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 natives, 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 reduces the volatility of native employment over the business cycle.

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1. Introduction

Data from recent years show that undocumented immigration rates dropped during the downturn in the US economy, most likely in response to weaker job opportunities.[1] However, little is known empirically on how undocumented immigrant wages change over the business cycle. Past work has found evidence of wage rigidity in the native population, implying that adjustments occur through the unemployment rate. This is typically explained by the permanence of labor market contracts. Due to the short-term nature of employment for undocumented immigrants, we might expect greater wage flexibility for this group than for natives. In this paper, we aim to understand how undocumented immigrant wages change over the business cycle.

Using data from the Mexican Migration Project (MMP), we study how undocumented immigrant wages respond to labor market conditions in the US. These data provide a unique opportunity to study this issue since the survey reports both legal status and wages. We expect greater flexibility than for natives due to the short-term nature of most jobs in this population. When wages decrease, fewer people will choose to move to the US.[2] Because of this, the observed equilibrium wage is capturing both lowered aggregate productivity and a smaller supply of migrant workers. We build an equilibrium model, where a firm hires immigrant and native workers, to study how this mechanism affects immigrant wages. The flexibility of immigrant wages could also affect native outcomes. By looking at this in a unified setting, we can use the model to understand how the variations in migrant wages affect native employment fluctuations over the business cycle.

Previous work has found greater flexibility in immigrant wages than in native wages, but did not differentiate between legal and undocumented immigrants. Bratsberg et al. (2006) and Orrenius and Zavodny (2010) find that immigrant wages are more cyclical than those of natives; however, they use CPS data which does not report legal status. Similarly, Chiswick et al. (1997) finds that the labor market status of immigrants is more sensitive to cyclical fluctuations than in the native born population. By using the MMP, we are able to isolate the effect to the undocumented immigrant population. Furthermore, these papers only look at overall changes, and do not separate out the effects of lowered productivity and reduced migration rates.

We use the MMP data to document that undocumented immigrant wages decrease as the US unemployment rate increases. In comparison to previous work, we control for selection by looking at the wage growth of immigrants over repeated trips to the US, and again find a negative correlation between wages and the unemployment rate. One com-

[1] For example, see `http://www.wsj.com/articles/SB125356996157829123`.

[2] Empirical work finds that immigration rates are affected by changes in US wages. See Hanson and Spilimbergo (1999), Lessem (2015), and Nakajima (2014).

ponent of this adjustment is that individuals move to lower paying occupations. However, when we look at each occupation separately, we see lower wages in most sectors during downturns. This shows that the overall wage decrease results from both lowered productivity as well as shifts to lower paying sectors. If this wage flexibility is due to undocumented status and short-term labor contracts, we should see a smaller effect in the legal immigrant population. We run the same analysis with legal immigrants in the MMP and Mexicans surveyed in the CPS, and see smaller effects.

The first part of the paper documents that undocumented immigrant wages adjust over the business cycle. However, as wages decrease, fewer people move to the US, decreasing the supply of immigrant workers. Motivated by these facts, we build a model where Mexicans migrate between the two countries, making decisions by comparing their wage options in the two countries. After seeing an aggregate productivity shock, a representative firm hires native and immigrant workers. Native wages are fixed, and immigrant wages are determined through firm demand in response to the productivity shock and immigrant labor supply. We calibrate the parameters of the model so as to replicate patterns in migration rates and native employment levels between 1980 and 2011.

We use our results to decompose the decrease in immigrant wages during a downturn into two factors: a negative aggregate productivity shock and the supply response of immigrants. In a counterfactual experiment, we shut down the migration channel and show a stronger relationship between aggregate shocks and immigrant wages. We also show that the flexible wage setting of immigrants mitigates native employment fluctuations over the business cycle.

The paper is organized as follows. Section 2 reviews the literature. Section 3 explains the data, and the empirical analysis is shown in Section 4. The equilibrium analysis is explained in Section 5. Section 6 concludes.

2. Literature review

This paper can be contrasted with the empirical findings that wages do not decrease as much as initially expected in a downturn. Hall (1980) finds that average wages fluctuate less than labor's marginal revenue product or the total volume of employment over the business cycle.[3] Other papers confirm this view, finding a weak relationship between wages and output or employment.[4] More recent work, such as Solon et al. (1994) find

[3]The parallel discussion is on nominal wage rigidity (See, for example, Fischer (1977)). Since we focus on the response of real wages to economic fluctuations, we discuss only real wage stickiness.

[4]See Abel and Bernanke (1992), Christiano and Eichenbaum (1992), Greenwald and Stiglitz (1988), Hall and Taylor (1991), and Prescott (1986).

evidence of wage cyclicality, claiming that the past work 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. We compare our results on immigrants to natives, testing if there are different effects in these populations.

There are numerous theoretical models to explain this trend.[5] The crucial assumption in these papers is that workers are in long-term contracts, which helps to explain this wage rigidity. These would imply that we should see greater flexibility in the undocumented immigrant population, where most jobs are short-term since contracts are not enforceable.

Some empirical studies support this view that newly-negotiated contracts will more easily adjust to the state of the economy. 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 undocumented immigrant wages would be affected by economic conditions, since wages are constantly negotiated due to the absence of long-run contracts.

3. Data

We use data from the MMP to estimate the relationship between 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.[6] Detailed information is collected about each person's first and last move to the US, including their wages and legal status, enabling us to study how wages change over the business cycle.[7] They also gather 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 immigrant flows over the business cycle. The panel dataset also reports each person's occupation at each point in time.

[5]Implicit contract theory (Baily (1974), Gordon (1974), Azariadis (1975)) explains this through a model where risk-neutral firms insure risk-averse workers. Beaudry and DiNardo (1991) find that a worker's current wage is more sensitive to the worst economic conditions since the start of a job than the contemporaneous unemployment rate. Their findings supports implicit contract theory. Search theoretic models can also be used to mimic the sluggish response of real wages in contrast to high fluctuations in unemployment (Pissarides (1985)).

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

[7]Unfortunately, there is only information on one job for each trip, and for a person who was in the US for multiple years, we do not know which job on the trip the data refer to.

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. We focus on men, since female labor force participation rates are low and their participation decisions – including migration decisions – are less affected 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. Since our goal is to contrast the reaction of wages under flexible wage settings and long-term contracts, we obtain better estimates by eliminating legal immigrants–including temporary visa holders–who are more likely to be working under similar conditions as natives. Third, we focus on 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, 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 2 years. Since the duration of stay correlates with their wage, eliminating workers who stayed longer potentially leads to some biased results.[8] Also, this restriction results in the loss of 39% of the data. In Section 4.3, we perform robustness checks using the full sample, to make sure that this data restriction is not affecting our findings.

The MMP data allows us to study how undocumented wages change over the business cycle. In particular, it is a very unique dataset because it provides information on undocumented immigrant wages, which is not possible to precisely pin down in other surveys.[9] 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

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

[9] 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.

selected randomly. Since there are booms and recessions repeatedly throughout the years we use, 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.

3.1 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 less 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.[10] 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. The third and fourth columns look at only household heads, for whom we have some extra information, most importantly monthly wages.

3.2 Measuring recessions

To study how 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 national unemployment rate to measure the state of the economy. Alternatively, we could have used state unemployment rates, but we chose to use national rates as our main specification

[10] 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.

because of the potential selection into low unemployment states. As a robustness check, we repeat our analysis using state level unemployment rates in Section 4.3.

4. 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. The MMP data provide wages for a person's first and last trip to the US, giving us two data points for people who have moved more than once. We use this to analyze how the an individual's wages change with the business cycle, which controls for selection effects. The decrease in immigrant wages could be due to lowered productivity or to shifts into lower paying occupations during a downturn. We find evidence that both mechanisms are important. Overall, we see that the wages of undocumented immigrants adjust over the business cycle. We argue that a potential cause of this flexibility is the short-term nature of labor contracts in this population. If this is true, we should see less flexibility in the wages of documented immigrants from Mexico. In the last part of this section, we repeat this exercise using legal immigrants, using both MMP and CPS data. We see a larger effect of recessions in the undocumented population.

4.1 Wage levels

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. In order to correctly evaluate the variations in wages over the business cycle, we need to control for any trends that are not caused by economic conditions or the distribution of demographic characteristics. The latter component is important because the MMP is a retrospective survey and hence, the distribution of demographic factors changes over time. For example, the average age in the sample increases monotonically from 1965 to 2011. To account for this, we use an HP filtered time trend. See Appendix A for details on how this was constructed.

We run the following wage regression using OLS:

$$\log(w_{it}) - \tau_t = \alpha_0 + \alpha_1 X_{it} + \alpha_2 u_t + \alpha_3 G_t + \epsilon_{it} \, , \tag{1}$$

where w_{it} is wages, τ_t is a HP filtered time trend and ε_{it} is an i.i.d. error. The vector X_{it} contains individual characteristics, such as age, education, and English skills. The English skills variable is only available for household heads. The term u_t is the national unemployment rate at time t. We also include controls for government policies G_t. This includes a dummy variable for years after 1986, when the Immigration Reform and Control Act (IRCA) was passed. This law legalized most undocumented immigrants currently living in the US and also led to increased border enforcement in future periods, and therefore could have caused changes in immigration decisions. In some specifications, we also include US border enforcement, to make sure we are capturing effects due to the state of the economy and not government policies.

Table 2 shows the results. Column (1) uses the full sample and finds that a one percentage point increase in the unemployment rate lowers hourly wages by 2%. 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 people whose migration was within 5 years of the survey to reduce recall bias, and we again see similar effects. Another concern is that changes in the state of the economy are correlated with US border enforcement efforts. Column (3) adds a control for US border enforcement, and this does not change the results. Column (4) shows the results using monthly instead of hourly wages, which are only reported for the household head's most recent trip to the US. This allows us to account for wage effects as well as unemployment effects, in that during a recession people may also find fewer hours of work. We can also control for English skills in this specification, since this variable is only available for household heads. In this case, the coefficient on the unemployment rate is still negative, but not statistically significant.[11] This sample is substantially different and smaller than the sample in column (1), since we only have this information for the household head's last trip to the US. To see whether the results are driven by sample composition or different effects for hourly versus monthly wages, in column (5) we keep the same sample as in column (4), but look at hourly wages. In this case, we see a negative and statistically significant effect of the unemployment rate on wages. This suggests that the effects on monthly and hourly wages are possibly different.

4.2 Wage growth

The previous section found that hourly wages decrease as the unemployment rate increases. However, as wages decrease, people become less likely to migrate, changing the composition of the migrant population. If an unobservable factor (ie skill) affects wage outcomes in the US, it will also affect migration decisions. As wages in the US decrease, the composition of the migrant population would change. In this setting, looking at just the average wages of those who chose to move will give biased results. In this section, we use data on repeat migrants to estimate the changes in wages during a recession while

[11] We find no statistically significant changes in the hours of work over the business cycle. We find similar results when we restrict the sample to those who worked for no less than 30 hours per week.

controlling for selection.

We use data from 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 selection will no longer bias our results.

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

$$\log(w_{it}) - \tau_t = \alpha_0 + \alpha_1 X_{it} + \alpha_2 u_t + \alpha_3 G_t + \mu_i + \epsilon_{it}\ , \tag{2}$$

where μ_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:

$$\Delta\log(w_i) - \Delta\tau_i = \alpha_0 + \alpha_1 \Delta X_i + \alpha_2 \Delta u_i + \alpha_3 \Delta G_i + \Delta\epsilon_i, \tag{3}$$

where $\Delta\log(w_i) = \log(w_{Fi}) - \log(w_{Li})$ is the difference in hourly wages between the first and last trip.[12] As in the analysis for the wage levels, we control for the state of the economy using the national unemployment rate u. Hence,

$$\Delta u_i = u_{Fi} - u_{Li} \tag{4}$$

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.

Table 3 shows the results. We can only look at hourly wages in this case because monthly wages are only reported for a household head's most recent trip to the US. In the first column, we see a negative and statistically significant coefficient on the unemployment rate, indicating that people earn lower wages in a recession. To interpret this, consider two workers with the 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 the worker B's wage on the last trip will be 1.9% lower than worker A's. In the second column, we add in some additional controls and do not see a substantial change in the results. In column (3), we attempt to address recall bias by using only people who had moved within 5 years of the survey. This substantially reduces the sample size because, for this analysis, we

[12] When we estimate this regression, we move $\Delta\tau_i$ to the right hand side of the equation. This is because there are 2 time trends in this regression, and if we leave it on the left hand side, we lose a lot of precision due to the inclusion of 2 estimated terms in the dependent variable. In this regression, $\Delta\tau_i$ becomes an independent variable. To keep our methodology consistent, we do this each time we run a wage growth regression in later parts of the paper.

need 2 observations for each person, and there are not many respondents with both their first and last US migration with 5 years of the survey. In this case the coefficient is still negative but we lose statistical significance. Column (4) adds in controls for US border enforcement, and this does not change the baseline results.

4.3 Robustness checks

In Sections 4.1 and 4.2, we find that increases in the unemployment rate lowered the wages for undocumented immigrants. However, our sample only included respondents who stayed in the US for less than 15 months. This is a strong restriction that results in a loss of almost 40% of the data. As a 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 may 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 Sections 4.1 and 4.2, and the results are in Appendix B.1. Table B.1.1 looks at the wage level regressions. The sign of the coefficient on the unemployment rate stays the same, although it decreases in magnitude. We also lose statistical significance when we control for US border enforcement. When we restrict the sample to household heads, we actually see a positive effect of the unemployment rate on wages. Table B.1.2 shows the wage growth regression. For the main specification, we see that an increase in the unemployment rate lowers wages. We do not see a statistically significant effect when we use the sample that moved within 5 years, or when we control for border enforcement.

The baseline results use the national unemployment rate. Appendix B.2 uses state level unemployment rates instead of the national unemployment rate.[13] Table B.2.1 shows the wage level regressions, and the results are very similar to the baseline specification. The only difference is that we see that increases in the unemployment rate lower monthly wages, which is an effect that was not statistically significant when we used the national unemployment rate. Table B.2.2 shows the results for wage growth, and we see an negative effect of the unemployment rate on wages in all specifications.

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

4.4 Occupation changes

The results in the previous sections show that as the unemployment rate increases, immigrants earn lower wages. We do not control for occupations, suspecting that occupations could be a choice variable that vary with the business cycle. In this section, we study what happens to occupations over the business cycle.

We estimate the probability that a person works in a given sector (agriculture, skilled manufacturing, unskilled manufacturing, transportation, services, and sales) using probit regressions. We control for demographic factors, a time trend, primary occupation in Mexico, and occupation held in the previous year. The MMP reports a worker's occupation for each year of US stay, so for this analysis, we also include immigrants who stayed for more than 15 months.[14] The results, reported as marginal effects in Table 4, demonstrate that people are more likely to work in agriculture when the unemployment rate is high. This suggests that people shift to different occupations over the business cycle. An alternative specification uses a multinomial logit regression, and these results are in Appendix B.3 in Table B.3.1. These results are very similar.

Table 5 repeats the OLS wage regressions in Section 4.1 using controls for occupations. The first column uses all men, and the second column uses just male household heads (allowing us to control for English skills). The third column restricts to wages within the past 5 years to limit recall bias, and column (4) uses all men and adds controls for border enforcement. In all specifications, we see that both skilled and unskilled manufacturing jobs pay more than jobs in agriculture. Since more people work in agriculture in downturns and agriculture pays lower wages, these occupational changes lead to lower average wages when the unemployment rate increases. This is one component of reduced wages in a recession. In addition, we see that even with these occupation controls, an increase in the unemployment rate lowers wages.

The previous wage regressions allowed for the effects of economic conditions to be constant across sectors. Table 6 runs the regressions separately for agriculture, non-agriculture, skilled manufacturing, unskilled manufacturing, and services, which are the occupations that the most migrants work in. In all of these sectors, increases in the unemployment rate lower wages, although the effect is smallest and insignificant in services and agriculture. One possible reason for small magnitude in agriculture is changes in composition of immigrants across sectors. If more productive workers usually work in skilled manufacturing but shift to agriculture during recessions, then the average produc-

[14] In the wage analysis, we had to drop these people, since wages are only reported for the first and last trip, so we do not know the year of each wage for people with long durations. In the occupation analysis, we can include these people since we have occupations in each year. We find a similar result when we restrict to those who stayed in the US for less than 15 months.

tivity of workers in agriculture increases during recessions. We do not find a statistically significant effect in other sectors that are not reported.[15]

4.5 Comparison: legal immigrants

In the previous section, we saw that increases in the unemployment rate lowered wages for undocumented immigrants in the US. These workers typically only obtain short-term jobs, meaning they constantly are renegotiating wages which can then easily respond to the state of the economy. This implies we should see smaller effects for documented immigrants. We test this using data from the CPS and the MMP. The CPS does not record legal status, but likely overweights legal Mexican workers relative to undocumented immigrants. In addition, we also follow the methodology used in Borjas (2016) to separate likely legal from undocumented immigrants. The MMP asks survey questions on legal status so we can isolate the sample of documented workers.

We first analyze how wages respond to the unemployment rate using data on Mexican born individuals (both with and without US citizenship) and native US workers in the CPS. We study how changes in the unemployment rate affect the wages of these workers. The sample contains men aged 25-55 from 1994-2012.[16] Table 7 shows the wage regressions for Mexican born individuals (both with and without US citizenship) and native workers. Column (1) shows that for Mexican born non-US citizens, a 1% increase in the unemployment rate reduces weekly earnings by 0.5%. This is much smaller than the effect that we saw in the MMP sample. In addition, we do not see a statistically significant effect of the unemployment rate on earnings for US citizens. The MMP sample has lower levels of education than Mexicans in the CPS, so one concern could be that these results are being driven by sample composition and not legal status. This is particularly relevant because past work such as Hoynes et al. (2012) find that recessions hit the lower skilled hardest. To account for this, in column (2) we restrict our sample to Mexicans with no more than a high school education, and the results do not change. Columns (3) and (4) look at native US workers. For the full sample of native whites and native Hispanics, we find almost no impact on weekly earnings during recessions. We only see a statistically significant effect of the unemployment rate on wages when we restrict the sample to white non-Hispanics with just a high school education. This effect is smaller than in the MMP, supporting our theory.

Since the CPS MORG data provides wage information for two consecutive years for each individual, we next test how a person's wage changes with the unemployment rate.

[15]The sample sizes get much smaller when we look at sectors that fewer immigrants work in.

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

As before, this controls for individual fixed effects. We regress $w_2 - w_1$ against $u_2 - u_1$, where w_t is the reported wage and u_t is the unemployment rate in the t-th interview. Table 8 shows the regression results for Mexican and native born workers. A 1% increase in a subsequent year's unemployment rate reduces Mexicans weekly earnings by 1.8%, and there is no effect in the native population. This clearly suggests immigrant wages are more flexible than native wages. These effects are again smaller than what we found using the sample of undocumented workers in the MMP.

In Tables 7 and 8, we did not know the legal status of each respondent, since that is not included in the CPS. Therefore those results are some mix of the 2 populations. Borjas (2016) 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: they were born before 1980, are a citizen, receive government benefits[17], are a veteran or are in the military, work in the government sector, reside in public housing or receive rental subsidies (or their spouse does), were born in Cuba, work in an occupation that requires licensing, or are married to a legal immigrant or citizen. We use this methodology to separate legal and undocumented immigrants in the ASEC data.[18] We then estimate the effect of the unemployment rate on wage levels, and the results are in Table 9. Column (1) shows the whole sample of Mexican born individuals in the ASEC, column (2) shows just those who we identify as undocumented immigrants, and column (3) shows those who we identify as legal immigrants. In each of these specifications, we do not see a statistically significant effect of the unemployment rate on wages. However, when we look at wage growth in the ASEC, we see that an increase in the unemployment rate lowers wages. Column (1) of Table 10 shows this effect for the whole sample. In column (2), which only looks at undocumented immigrants, the magnitude of the coefficient increases, whereas in column (3), which only includes legal immigrants, we see no statistically significant effect of the unemployment rate on wages. This supports our hypothesis that we are seeing a wage effect in a segment of the population more likely to work under short-term contracts.

Finally, we run another comparison using data on legal immigrants from the MMP. Table 11 shows the results of the wage regression using MMP data and allowing for differential effects for legal and undocumented immigrants. We find that the wages of undocumented immigrants drop during recessions while we see almost no impact on those of legals. These results support our findings using the CPS data when we looked at documented and undocumented immigrants separately.

[17] Specifically, if they receive Social Security benefits, SSI, Medicaid, Medicare, or Military insurance

[18] 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 was collected from the O*NET database.

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 the next section, we first show that migration rates respond to these lower wages in downturns, hence lowering the supply of migrants. This could potentially raise immigrant wages. We then analyze an equilibrium model to account for this mechanism.

5. Equilibrium analysis

The previous sections suggest that undocumented Mexican workers experience larger wage drops during recessions than natives. Undocumented immigrants are more likely to work under short-term contracts than native workers, and in this setting wages will be more flexible since they must be constantly renegotiated. Since migration patterns change over the business cycle, the supply of immigrant labor in the US fluctuates. The goal of this section is to understand how these specific features impact immigrant wages and native employment fluctuations over the business cycle.

5.1 Migration response to recessions

Before we present our model, we show how migration rates change over the business cycle. 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 the US unemployment rate, the US real GDP growth rate, the Mexican unemployment rate, and a HP filtered time trend.[19] We also control for age, education, marital status, and whether or not a person is from a high migration state in Mexico.[20]

Table 12 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 (Table 13). Although the estimated coefficients are not statistically significant, we find a positive coefficient on the US unemployment rate, indicating that more workers return to Mexico during when the US is in recessions.

[19] US GDP is in billions of chained 2005 dollars taken from Bureau of Economic Analysis. The Mexican unemployment rates are taken from the MMP for 1973-2010 and from the OECD for 2011.

[20] 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.

5.2 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 native workers and immigrant workers to produce output.[21] In the model, Mexicans decide which country to reside in based on relative wages and the cost of crossing the border.

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

5.2.1 Firm side

A firm's output in period t depends on aggregate productivity z_t and the quantity of native and immigrant workers, N_t and I_t, respectively. We write the firm's output as $z_t F(N_t, I_t)$. Given wages w_{Nt} and w_{It}, the firm solves the following profit maximization problem:

$$\max_{N_t, I_t} \quad z_t F(N_t, I_t) - w_{Nt} N_t - w_{It} I_t \, , \tag{5}$$

where

$$F(N_t, I_t) = \left([\theta N_t^\gamma + (1-\theta) I_t^\gamma]^{1/\gamma} \right)^\psi . \tag{6}$$

Equation (6) uses 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 a CES aggregation of native and immigrant labor. Because the model is static, the firm only considers current period profits when making hiring decisions.

The first order conditions are

$$w_{Nt} = z_t \psi [\theta N_t^\gamma + (1-\theta) I_t^\gamma]^{\frac{\psi}{\gamma} - 1} \theta N_t^{\gamma - 1} \tag{7}$$

$$w_{It} = z_t \psi [\theta N_t^\gamma + (1-\theta) I_t^\gamma]^{\frac{\psi}{\gamma} - 1} (1-\theta) I_t^{\gamma - 1}, \tag{8}$$

[21] In an alternative setup, we could allow firm to hire skilled native labor and to purchase an intermediate input, which is produced by unskilled native and 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 the legal and native workers do the more complicated tasks, as in the framework in Djajic (1997). This setup is more realistic because it allows for possibility that the US can produce without undocumented immigrants labor; however, we use a simpler model here which demonstrates the key mechanisms.

which implies

$$N_t = \left(\frac{\theta}{1-\theta} \frac{w_{It}}{w_{Nt}} \right)^{\frac{1}{1-\gamma}} I_t. \tag{9}$$

Because immigrant wages are flexible, there is no unemployment for immigrants. Let $I_t^D(w_{It}, w_{Nt})$ denote the firm's demand for 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 $\bar{N}$ natives are always hired at a different firm. This reflects the reality that not all natives work at firms that hire undocumented immigrants.[22]

5.2.2 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 3 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:

$$w_t(\hat{\ell}) = \begin{cases} w_{Mt} & \text{if } \hat{\ell} = MEX \\ w_{It} & \text{if } \hat{\ell} = US. \end{cases} \tag{10}$$

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

$$c(\ell_t, \hat{\ell}) = \begin{cases} c_1 & \text{if } \ell_t = MEX \text{ and } \hat{\ell} = US \\ c_2 & \text{if } \ell_t = US \text{ and } \hat{\ell} = MEX \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

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

[22] We impose this assumption to make the model more flexible. Since I and N move in one-to-one (in log-terms) in the CES production function, the volatility of native employment must equal that of the immigrant labor in the model. However, in the data, the volatility of native employment is lower than that of the immigrants over the business cycle. Therefore, in order to accommodate these differences, we assume that there are some portion of natives who are always hired at a different firm and calibrate this proportion.

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

$$V_t(\ell_t) = \max_{\hat{\ell} \in \{US, MEX\}} \left\{ \alpha(w_t(\hat{\ell}) - c(\ell_t, \hat{\ell})) + \eta_{\hat{\ell}} \right\}. \tag{12}$$

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

$$p_t(MEX) = \frac{\exp(\alpha(w_{It} - c_1))}{\exp(\alpha(w_{It} - c_1)) + \exp(\alpha w_{Mt})} \tag{13}$$

$$p_t(US) = \frac{\exp(\alpha w_{It})}{\exp(\alpha w_{It}) + \exp(\alpha(w_{Mt} - c_2))}. \tag{14}$$

Equation (13) gives the probability that someone who is in Mexico moves to the US, and equation (14) 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 immigrants in the US after workers make their migration decisions is

$$I_{US,t}^S(w_{It}) = p_t(MEX) I_{1t}^0 + p_t(US) I_{2t}^0. \tag{15}$$

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

$$I_t^D(w_{It}, w_{Nt}) = I_{US,t}^S(w_{It}) \,, \tag{16}$$

where $I_t^D(w_{It}, w_{Nt})$ comes from the firm's first order conditions in equations (7) and (8).

To summarize, the variables determined in equilibrium are the immigrant wage w_{It}, immigrant labor in the US $I_{US,t}^S(w_{It})$, and native employment N_t. These are solved using the firm's first order conditions and the labor market clearing condition.

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, immigrants may be less productive compared to the natives due to lower English skills. Moreover, 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.[23]

[23] See Cadena and Kovak (2015).

However, it is impossible to separately identify lower productivity and an additional hiring cost in the MMP data. Therefore, instead of considering an additional hiring cost for each immigrant worker, we assume that all costs associated with hiring an immigrant are captured through the substitutability of immigrant and natives in the production function.

5.3 Analytical exercises

In this section, we analytically show how the flexible wage setting of immigrants affects the employment fluctuations of natives over the business cycle. We drop the time subscripts in this section for ease of exposition.

We first show that the equilibrium wage exists and is unique.

Remark 1. If c_2 or I_2^0 is sufficiently small, an equilibrium with $w_I > 0$ uniquely exists.

Proof See Appendix C.

Note that in equation (8), a higher z_t shifts the demand curve upward, which increases the equilibrium wage of immigrant (i.e. $\frac{\partial w_{It}^*}{\partial z_t} > 0$). Thus, this simple model is able to capture a possible economic mechanism that allows for changes in immigrant wages over the business cycle. In the model, the equilibrium wage is low when aggregate productivity is low, which is consistent with the observed phenomenon.

The next remark shows that the flexible wage setting of immigrants mitigates (respectively accelerates) native labor demand fluctuations over the business cycle if native and immigrant labor are complements (respectively substitutes).

Remark 2. If γ is a large negative number, $\frac{\partial N}{\partial z} < \frac{\partial N}{\partial z}|_{w_I=\bar{w}_I}$ where $\bar{w}_I$ is a constant. If γ is close to 1, $\frac{\partial N}{\partial z} > \frac{\partial N}{\partial z}|_{w_I=\bar{w}_I}$.

Proof See Appendix C.

This remark shows that the effect of the flexibility of immigrant wages on native outcomes is ambiguous. In the empirical section, we will calibrate the model parameters, and then be able to understand how this immigrant wage flexibility impacts natives.

5.4 Calibration procedure

This section explains how the time-invariant model parameters $\Theta \equiv (\alpha, \gamma, c_1, c_2, \bar{N})$, endogenous variables (natives labor N_t, immigrant stock in the US I_t), and TFP z_t are solved for.[24] We assume $\psi = 0.67$, which is the labor share of output used in the macroeconomics literature. We assume $\theta = 0.5$. We calibrate the model using a procedure similar to indirect inference.

We take the following values from the data: wages in Mexico w_{Mt}, native wages w_{Nt}, immigrant wages w_{It}, and the stock of Mexicans in the US and in Mexico at the start of the period, I^0_{1t} and I^0_{2t}, 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 (13) and (14). Using equation (15), we can then solve for the supply of immigrants in the US in a period (again conditional on our parameter guess Θ). We then solve for N_t using the firm's first order condition in equation (9), assuming that the supply of immigrants equals the demand for immigrant workers under the given wages (w_{Nt}, w_{It}). Once we know N_t and I_t, we can calculate TFP z_t using equation (7). This allows us to get year-by-year model predictions for migration rates, return migration rates, native employment, and stock of immigrants in the US $(p_t(MEX), p_t(US), N_t, I_t)$. We can repeat this procedure for any set of parameters Θ.

We find the values for $(\alpha, \gamma, c_1, c_2, \bar{N})$ so that the model predictions replicate the migration levels and key data patterns over the business cycle. The former is done by matching 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 immigrants drop during recessions.[25] We capture the elasticities using the coefficient on the unemployment rate in the following regressions:

$$\log(p_t(MEX)) = \kappa^p_0 + \kappa^p_1 u_t + \varepsilon^p_t \tag{17}$$

$$\log(I_t) = \kappa^I_0 + \kappa^I_1 u_t + \kappa^I_2[\text{calendar year dummies}] + \varepsilon^I_t \tag{18}$$

$$\log(N_t + \bar{N}) = \kappa^N_0 + \kappa^N_1 u_t + \kappa^N_2[\text{calendar year dummies}] + \varepsilon^N_t\ , \tag{19}$$

where $\varepsilon^p_t, \varepsilon^I_t$, and ε^N_t are i.i.d. errors. We use the above regressions to compute the model moments.[26]

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

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

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

[26] Since the model does not contain any demographic features that affect the migration rate or the number of 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 immigrants over the business cycle.

behavior and the distributions of such factors change over time in the MMP. Table 14 shows the regression results for the data moments.

5.5 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 where we have lifetime migration histories, which is the data necessary for this exercise. The supply of immigrant workers also comes from the MMP, weighted so that the sample matches the size of the Mexican population in each year.[27],[28]

The average wages of immigrants in the US come from the MMP. For native hourly wages, we use data from the CPS for men aged 22-25. 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.[29] Because the Census data is only available every 10 years, we smooth out the year to year fluctuations using GDP growth in Mexico in each year.[30] 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.[31] We also show hourly wages of undocumented Mexicans from the MMP for comparison. Native wages are much higher than the wages for 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.

The last data source we need is the native employment level, which we take as the number of nonsupervisory employees reported in the Current Employment Statistics from the Bureau of Labor Statistics.

[27]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.

[28]Rigorously speaking, since the MMP surveys communities where migration is prevalent, this gives an over-estimate of the number of undocumented workers in the US. However, the MMP's sampling method also fails to survey migrants where the entire family moved to the US, so the direction of the bias is unclear.

[29]Downloaded from IPUMS.

[30]Data from the World Bank.

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

5.6 Results

Table 15 shows the parameter values. We find native and immigrant workers to be complements, which contradicts with Piyapromdee (2014), which finds that they are substitutes. One possibility as to why we obtain a different result from Piyapromdee (2014) is that we use time series data where both native and immigrant stocks fluctuate in the same direction across business cycles, whereas Piyapromdee (2014) uses cross-sectional data. To see why this suggests that there is some complementarity between natives and undocumented immigrants, suppose they are perfect substitutes. In this case, since native wages do not drop during recessions (because their wages are rigid), wages of natives are relatively higher than immigrants during recessions. Then the firm would hire fewer natives and more immigrants during recessions. In this case, the stock of immigrants in the US would be counter-cyclical and the demand for native and immigrant workers would fluctuate in opposite directions across the business cycle, which contradicts with the data. Another possible explanation for our different result is we focus only on undocumented immigrants, as opposed to low-skilled immigrants in general, as in Piyapromdee (2014). Undocumented immigrants may not be competing with natives for similar jobs, and instead could be helping overall production by taking unattractive jobs that natives will not take.

The results 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 as well as a moving cost that make people likely to stay in their home location.[32] In this context, because the model only has 2 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 16 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, immigrant stock and native employment with respect to the unemployment rate. We see that the model moments match the data moments very closely.

5.7 Counterfactual 1: constant immigrant stock

The reduced form evidence shows that migrant wages decrease during downturns. However, we also know that as wages decrease, fewer people will move, driving up the equi-

[32] See Kennan and Walker (2011) and Lessem (2015).

librium 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 immigrant stock constant at the predicted value under the calendar year trend, and calculate the resulting immigrant wages that make the firm optimally hire that level of immigrants. In doing this exercise, we take native wages and employment level to be equal to the baseline values, and solve for the counterfactual immigrant wage w_I using equation (9).

When immigrant stocks do not adjust to economic fluctuations, there will be a steeper relationship between the state of the economy and immigrant wages. Figure 3 shows the relationship between TFP and hourly wages in the baseline and the counterfactual. To see the magnitude, we regress immigrant wages against TFP:

$$w_{It} \quad = \quad \kappa_0^{wI} + \kappa_1^{wI} \log(z_t) + \epsilon_t^{w_I} \, , \tag{20}$$

where $\epsilon_t^{w_I}$ is an i.i.d. error. We run this regression in the baseline and counterfactual case to compare the results. The coefficient on z_t for immigrant wages is 0.30 in the baseline and 1.70 in the counterfactual (Table 17).[33] Using the estimated relationship between TFP and unemployment (Table 18), we find that when unemployment goes up by 1 percentage point, immigrant wages drop by 1.3% in the baseline and 7.7% in the counterfactual.[34] This shows that the lowered supply of immigrants in a recession helps to mitigate the negative wage impact of the productivity shock.

5.8 Counterfactual 2: constant immigrants' wages

In the next counterfactual, we study how the flexible wage setting of immigrants affects the firm's demand for native and immigrant labor. To do this, we set native wages as in the data and fix immigrant wages at the average wage. We calculate the firm's demand for native workers using equation (24) and the firm's demand for immigrant workers using equation (9). Figure 4 illustrates the relationship between both types of labor and TFP. The figure shows that the relationship, for both natives and immigrants, becomes steeper when immigrant wages are fixed. This implies that if immigrant wages were rigid, the firm would demand more native and immigrant workers during booms and fewer native and immigrant workers during recessions. In order to calculate the magnitude of these differences, we regress the demand for both types of labor against TFP and calendar year

[33] We find similar results replacing TFP with unemployment rate, but the coefficients are not statistically different at the 5 % level of significance.

[34] In the baseline, a unit increase in unemployment rate corresponds to 4.6% decrease in TFP (Table 18), and 1% decrease in TFP corresponds to 29.4% decrease in the wages. The counterfactual numbers are calculated analogously.

dummy variables:

$$\log(N_t) = \kappa_0^N + \kappa_1^N \log(z_t) + \kappa_2^N[\text{calendar year dummies}] + \varepsilon_t^N \quad (21)$$
$$\log(I_t) = \kappa_0^I + \kappa_1^I \log(z_t) + \kappa_2^I[\text{calendar year dummies}] + \varepsilon_t^I, \quad (22)$$

where ε_t^N 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 19 shows the results. We find that the coefficient on z_t is larger when immigrant wages are fixed (1.99 in the baseline, 2.79 in the counterfactual). Using the estimated relationship between TFP and unemployment (Table 18), we find that when unemployment rate goes up by 1 percentage point, the firm's demand for native workers drops by 9.1% in the baseline and by 12.7% in the counterfactual.[35] Similarly, we find that the coefficient on z_t for immigrant labor becomes larger when immigrant wages are fixed (1.87 in the baseline and 2.81 in the counterfactual.) Again using the estimated relationship between TFP and unemployment (Table 18), we find that when the unemployment rate goes up by 1 percentage point, the firm's demand for native workers drops by 8.5% in the baseline and by 12.8% in the counterfactual. This indicates that there would be higher employment fluctuations for both natives and immigrants in response to aggregate productivity shocks if immigrant wages were fixed.[36]

Intuitively, since immigrant wages are fixed in the counterfactual, the firm will hire more immigrants during the good times (i.e. high aggregate productivity shock) and fewer during the bad times (i.e. low aggregate productivity shock). Since immigrant labor and native labor are complements, the demand for native labor moves in the same direction as immigrant labor. This creates a steeper relationship between productivity shocks and native labor demand when immigrant wages are rigid. In contrast, when immigrant wages are flexible, the equilibrium wage of immigrants decreases during the bad times so that the demand for immigrant labor does not fall as much. This experiment implies that the flexible wage setting of immigrants mitigates the large impact on native employment over the business cycle.

6. Conclusion

Undocumented immigration from Mexico decreases during downturns. 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

[35] These numbers are not unrealistically high given that we focus on a special firm that hires both native and immigrant workers.

[36] We find similar results replacing TFP with unemployment rate, but the coefficients are not statistically different at the 5 % level of significance.

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 native workers. Consistent with this theory, reduced form evidence shows that immigrant wages decrease with the US unemployment rate. We find evidence that part of this reduction is due to immigrants shifting to lower paying sectors, but still see that the increases in the unemployment rate decrease wages when we control for occupation. 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 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 migrant flows over the business cycle. Counterfactuals show that, were the immigrant stock to be held constant during recessions, we would see larger drops in immigrant wages. We also show that the flexible wage setting of immigrants mitigates native employment fluctuations over the business cycle.

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Tables and figures

Table 1: Summary statistics

	(1)	(2)	(3)	(4)
Household head only or all members	All	All	Head only	Head only
Duration of a trip in the US (months)	Any	less than 15	Any	less than 15
First and/or last US trip	Both	Both	Last only	Last only
Education distribution				
-6 or fewer years	63%	70%	68%	75%
-7 to 11 years	27%	22%	23%	17%
-12 years	6%	4%	5%	4%
-13 or more years	3%	3%	4%	3%
Mean age at first trip	25.85	27.04	30.67	31.82
Number of trips to US among migrants	2.59	3.21	2.15	2.46
Percentage of migrants that take only one trip	44%	31%	52%	46%
Mean duration of a single US trip (months)	39.57	7.44	32.94	7.24
Mean hourly wage (2012 US$)	10.81	10.06	11.10	9.94
Percent working in each occupation				
-Agriculture	27%	37%	26%	34%
-Skilled manufacturing	21%	15%	24%	18%
-Unskilled manufacturing	22%	21%	22%	22%
-Services	18%	16%	20%	17%
Number of person	6,938	3,055	1,148	676

Notes: 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: Wage regressions

	Dependent variable = Wages				
	(1)	(2)	(3)	(4)	(5)
	Hourly	Hourly	Hourly	Monthly	Hourly
US unemployment	-0.020***	-0.025***	-0.018**	-0.012	-0.020**
	(0.005)	(0.008)	(0.007)	(0.014)	(0.008)
Age	0.009***	0.016***	0.008**	0.000	0.010
	(0.003)	(0.006)	(0.004)	(0.010)	(0.006)
Age squared	-0.009**	-0.024***	-0.009*	0.001	-0.011
	(0.004)	(0.008)	(0.005)	(0.011)	(0.007)
7-12 years education	0.053***	0.016	0.052***	0.051	0.044*
	(0.015)	(0.019)	(0.015)	(0.039)	(0.024)
13+ years education	0.120***	0.093**	0.098***	0.156*	0.091*
	(0.033)	(0.042)	(0.034)	(0.085)	(0.052)
IRCA dummy variable	-0.052***	-0.087***	-0.042**	-0.075*	-0.114***
	(0.015)	(0.030)	(0.018)	(0.039)	(0.024)
No English				-0.168***	-0.135***
				(0.032)	(0.020)
Border enforcement			0.000		
			(0.000)		
Constant	2.160***	2.149***	2.155***	7.612***	2.273***
	(0.077)	(0.122)	(0.090)	(0.226)	(0.139)
Observations	3258	1454	2780	1333	1366
Adjusted R^2	0.015	0.014	0.010	0.021	0.044

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions are using data from the MMP. We drop the top and bottom 2% of observations. Wages are net of HP filtered time trend. For education variables, the excluded group is people with fewer than seven years of education. "IRCA dummy variable" equals 1 for years after 1986 and 0 otherwise. The variable "No English" equals 1 if they "neither speak nor understand" English and 0 otherwise. The variable "Border enforcement" is the sample average of hours (in ten thousands) spent patrolling the border during each trip. Columns (1) and (3) use all men. Columns (4) and (5) restrict to the last trip for male household heads. Column (2) uses all male wages within five years of each survey.

Table 3: Wage growth

	Dependent variable = change in hourly wages			
	(1)	(2)	(3)	(4)
Change in unemployment rate	-0.019**	-0.016*	-0.029	-0.022*
	(0.009)	(0.009)	(0.018)	(0.012)
Change in age	0.003	-0.004	0.049	-0.020
	(0.009)	(0.009)	(0.067)	(0.013)
Change in age squared	-0.097**	-0.071	-0.454	-0.048
	(0.043)	(0.044)	(1.076)	(0.062)
7-12 years education	0.025	0.018	0.054	0.010
	(0.034)	(0.034)	(0.042)	(0.034)
13+ years education	0.028	0.014	0.062	0.065
	(0.090)	(0.090)	(0.091)	(0.090)
IRCA	0.017	-0.046	0.075	-0.010
	(0.037)	(0.053)	(0.074)	(0.056)
Change in border enforcement				0.007**
				(0.003)
Year of first US migration		0.006*	-0.002	0.004
		(0.004)	(0.006)	(0.005)
Conducted more than two trips		0.082***	0.021	0.059*
		(0.031)	(0.049)	(0.033)
Change in HP-filtered year trend	0.480**	0.375	0.037	-0.770
	(0.243)	(0.253)	(0.858)	(0.706)
Constant	0.046	-12.152*	3.396	-8.641
	(0.038)	(7.089)	(11.958)	(10.129)
Observations	584	584	150	434
Adjusted R^2	0.129	0.139	-0.004	0.045

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use data from the MMP. We drop the top and bottom 2% of wage observations. For education variables, the excluded group is people with less than 7 years of education. IRCA equals 1 for years past 1986 and 0 otherwise. The variable "Border enforcement" is the sample average of hours (in ten thousands) spent patrolling the border during each trip. Columns (1), (2) and (4) use all men. Column (3) uses all male wages within five years of each survey.

Table 4: Probit 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	0.007***	-0.002	-0.003	0.000	-0.005	-0.001
	(0.003)	(0.005)	(0.004)	(0.000)	(0.004)	(0.001)
Age	-0.005*	-0.001	0.005	0.000	-0.003	0.001
	(0.003)	(0.005)	(0.004)	(0.000)	(0.003)	(0.001)
7-12 years education	-0.029***	0.010	0.014	0.001	-0.001	0.000
	(0.008)	(0.013)	(0.010)	(0.001)	(0.009)	(0.002)
13+ years education	-0.072**	0.009	0.038	-0.003	0.024	-0.002
	(0.029)	(0.033)	(0.024)	(0.003)	(0.019)	(0.004)
Dummy for Primary	0.071***	0.167***	0.149***	0.006***	0.128***	0.016***
	(0.007)	(0.013)	(0.011)	(0.001)	(0.010)	(0.002)
Dummy for Previous	0.418***	0.855***	0.652***	0.022***	0.545***	0.072***
	(0.016)	(0.020)	(0.016)	(0.005)	(0.015)	(0.008)
IRCA	0.030**	0.014	-0.032***	-0.001	0.005	-0.005
	(0.014)	(0.016)	(0.011)	(0.001)	(0.015)	(0.004)
HP-filtered Year Trend	0.359***	0.323***	0.471***	0.082	0.064	0.210**
	(0.096)	(0.083)	(0.099)	(0.073)	(0.242)	(0.102)
Observations	12101	12101	12101	12101	12101	12101

Table reports marginal effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample is all men in the MMP younger than 55, covering years 1970-2011, and only includes those who stayed in the US for no more than 25 years. For education variables, the excluded group is those with less than 7 years of education. The variable "Dummy for Primary" equals 1 if the primary occupation is the same as the dependent variable and 0 otherwise. "Dummy for Previous" equals 1 if the respondent was in the US last year and his occupation was the same as the dependent variable and 0 otherwise. IRCA equals 1 for years past 1986 and 0 otherwise. Control for age-square included but not reported.

Table 5: Wage regressions with occupation controls

	Dependent variable = hourly wages			
	(1)	(2)	(3)	(4)
US unemployment	-0.018***	-0.017***	-0.021**	-0.017**
	(0.005)	(0.006)	(0.009)	(0.007)
Age	0.007**	0.010**	0.014**	0.007*
	(0.003)	(0.005)	(0.006)	(0.004)
7-12 years education	0.040***	0.030	0.012	0.041***
	(0.015)	(0.020)	(0.019)	(0.015)
13+ years education	0.104***	0.067	0.094**	0.084**
	(0.034)	(0.042)	(0.043)	(0.034)
Skilled manufacturing	0.116***	0.094***	0.082***	0.108***
	(0.019)	(0.023)	(0.025)	(0.020)
Unskilled manufacturing	0.104***	0.114***	0.072***	0.094***
	(0.016)	(0.020)	(0.023)	(0.017)
Transportation	0.190**	0.196**	0.123	0.149*
	(0.082)	(0.100)	(0.101)	(0.082)
Services	-0.028	-0.033	-0.062**	-0.045**
	(0.018)	(0.022)	(0.025)	(0.019)
Sales	-0.020	-0.029	-0.058	-0.035
	(0.039)	(0.049)	(0.048)	(0.039)
IRCA	-0.061***	-0.066***	-0.090***	-0.042**
	(0.015)	(0.018)	(0.030)	(0.018)
No English		-0.100***		
		(0.016)		
Border enforcement				-0.000
				(0.000)
Observations	3233	2263	1442	2758
Adjusted R^2	0.040	0.053	0.040	0.038

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wages are net of HP filtered time trend. These regressions use data from the MMP. We drop the top and bottom 2% of wage observations. For education variables, the excluded group is people with fewer than seven years of education. For occupations, the excluded group is agriculture. IRCA equals 1 for years past 1986 and 0 otherwise. The variable "No English" equals 1 if they "neither speak nor understand" English and 0 otherwise. The variable "Border enforcement" is sample average of hours (in ten thousands) spent patrolling the border. Column (1) and (4) use all men. Column (2) restricts to male household heads. Column (3) uses all male wages within five years of the survey. Controls for age-squared and constant term included but not reported.

Table 6: Wage regressions: split by occupation

	Dependent variable = hourly wages				
	(1) Agriculture	(2) Non-Agriculture	(3) Skilled Manufacturing	(4) Unskilled Manufacturing	(5) Services
US unemployment	-0.005	-0.031***	-0.038***	-0.035***	-0.018
	(0.007)	(0.007)	(0.014)	(0.011)	(0.011)
Age	0.008	0.008*	0.007	0.009	0.006
	(0.005)	(0.004)	(0.010)	(0.007)	(0.007)
Age squared	-0.009	-0.008	-0.012	-0.006	-0.005
	(0.006)	(0.005)	(0.012)	(0.009)	(0.008)
7-12 years education	0.021	0.054***	0.031	0.072**	0.030
	(0.026)	(0.018)	(0.036)	(0.030)	(0.032)
13+ years education	0.129	0.102***	0.060	0.104*	0.127**
	(0.100)	(0.037)	(0.080)	(0.059)	(0.059)
IRCA	-0.042*	-0.083***	-0.097**	-0.056*	-0.074**
	(0.023)	(0.020)	(0.044)	(0.030)	(0.035)
Constant	2.058***	2.293***	2.495***	2.279***	2.129***
	(0.119)	(0.101)	(0.219)	(0.165)	(0.162)
Observations	1280	1953	502	764	583
Adjusted R^2	0.003	0.021	0.013	0.028	0.016

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use data from the MMP. Wages are net of HP filtered time trend. We eliminate the top and bottom 2% of wage observations. For education variables, the excluded group is those with less than 7 years of education. IRCA equals 1 for years past 1986 and 0 otherwise. Non-agriculture refers to any occupation in skilled manufacturing, unskilled manufacturing, services, transportation, and sales.

Table 7: CPS earnings regressions

	Dependent variable = weekly earnings			
	(1)	(2)	(3)	(4)
	Mexican	Mexican High school	Natives	Native High school
Unemployment rate × US citizen	0.001	-0.006		
	(0.005)	(0.006)		
Unemployment rate × non-citizen	-0.005**	-0.005*		
	(0.002)	(0.002)		
Unemployment rate × Hispanic			-0.001	0.006
			(0.002)	(0.006)
Unemployment rate × white non-Hispanic			-0.001	-0.013***
			(0.001)	(0.002)
7-12 years education	0.099***	0.041***	0.461***	0.238***
	(0.007)	(0.008)	(0.018)	(0.017)
13+ years education	0.318***		0.772***	
	(0.011)		(0.018)	
Age	0.046***	0.041***	0.120***	0.049***
	(0.003)	(0.004)	(0.001)	(0.003)
Age squared	-0.051***	-0.045***	-0.132***	-0.050***
	(0.004)	(0.005)	(0.001)	(0.004)
Non-citizen	-0.133***	-0.170***		
	(0.032)	(0.041)		
Hispanic			-0.108***	-0.202***
			(0.014)	(0.039)
Constant	5.282***	5.446***	3.595***	5.132***
	(0.067)	(0.080)	(0.023)	(0.060)
Observations	18706	11681	429897	22958
Adjusted R^2	0.095	0.048	0.186	0.057

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wages are net of HP filtered time trend. For education variables, the excluded group is those with less than 7 years of education. Columns (2) and (4) restrict to respondents with fewer than 12 years of education.

Table 8: CPS panel earnings regressions

	Dependent variable = change in weekly earnings			
	(1)	(2)	(3)	(4)
	Mexican	Mexican High school	Natives	Natives High school
Change in unemployment rate	-0.018***	-0.019***	0.002**	-0.002
	(0.005)	(0.006)	(0.001)	(0.005)
Age	-0.007	-0.007	-0.011***	-0.000
	(0.005)	(0.006)	(0.001)	(0.004)
Age squared	0.009	0.010	0.011***	-0.001
	(0.006)	(0.008)	(0.001)	(0.005)
Change in HP-filtered year trend	1.262***	1.409***	0.780***	0.953*
	(0.329)	(0.396)	(0.114)	(0.557)
7-12 years education	0.007	0.012	0.004	0.011
	(0.011)	(0.012)	(0.022)	(0.022)
13+ years education	0.000		0.015	
	(0.016)		(0.022)	
Constant	0.138	0.148	0.257***	0.039
	(0.093)	(0.112)	(0.027)	(0.078)
Observations	8830	5650	259774	11743
Adjusted R^2	0.004	0.006	0.002	0.000

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For education variables, the excluded group is those with less than 7 years of education. Columns (2) and (4) restrict to those with fewer than 12 years of education.

Table 9: Earnings regressions for documented and undocumented immigrants in the CPS

	Dependent variable=log earnings		
	(1)	(2)	(3)
	All	Undocumented	Documented
Unemployment rate	-0.005	-0.006	0.001
	(0.004)	(0.006)	(0.006)
7-12 years education	0.096***	0.078***	0.103***
	(0.018)	(0.025)	(0.025)
13+ years education	0.379***	0.371***	0.373***
	(0.027)	(0.041)	(0.036)
Age	0.063***	0.076***	0.059***
	(0.008)	(0.012)	(0.013)
Age squared	-0.072***	-0.094***	-0.065***
	(0.011)	(0.016)	(0.016)
Constant	4.865***	4.682***	4.942***
	(0.161)	(0.218)	(0.249)
Observations	3284	1510	1774
Adjusted R^2	0.082	0.082	0.069

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This is using the ASEC files in the CPS. Documented immigrants are identified using the criterion in Borjas (2016). Wages are net of HP filtered time trend. For education, the excluded group is those with fewer than 12 years of education.

Table 10: 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	-0.019**	-0.031**	-0.009
	(0.009)	(0.013)	(0.012)
Age	-0.015	-0.023	-0.008
	(0.009)	(0.014)	(0.013)
Age squared	0.020*	0.031	0.012
	(0.012)	(0.019)	(0.016)
Change in HP-filtered year trend	1.640***	1.050*	2.268***
	(0.420)	(0.628)	(0.571)
7-12 years education	0.010	0.008	0.014
	(0.019)	(0.030)	(0.026)
13+ years education	-0.011	-0.024	0.004
	(0.030)	(0.049)	(0.038)
Constant	0.284	0.438*	0.105
	(0.177)	(0.263)	(0.256)
Observations	2543	1147	1396
Adjusted R^2	0.010	0.007	0.011

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This is using the ASEC files in the CPS. Documented immigrants are identified using the criterion in Borjas (2016). For education variables, the excluded group is those with fewer than 12 years of education.

Table 11: Comparison with legal immigrant wages in the MMP

	Dependent variable = hourly wages			
	(1)	(2)	(3)	(4)
US Unemp. × Legal	-0.014	-0.018	-0.019*	-0.008
	(0.009)	(0.011)	(0.010)	(0.012)
US Unemp. × Undocumented	-0.016***	-0.015**	-0.029***	-0.017**
	(0.005)	(0.006)	(0.009)	(0.007)
Dummy for legal	0.108*	0.128*	0.085	0.075
	(0.064)	(0.076)	(0.078)	(0.073)
Age	0.010***	0.008*	0.020***	0.010***
	(0.003)	(0.004)	(0.005)	(0.003)
Age squared	-0.012***	-0.008*	-0.029***	-0.012***
	(0.004)	(0.005)	(0.006)	(0.004)
7-12 years education	0.049***	0.040**	0.021	0.045***
	(0.013)	(0.017)	(0.016)	(0.013)
13+ years education	0.072***	0.051*	0.063**	0.061**
	(0.025)	(0.030)	(0.032)	(0.026)
IRCA dummy variable	-0.064***	-0.074***	-0.143***	-0.076***
	(0.014)	(0.017)	(0.029)	(0.016)
No English		-0.102***		
		(0.014)		
Border enforcement				0.000
				(0.000)
Constant	2.117***	2.216***	2.146***	2.129***
	(0.071)	(0.101)	(0.107)	(0.081)
Observations	4240	2935	2324	3755
Adjusted R^2	0.030	0.045	0.056	0.034

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wages are net of HP filtered time trend. We eliminate the top and bottom 2% of the wage observations. For education variables, the excluded group is those with less than 7 years of education. IRCA equals 1 for years past 1986 and 0 otherwise. The variable "No English" takes value of one if they "neither speak nor understand" English and zero otherwise. The variable "Border enforcement" is sample average of hours (in ten thousands) spent patrolling the border. Column (1) and (4) use all men. Columns (2) restricts to male household heads. Column (3) uses all male wages within five years of each survey.

Table 12: US to Mexico migration decisions

	Dependent variable=1 if move to US			
	(1)	(2)	(3)	(4)
US unemployment	-0.001***	-0.001***	-0.001*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment in Mexico		0.000	0.000	
		(0.000)	(0.000)	
Lagged Mexican unemployment			-0.000	
			(0.000)	
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
7-12 years education	-0.006***	-0.007***	-0.007***	-0.007***
	(0.000)	(0.001)	(0.001)	(0.001)
13+ years education	-0.016***	-0.018***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Married	0.002***	0.002***	0.002***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
IRCA	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Border enforcement				-0.000
				(0.000)
HP-filtered year trend	1.126***	1.151***	1.204***	1.230***
	(0.048)	(0.096)	(0.110)	(0.202)
High migration community	0.012***	0.013***	0.013***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	382355	329364	321070	299249

Notes: Table reports marginal effects from a probit regression using the MMP data. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For education variables, the excluded group is those with less than 7 years of education. IRCA is a dummy variable that equals 1 for years after 1986 and 0 otherwise. The variable "Border enforcement" is hours (in ten thousands) spent patrolling the border.

Table 13: Return migration decisions

	Dependent variable =1 if return to Mexico			
	(1)	(2)	(3)	(4)
US unemployment	0.001	0.001	0.002	0.000
	(0.002)	(0.002)	(0.003)	(0.003)
Unemployment in Mexico		-0.002	-0.003	
		(0.002)	(0.003)	
Lagged Mexican unemployment			0.002	
			(0.003)	
Age	-0.010***	-0.010***	-0.010***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	0.008***	0.009***	0.009***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
7-12 years education	-0.064***	-0.063***	-0.063***	-0.061***
	(0.005)	(0.005)	(0.005)	(0.006)
13+ years education	-0.039***	-0.041***	-0.041***	-0.039***
	(0.010)	(0.011)	(0.011)	(0.011)
Married	0.063***	0.061***	0.061***	0.058***
	(0.006)	(0.006)	(0.006)	(0.006)
IRCA	0.005	-0.001	0.004	0.019
	(0.005)	(0.008)	(0.010)	(0.012)
Border enforcement				-0.001
				(0.001)
HP-filtered year trend	1.019***	1.003***	1.018***	1.460***
	(0.060)	(0.062)	(0.066)	(0.344)
Observations	33171	31664	31189	29701

Notes: Table reports marginal effects from a probit regression using the MMP data. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For education variables, the excluded group is those with less than 7 years of education. IRCA is a dummy variable that equals 1 for years after 1986 and 0 otherwise. The variable "Border enforcement" is hours (in ten thousands) spent patrolling the border.

Table 14: Elasticities in the data

	Dependent variable=log(X)		
	X=migration rate	X=immigrant stock	X=native employment
	(1)	(2)	(3)
US unemployment	-0.087**	-0.026*	-0.016***
	(0.040)	(0.013)	(0.003)
Share with 6 or fewer	-12.759	-0.357	
years education	(14.615)	(4.476)	
Share with 7 to 11	0.502	4.342	
years education	(17.508)	(5.453)	
Share with 12	-72.023**	-27.853***	
years education	(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	-1.040	-0.720**	
prevalent community	(0.989)	(0.336)	
Year 1980 to 1984	-0.656	-0.294	-0.388***
	(0.620)	(0.201)	(0.015)
Year 1985 to 1989	-0.622	-0.212	-0.295***
	(0.514)	(0.165)	(0.014)
Year 1990 to 1994	-0.506	-0.024	-0.215***
	(0.409)	(0.130)	(0.014)
Year 1995 to 1999	-0.163	0.056	-0.116***
	(0.281)	(0.089)	(0.015)
Year 2000 to 2004	0.102	0.074	-0.053***
	(0.213)	(0.066)	(0.015)
Constant	8.343	2.608	11.532***
	(13.903)	(4.303)	(0.025)
Observations	32	32	32
Adjusted R^2	0.898	0.971	0.977

Notes: 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 education variables, the excluded group is those with less than 7 years of education. For calendar year dummies, the excluded group is 2005 to 2011.

Table 15: Time-Invariant parameter values

Parameter	Notation	Value
Scaling parameter	α	0.30
Elasticity of substitution between natives and immigrants	$1/(1-\gamma)$	0.17
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	$\bar{N}$	2.01

Table 16: Moments

Moments	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 natives' total employment	κ_1^N	-0.0154	-0.0155

Table 17: Counterfactual 1: fixed immigrant stock

Dependent variable = immigrant wages		
	(1)	(2)
	Baseline	Counterfactual
Logged TFP	0.294***	1.699**
	(0.056)	(0.765)
Constant	1.139***	-4.567
	(0.224)	(3.084)
Observations	32	32
Adjusted R^2	0.466	0.113

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: Relationship between estimated TFP and US unemployment rate

Dependent variable = estimated TFP	
US unemployment rate	-0.046**
	(0.018)
Constant	4.320***
	(0.116)
Observations	32
Adjusted R^2	0.154

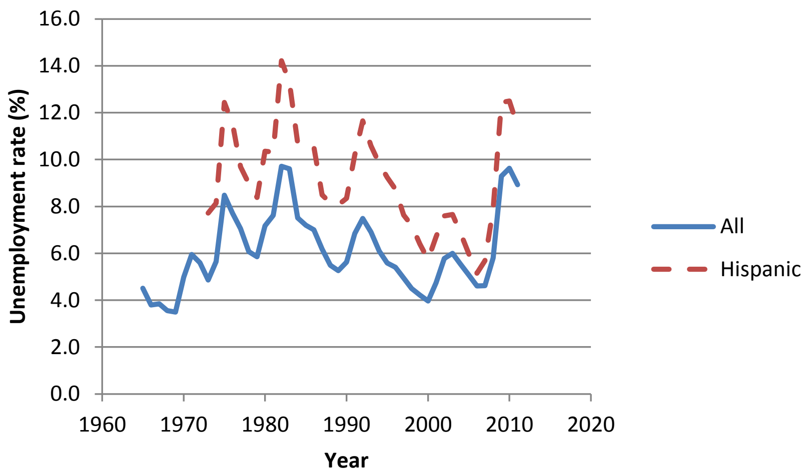
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Counterfactual 2: fix immigrants' wages

	Dependent variable = labor demand			
	(1)	(2)	(3)	(4)
	Native labor demand		Immigrant labor demand	
	Baseline	Counterfactual	Baseline	Counterfactual
Logged TFP	1.991***	2.791***	1.871***	2.810***
	(0.089)	(0.079)	(0.093)	(0.072)
Year 1980 to 1984	-0.170***	0.098**	-0.225***	0.091**
	(0.041)	(0.036)	(0.043)	(0.033)
Year 1985 to 1989	-0.125***	0.048	-0.159***	0.044
	(0.034)	(0.030)	(0.035)	(0.027)
Year 1990 to 1994	0.049	0.162***	0.016	0.149***
	(0.032)	(0.028)	(0.033)	(0.026)
Year 1995 to 1999	0.112***	0.138***	0.097***	0.127***
	(0.022)	(0.019)	(0.023)	(0.018)
Year 2000 to 2004	0.042**	0.028	0.042**	0.026*
	(0.019)	(0.017)	(0.020)	(0.015)
Constant	-7.669***	-10.983***	-7.029***	-10.918***
	(0.373)	(0.331)	(0.390)	(0.304)
Observations	32	32	32	32
Adjusted R^2	0.994	0.996	0.994	0.997

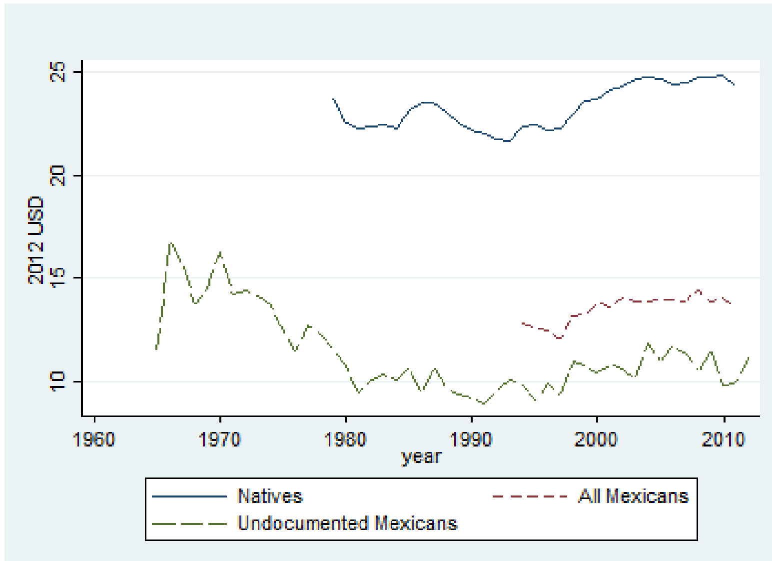
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. For calendar year dummies, the excluded group is 2005 to 2011.

Figure 1: US unemployment rate



Notes: Using data on people aged 16 and over from the CPS.

Figure 2: Hourly wages in the US



Notes: 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

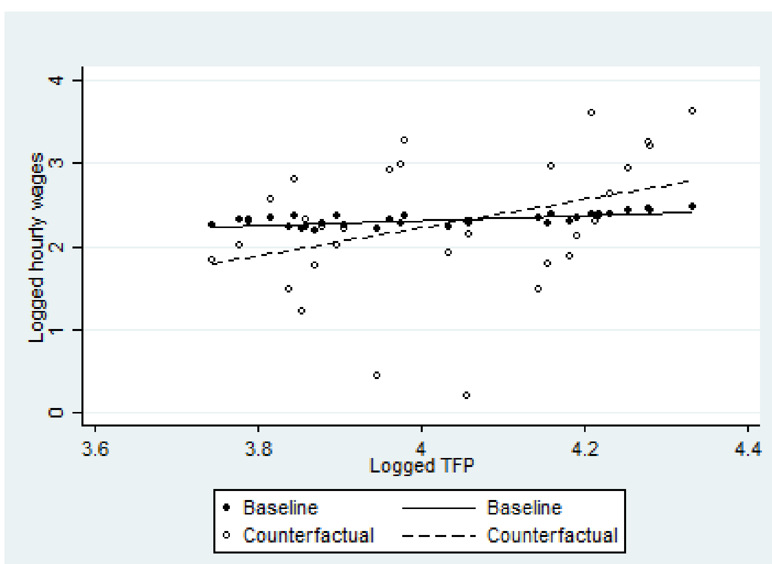
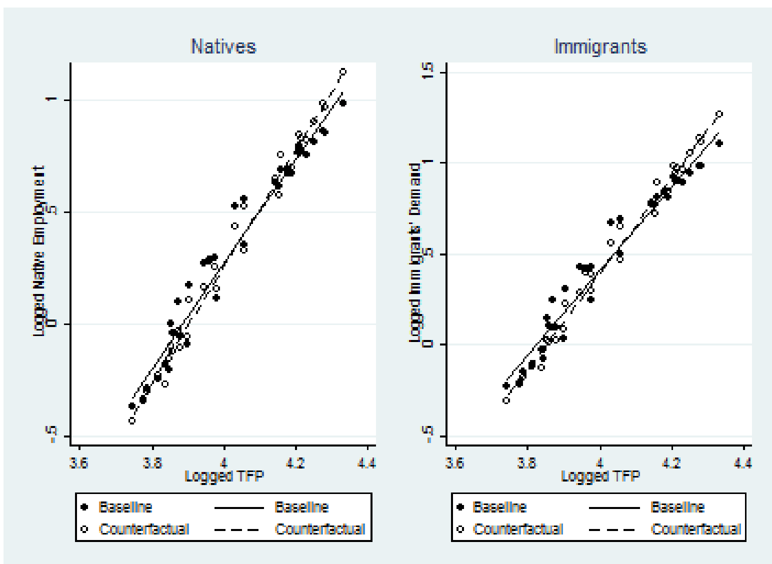


Figure 4: Counterfactual 2: firm's labor demand and TFP



Appendices

A. HP-filter calculation

To compute the time trend, we first regress $\log(w_{it})$ against year dummies and characteristics X_{it}, and obtain the coefficients on the year dummies. We then apply HP filtering to the coefficients on the year dummies so that we can decompose them into trend and cyclical components. We use year-by-year trend components as the time trend τ_t. When applying HP filtering, we set $\lambda = 6.25$, following Ravn and Uhlig (2001). We find a negative relationship between the coefficient on year dummies and unemployment rates. Our regression result is robust to how we control for the time trend. For example, consider an alternative method. We first regress $\log(w_{it})$ against X_{it} only, and then use the HP filtered time trend of the year-by-year average OLS residuals. This alternative time trend series shows almost identical patterns to the original time trend, and we obtain a similar estimated coefficient on the unemployment rate. We also consider an alternative method where use regress $\log(w_{it})$ against year-by-year trend components and X_{it}. We again find a similar estimated coefficient on the unemployment rate. We use this method when running probit regressions. We compute the time trend for other regressions analogously.

B. Robustness checks

B.1 Keeping respondents who stayed in the US for more than 15 months

Table B.1.1: Wage regressions

	Dependent variable = wages				
	(1)	(2)	(3)	(4)	(5)
	Hourly wages	Hourly wages	Hourly wages	Monthly wages	Hourly wages
US unemployment	-0.007**	-0.011**	-0.002	0.013	0.011*
	(0.004)	(0.006)	(0.004)	(0.009)	(0.006)
Age	0.012***	0.017***	0.011***	0.008	0.011**
	(0.003)	(0.005)	(0.003)	(0.006)	(0.004)
Age squared	-0.013***	-0.024***	-0.013***	-0.010	-0.013***
	(0.003)	(0.007)	(0.004)	(0.007)	(0.005)
7-12 years education	0.056***	0.041***	0.060***	0.050*	0.039**
	(0.011)	(0.014)	(0.011)	(0.026)	(0.017)
13+ years education	0.139***	0.136***	0.116***	0.089	0.087**
	(0.026)	(0.037)	(0.027)	(0.059)	(0.040)
IRCA	-0.023**	-0.066***	-0.017	-0.021	-0.037**
	(0.011)	(0.022)	(0.014)	(0.027)	(0.018)
No English				-0.150***	-0.118***
				(0.024)	(0.016)
Border enforcement			0.001**		
			(0.000)		
Constant	1.999***	2.012***	1.950***	7.274***	1.996***
	(0.056)	(0.091)	(0.063)	(0.149)	(0.099)
Observations	5983	2514	5106	2415	2470
Adjusted R^2	0.011	0.013	0.012	0.020	0.031

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use the MMP data. We drop the top and bottom 2% of wage observations. Wages are net of HP filtered time trend. For education variables, the excluded group is people with fewer than seven years of education. IRCA equals 1 for years after 1986 and 0 otherwise. The variable "No English" equals 1 if they "neither speak nor understand" English and 0 otherwise. The variable "Border enforcement" is sample average of hours (in ten thousands) spent patrolling the border. Columns (1) and (3) use all men. Columns (4) and (5) restrict to the last trip for the male household head. Column (2) uses all male wages within five years of each survey.

Table B.1.2: Wage growth

	Dependent variable = change in hourly wages			
	(1)	(2)	(3)	(4)
Change in unemployment rate	-0.016***	-0.015**	-0.025	-0.013
	(0.006)	(0.006)	(0.016)	(0.008)
Change in age	-0.002	-0.002	0.017	-0.012
	(0.007)	(0.007)	(0.054)	(0.010)
7-12 years education	0.043*	0.041	0.042	0.051*
	(0.026)	(0.026)	(0.037)	(0.026)
13+ years education	0.159**	0.156**	0.075	0.115*
	(0.065)	(0.065)	(0.089)	(0.067)
IRCA	-0.025	-0.054	-0.089	-0.020
	(0.030)	(0.043)	(0.064)	(0.045)
Change in border enforcement				0.002
				(0.002)
Year of first US migration		0.003	0.003	-0.003
		(0.003)	(0.005)	(0.004)
Conducted more than two trips		0.006	0.015	-0.007
		(0.025)	(0.044)	(0.027)
Change in HP-filtered year trend	0.802***	0.744***	-0.242	0.434
	(0.186)	(0.196)	(0.812)	(0.473)
Observations	1194	1194	264	898
Adjusted R^2	0.075	0.074	0.002	0.027

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use the MMP data. We drop the top and bottom 2% of wage observations. For education variables, the excluded group is people with less than 7 years of education. IRCA equals 1 for years past 1986 and 0 otherwise. The variable "Border enforcement" is the sample average of hours (in ten thousands) spent patrolling the border during each trip. Columns (1), (2) and (4) use all men. Column (3) uses all male wages within five years of each survey. Constant term and change in age-squared included but not reported.

B.2 State-level unemployment rate

Table B.2.1: Wage regressions

	Dependent variable = wages				
	(1) Hourly wages	(2) Hourly wages	(3) Hourly wages	(4) Monthly wages	(5) Hourly wages
State unemployment	-0.018***	-0.026***	-0.017***	-0.022**	-0.020***
	(0.004)	(0.006)	(0.005)	(0.010)	(0.006)
Age	0.008**	0.016***	0.008**	-0.001	0.010*
	(0.004)	(0.006)	(0.004)	(0.010)	(0.006)
Age squared	-0.010**	-0.023***	-0.009**	0.001	-0.013*
	(0.004)	(0.008)	(0.005)	(0.012)	(0.007)
7-12 years education	0.048***	0.017	0.050***	0.047	0.047*
	(0.015)	(0.019)	(0.015)	(0.038)	(0.024)
13+ years education	0.101***	0.092**	0.099***	0.150*	0.082
	(0.033)	(0.042)	(0.033)	(0.082)	(0.051)
No English				-0.159***	-0.130***
				(0.032)	(0.020)
IRCA	-0.023	-0.076***	-0.026	-0.058	-0.071***
	(0.015)	(0.027)	(0.016)	(0.037)	(0.023)
Border enforcement			0.000		
			(0.000)		
Constant	2.121***	2.147***	2.110***	7.657***	2.209***
	(0.076)	(0.110)	(0.078)	(0.222)	(0.137)
Observations	2802	1444	2760	1225	1252
Adjusted R^2	0.013	0.023	0.013	0.025	0.049

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use the MMP data. We drop the top and bottom 2% of wage observations. Wages are net of HP filtered time trend. State unemployment is the unemployment rate in the US state they are living in. For education variables, the excluded group is people with fewer than seven years of education. The variable "No English" equals 1 if they "neither speak nor understand" English and 0 otherwise. IRCA equals 1 for years after 1986 and 0 otherwise. The variable "Border enforcement" is sample average of hours (in ten thousands) spent patrolling the border during each trip. Columns (1) and (3) use all men. Columns (4) and (5) restrict to the last trip for the male household head. Column (2) uses all male's wages within five years of each survey.

Table B.2.2: Wage growth

	Dependent variable = change in hourly wages			
	(1)	(2)	(3)	(4)
Change in unemployment rate	-0.029***	-0.029***	-0.033**	-0.032***
	(0.008)	(0.008)	(0.015)	(0.008)
Change in age	0.005	0.000	0.037	-0.023*
	(0.010)	(0.010)	(0.068)	(0.013)
Change in age squared	-0.096*	-0.078	-0.273	-0.043
	(0.056)	(0.057)	(1.083)	(0.059)
7-12 years education	0.015	0.011	0.042	0.014
	(0.032)	(0.032)	(0.043)	(0.032)
13+ years education	0.057	0.049	0.055	0.057
	(0.087)	(0.087)	(0.091)	(0.086)
IRCA	0.050	0.011	0.076	0.021
	(0.038)	(0.053)	(0.074)	(0.053)
Change in border enforcement				0.008**
				(0.003)
Year of first US migration		0.005	-0.000	0.006
		(0.005)	(0.006)	(0.005)
Conducted more than two trips		0.043	0.020	0.056*
		(0.032)	(0.051)	(0.032)
Change in HP-filtered year trend	0.173	0.068	-0.264	-1.195*
	(0.271)	(0.304)	(0.860)	(0.674)
Constant	0.019	-9.363	0.200	-10.914
	(0.041)	(9.165)	(12.409)	(9.741)
Observations	438	438	148	428
Adjusted R^2	0.072	0.073	0.010	0.087

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These regressions use the MMP data. We drop the top and bottom 2% of wage observations. We use the unemployment rate in the state a person is living in. For education variables, the excluded group is people with less than 7 years of education. IRCA equals 1 for years after 1986 and 0 otherwise. The variable "Border enforcement" is the sample average of hours (in ten thousands) spent patrolling the border during each trip. Columns (1), (2) and (4) use all men. Column (3) uses all male wages within five years of each survey.

B.3 Multinomial logit regression

Table B.3.1: 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	0.006**	-0.015***	0.015***	0.001	-0.010***	0.003*
	(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.002)
Age	-0.009***	0.005	0.003	0.004***	(0.005)	0.002
	(0.003)	(0.004)	(0.004)	(0.001)	(0.003)	(0.002)
Age squared	0.016***	(0.007)	(0.003)	-0.005***	0.004	(0.004)
	(0.004)	(0.005)	(0.005)	(0.002)	(0.005)	(0.003)
7-12 years education	-0.134***	0.081***	0.032***	0.017***	0.003	0.000
	(0.009)	(0.009)	(0.010)	(0.002)	(0.009)	(0.004)
13+ years education	-0.305***	0.114***	0.064**	(0.023)	0.130***	0.020**
	(0.041)	(0.026)	(0.026)	(0.016)	(0.021)	(0.009)
Dummy for Primary	0.067***	0.021**	-0.032***	0.005**	-0.067***	0.005
	(0.007)	(0.009)	(0.008)	(0.002)	(0.008)	(0.004)
Dummy for Previous	0.034***	0.002	(0.003)	(0.005)	(0.008)	-0.021***
	(0.013)	(0.015)	(0.014)	(0.004)	(0.013)	(0.005)
IRCA dummy variable	0.047***	-0.117***	0.053***	0.004	(0.005)	0.017*
	(0.015)	(0.021)	(0.019)	(0.005)	(0.019)	(0.009)
HP-filtered Year Trend	1.240***	-1.724***	0.955***	0.098***	-0.433***	-0.136**
	(0.106)	(0.144)	(0.132)	(0.035)	(0.128)	(0.063)
Observations	12101	12101	12101	12101	12101	12101

Notes: Table reports marginal effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample is all men in the MMP. For education variables, excluded group is those with less than 7 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 zero otherwise. The variable "Dummy for Previous" equals 1 if the respondent was in the US last year and his occupation was the same as the the dependent variable and zero otherwise. HP-filtered year trend is the trend in the probability of being in an agricultural occupation.

C. Proofs

Remark 1. If c_2 or I_2^0 is sufficiently small, an equilibrium with $w_I > 0$ uniquely exists.

Proof: By substituting equation (9) into equation (8), it follows that

$$\begin{aligned} w_I &= z\psi[\theta \left(\frac{\theta}{1-\theta}\frac{w_I}{w_N}\right)^{\frac{\gamma}{1-\gamma}} I^{\gamma} + (1-\theta)I^{\gamma}]^{\frac{\psi}{\gamma}-1}(1-\theta)I^{\gamma-1} \\ I^D(w_I, w_N) &= \left\{ z\psi(1-\theta)\left[\theta\left(\frac{\theta}{1-\theta}\frac{w_I}{w_N}\right)^{\frac{\gamma}{1-\gamma}} w_I^{\frac{\gamma(1-\psi)}{(1-\gamma)(\gamma-\psi)}} + (1-\theta)(w_I)^{\frac{\gamma}{\gamma-\psi}}\right]^{\frac{\psi}{\gamma}-1}\right\}^{\frac{1}{1-\psi}}. \end{aligned} \tag{23}$$

Recall that the immigrant labor supply is given by $I_{US}^S(w_I) = p(MEX)I_1^0 + p(US)I_2^0$, and the equilibrium w_I is given by $I^D(w_I, w_N) = I_{US}^S(w_I)$. If $w_I = 0$, then $I^D > I^S$ (if c_2 or I_2^0 is sufficiently low). If w_I is very large, then $I^D < I^S$. Since the demand for immigrant labor is decreasing with respect to w_I and the supply of immigrants I_{US}^S increases with w_I, there is a unique equilibrium wage for immigrants w_I^*. □

Remark 2. If γ is a large negative number, $\frac{\partial N}{\partial z} < \frac{\partial N}{\partial z}|_{w_I=\bar{w}_I}$ where $\bar{w}_I$ is a constant. If γ is close to 1, $\frac{\partial N}{\partial z} > \frac{\partial N}{\partial z}|_{w_I=\bar{w}_I}$.

Proof By substituting for I in equation (7) using equation (9), it follows that

$$\begin{aligned} w_N &= z\psi[\theta N^{\gamma} + (1-\theta)\left(\frac{1-\theta}{\theta}\frac{w_N}{w_I}\right)^{\frac{\gamma}{1-\gamma}} N^{\gamma}]^{\frac{\psi}{\gamma}-1}\theta N^{\gamma-1} \\ N &= \left\{ z\psi\frac{\theta}{w_N}[\theta + (1-\theta)\left(\frac{1-\theta}{\theta}w_N\right)^{\frac{\gamma}{1-\gamma}}(w_I)^{\frac{\gamma}{\gamma-1}}]^{\frac{\psi}{\gamma}-1}\right\}^{\frac{1}{1-\psi}}. \end{aligned} \tag{24}$$

Therefore,

$$\begin{aligned} \frac{\partial N}{\partial z} &= \frac{1}{1-\psi}G^{\frac{1}{1-\psi}-1}\psi\frac{\theta}{w_N}\left[\theta + (1-\theta)\left(\frac{1-\theta}{\theta}w_N\right)^{\frac{\gamma}{1-\gamma}}(w_I)^{\frac{\gamma}{\gamma-1}}\right]^{\frac{\psi}{\gamma}-1} \\ &+ \frac{1}{1-\psi}G^{\frac{1}{1-\psi}-1}z\psi\frac{\theta}{w_N}(\frac{\psi}{\gamma}-1)\left[\theta + (1-\theta)\left(\frac{1-\theta}{\theta}w_N\right)^{\frac{\gamma}{1-\gamma}}(w_I)^{\frac{\gamma}{\gamma-1}}\right]^{\frac{\psi}{\gamma}-2} \\ &\times(1-\theta)\left(\frac{1-\theta}{\theta}w_N\right)^{\frac{\gamma}{1-\gamma}}\frac{\gamma}{\gamma-1}(w_I)^{\frac{\gamma}{\gamma-1}-1}\frac{\partial w_I}{\partial z} \end{aligned}$$

where $G \equiv z\psi \frac{\theta}{w_N} \left[\theta + (1-\theta) \left(\frac{1-\theta}{\theta} w_N \right)^{\frac{\gamma}{1-\gamma}} (w_I)^{\frac{\gamma}{\gamma-1}} \right]^{\frac{\psi}{\gamma}-1}$.

If γ is a large negative number, then $(\frac{\psi}{\gamma} - 1)\frac{\gamma}{\gamma-1} < 0$ so that the coefficient on $\frac{\partial w_I}{\partial z}$ is negative. Hence, $\frac{\partial N}{\partial z} < \frac{\partial N}{\partial z}|_{w_I = \bar{w}_I}$ under $w_I = \bar{w}_I$ (i.e. $\frac{\partial w_I}{\partial z} = 0$). This means that when immigrant and native labor are complements, the demand for native labor responds more strongly to productivity shocks when immigrant wages are fixed than when immigrant wages are flexible.

On the other hand, if γ is close to 1, then $(\frac{\psi}{\gamma} - 1)\frac{\gamma}{\gamma-1} > 0$ so that the coefficient on $\frac{\partial w_I}{\partial z}$ is a large positive number. Hence, $\frac{\partial N}{\partial z} > \frac{\partial N}{\partial z}|_{w_I = \bar{w}_I}$ under $w_I = \bar{w}_I$ (i.e. $\frac{\partial w_I}{\partial z} = 0$). This means that when immigrant and native labor are close to perfect substitutes, the demand for native labor responds more weakly to productivity shocks when immigrant's wages are fixed than when immigrant wages are flexible. $\square$