2,789	2,452	1,445

Standard errors, clustered by state, in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These regressions use the MMP data, and we use the provided sample weights. We drop the top and bottom 2% of wage observations. We include state, year, and occupation fixed effects. We use state unemployment rates. For education variables, the excluded group is people with fewer than seven years of education. Log rainfall is the rainfall in a person's home state. Columns (1) and (2) use all men, and columns (3) and (4) use all men where wages are reported within five years of the survey. Columns (1) and (3) are the first-stage probits, and columns (2) and (4) are the wage regressions controlling for selection.

National unemployment rate

Table A.3: Relationship between wages and the national unemployment rate

	Log wages		Change in log wages	
	(1)	(2)	(3)	(4)
US unemployment	-0.021***	-0.021***	-0.022***	-0.023***
	(0.005)	(0.005)	(0.007)	(0.007)
Age	0.014***	0.012***	0.002	0.088**
	(0.001)	(0.003)	(0.019)	(0.037)
Age squared	-0.017***	-0.018***	-0.083	-0.592
	(0.001)	(0.004)	(0.082)	(0.682)
7-12 years education	0.010	-0.006	0.016	0.024
	(0.014)	(0.030)	(0.023)	(0.027)
13+ years education	0.095***	0.099*	-0.025	0.033
	(0.031)	(0.056)	(0.068)	(0.051)
Year of first US migration			0.003	-0.002
			(0.002)	(0.002)
Conducted more than two trips			-0.012	-0.051***
			(0.030)	(0.017)
Constant	2.011***	2.042***	-5.778	4.879
	(0.062)	(0.060)	(4.963)	(4.283)
Observations	2699	1399	420	144

Notes: Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state, year, and occupation fixed effects. Regressions use data from the MMP, using the provided sample weights. We drop the top and bottom 2% of observations. We calculate a weighted average of state unemployment rates to construct the unemployment rate for each year. For education variables, the excluded group is people with fewer than seven years of education. Columns (1) and 3 use all men. Columns (2) and (4) use all male wages within five years of each survey.

Per capita GDP

Table A.4: Relationship between wages and the per capita GDP

	Dependent variable = log wages		Change in log wages	
	(1)	(2)	(3)	(4)
Per capita GDP	0.143***	0.163***	0.010	0.044
	(0.033)	(0.057)	(0.074)	(0.093)
Age	0.007***	0.011***	-0.003	0.050
	(0.002)	(0.003)	(0.011)	(0.048)
Age squared	-0.010***	-0.017***	-0.067	-0.252
	(0.002)	(0.004)	(0.070)	(0.763)
7-12 years education	0.009	0.004	0.009	0.025
	(0.015)	(0.023)	(0.015)	(0.041)
13+ years education	0.108***	0.128**	-0.029	0.063
	(0.033)	(0.055)	(0.114)	(0.077)
Year of first US migration			0.007*	0.008***
			(0.004)	(0.002)
Conducted more than two trips			0.001	-0.028
			(0.032)	(0.039)
Constant	1.532***	1.297***	-14.165*	-14.991***
	(0.397)	(0.395)	(7.885)	(3.334)
Observations	2629	1399	401	144

Notes: Standard errors, clustered by state, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We include state, year and occupation fixed effects. These regressions use the MMP data, using the provided sample weights. We drop the top and bottom 2% of wage observations. We use state per capita GDP levels divided by 10,000. For education variables, the excluded group is people with fewer than seven years of education. Columns (1) and (3) use all men. Columns (2) and (4) use all male wages within 5 years of each survey.

Appendix B Identification of the elasticity of substitution between low-skilled natives and immigrants

The elasticity of substitution between low-skilled natives and immigrants ($\frac{1}{1-\rho}$) is pinned down by (i) the relationship between the US unemployment rate and the immigrant stock and (ii) the relationship between the US unemployment rate and low-skilled natives' employment. The data moments (Table 12) show that the relationship is steeper for the low-skilled natives than that for the immigrants. That is, a percentage point increase in the US unemployment rate corresponds to a 2.6% drop in immigrant stock in the US and a 5.2% drop in low-skilled native's employment. This means that, under a good economy, we have relatively fewer immigrants than low-skilled natives, while under a bad economy, we have relatively more immigrants than low-skilled natives.

The identification comes from the fact that, if we increase the elasticity of substitution between low-skilled natives and immigrants ($\frac{1}{1-\rho}$), the relationship between the US unemployment rate and low-skilled natives' employment becomes steeper. Suppose the elasticity of substitution between low-skilled natives and immigrants ($\frac{1}{1-\rho}$) is high so that low-skilled native labor and undocumented immigrants are perfectly substitutable. Then, under a good economy, the firm would try to fill-in the "shortage" of immigrants by increasing the low-skilled hires, whereas under recessions, the firm would replace low-skilled natives with immigrants who are willing to work for lower wages. Combining these effects, low-skilled natives will be hired more during good times and hired less during bad times. Hence, low-skilled natives experience large employment fluctuations over the business cycle.

On the other hand, suppose the elasticity of substitution between low-skilled natives and immigrants ($\frac{1}{1-\rho}$) is low so that low-skilled native labor and undocumented immigrants are more complementary to each other. Then, under a good economy, because there are not enough immigrants, the firm would also not hire low-skilled natives. Meanwhile, under recessions, because there are many immigrants willing to work at low wages, the firm would hire low-skilled natives to complement immigrants. Combining these effects, fewer low-skilled natives will be hired during good times and more will be hired during bad times. Hence, low-skilled natives will experience small employment fluctuations over the business cycle.

Appendix C Alternative grouping

Table C.1: Parameter values using the alternative grouping

	Notation	Value
Scaling parameter	α	0.30
Elasticity of substitution between low-skilled natives and immigrants	$1/(1-\rho)$	0.4
Moving cost from Mexico to the US	c_1	20.24
Moving cost from the US to Mexico	c_2	-2.00
Fixed number of natives hired under a different firm	$\bar{N}$	8.90

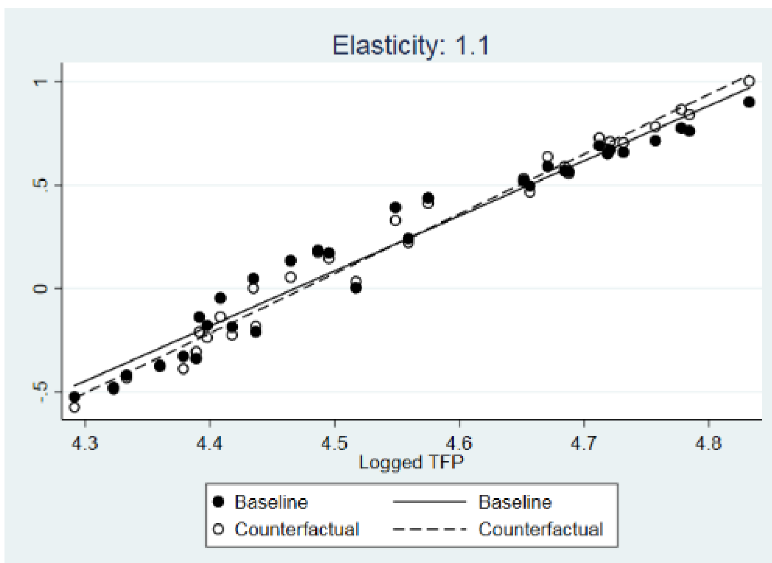
The table shows calibrated parameters attained via implementing the calibration strategy explained in Section 4.2 under the alternative grouping of high and skilled native labor. We set the elasticity of substitution between high and low skilled labor at 1.1.

Table C.2: Moments using the alternative grouping

	Notation	Model	Data
Average migration rate from Mexico to the US	$\mathbb{E}[p_t(MX)]$	0.013	0.013
Average rate of staying in the US	$\mathbb{E}[p_t(US)]$	0.740	0.717
Elasticity of migration rate from Mexico to the US	κ_1^p	-0.070	-0.087
Elasticity of immigrants' stock in the US	κ_1^I	-0.031	-0.026
Elasticity of high-skilled natives' employment	κ_1^{NH}	-0.008	-0.008
Elasticity of low-skilled natives' employment	κ_1^{NL}	-0.036	-0.032

The table shows the six moments we used to pin down parameters of the model using the alternative grouping for high and low skilled native labor. The first moment is the average migration rate from Mexico to the US between 1980 to 2011. The second moment is the proportion of Mexican immigrants in the US who choose to remain in the US in that year, which is averaged across years between 1980 to 2011. The third moment is the estimated coefficient on US unemployment rate attained by regressing the simulated likelihood of Mexicans migrating to the US against US unemployment rate. The fourth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated immigrant stock in the US against US unemployment rate and calendar year dummies. The fifth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated high-skilled natives' total employment against US unemployment rate and calendar year dummies. Lastly, the sixth moment is the estimated coefficient on US unemployment rate attained by regressing the simulated low-skilled natives' total employment against US unemployment rate and calendar year dummies. We set the elasticity of substitution between high and low skilled labor at 1.1.

Figure C.1: Counterfactual 2: firm's labor demand for low-skilled natives and TFP under the alternative grouping



We assume an elasticity of substitution between high and low skilled labor of 1.1.